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Four essays on digital entrepreneurship: new ventures and ecosystems development

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Summary

Introduction

In recent decades, numerous innovations in the digital industry have led to major competitive tensions in global markets, such as Netflix versus Disney, Amazon's impact on bookstores, Uber's rivalry with taxis, Airbnb's disruption of the hotel industry, or even Spotify's conflicts with record labels. These confrontations highlight the big business clashes of our era, with new digital players aiming to challenge the monopoly rents of incumbents. Beyond global competition, concerns about data privacy and the corporate taxation of the digital industry emerge in our daily lives and have consequently become focal points in academic research (Corkery et al., 2013; Kerber, 2016). Policymakers, on their side, have proactively shaped external environments to foster digital innovation and entrepreneurship. Their commitment is rooted in the belief that digital technologies enable entrepreneurship (Sahut et al., 2021), who in turn, catalyze innovation, create jobs, and strengthen democratic stability (Audretsch and Moog, 2022; Autio et al., 2020; Balsmeier and Woerter, 2019). Highlighting this trend, Silicon Valley, home to digital industry giants such as Google, Apple, Facebook, and newcomers like OpenAI (ChatGPT), stands as the epitome of successful entrepreneurial ventures and digital innovation for policymakers (Hospers et al., 2009). As an illustration, on January 17, 2022, President Emmanuel Macron announced France's 25th digital unicorn (Source: Elysée.fr), praising such entrepreneurial ventures as "role models for the entire ecosystem", as they are a source of job creation (France-Digitale, 2023).

However, while role models significantly influence occupational and career decisions (Bosma et al., 2012), forms of digital entrepreneurial activities go far beyond the archetypal celebrated unicorns (Stam et al., 2011) and although we often hear of successful entrepreneurial stories, we rarely hear about the factors and conditions that help or limit them. On the one hand, the entrepreneurship landscape presents a variety of expressions (Matt and Schaeffer, 2018; Kapturkiewicz, 2022), each with its own interaction forces and unique micro-characteristics (Chowdhury et al., 2015). For instance, the landscape of business spans a diverse range. From unicorns (startups valued at over one billion US dollars, a term coined by venture capitalist Aileen Lee) and gazelles (rapidly growing companies), to necessity-driven entrepreneurs, family businesses, pioneers of Silicon Valley, bootstrapped startups, student or academic entrepreneurship and *intrapreneurial* firms, the challenges in business and technology are vast. Consequently, they require distinct financing methods (Klein et al., 2020) as well as specialized skills and knowledge (Wang et al., 2016). On the other hand, the heroic stories and narratives of self-made entrepreneurs have often overshadowed the interdependent actors, factors and conditions that enable and constrain entrepreneurship (Stam and Van de Ven, 2021). For instance, supporting institutions (Audretsch et al., 2021), financial and labour resources, technology, exit avenues, markets, infrastructures (Kapturkiewicz, 2022), industrial strategies, regulatory approaches on technological standards, and geographical considerations significantly influence the extent of entrepreneurial opportunities and their success. These observations underscore the importance of a cautious approach when studying entrepreneurship at the digital age. This thesis dissertation aims to meticulously explore very specific entrepreneurial "expressions" within *Digital Entrepreneurship* field and present fresh insights on two intertwined dimensions: one that is systemic in nature and another grounded in the micro-behavioral characteristics of individuals and firms.

Regarding the systemic dimension, the *Entrepreneurial Ecosystem* (EE) concept (Malecki, 2018; Mason and Brown, 2014; Stam, 2015) and its digital version, the Digital Entrepreneurial Ecosystem (DEE) (Sussan and Acs, 2017; Song, 2019), highlight the interdependence between actors and factors. In this perspective, entrepreneurial activity, defined as the creation of new value by individuals or entities, is viewed as the output of an EE, where entrepreneurial opportunities are rooted in specific markets, technologies, and places. Although in recent years the research community has generated numerous works and publications deepening the understanding of the systemic perspective on entrepreneurship, offering for example insights into the mechanisms of the EE (Wurth et al., 2023), we identified two gaps in the literature that are addressed in this dissertation. In a nutshell, the first one concerns the lack of understanding about the structuring of the research field around the concept of DEE, thus allowing us to explore through a socio-semantic analysis the way in which the scientific community organizes and collaborates. The second gap relates to understanding the multi-scalar and evolutionary forces behind the development of EE, which are nested in broader macro dynamics. These global dynamics include, for instance, battles over technological standards and the recent phenomenon of market *platformization* (Cusumano et al., 2008).

When looking at the micro-behavioral characteristics of individuals and firms' dimensions, much research has been conducted to identify the distinct characteristics inherent in successful entrepreneurial teams (e.g., Beckman et al. (2007); Colombo and Grilli (2005); Jin et al. (2017)). This was done by, in particular, studying the relationship between venture growth via the informational diversity-cognitive resources perspective (Harrison and Klein, 2007) or by studying the link between the fundraising of startup teams and the signaling value of human capital (Colombo, 2021; Courtney et al., 2017; Ko and McKelvie, 2018). However, here again, we identified two gaps in the literature that we address in this dissertation. On the one hand, much work has focused on skill diversity within *Top Management Teams* (TMTs) and its association with venture capital growth (Aboramadan, 2021; Eesley et al., 2014). However, a significant caveat remains when it comes to understanding the influence of other levels of an organization, notably *Middle Management Teams* (MMTs) and *Operating Core Workers* (OCWs), through the different stages of the evolution of the organization. On the other hand, as investors nowadays increasingly draw on a wide range of signals to assess the relevance of investing in a start-up team (Banerji and Reimer, 2019; Mollick, 2014), we identified a need for more in-depth investigation into the signaling role of skills diversity during the initial acquisition of financial resources phase for startups (Drakopoulos et al., 2020; Knight et al., 2020; Yan et al., 2019) Thus, anchored in the micro-behavioral characteristics of individuals and ventures, these investigations aim to shed light on the mechanisms that govern venture growth.

In summary, building upon the shoulders of giants, the objectives of this dissertation are twofold. First, by emphasizing the systemic dimension of entrepreneurship, we endeavor to elucidate the socio-semantic structure of the DEE academic field and the evolution and development of local EE embedded in broader technological market dynamics. Second, it seeks to examine the micro-characteristics of both individuals and firms in the digital era, specifically focusing on the nuanced effects of functional skill diversity across various organizational levels and phases of new venture development.

This thesis dissertation is organized as follows: first, in the introduction, we discuss the implications of the recent digital shift, define the *Digital Entrepreneurship* concept and position it within the literature. Subsequently, we present four chapters, each associated with a specific research question. We conclude with a summary of the main results, policy implications, and future perspectives.

The digital turn of entrepreneurship

Beyond a merely context

In recent years, the revolution of the New Information and Communication Technologies, coupled with the widespread use of the Internet, has reshaped the *techno-economic paradigm* (Perez, 2010), altering the *modus vivendi* of billions of people, transforming traditional businesses through the use of digital technologies, and offering new opportunities to entrepreneurs (Nambisan, 2017; Song, 2019). From a historical perspective, digitization has been a continuous force in the global business world since the early 1990s. For practical purposes, Zaheer et al. (2019) identified three phases of development of research: (i) *internet economy* (ii) *e-entrepreneurship* and (iii) *digital entrepreneurship*.

During the initial *internet economy* phase, the internet was concentrated on digitizing content, sharing information, and executing transactions. A perfect example of that is the success of companies like Yahoo! and eBay. According to Autio (2017) policy brief, the *Wintel* collaboration (i.e., the partnership between Microsoft and Intel, initiated in the early 90s) significantly influenced the internet economy at that time. Even though they had proprietary components like the Windows OS and Intel's chip designs, their open interfaces facilitated a wide-ranging contribution to software. Coinciding with the rise of the Internet, this ignited the 90s' *internet revolution*, transitioning the computer industry from a hardware-centric to a software-driven approach.

The subsequent phase saw an increased focus on interactivity, showcased by broadband, smartphones, and social media. The *e-entrepreneurship* phase was marked by the emergence of platforms such as Facebook (now known as Meta) in 2004 and Twitter (now known as X) in 2006. As highlighted by Autio (2017), the most recent impactful digital transformation started in the early 2000s, characterized by the introduction of the term "Web 2.0" in 2004, the launch of iPhone and Android between 2006 and 2007, and the proliferation of cloud computing, online storage, learning algorithms, and Big Data. These digital innovations enabled consistent, access to powerful data processing and storage for entrepreneurs. Overall, in these two phases, an increasing number of entrepreneurs exploited various digital opportunities, challenging regulated markets and the rents of historical operators, thus posing intensified competition and a tangible threat to "offline" businesses such as the US television sector or automotive industry (Ansari et al., 2016; Ferràs-Hernández et al., 2017).

However, following the dot-com bubble and the emergence of Web 2.0, the technological landscape shifted, leading to a global surge in entrepreneurial digital ventures. Today, major cities such as Paris, Cape Town, and Singapore, as well as countries labeled as *start-up nations*, feature robust *startup ecosystems* (Fraiberg, 2017). These ecosystems are home to hundreds of incubators, accelerators, and other entrepreneurial support infrastructures (Del Sarto et al., 2020). The catalyst behind this *digital entrepreneurial boom* (Elia et al., 2020) has been the foundational elements of digital services and products which have become flexible, affordable, and ubiquitous. Indeed, digital technologies can seamlessly be integrated and re-integrated: snippets of code, cloud computing, platforms, infrastructures and the Internet itself, which is now fast, universal, and wireless (Zaheer et al., 2019). As a result, startups adopted a *lean* approach (Ries, 2011): they no longer need to operate their own servers; they can outsource a significant portion of their operations, from software development to user testing, and they can continuously iterate to find a place in the market with their products. Indeed, during the Internet bubble boom, launching a startup was a substantial gamble based on a business plan; now, it is a continuous cycle of iteration and exploration until a market niche is discovered and exploited. Recent examples of these entrepreneurial digital ventures abound, such as GPS on smartphones through Waze (an Israeli startup), booking a medical appointment online with Doctolib (a French startup), online shopping with Alibaba (from China), watching live professional video gaming achievements on Twitch (from the USA) and enhancing productivity with LLM-based tools like ChatGPT from OpenAI (from the USA) (Dell'Acqua et al., 2023). Therefore, by now, aside from stock market listings (IPOs), acquisitions of startups, and the dizzying valuations of unicorns, the digital turn goes beyond a merely context. Indeed, this third phase, termed *digital entrepreneurship*, witnessed a transition to pervasive connectivity and the transformation of digital business models (Blank, 2005), and leading digital enterprises during this phase, such as Uber and AirBNB, harnessed the adaptability, generative properties, and network effects of digital technology to swiftly establish substantial user and customer bases (Huang et al., 2017; Sun et al., 2004).

Defining Digital Entrepreneurship

Given the far-reaching implications of the recent digital turn, it is unsurprising that the discourse surrounding *digital entrepreneurship* has piqued significant academic interest. However, the concept of *digital entrepreneurship* has been defined in various ways over the recent years, and the definitions have seen a transformation as technology, society, and research in the field evolves.

For example, the definition from Kollmann focused on the use of the Internet and electronic platforms to create new products and services: *"E-entrepreneurship refers to establishing a new company with an innovative business idea within the net economy, which, using an electronic platform in data networks, offers its products and/or services based upon a purely electronic creation of value."* (Kollmann, 2006, p.333). Later on, the definition from Sussan and Acs shifted and incorporated the concept of entrepreneurial agents and ecosystems, which is a more comprehensive perspective of digital entrepreneurship: *"Digital Entrepreneurship is the combination of digital infrastructure and entrepreneurial agents within the context of both ecosystems."* (Sussan and Acs, 2017, p.26). Complementing this definition, in 2017, Nambisan further elaborated on the concept, defining digital entrepreneurship as occurring *"at the intersection of digital technologies and entrepreneurship"* (Nambisan, 2017, p.1). Concurrently, Sahut and colleagues contend that *digital entrepreneurship* definitions can be *bifurcated into* *two primary categories: "digital technologies as enablers" and "digital technologies as both enablers and outputs"* (Sahut et al., 2021, p.2).

Therefore, in this dissertation, we propose defining *digital entrepreneurship* as the process of creating value through the utilization of digital technologies and business models. This process, for instance, encompasses the development of new products and services, leveraging data to optimize operations, and the establishment and/or use of platforms and ecosystems.

Positioning the Digital Entrepreneurship field in the literature

The entrepreneurship phenomenon is influenced by numerous variables, spanning an extensive range of determinants, from economic and historical to psychological, sociopolitical, and cultural. Therefore, it is clear that no single field of study can lay exclusive claim to a comprehensive understanding this phenomenon. For instance, psychology as a discipline has dedicated study to the motives and characteristics inherent in entrepreneurs. Sociology, on the other hand, has probed into the collective origins of entrepreneurs, while economics has ventured into exploring the mechanisms of evolution and innovation. In this context, Sahut and his colleagues have emphasized that *digital entrepreneurship* (DE) has garnered significant attention in the literature, and that *"digital entrepreneurship the object of several reviews and special issues arising from different disciplines including: (i) information systems (Du et al., 2018); (ii) innovation (Nambissan et al., 2018); (iii) management and business (Berger et al., 2015; Lanzolla et al., forthcoming); (iv) policy (Nambisan et al., 2019); and (v) strategy (Autio et al., 2018)."* (Sahut et al., 2021, p.2). Consequently, the variety of academic domains contributing to this research area indicates a scattered progression, with each having unique study scopes and boundaries. As a result, as the multidisciplinary and multi-theoretical advancements proliferate, there emerges an abundance of academic opportunities to consolidate the sprawling literature and gain a comprehensive understanding of *Digital Entrepreneurship.*

In this thesis, we suggest positioning the *Digital Entrepreneurship* field of study at an intersection of two dimensions, the spatio-temporal & technological systemic dimension and the micro-behavioral characteristics of individuals and firms. On the one hand, inspired and informed research on industrial districts and agglomerations, clusters, and systems of innovation that suggest an articulation of digital and spatial affordances in EE development (Autio et al., 2018), this perspective suggests that digital opportunities and global market dynamics have consequences on places (Feldman et al., 2021), and that this, along with its associated information technology mechanisms, is therefore contingent upon factors such as spatial competition, monopolistic regulatory oversight, technological standards, and network externalities (Katz and Shapiro, 1985). On the other hand, because business model's innovation is a critical determinant of the productivity for nascent entrepreneurial firms in the digital age (Nambisan, 2017), and because such innovation depends on resources orchestration to create competitive advantage (Sirmon et al., 2011), inclusive of but not limited to human and financial capital (Cooper et al., 1994; Crook et al., 2011), we argue that entrepreneurship relies on micro-level complex decision-making processes rhythmed by venture life cycles.

Navigating the facets of Digital Entrepreneurship

The systemic and micro dimensions in Digital Entrepreneurship

As instilled in the very first part of the introduction, the way of apprehending the concept of *Digital Entrepreneurship* differs depending on whether we adopt a perspective centered on the system or on the micro characteristics of individuals or firms. The challenge of this thesis lies in adding new perspectives to the systemic levels and micro factors. Typically, the bridge between two realms has been built through aggregation. Nonetheless, emphasizing various analytical prisms within a same discipline often spawns disparate lines of research that maintain internal coherence but lack comprehensive integration. Consider physics: it robustly explores both quantum mechanics and relativistic paradigms separately. To put it simply, quantum mechanics investigates phenomena at extremely fine scales – spanning atomic to subatomic levels. Relativistic paradigms, however, encompass a wider analytical spectrum – covering celestial entities from stars to galaxies. However, beyond their divergent focal points, these viewpoints are inherently antithetical in their foundational principles. Furthermore, even if elements like time are consistently present, each segment interprets such elements distinctively.

Similar fragmentation can be observed in the field of *Digital Entrepreneurship*. However, the objective of this thesis is not to harmonize these levels; instead, by exploring the systemic nature and the micro-behavioral characteristics of individuals and firms, our purpose is to accurately identify and fill some important gaps in the literature and thus participate in collective academic efforts.

On the one hand, vibrant debates within the field of entrepreneurial economics focus on the advent of digitization and its consubstantial implication for entrepreneurship (Nambisan, 2017; Zaheer et al., 2019; Sahut et al., 2021). For instance, Autio (2017) highlighted substantial shifts in entrepreneurial methodologies and approaches, asserting that digitization not only re-delineates the nexus of entrepreneurial opportunities within the economy but also redefines optimal strategies for capitalizing on these opportunities. This has catalyzed the emergence of Entrepreneurial Ecosystems – a distinct cluster type, where knowledge assumes a different role – which shape the interactions among individuals, firms, and other socio-economic stakeholders and institutions (Autio et al., 2018; Spigel and Stam, 2018). Besides there being no generally accepted definition of what an Entrepreneurial Ecosystem is, a large part of the community agrees on their constituent elements, their interactions, the multiscalarity that characterizes any ecosystem (Stam and Van de Ven, 2021). By synthesizing perspectives from seminal concepts – the Digital Ecosystem as refined by Song (2019), and the Entrepreneurial Ecosystems (EE) Spigel and Stam (2018) culminating in its digital variation, the Digital Entrepreneurial Ecosystem (Sussan and Acs, 2017; Song, 2019; Bejjani et al., 2023) – Digital Entrepreneurship integrates the systemic dimensions and interplay amongst, for example, the digitization of the multi-sided markets (Rochet and Tirole, 2003; Cusumano et al., 2008) or the governance of digital infrastructures and regulation of technological standards (Mansell and Steinmueller, 2020). Said differently, the systemic perspective of Digital Entrepreneurship concepts call into question the individual and firm-centric dimension prevailing in the entrepreneurship literature. Yet, though the focus on individuals or firms has enriched the Digital Entrepreneurship field of study, it has overshadowed the complexity of today's digital framework, bypassing the systemic conditions of entrepreneurship. However, the "systemic frameworks" present notable blind spots. For example, there is a need for investigations into several issues, including the role played by digital technologies within these ecosystems, their implications for the structuration of research communities, and how digitization has reshaped the entrepreneurial landscape and the competitive dynamics inherent to these ecosystems. These inquiries, among others, are of great interest in current academic research.

On the other hand, if holistic concepts strengthen the understanding of the systemic dimension of Digital Entrepreneurship, it is also necessary to examine the micro dimensions that drive it (Marvel and Lumpkin, 2007). In this part of the literature, investigations have focused on, for instance, the individual decision-making process (Knight et al., 2020) or the motives of individuals towards self-employment trajectories (Raffiee and Feng, 2014). Therefore, this perspective narrows down on personal determinants of entrepreneurship and firm growth such as psychological attributes, academic pedigree, competencies, financial assets, familial legacies, and antecedent professional engagements. For instance, skills and knowledge are known to empower founders to undertake larger risks and exhibit proactive behavior (Becherer and Maurer, 1999), thereby optimizing business opportunities (Shane and Venkataraman, 2000). In the same vein, empirical work shows that skills proficiency also equips entrepreneurs to secure resources beyond the financial realm, a common challenge for firms in early developmental stages (Beckman et al., 2007). Thus, individuals' micro characteristics such as skills and knowledge serve as foundations for entrepreneurial learning and growth, supplementing the firm's capability to acquire further resources necessary for expansion and development. However, the prevailing works exhibit inconclusive findings on the effects of skills and knowledge diversity on venture performance, particularly when addressing through a diversity-cognitive resources perspective (Harrison and Klein, 2007). Indeed, besides adding moderating and contextual variables in an attempt to clarify this relationship (see e.g., Hmieleski and Ensley (2007)), until recently, the depth and scope of the impact of diversity on growth in venture-backed digital firms, a specific entrepreneurial "expression", remained a lingering debate in academic spheres. Again here, pending investigations such as the role of specific skill sets diversity in shaping the trajectory of digital firms or performance remain important inquiries in ongoing academic discussions.

Research questions

In this thesis, we aim to provide four unique contributions corresponding to a distinct gap spotted in the *Digital Entrepreneurship* field related to one of the two dimensions detailed in the previous section.

On the one hand, central to the systemic perspective are the principles of interaction, temporality, and inherent dynamics. Within this context, we put forth two research questions: *(i)* Within a socio-semantic network framework, how is the scientific community structured around the concept of Digital Entrepreneurial Ecosystems? And *(ii)* how do global technological competition and regulatory dynamics mutually influence the formation and evolution of local Entrepreneurial Ecosystems?

On the other hand, anchoring the discussion in micro-level determinants, we advocate for an understanding of entrepreneurship as fundamentally springing from individual actions. This perspective does not overshadow the pertinence of macro-level considerations but rather situates the essence of entrepreneurship within individual behaviors and characteristics. This leads us to two other research inquiries: *(iii)* What are the impacts of functional skills diversity across different organizational levels and stages of a new venture development in the Digital Industry? And *(iv)* how do online skill endorsements level and variety shape the ability of start-up teams to secure early-stage venture funding?

Outline of the thesis

Chapter 1 offers a socio-semantic exploration of Digital Entrepreneurial Ecosystems (DEE) research community. The motivation behind this chapter is to untangle the intricate layers of co-authorship and semantic content shaping the DEE literature, up to the year 2023, thus offering a complement to qualitative state-of-the-art reviews. By discerning communities and their inherent semantic nuances, we detail the idiosyncratic scientific character of different areas of scientific authority that shape the research community. The results suggest that the scientific field of DEE is characterized by a rich range of themes and disciplines, although with limited integration, as it is largely anchored on a restricted set of contributions linking these different areas of authority. This fragmented academic cohesion is further corroborated by collaboration patterns showing assortative behaviors within communities and by certain semantic bridges between cohesive groups, signifying an emerging effort towards an integration process. Additionally, the analysis reveals overlapping semantic areas within certain pairs of communities, indicating shared research inquiries addressed by distinct and loosely connected communities. However, the two predominant communities, although partially interacting with other communities, lack common semantic foundations. As academic research evolves, it remains to be seen whether this divergence is "a network failure" or stands as a testament to the dynamic nature of scientific evolution.

Chapter 2 goes deeper into the practical implications of the systemic dimension of Entrepreneurial Ecosystems (EE) with the purpose to understand how the structure and evolution of EEs are shaped by, and in turn influence, the broader dynamics of the technology market in which these EEs are nested. In this chapter, EEs are viewed as systems directly linked to entrepreneurial opportunities opened up by market *platformization*. In order to capture this kinetics of interactions, we employ the Historical Event Analysis (HEA) approach, and bridge the gap between qualitative investigations and systematic data modeling on EEs. We apply this methodology to the case study of IoT Valley in Toulouse, France, a digital EE specialized in Internet of Things (IoT) technologies. The results reveal that omitting the mechanisms of digital platforms when searching for critical drivers of local EE evolution, may result in a considerable misinterpretation of how EE evolves over time. Furthermore, we illustrate how a blockbuster firm, based in a local EE, relies, in the context of a global battle for standards, on a set of varied actors at different geographical levels. Such insights enable us to assert that beneath the global battle over technological standards lies a hidden battle between places, and that the dynamics of an EE driven by a blockbuster firm can enter a virtuous circle of self-reinforcement created thanks to the increasing returns of adoption and the network externalities stemming from its position as a digital platform.

Chapter 3 transitions from the systemic nature of *Digital Entrepreneurship* to that rooted at the micro level. By drawing on the problem-solving perspective, the objective of this chapter is to understand how functional skill diversity influences venture development. Instead of just looking at top management as most previous studies did, we include middle managers and core operational workers' skill diversity. Additionally, we consider the venture's financing stage, because it influences the challenges the firm faces and subsequently affects how diversity impacts the firm. Therefore, we propose a multi-level framework that links functional diversity at top, middle, and operational levels to new venture growth over time. Using a dataset from France's digital sector (2010-2020) with 296 venture capital-backed companies in Greater Paris, we find that an exclusive focus on top management could potentially be overemphasized, especially when other organizational layers are disregarded. Furthermore, we show that making the distinction between funding stages is crucial in understanding the diversity-growth relationship. Last but not least, we developed a robust and fully replicable classification of skill and therefore illustrate the potential of LinkedIn's skill endorsement data to address some limitations in skills-related research diversity in management and organizational sciences.

Finally, **chapter 4**, by focusing on signaling theory, human capital literature, and cognitive psychology, analyzes the influence of "online skill endorsements" - peer-reviewed indicators of human capital available on professional social networks that signal a team's expertise - on the likelihood of securing funding from investors. This chapter presents an empirical analysis of 439 French start-ups and goes into the specific question of whether a high level of skills endorsed and a broad variety of skills endorsed impact the fundraising of start-up teams. Findings suggest that investors favor start-up teams that have either a high level of skills endorsed or a high level of variety of skills endorsed, but not both at once. Such findings deepen our understanding of the nuanced role that online skills endorsement play as an additional layer of human capital representation, shedding light on their signaling effects during the initial stages of fundraising, and on its potential to complement other metrics of human capital (e.g., a diploma or previous job experiences) commonly used in entrepreneurship research. This paper also illustrates the potential of skill endorsement data in LinkedIn in addressing some significant limitations in diversity-related research in management and organizational science.

Chapter 1

How is the literature on Digital Entrepreneurial Ecosystems structured? A socio-semantic network approach

The paper provides a socio-semantic analysis of a scientific field which is of a growing importance to the academic community and policy makers: the field of digital entrepreneurial ecosystems. The purpose is to understand the way in which the ideas, theories and knowledge domains that nourish the field are structured. For this, we propose a methodology that combines the analysis of the structural properties of the coauthorship network with the semantic specificities that shape the sub-communities that interact within the field. The results show that despite the sign of a scientific integration, some key scientific issues on digital entrepreneurial ecosystems remain under-explored. We conclude on the importance of the method to identify knowledge gaps to be filled and better frame private and public incentives for future collaborations.

This manuscript has been submitted to a WoS journal.

In this chapter, my responsibilities were allocated as follows:
- Paper design and writing: 40%
- Empirical design and findings discussion: 25%
- Data collection and cleaning: 20%

1.1. Introduction

After exponential growth from 2015 to 2019, the research on *Entrepreneurial Ecosystems* (EE) (Spigel and Stam, 2018; Wurth et al., 2023) and their variation in *Digital Entrepreneurial Ecosystem* (DEE) (Autio et al., 2018; Sussan and Acs, 2017; Song, 2019; Bejjani et al., 2023) has reached maturity in 2020 with about 250/300 papers per year in Web of Science (WoS) journals until 2023. The concept has given new impetus to research on entrepreneurship (Nambisan and Baron, 2013), market and industry platforms (Gawer and Cusumano, 2014; Hein et al., 2020), the servitization of the economy (Lusch and Nambisan, 2015; Kohtamäki et al., 2019), and urban and regional development (Stam, 2015; Audretsch and Belitski, 2017; Li et al., 2023).

There is no more consensus of the definition of EEs (Acs et al., 2017; Cavallo et al., 2019a) than on that of DEEs, but a large literature on their constituent elements (Alvedalen and Boschma, 2017; Stam and Van de Ven, 2021). The characterization of Sussan and Acs (2017) refined by Song (2019) represents a clear delimitation of what a DEE is. They suggest crossing EEs with digital ecosystems (DEs). According to them, the study of the interactions between the digitization of markets, the governance of digital infrastructures, the digital uses, and the digital turn of entrepreneurship, constitute the elements of a general framework. Each of these blocks is a research program which calls for others. For the first two, for example, the digitization of markets calls for research in business strategy and industrial organization of platforms and multi-sided markets (Rochet and Tirole, 2003; Cusumano et al., 2008), the second for research in regulation of technological standards (Mansell and Steinmueller, 2020; Bessagnet et al., 2021; Jenny, 2021). The interaction and the multiscalarity of these blocks suggest a broad field of research built from different knowledge backgrounds (Wurth et al., 2023).

Several state-of-the-art papers have been proposed. The most diffused ones value different starting points and weights to the digital dimension, from the search of the drivers of performance in competing DEE (Hein et al., 2020), to the changes in entrepreneurial dynamics related to digital turn (Autio et al., 2018), until the capture of scientific antecedents of the concept (Cavallo et al., 2019a), or the new drivers of regional growth (Stam, 2015; Malecki, 2018). The coexistence of these review papers reveals a scientific enthusiasm for the topic, and results in new priorities in public policies. But it could mask a risk: a too fuzzy concept that would limit the rigor of an evaluation framework (Acs et al., 2017). Like clusters in previous decades (Martin and Sunley, 2003), this risk relates to the dissemination of a buzzword concept with fragile foundations. Looking for the links and bridges between the different origins of the concept is a way to partially remedy it.

Thus, we suggest applying scientometrics tools to analyze the socio-semantic structure of DEE research community. This way of proceeding has already been implemented, including for EEs (Zhang and Guan, 2017; Kang et al., 2021; Theodoraki et al., 2022; Bejjani et al., 2023). In this contribution we suggest going further on three points. First, on the methodological side, we consider co-authorship-based network analysis (Moody, 2004; Battiston et al., 2016) instead of co-citations or bibliographic coupling. To put it differently, we overvalue social on knowledge communities, and then scientific collaborations on knowledge flows. If citations are the most visible mark of the flow of knowledge, they cannot be that of social relations. Are we producing new knowledge with all the authors we cite? And if we collaborate with some of them, are those with whom we never collaborate part of our community? If citations are the most appropriate indicator to measure the flow of knowledge that irrigates a scientific community, they are only the proof of the use and absorption of existing knowledge, and not that of collaboration for generating new ideas. Second, still methodologically, we consider that coupling semantic and structural dimensions of networks requires caveats and more sophisticated methodologies than those used previously. Following Roth and Cointet (2010) and Raimbault (2019), we show how to better control and distinguish the semantic specificities which characterize sub-communities at a finer grain. Third, we consider DEE publications until 2023 with a large part of publications produced during the mature phase between 2021 and 2023, while prior studies considered publications up to early growth phase. We defend the idea that such a scientometric analysis can reconcile existing qualitative state-of-the-art reviews and solidify the foundations of a concept increasingly central in the rhetoric of practitioners and policymakers.

The dynamics of scientific networks received a growing attention since the work of Newman (2001, 2004), with some key features of collaborative patterns, such as preferential attachment and the resulting hierarchy in the distribution of the social position of authors, or a structural homophily in relational behaviors giving rise to highly assortative structure of collaboration, just to name a few. Beyond these general patterns, some noticeable deviations from general principles may appear. Studying a scientific network in a broad disciplinary field in which several paradigms compete, or studying a specific concept on which several disciplines converge, can lead to more complex structures where several communities coexist and evolve together towards more or less connectivity (Moody, 2004). To deal with this, semantic features of the nodes of the network become essential, because the dynamics of collaboration respond to social but also cognitive mechanisms, which can influence one another (Roth and Cointet, 2010; Raimbault, 2019). DEE is a good candidate for such a socio-semantic network approach since the concept enters a clear perimeter of keywords from different literature backgrounds (Song, 2019), from which a particular articulation of the associated communities can be expected.

The paper is organized as follow: Section 1.2 introduces the research by analyzing the multiple origins of DEEs and presenting the methodological caveats of scientometrics for community detection and socio-semantic analysis. Section 1.3 presents the primary database of publications, the protocol for filtering scientific contributions, and the construction of the socio-semantic network. It also presents the descriptive statistics of the network, where the publications are the events (the vertices) linked by common authors (the edges). Section 1.4 offers an analysis of the social dimension of the network, focusing on the global structural properties of the network. Section 5 goes one step beyond by linking the structural and semantic dimensions, through an analysis of the semantic specificities within and between communities. Section 6 discusses all the results, pointing out the contribution of our methodology to traditional state-of-the-art reviews, as the limits and possible extensions.

1.2. Capturing the structuring of DEE research community: literature overview and scientometric caveats

1.2.1. The scientific common good of the EE research community and the emergence of the DEE community

1.2.1.1. *Entrepreneurial Ecosystems* (EE)

The EE concept has been widely documented in the 2010s since the work of Isenberg (2010) and Adner (2017), with a growing attention on its theoretical foundations to avoid its fuzzy character Theodoraki et al. (2022). Many definitions coexist and it seems unproductive to choose a too slack median, since our study seeks to understand how these different origins could be articulated. However, several significant contributions give attributes to the concept and delimit its scope, which helps positioning the concept in a space of related literatures. The scientific "common good" of the community is about accumulated knowledge on the constituents that foster (and scale) entrepreneurship. From this common good, the authors develop the constituents by giving content to the biological metaphor of ecosystem (Cavallo et al., 2019a). For some contributors, the notion of ecosystem will refer to complex multi-actor technological environments in which entrepreneurial opportunities occur. In that context, strategies of coopetition, interoperability, modularity or standardization play a critical role in technological competition and ecosystems success (Gawer and Cusumano, 2014; Teece, 2018; Bessagnet et al., 2021; Kretschmer et al., 2022; Nylund and Brem, 2023). For others, the notion of ecosystem will rather emphasize the role of contextual elements producing entrepreneurial incentives. These elements gather different resources and institutions that enter explanatory variables of EEs performance (Spigel, 2017; Audretsch et al., 2021; Stam and Van de Ven, 2021; Lechner et al., 2022).

These constituents and their interactions are applied at a plurality of possible scales. Some of the research integrates EEs at the industry level. Studies on healthcare (Schiavone et al., 2021), media (Ansari et al., 2016), tourism (Eichelberger et al., 2020; Santos et al., 2022), are among the many industries documented in the literature. Other research goes beyond the scope of an industry to focus on the regional and/or urban level and promote the digitization of services as a driving force for innovation and value creation. Thus, several works on smart cities (Gorelova et al., 2021; Linde et al., 2021) or the renewal of regional innovation policy (Stam, 2015; Audretsch and Belitski, 2017; Carayannis et al., 2018; Szerb et al., 2019) call on the literature on EEs or DEEs as a driving force of growth and efficiency in urban and regional policy.

1.2.1.2. *Digital Entrepreneurial Ecosystems* (DEE)

The DEE concept appears in 2017, and remains less documented, although the contributions of Sussan and Acs (2017) and Song (2019) have thoroughly – and more strictly than for EE – defined and delimitated its scope. Its degree of separation and/or embeddedness with EEs questions the community. On the one hand, the digital dimension differentiates DEEs from EEs by their technology dimension, so that they can be considered as a specific type of EE. On the other hand, the digitization of the economy enables transformations of the entrepreneurial process and becomes the central driver of the development of EEs themselves, so they are the natural extension of EEs at the digital age. In the first case, new digital technology is at the heart of the business. New ventures emerge, develop, and orchestrate technological ecosystems whose they are the leading player in some digital markets such as IoT, cloud technologies or AI. In the second case, the use of digital technologies to develop communities of users becomes the engine of value creation, more than the development of the technology itself. In that case, the ecosystem values the development of market and social interaction platforms, and entrepreneurial opportunities are more market than technology based. Very often, the two models cross the same ecosystem, when the players combine the two ambitions (Bessagnet et al., 2021).

The DEE concept emerged with the deployment of digital platforms, which are disrupting both the industrial organization in many sectors and the business models for creating value. They foster growth capabilities for established digital players (Song, 2019), open transformative opportunities for some incumbents in other industries (Ferràs-Hernández et al., 2017), and initiate a wave of new ventures involved in the platform development. On the side of the industrial organization, the need to integrate complementary technological bricks to offer complete systems around standardized and modular interfaces has led to the emergence of what Nylund and Brem (2023) call the "ecosystem-based standards". As digital platforms develop, the embodiment of technology moves from the firm to the platform ecosystem (Gawer and Cusumano, 2014). Complementary entrepreneurs and the platform sponsor involved in the ecosystem can increase their profit as new ventures enter and bring complementary assets (Teece, 2018). On the side of value creation and business models developed by DEEs, the monetization of network externalities, whether direct between users or indirect between users and service providers, prevails in the scaling capacities of platforms. Depending on the type of technology platforms, users can be simple consumers in multi-sided markets in which the platform creates value through its disintermediation function. However they can also become digital entrepreneurs entering the ecosystem, when they propose technological improvements and innovations likely to further increase demand (Evans and Gawer, 2016).

1.2.1.3. *Are EEs not digital?*

But does the diffusion of the DEE concept since 2017 mean that the concept of EE was not intrinsically connected to the digital dimension? A close look shows that most research on EEs was already based on the digital traits of entrepreneurial opportunities, without directly mobilizing the concept of DEE. That is the case in papers centered on technologies and industries. Across a wide range of domains, from transportation to tourism, to advertising and healthcare, or finance and culture, many EE entitled empirical contributions have emphasized on how entrepreneurial ecosystems were enabled by the digital turn. Several contributions highlighted the way in which digital technologies gave rise to EEs and shifted the analysis of innovation and value creation from the firm toward this larger scale. Among these contributions, Ferràs-Hernández et al. (2017) captured the formation of EEs in the automotive industry with the rise of connected cars technologies that push OEMs to develop and orchestrate digital technology platforms. Ansari et al. (2016) observed the same phenomenon by analyzing how the US television incumbent's business models have been transformed by new digital ventures developing demand-driven instead of network-centric programs. Even though installed in traditional industries, the main driver of value creation within these EEs relied jointly on the technological development of digital platforms and their specific business model based on the capture of direct and indirect network externalities.

On the contrary, when we look at research on EEs prior to the diffusion of the DEE concept through the contributions on regional and urban analysis, the digital traits were much less obvious. Except very specific contributions on smart cities which explicitly link the emergence of EEs to digital solutions for the sustainable management of cities, research in Regional Sciences and Geography of Innovation remains on a more global approach to local conditions conducive to EEs. Digital technologies enter a large set of drivers that interact to foster entrepreneurship (with culture, amenities, human and venture capital, openness, ...) but as available technologies for new ventures in different fields and not as the technological output of emerging EEs (Stam, 2015; Audretsch and Belitski, 2017; Bruns et al., 2017).

Therefore, the way of apprehending the concept of EE and its evolution towards that of DEE differs between the research in Industrial Organization and Business Strategy and the research in Geography of Innovation. Contributors to the former understand EEs as forms of partially regulated markets whose sponsors promote both entrepreneurial action and transactions between distinct groups of users. They more specifically use the notion of DEE to highlight the key role of innovation in the digital industry, what Autio et al. (2018) call “digital affordances”. In a certain sense, for this research, efficiency analysis has moved upward, from the level of the organization of the firm to that of the ecosystem and its orchestration (Helfat and Raubitschek, 2018; Bejjani et al., 2023). On the other hand, the contributors in Geography of Innovation maintain a more global level of analysis by considering EEs as local communities with more blurred organizational boundaries. Within these communities, actors and institutions with shared aspirations interact to promote entrepreneurial opportunities (Stam and Van de Ven, 2021; Wurth et al., 2023), but the use (of) or the innovation (in) digital technologies are not at the center of the analysis as they are in the previous disciplines mentioned. The focus remains on what Autio et al. (2018) call “spatial affordances”, i.e. the different positive externalities favored by proximity, previously central in research on clusters (Vicente, 2018). This time, the movement of the analysis of efficiency is downward, moving from clusters to EEs. As researchers and policymakers had grasped that regional growth issues had shifted from boosting collaborations between firms and research institutions to fostering entrepreneurial behaviors and context, research on EEs developed to complement those on clusters or regional innovation systems (Rocha and Audretsch, 2022).

1.2.2. Socio-semantic network approach for analyzing the DEE research community: opportunities and caveats

1.2.2.1. *Opportunities: DEE network properties as markers of field structuring*

The multiple origins and motivations of research on DEE raise the question of the structural dimension of the community underlying its development and its degree of cohesion and scientific integration. As showed by Moody (2004), the consensus on any scientific concept can be analyzed from the structural form of the network of people involved through collaborative research. For that, network theories offer a wide range of structural properties to highlight collaboration patterns in scientific networks. Pioneered by Newman (2001, 2004) and Barabâsi et al. (2002), and largely developed later in specific areas and disciplines or sub-disciplines (Acedo et al., 2006; Zhang et al., 2018), the methodologies remain useful for capturing collaboration patterns on specific topics originating from different disciplines. DEEs enter this category since they combine knowledge at the crossroad of research on EE, themselves gathering research on entrepreneurship in Management, Regional Science, Innovation Studies, and research on digital ecosystems, themselves gathering research on digital entrepreneurship and platforms in Industrial Organization and Management.

The search for the network structural properties within this research community will tell us if behind the development of the same concept we observe a permeability, and therefore a cross-fertilization of knowledge, or a fragmentation in the collaboration patterns. To put it differently, behind the same concept, are there different reconcilable or irreconcilable scientific proofs of the phenomenon that the concept intends to signify? The property of small-world (Watts and Strogatz, 1998) provides the possibility to observe if within the network some sub-communities appear, and if these islands of social cohesion connect to ensure the dissemination and integration of knowledge. This search for structural properties will also tell us whether a hierarchy appears in the collaborative forces of researchers in the community. This property refers to a process of preferential attachment (measurable by the degree distribution) giving rise to a concentration around a core of star scientists with whom newcomers seek to collaborate as a priority. This can lead to the formation of a “dominant thinking”, and consequently to a form of control over knowledge that can reduce the dissemination of alternative knowledge in the network (Moody, 2004). In the same vein, ceteris paribus the hierarchy, the community can exhibit strong or weak assortativity (measurable by the degree correlation). It depends on whether the “star scientists” collaborate each other (positive correlation) or devote a large part of their collaborative capacity to new entrants (negative correlation) (Newman, 2002). Strong assortativity may generate an excess of scientific conformism, but this will depend on the number of cohesive islands within the network and their degree of connection, i.e. whether the exchanges between various ideas are maintained (Moody, 2004; Crespo et al., 2014).

DEEs as scientific field also raise the question of the semantic dimension of the network. If the members of the DEE research community share the same scientific interest at the intersection between the concepts of EE and DE, these concepts can be related to distinct scientific underpinnings that are not necessarily homogeneously distributed across all the network's sub-communities. When the coauthorship game shapes social islands of dense collaborations within the network, it may shape distinct cognitive islands if the sharing of scientific underpinnings come first among all the motives that drive collaboration, including prior to spatial and institutional ones (Katz and Martin, 1997; Hoekman et al., 2010). Therefore, adding and connecting a semantic dimension to structural properties of the DEE network becomes a fundamental issue for understanding how a new topic arises from collaborations between relatively distinct knowledge or disciplines. For that, a scientometric methodology inspired of Rafols and Meyer (2010) and Raimbault (2019), which consists in analyzing how the diversity of knowledge brought by each actor is distributed through collaborations, can help to study whether the structure of co-authorship goes with a semantic specialization within sub-communities or with an integrative process of ideas through the entire network. It can also help to assess if network fragmentation corresponds to failures in the collaboration pattern that reduce the integrative ambition of the concept defended in the literature. As we have seen in section 1.2, given the many sources of scientific topics that have contributed to DEEs, applying socio-semantic network analysis should make it possible to better understand through which semantic and/or social channels the bridging and integration of knowledge occurred.

1.2.2.2. *Caveats: The critical choice of nodes and links to analyze the socio-semantic field structuring*

The literature on the analysis of socio-semantic networks (Rafols and Meyer, 2010; Hellsten et al., 2020) is useful to understand and integrate the different biases related to the characterization of nodes and links together with the semantic selection methods. Most of methodologies favor bibliographic coupling and co-citation networks (Boyack and Klavans, 2010). Bibliographic coupling connects two articles when they refer to a third common article (older in date) in their reference list. In a co-citation network, two articles will be connected each time they are both cited by one or more other (subsequent) articles. These methodologies make it possible to observe structural properties that provide information on the organization of the research community. Within the community that interests us here, Zhang and Guan (2017), Kang et al. (2021), and Theodoraki et al. (2022) use this type of methodology. Other methods favor co-authorship networks. In this case, the nodes can be either the papers or the authors. In the last case, all the authors of the same paper compose a fully connected clique, which is of little interest for the analysis of collaboration patterns. Usually, the node is therefore the article and the link refers to the collaboration: two papers will be connected if they share at least one of the authors. To the best of our knowledge, this latter methodology has not been used to analyze the structure of the scientific community working on EEs and DEEs.

We will use this last method for at least two reasons. The first is the ever-increasing share of copublications in the social sciences over time (Henriksen, 2016) that makes networks of co-authors important alternative candidate. The level reached by management and economics gravitates in a range of 75-80% in the mid-2010s, with a significant growth in the average number of co-authors per article (Henriksen, 2016; Rath and Wohlrabe, 2016; Kuld and O'Hagan, 2018). The second reason, the most important, concerns the key objective of our paper: to combine the social and semantic dimensions to complete the different existing state of the art on DEEs. If citations are the most visible mark of the flow of knowledge within a scientific community, they cannot be that of social relationships. This is precisely the notion of community at the center of our contribution. In that sense, we follow Moody (2004) in considering a social community as a knowledge production community. It fits together with but distinguishes from a community of knowledge, broader, but not allowing to discriminate the finer level of social relations of production.

1.3. Data and methodology

1.3.1. Data collection

To analyze the socio-semantic structure of DEE scientific community, we use the Web of Science (WoS) Core Collection database. Three queries are formulated to obtain papers that use in their Title or Abstract fields certain Boolean combinations of words that are consistent with a relevant overarching representation of DEEs. They have similar structure and require the generic term "ecosystem*" that we associate (AND operator) in each query with "digital*", "entrepreneur*" and "platform*" respectively. Moreover, to increase the accuracy, we apply a set of additional filters: we restrain only to papers written in English, published (or being in press) by a journal indexed by the Social Science Citation Index (SSCI). Contrary, we do not introduce any chronological filter, so the period considered ends up in March 2023 (with in press papers affiliated

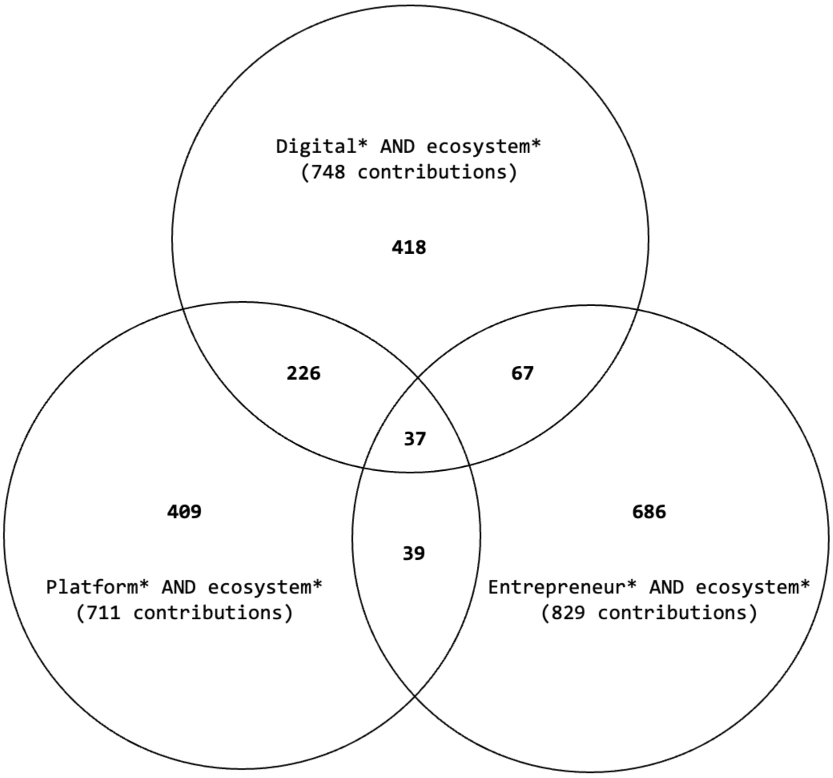

Figure 1.1: Number of papers for each query and their overlap

to this year). Thus, after aggregating the results of the three queries and deleting duplicates, we get a dataset of 1882 papers, resulting from an almost balanced numbers of papers in each query. For each paper we have information about the authors and their affiliations, the journal of publication, the date, the title, abstract, keywords, and citation counts. Figure 1.1 shows the aggregate counts of papers in our dataset, including the count of papers overlapping categories.

Some clarifications on data collection, cleaning and filtering are necessary. First, our starting point is that resulting from the theoretical proposal of Sussan and Acs (2017) and Song (2019), which consists of crossing research on EEs with that on digital ecosystems (DEs). Since the titles and abstracts of the articles generally contain the most representative words, two queries could have been sufficient, and in the most extreme case, only the publications at the intersection of the two queries could have constituted our primary data material (67 papers). However, two limitations appear in this method. As we have seen, studies on DEs value the term "platform" to analyze the digital shift in industrial and market organization models. Not associating this term with the global query runs the risk of missing significant contributions, especially since, beyond the 30% of articles in common with the "digital" query, there are 39 papers in common with "entrepreneur*". In the same vein, wouldn't it have been better to consider only the papers intersecting the requests (67 or 37 depending on the crossing of two or three of the queries)? We do not think so because DEEs are the result of thematic cross-referencing carried by authors and knowledge that each nourishes the scientific field, and nothing says that the absence of one of the words in the title and the abstract induces an exclusion from the field. This is all the truer since, as tested, the meaning of the terms is not necessarily excluded from the contributions using equivalent terms. For example, in the "digital*" and "platform*" queries associated with "ecosystem*" but which do not contain "entrepreneur*", it is common to observe in the abstract or the full text the terms "venture, new firm, spinoff, start-up, ...". Similarly, in the "entrepreneur*" queries associated with "ecosystem*", it is also very common to see the terms "web, IT, Internet, ..." in papers which do not contain "digital*" or "platform".

1.3.2. Data cleaning and papers' filtering

Since the links connecting the nodes are common authorship, we first proceed to disambiguate their names. Cases in which the same author has two different names (e.g., "Andrews, R" and "Andrews RJ") or two authors have the same name (e.g., "Asemi, A" corresponding to "Asemi, Adeleh" and "Asemi, Asefeh") need to be distinguished. To clean them we made a search by CV. After this cleaning, 4563 authors contribute to the 1882 publications.

Second, we proceed to network construction and visualization. As expected, when co-authorship instead of citations, co-citations or bibliographical coupling are considered, the network is not entirely connected. It contains a myriad of isolated papers (the co-authors of these papers did not contribute to any other paper among the 1881 other papers), and some isolated dyads and triads, but a giant component of 316 papers appears (there is always a path to reach any pairs of papers drawn randomly within the component). Between the few triads and this giant component, no other connected structure of intermediate size appears.

This first visualization reveals that part of the network is poorly or not connected, and therefore would not contain the most significant contributions. Following the scientometric literature which shows that the degree of embeddedness in co-authorship networks is positively correlated with citations, we could only consider the giant component of the network (316 articles). However, this would leave aside a significant part of the semantic depth of the scientific field. This is all the truer if we consider that isolated articles by a single author, particularly the early published ones, could have influenced the semantic content of the knowledge dynamics at work in the giant component.

After calculating the average of annual citations for the entire network and for the giant component (3.57 citations per year outside the giant component, 9.5 citations per year inside), we use a double non-exclusive criterion to select the most relevant papers of the domain: all the papers of the giant component and the papers among the isolates that have received, on average since their publication, 10 or more citations per year. This way to proceed allow selecting for the socio-semantic analysis 8.3% of the isolates, i.e. the top of the distribution of the most influential papers. In the end, 447 papers will be selected, 71% being part of the main component, with a significant higher value for the “entrepreneur*” AND “ecosystem*” query as regard the two other queries. See Table 1.1 for descriptives statistics and Figure 1.2 for the distribution of papers per year.

	Total	Share of selected contributions	Share of contributions in the main component
Digital* AND	748	19.9% (149)	57.7% (86)
Entrepreneur* AND	829	32% (265)	84.2% (223)
Platform* AND	711	20.8% (148)	59.5% (88)

Table 1.1: Descriptives of the network

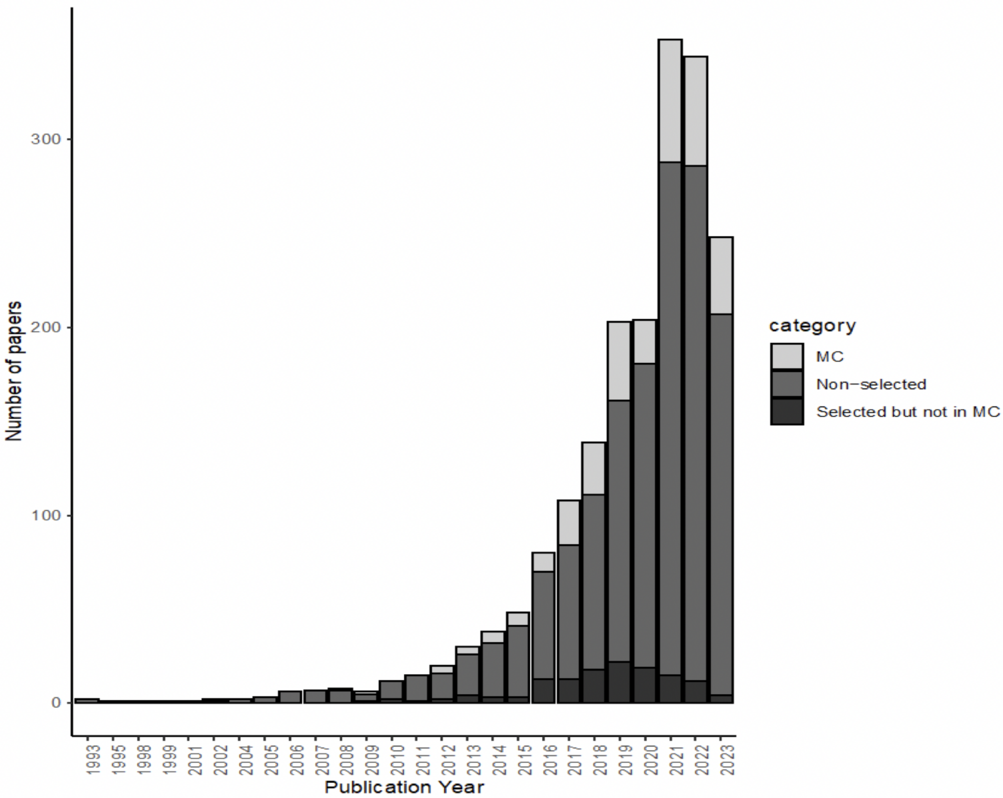

Figure 1.2: The annual distribution of DDE contributions

1.3.3. Sub-communities' identification

We seek to identify social sub-communities. For that we apply the Girvan-Newman (GN) algorithm of community detection (Girvan and Newman, 2002). This algorithm allows for an iterative partitioning of the network to detect cohesive groups of papers based on the distribution of linkages within and between groups. Note that our starting point by the combination of three semantic queries using meta concepts could have suggested that three sub-communities naturally appear within the network. Nothing is less certain, and this would presuppose that the sharing of meta-concepts translates into a higher propensity to collaborate, while some islands of (social) cohesion could appear within but especially between semantic (and non-social) communities resulting from meta-concepts. The configuration of the GN algorithm makes it possible to iteratively search for a greater number of cohesive sub-communities. We will seek out a number of these until the critical mass of strongly connected members within them is still sufficient to be able to characterize sub-communities by finer grained and non-predefined concepts. However, as the algorithm only works for connected components, the 131 out of the 447 papers that are not part of the main component but that have more than 10 citations per year in average will be assigned to an additional sub-community. Together with the average number of citations per year, the subcommunity to which a paper is affiliated will be considered as a categorical attribute in the network analysis.

1.3.4. Words' filtering for semantic analysis

For the semantic analysis, we use information recorded on the title and abstract fields of the 447 DEE papers to build a list of most frequent terms. A term can be both a word (such as "stakeholder") or an expression (such as "new venture") of maximum 3 words. We prefer terms used in the title and abstract fields to author keywords because the last are less often available and more subjective (Roth and Cointet, 2010). We sequentially combined automatized steps with others based on experts' insights. For the automatized steps, we use Cortext.net online platform to extract the list of 2000 most frequent terms in the title and abstract of papers. To do so, Cortext first applies lemmatization, it aggregates various forms of an identical term under the same main form or lemma (e.g., the "startups" main form aggregates "startup", "start-up", "startups" forms); and second, it excludes meaningless words (or "stop-words", see Raimbault (2019)) such as "example", "then", etc. As output, for each term, we obtain its main form, the associated forms, and a count of occurrences.

We use that output for the following step based on experts' insights. The list is curated with four criteria. First, only terms with more than 5 occurrences are retained. Second, generic terms related to research activity rather than to DEE are deleted (e.g., "literature review", "research agenda", etc.). Third, among the one-word terms that are not "stop-words", highly generic ones such as "knowledge", "activities", etc., are deleted, while more specific such as "gender", "skills", "standardization", etc., are maintained. Fourth, merging terms that the automatic procedure has classified under two different main forms into a unique main form (e.g., although "academic entrepreneurship" and "academic spin-off" were classified as to terms from the Cortext procedure, they were merged in a single term after the experts' insights step). As a result of this procedure, we get a list of 210 specific words and expressions commonly used in the DEE literature. Then, we proceed to paper indexation, i.e. we associate the list of 210 words and expressions to the 447 papers that use them in their abstract or title.

Lastly, we combine the list of terms indexed to papers with the output of the GN algorithm for community detection to obtain relative advantage measures about the over or under use of a term in a community. The Relative Comparative Advantage (RCA) compares the relative presence of a term in a community compared to the relative presence of that term in the overall set of papers. Thus, it is computed for each term-community pair, and it ranges from 0 to infinity. Values over 1 mean that term is over-represented in the community, and values below 1 mean that the term is under-represented.

1.4. The structure of the social network of DEE key contributors

1.4.1. Network visualization

Let's start by a strictly socio-structural analysis of the network. Figure 1.3 represents the network graph, where each vertex represents a paper, while each edge represents the co-occurrence of at least one author in the papers. The size of the vertices refers to the average number of citations per year. Primary colors represent each of the three initial queries for papers appearing in a single query, while secondary colors characterize articles appearing in two of the queries, and the color grey for the papers resulting from the 3 queries. Visually, the giant component appears in the center of the graph, with isolated dyads and triads around, and papers whose authors have not collaborated on any other paper in the corpus on the left of the graph.

We observe that even if there is a propensity of nodes to connect more to the nodes of the same initial semantic query, the structure of the giant component is not directly

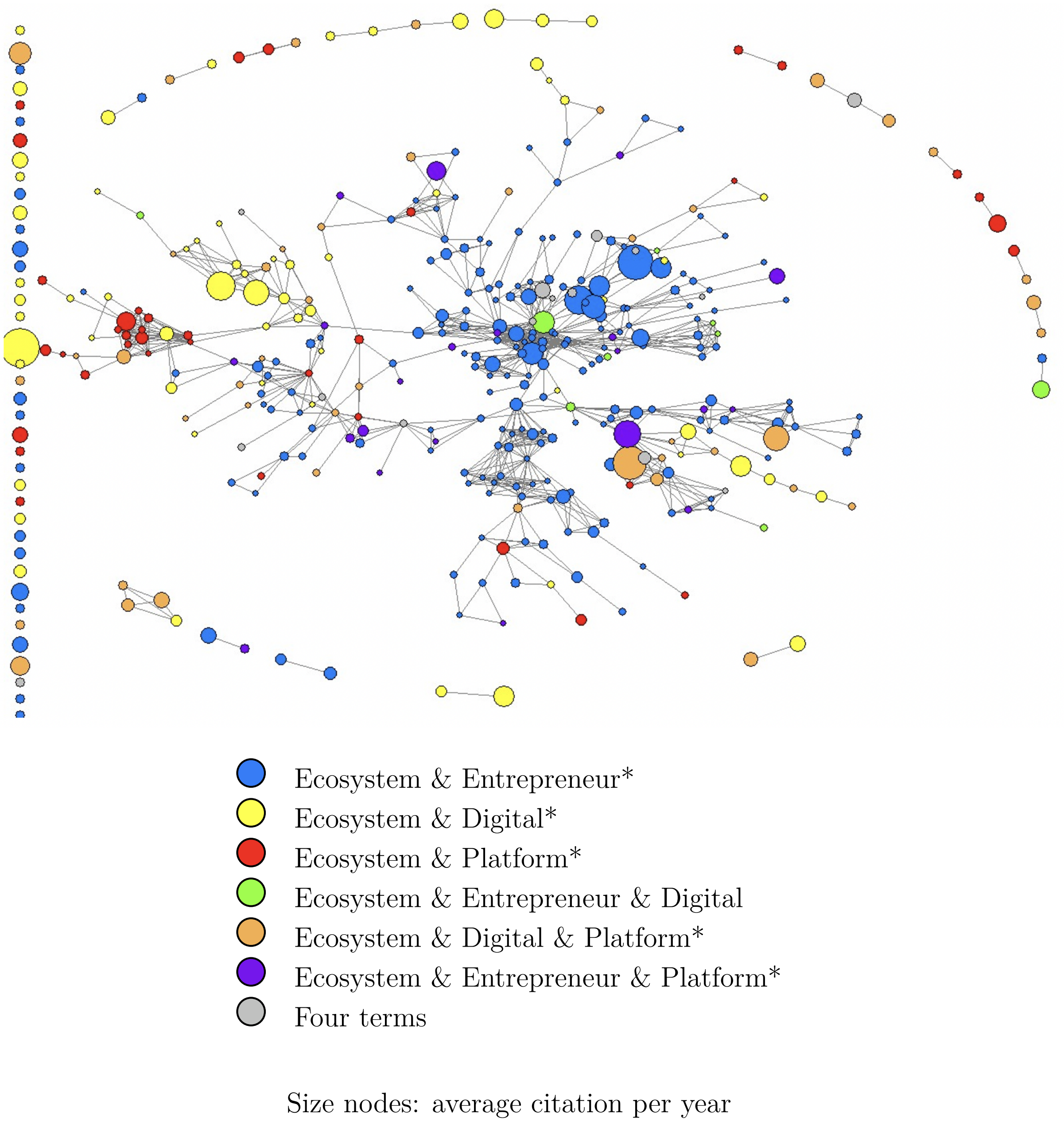

Figure 1.3: The Digital Entrepreneurship Ecosystem network (1)

related to them, because we also observe that *(i)* the number of highly cohesive groups is largely superior to the number of queries; *(ii)* a same query gives rise to several cohesive groups poorly connected to each other; *(iii)* nodes mixing 2 or 3 requests irrigate many of the cohesive groups, and (iv) some highly cohesive groups host a balanced number of nodes from the three queries. It means for *(ii)* that scholars use and work on same pair of concepts in different social groups with few social relationships between groups. That is particularly the case for the "ecosystem* AND entrepreneur*" query that gives rise to more than four easily visible poorly connected cohesive groups. It is also the case that for the query "ecosystem* AND digital*" for which we observe two very distant social groups. But it also means for *(iii)* and *(iv)* that, in a few islands of the giant component, dense scientific relationships have mixed the digital and platform dimensions of ecosystems to its entrepreneurial dimension. That is particularly the case for two of the cohesive groups located at the right and left of the graph.

We also visually observe the over-representation within the giant component of papers from the query "Ecosystem* AND entrepreneur*" compared to articles from other queries. While the 3 queries resulted in a roughly balanced distribution of the number of papers, the giant component no longer reflects this balance. Conversely, we observe a strong predominance of papers mixing Ecosytem* and Entrepreneur* over the papers extracted from the other two queries (which appear isolated and/or with less than 10 citations per year). This can be interpreted by a stronger continuity in the relational paths within this thematic sub-community and the presence of authors capable of bridging between previously distant groups of authors. Conversely, this continuity and these bridging seem to be lacking in the subcommunities resulting from the other two queries, although for the latter two, some contributions are linked via contributions from the first query. Thus, according to a strictly socio-structural approach, the communities working on digital and platform ecosystems do not seem to have reached the level of relational thickness reached by the community working on EEs. However, some of their work entered through the periphery of the giant component via co-authored contributions with central authors from the EE community. In a certain sense, we observe the premises of a structure in line with the recommendations defended by Sussan and Acs (2017) and Song (2019) to bring about a program of research on DEEs which would cross-fertilize research on EEs and DEs.

1.4.2. Some salient structural properties of the DEE network

At a strictly structural level, collaboration patterns within the giant component can be analyzed through the distribution and correlation of node degrees. First, Figure 1.4 shows the level of hierarchy in the degree distribution, signifying a continuum of

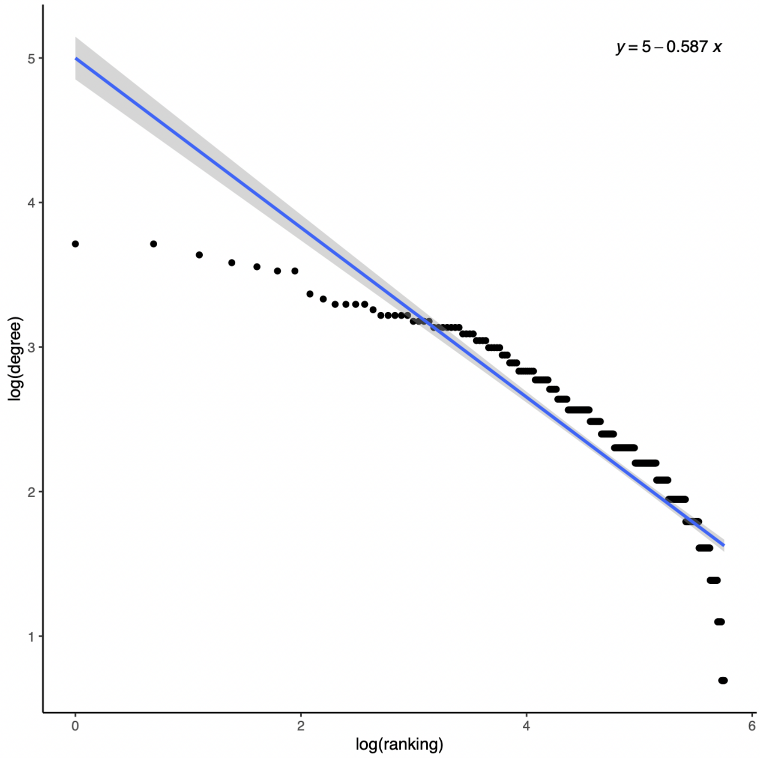

Figure 1.4: Structural properties of the DEE network: Degree distribution

strongly to very weakly connected nodes. This is illustrative of the presence of very productive authors who diversify their portfolio of co-authors within the field, and of the existence of peripheral contributions from either young authors with their first coauthored publications or established researchers in other scientific communities entering the DEE field. This hierarchy of degrees is typical of a preferential attachment mechanism (Barabási and Albert, 1999) which leads to the existence of reference contributions in the community, whose authors are attractive for any new collaboration, and whose ideas structure the scientific field.

Second, the correlation of degrees provides additional elements on collaboration patterns. Figure 1.5 shows a positive correlation: high (low) degree nodes have a stronger propensity to connect to high (low) degree nodes, indicating an assortative network (Newman, 2002). This means that the authors with high (low) degrees tend to co-write with authors who are themselves central (peripheral), such that the status of the authors appears to be a central determinant of collaboration choices. Assortativity in the matching of collaborations is generally associated with strong relational conformism in knowledge production (Ahuja et al., 2012). For Crespo et al. (2014), this assortativity reveals a weak capacity of the community to experiment with collaborations with new entrants, whether they are young researchers or experienced researchers providing knowledge from other scientific fields. However, we observe in Figure 1.5 a very strong dispersion of the nodes on either side of the regression line, which shows

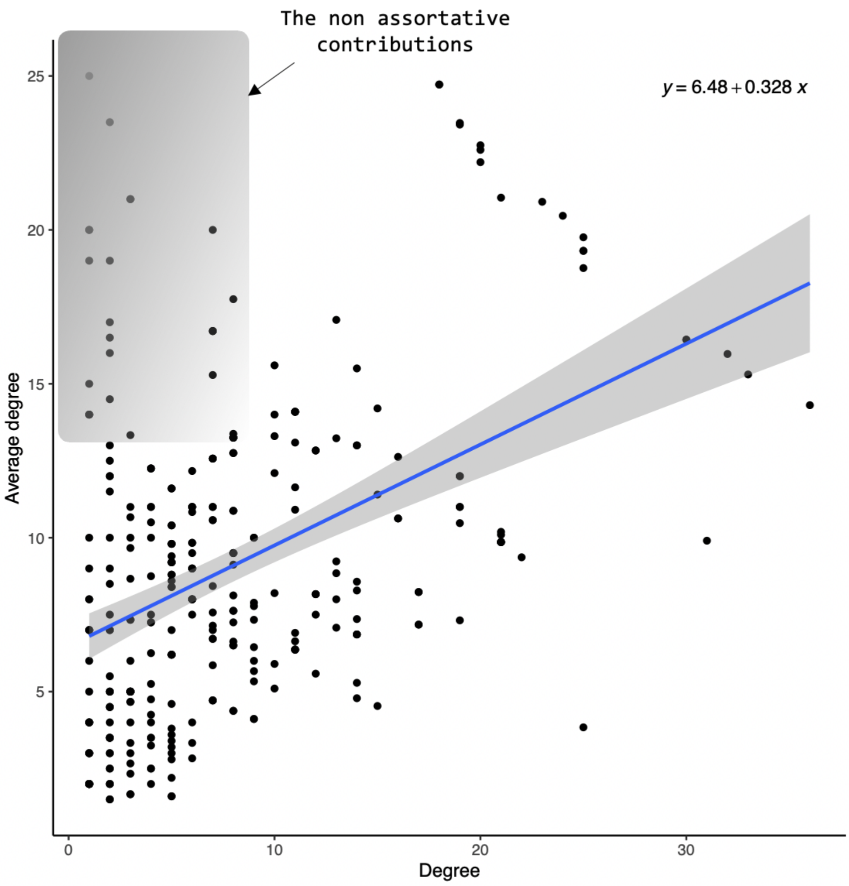

Figure 1.5: Structural properties of the DEE network: Degree correlation

that the assortative pattern at the aggregate level of the network hides a non-negligible number of nodes with a significant non-assortative behavior. This is typically the case in the top left part of the graph where very low degree nodes concentrate their collaboration with high degree nodes. This suggests the entry of fresh knowledge towards the core of the network. This may be explained by the burgeoning scientific cross-fertilization between the digital and entrepreneurial dimensions of ecosystem research from which the field of DEE arises, even if this observation must be accompanied by a contribution-by-contribution verification to be confirmed.

When linked to the volume of citations, as measure of recognition and dissemination of ideas, the sociostructural analysis reveals the most cited papers have a central positioning in each of the cohesive groups. This observation is in line with the literature on the relational determinants of scientific impact, which recurrently shows that the degree centrality of authors in co-authorship networks is significantly correlated with citations (Yan and Ding, 2009). This is explained by the social capital built by the authors as far as the number of co-authors increases. But second, the literature emphasizes the same correlation with betweenness centrality. Recall that the betweenness centrality of a vertex measures the number of shortest paths between other vertices

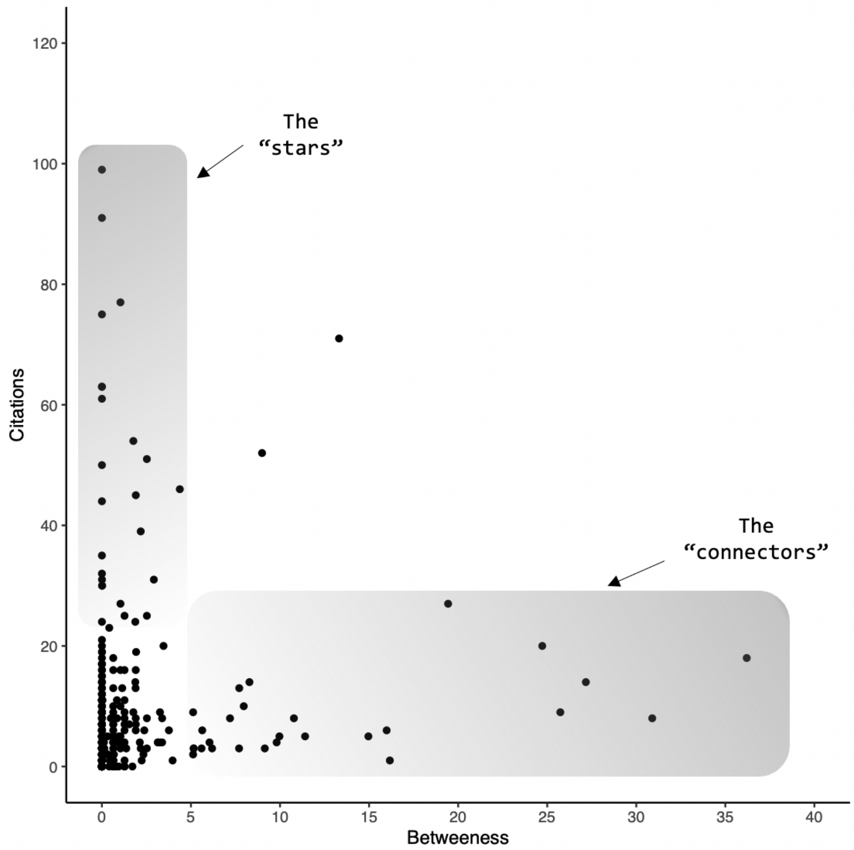

Figure 1.6: Betweenness centrality and citation count

passing through it. Papers with strong betweenness are then those co-authored by scholars collaborating with other authors who are little or not connected to each other, giving the former a leading position for bridging between different cohesive groups, or, to say in other words, those without which the giant component could be split into several disconnected components. As their contributions are produced by authors from different communities, the potential for dissemination and citation is broader.

As shown in Figure 1.6, this recurring pattern is not verified. Alongside a majority of papers from the giant component having received few citations and having a low betweenness score (at the bottom left of the graph), two groups of contributions appear that are significantly distinct and of important size. The stars group on the top corner left is made up of highly cited contributions with a zero or low betweenness score. These are key papers that are highly recognized within sub-communities, but whose authors have not or only rarely established collaborations with authors from distant sub-communities. The connectors group at the bottom right has a roughly equivalent number of contributions and a strict inversion of scores. Here, the papers come from scientific collaborations between authors belonging to very distinct communities, i.e. research combining scientific expertise developed in poorly connected social groups. The fact that these groups are distinct does not mean *a priori* that the knowledge mobilized is also necessarily distinct, in accordance with the distinction we have made between the analyzes of citation networks (diffusion and absorption of knowledge) and those of collaboration networks (production of new knowledge). But this means when we focus only on the structural dimension that the production of new knowledge is based on collaborations never or very little explored during the period. These are collaborations between scholars involved in groups whose other members have little explored an equivalent strategy of collaboration outside their own group, which can suggest the emergence of innovative scientific results, but which however remain little recognized.

1.4.3. Is the DEE network a small world?

In summary, if we refer to the three structural forms of scientific collaboration networks identified by Moody (2004), the DEE network typically falls into one of these. First, it does not exhibit the characteristics of a preferential attachment mechanism. In the latter, most relational paths pass through high-degree nodes, which, if removed, would disconnect the network. In our network, if these high degree nodes control the circulation of ideas, they do it only in a few parts of social sub-communities and not in the overall giant component. These are lower degree nodes which ensure a large part of the connectivity between the sub-communities, and therefore the overall connectivity of the network. Second, the network does not actually exhibit the features of a structurally cohesive network. The latter presents a uniform distribution of links across the network, and therefore little fragility when faced with the removal of connector nodes. This topological form is in line with a strong integration of knowledge within the overall community. This is not the case in our network since "star" and "connector" contributions play different but crucial role in the distribution of ideas. Third, the DEE network presents the structural features of a small world, i.e. a connected and very clustered network, within which several islands with strong cohesion coexist and give rise to distinct dynamics of scientific progress. The theoretical integration typical of structurally cohesive networks cannot therefore develop here, but the non-fractalization of the overall community gives each node access to different sources of theoretical advances and relatively short social paths to access potential collaborations outside one's own island. The network is therefore organized, to use Moody's own terms, around different areas of authority carried by a few central researchers in different social sub-communities who develop a form of control over particular approaches, ideas, and methods. But these are not the areas at the heart of the overall structuring of the field. Conversely, these are contributions published by authors with a lower degree but combining the approaches, ideas and methods of different areas of authority to increase the scientific integration of the field.

So why are these contributions less recognized when citations are considered, even though they would potentially contribute more strongly to scientific advances within the field? The explanations are twofold. First, by the propensity of "connector" contributions to be interdisciplinary or inter-domain research. As shown by Wang et al. (2015), the recognition delays for these contributions are much longer, and can increase after several years, including when citations to mono-disciplinary papers start to decline. As the field of DEE emerged at the end of the 2010s with the reference contributions of Sussan and Acs (2017) and Song (2019), we cannot exclude that connector contributions will become the star ones in a few years, after having been sleeping beauties during a long period. This negative correlation between citation and betweenness centrality would then be the mark of the emerging dimension of the field rather than the one of an intrinsic fragility. Secondly, as shown by Biscaro and Giupponi (2014), the status of the authors being a determining factor in the number of citations, we can infer that the risk-taking of exploring collaborations at the frontiers of communities is carried out mainly by researchers whose level of recognition has not yet reached that of the most recognized authors within their sub-communities. If such a conjecture was verified, it would then confirm, with the small world property, the ongoing structuring of a DEE community from diverse and previously unconnected origins. However, we observe in Figure 1.6 that two contributions stand out by the combination of a high citation score and a betweenness score which is well above the median. These two contributions (Acs et al., 2017; Autio et al., 2018), when we go into their detail, have two characteristics in common: they were published in the same period (2017 - 2018), and both promote the need to bring together research on EEs and that on platform and digital ecosystems. Following Newman (2009), these two contributions connecting authors from previously poorly connected communities benefit from a first mover advantage which can confirm that the field of DEEs is in its early phase of development.

1.5. The semantic representation of the social network of DEE key contributors

1.5.1. In search of the semantic mirror of the social structure of the DEE network

What are precisely these origins, and how do they fit into collaboration patterns? Section 1.2 provided us with a first vision of the diversity of these origins, from upward approaches developing DEEs as a move beyond theories of the firm towards platform ecosystems supported by the development of digital technologies, to downward approaches gradually shifting from innovation systems to the determinants of entrepreneurship within ecosystems. Beyond these two movements, a variety of methods and ideas also appeared. Numerous works have relied on methods and ideas from the economics and geography of innovation, to capture the effects of geographical and institutional context on entrepreneurship. Others developed new theoretical ideas from industrial organization and strategic management to explain and demonstrate the nature of organizational changes and market strategies supported by the deployment of digital platforms. The aim now is to see how the ideas are articulated in the social structure of collaboration, and through which knowledge and cognitive content the scientific field progresses.

To do this, we proceed in two stages. *(i)* We apply the community detection algorithm to distinguish the cohesive blocks that make up the overall social structure. *(ii)* We characterize the cohesive blocks according to their semantic specificity and look for semantic transversalities in pairs of blocks. As regard previous studies, this last methodological point enables us to grasp at a finer grain which words or expressions prevails in sub-communities and to reduce the representation of more generic words or expressions within the overall domain.

Figure 1.7 represents the same network as previously, but now nodes' colors reflect the affiliation to a community according to the Girvan-Newman algorithm. We set the detection algorithm to 5 communities and focus on the search for non-predefined words and expressions which emerge from cohesive substructures. Communities' size ranges from 16 to 119 nodes within the giant component, while the isolated, dyads and triads are grouped within a sixth community of 126 contributions. As the 5 communities belong to the giant component, there always exists a path between two contributions taken randomly regardless of the community they belong to. But if some of the communities are connected directly to each other, by authors having published at least one paper in at least two of the communities, other pairs of communities are only connected through contributions from a third community, therefore without authors in common.

1.5.2. The semantic drivers of cohesive groups

Inspired by Roth and Cointet (2010) and Raimbault (2019), we first seek to determine whether cohesive groups exhibit specific semantic usage. If such specificities are confirmed, we obtain a first approximation of the content of the ideas which feed each of these groups, and of their scientific origin. To do this, we compute the RCA scores for each words-community pair. Then we define specificity thresholds to each community,

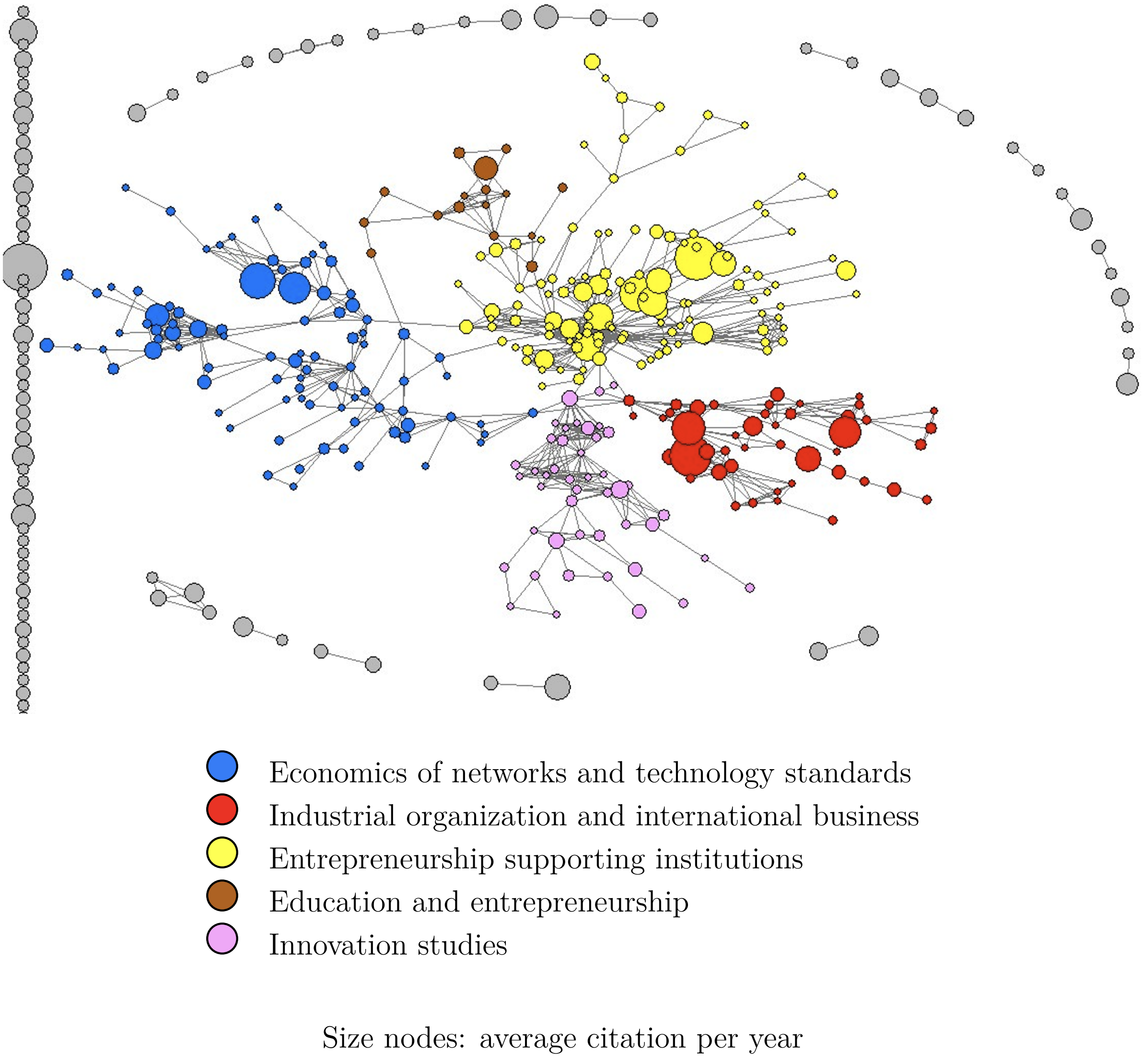

Figure 1.7: The Digital Entrepreneurship Ecosystem network (2)

both to portray them semantically and to assess the degree to which the words and expressions used distinguish them regarding the overall semantic landscape. The results are presented in Table 1.2.

The first community, C1, gathers the highest number of contributions (119) connected to each other either directly by common authors, with a core of strongly connected contributions, or by relational chains, which allows contributions of a lower degree to "stay tuned" to this community. The size of this community goes with a very moderate degree of semantic specificity. If this community, because of its size, contains a large part of the semantic landscape, few words and expressions have a high RCA. Only 5 words and expressions are used at least 2 times more in this community than the average in the DEE network, and at the same time less than 1.5 times less than the average in at least one of the other communities. However, these words and expressions turn around the question of entrepreneurship supporting institutions, and the diversity of contexts and configurations of EEs, i.e contributions which favor holistic approaches, mainly according to the downward shift we previously identified from innovation systems to EEs.

From C2 to C5, we observe an interesting increase in semantic specificity. For C2 (90 contributions), the RCA results make it possible to raise the specificity threshold (from 2 to 2,5) while obtaining a higher number of words and expressions (from 5 to 7) specific to this community (and not specific to the others). The most distinctive words and expressions of this community echo the conceptual landscape of the economics of networks and technological standards. They fall into the category of keywords introduced from the beginning in the foundations of this paradigm initiated by authors like Arthur (1989) and Katz and Shapiro (1994), among others. Still applied 30 years later to platform ecosystems, these words and expressions remain the basis of research that links new forms of disintermediation enabled by the digitization of services to strategies of modularity and complementarity supported by technological standardization.

For C3 (45 contributions), we also observe high RCA thresholds for several words and expressions (>2.5). The international and organizational dimensions of DEEs distinguish this community from others. The topics concern the international growth of digital companies and the development of new ventures. They also concern the problems of agencies and transaction costs. Due to a change in scale from the firm to the ecosystem, the analysis of new value chains as well as that of new patterns of distribution of authority and decisions becomes critical in understanding DEEs and the sources of their growth. The social cohesion within this group mirrors a semantic cohesion around the topics of industrial organization and international business. If we look at the position of C3 within the network, it may seem surprising to observe its social distance from C2. Only one contribution directly links both communities, while

Community	Size	Scientific field	Keywords (occurrence) – ranked by decreasing RCA	RCA conditions for selection	Specificity degree to the community	Highest cited paper (average citation per year)
C1	119	Entrepreneurship supporting Institutions	*Ecosystem elements (6), Formal institutions (6), Gender (12), Different ecosystems (8), Support organizations (5)*	RCA>2 in $C_{i=1}$ and <1.5 in C_j	*Moderate*	*SPIGEL, B. 2017. The Relational Organization of Entrepreneurial Ecosystems. ENTREP THEORY PRACT (99)*
C2	90	Economics of networks and technology standards	*Complementary innovation (6), Digital servitization (13), Standardization (8), Suppliers (13), Platform owners (13), Industry platform (13), app.develop (6), network effects (16)*	RCA >2,5 in $C_{i=2}$ and <1.5 in C_j	*High*	*CUSUMANO, MA., GAWER, A. 2014. Industry Platforms and Ecosystem Innovation. J PROD INNOVAT MANAG (77)*
C3	45	Industrial organization and international business	*Multinational enterprises (8), International business (5), venture development (15), transaction costs (7), agency (11), New venture creation (28)*	RCA>2.5 in $C_{i=3}$ and <1.5 in C_j	*High*	*AUTIO, E. et al. 2018. Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. STRATEG ENTREP J (71)*
C4	45	Innovation studies	*Knowledge intensive (10), Social innovation (5), Innovation networks (5), Innovation literature (11), Risk (14), Innovation and entrepreneurship (18)*	RCA>3 in $C_{i=4}$ and <1 in C_j	*Very high*	*CARAYANNIS, EG. et al. 2018. The ecosystem as helix: an exploratory theory-building study of regional coopetitive entrepreneurial ecosystems as Quadruple/Quintuple Helix Innovation Models. R&D MANAGE (27)*
C5	16	Education and entrepreneurship	*Entrepreneurship education (7), Education (15), Innovation process (12), Students (18), Skills (13), Blockchain platforms (10)*	RCA>5 in $C_{i=5}$ and <1,5 in C_j	*Very high*	*ELIA, G. et al. 2020. Digital entrepreneurship ecosystem: How digital technologies and collective intelligence are reshaping the entrepreneurial process. TECHNOL FORECAST SOC (44)*
C6	126		Not relevant			

Table 1.2: The semantic drivers and specificities of the cohesive blocks of the DEE collaboration network

the economics of networks can be considered as a branch of industrial organization theories. C2 emphasizes more on strategic management of platform companies, with a strong focus on technology, while in C3 the emphasis is more focused on international development and growth. However, the question of the degree of dissociation between social and semantic dimensions will deserve our attention in the final discussion.

The fourth community of an identical size to the previous one (45 contributions) presents a significantly high number of words and expressions with an even higher RCA (>3), reflecting a stronger semantic specificity. This is even more noteworthy since the six words and expressions above the threshold have a value less than 1 in the other communities (this threshold was set at 1.5 in communities C1-C3). Social cohesion within this block reflects a strong interest in innovation studies, with a semantic field oriented on the links between entrepreneurship, knowledge, and innovation. DEEs are therefore understood in a logic of innovative behavior, which is not surprising. What is more surprising, for a scientific field seemingly naturally linked to innovation issues, is that the associations in the same expression of the words "innovation" and "entrepreneurship", or "innovation" and "networks", or the expression "knowledge intensive", are so specific to one community while they are under-represented in other communities. Here too, we will address this observation in the discussion.

The fifth community, the smallest of the five communities (16 contributions), is distinguished by a very strong specificity of words and expressions (RCA>5). Socially connected to the C1 and C2 communities, it is strongly distinguished by the education and entrepreneurship dimension of its semantic landscape. The development of DEEs being recent, the questions of education and incentives for students to acquire entrepreneurial skills in accordance with the changes caused by the growth of digital businesses in terms of human capital are probably the reasons for the formation of this community.

Finally, the C6 community has a special status. Made up of numerous isolates and a few dyads and triads, it presents no semantic specificity (none of these words and expressions among the 210 in the corpus exceeds an RCA of 1.5). This confirms its status as a "control community" and supports the proposition according to which in a certain extent it exists a mirror effect between social thickness and semantic specificity.

1.5.3. The transversal semantic drivers

The analysis could stop there before a final discussion. However, nothing excludes the existence of specific semantic fields other than those specific to a single community, and nothing excludes the possibility that semantic blocks cross several social communities without the latter being connected.

Table 1.3 summarizes the search for semantic specificities crossing two communities. Note that previously we measured the semantic specificity of a word or an expression to a community by an RCA at least greater than 2, and at most less than 1.5 in another community. The same method makes it possible to search for semantic fields specific to two communities, i.e. transversal semantic fields whose social mirror effect can be discussed. To do this, we seek to identify for all pairs of communities the words and expressions having an RCA strictly greater than 2 in one community, and this time strictly greater than 1.5 in another.

The results can be analyzed according to two categories. First, pairs of communities may exhibit common semantic markers, which would not be common to any other pair of communities. This category can be divided into two cases: *(i)* these pairs of communities are connected to each other by contributions co-written by authors from both communities; *(ii)* these pairs of communities are not directly connected by one or more contributions. Second, community pairs do not have common semantic markers. This category can also be divided into two cases: *(i)* these pairs are directly connected by contributions co-written by authors from both communities; *(ii)* these pairs of communities are not directly connected by one or more contributions. Each of these categories provide additional information on the socio-semantic structuring of the scientific field. In particular, the analysis makes it possible to see whether transversal semantic markers not specific to a community emerge and complete the socio-semantic characterization of the scientific field, and whether or not the sharing of semantic markers is driven by collaborations between communities.

Let's start with the pairs of communities that reveal common distinctive semantic markers. Among them, we note the pairs C1-C3, C1-C4, C3-C5. These three pairs have their own set of markers that distinguish them semantically from any other pair. We see that a majority of these markers within the three sets refer to issues relating to regional development and locational aspects. If the "geographic" marker did not appear in the semantic characterization of the cohesive blocks, it appears now in a salient manner when it comes to studying pairwise the semantic landscape, i.e. when we seek to identify scientific markers that go beyond the perimeter of separated small worlds of dense collaborations. Thus, issues on DEEs relating to local entrepreneurial dynamics, clusters or regional policies constitute topics which cross the communities working on institutional aspects (C1), on those on industrial organization and international development (C3), on those on innovation studies (C4), or those on education and entrepreneurship issues (C5). These common markers can in some cases translate into connections between communities, and sometimes not.

Communities' intersection	Cross communities' keywords (ranked by occurrence)*	Connecting contributions (examples)	Key topics
C1-C3	*Regional development (12), Embeddedness (10), Local entrepreneurs (9), Ecosystem regional clusters (6)*	*Lamine, W et al. 2018. Technology business incubation mechanisms and sustainable regional development. J TECHNOL TRANSFER*	Regional ecosystem policy
C1-C4	*Clusters (19), Public policy (14), High growth entrepreneurship (6), Entrepreneurial dynamics (5)*	*GERMAIN, E. et al. 2023. Science parks as key players in entrepreneurial ecosystems. R&D Management*	
C3-C5	*Accelerators (28), Regional entrepreneurial ecosystems (26), Dynamic capabilities (13), Organizational design (12), Innovation digital (10)*	(Some keywords connect communities, but papers do not)	
C3-C4	*University research (21), Spillovers (14), Location (10), Dynamic interactions (9), Academic entrepreneurship (7), Entrepreneurial ventures (5)*	*GUERRERO, M. et al. 2016. Entrepreneurial universities: emerging models in the new social and economic landscape. SMALL BUS ECON*	Knowledge transfer and entrepreneurial universities
C1-C5	*Digital entrepreneurship (11), Technology transfer offices (6), Supporting entrepreneurship (5), Sustainable entrepreneurial ecosystems (5)*	*COLOMBELLI, A. et al. 2019. Hierarchical and relational governance and the life cycle of entrepreneurial ecosystems. SMALL BUS ECON*	
C4-C5	*University (63), Science (21), Entrepreneurial university (20), Open innovation (20), developing countries (19), Uncertainty (12), Exploitation (11), Knowledge transfer (7), Different configurations (5), Knowledge creation (5)*	(Some keywords connect communities, but papers do not)	
C2-C3	*Platform strategies (20), Leadership (11), Appropriation (10), Competitive advantage (9), Ecosystem development (6), Ecosystem value (5)*	*FERREIRA, J. et al. 2016. Effects of Schumpeterian and Kirznerian entrepreneurship on economic growth: panel data evidence. Entrep & Reg Dev*	Platform competition and growth
C2-C1	(Communities are connected by co-authorship, but not by very specific keywords)		*(None)*
C2-C4	(Communities are connected by co-authorship, but not by very specific keywords)		
C2-C5	(Communities are connected by co-authorship, but not by very specific keywords)		

*Words or expressions having for each an RCA>2 in one community and >1,5 in another one.

Table 1.3: The transversal semantic drivers of the DEE collaboration network

We observe contributions published by authors who connect C1 to C3, and C1 to C4, and whose geographical dimension appears central in the title (see Table 1.3). But conversely, the sharing of common markers does not result in collaborative links for the pair C3-C4. We will return to this aspect of disconnection between the social and semantic dimensions in the final discussion.

We also note a set of markers relating to the issues of academic entrepreneurship, technological transfer and the role of universities in the emergence of DEEs. These words and expressions are distinguished in the semantic landscape in the pairs C3-C4, C1-C5 and C4-C5, i.e. the same communities as previously, but according to a different pairwise distribution. Here again, if the issues of universities did not emerge as a specific marker of a community, it appears central as soon as we expand to pairs of cohesive blocks of collaboration, with, as previously, contributions which confirm this connection between communities (C3-C4 and C1-C5), and sometimes not (C4-C5).

We further note that the cohesive block C2 “behaves” very differently from its “neighbors”. On the one hand, common semantic markers appear with C3, confirming the natural proximity between the economics of networks and technological standards and the economics of industrial organization. These markers refer to the issues of competition between digital platforms and their growth, in a digital industry typified by network externalities which push towards oligopolistic industrial structures. But on the other hand, what should attract our attention is the absence of common semantic markers with other communities in the network (despite a small number of social connections). So, we deduce that the second cohesive block in size does not yet seem to have constructed a distinctive semantic landscape with the other communities, except for its closest natural neighbor C3.

This C2 block of contributions focuses on one of the most central aspects of the economic dynamics of platform ecosystems, namely what Nylund and Brem (2023) call “ecosystem-based standards”. This would then mean that the dynamics of collaboration on this theme would not have yet led to the construction of a common language and topics shared with institutional and holistic approaches (C1), with innovation studies (C4), or with research on education and entrepreneurship (C5).

1.6. Discussion and conclusion

Where does the scientific community stand along the process of social (the collaboration network) and semantic (the conceptual and theoretical landscape) structuring of the field of DEEs? Recall that, while the research community on EEs reached a critical mass of contributions and a recognition within the scientific community and within the circle of policy makers at the middle of the 2010s, two important contributions Sussan and Acs (2017); Song (2019) appeared a couple of years later to outline the framing of a new field dedicated to DEEs. At the same period, in a different way, Acs et al. (2017) and Autio et al. (2018) propose to better integrate the constituent of platform ecosystem theory into the framework of EEs and analyze more in depth the articulation of digital and spatial affordances in EE development, but without proposing a new and specific framework for DEE. While for the former, an autonomous recognition of the DEE field is expressed, it is not the case for the latter, who limit to the integration of some key elements relating to platform ecosystems in the existing EE research program. The socio-semantic approach developed here provides an interesting interpretation of these debates. While it cannot replace the rigor of a discursive analysis of the state of the art, it offers a rich complement based on objective data and reproducible methodology. Based on sections 1.4 and 1.5, we can now discuss how social and semantic dimensions interact.

At the first glance, the DEE collaboration network enters the category of small world networks Moody (2004). These are networks that are neither perfectly integrated nor perfectly fragmented (even if fragmentation remains outside the giant component). These are multi-cluster networks, representing different areas of cohesive scientific authorities, and connected to each other by a few connectors who play a role as a knowledge conduit within the overall structure. The analysis through the detection of communities and their semantic content made it possible to specify the scientific nature of these areas of authority. We thus identify two communities of significant size in terms of number of contributions (labelled as “Entrepreneurship supporting institutions” and “Economics of networks and technology standards”), whose semantic landscape of each reflects the two scientific dynamics considered by Sussan and Acs (2017) as those whose intersection defines the perimeter of the research program on DEEs. These two central communities also connect to three other smaller cohesive communities dedicated to the educational aspects of entrepreneurship, innovation studies and the international dimension of the industrial organization of the digital economy. The scientific field of DEEs is therefore marked by a thematic and disciplinary pluralism of approaches whose integration is still weak at this stage and based only on a small number of contributions connecting these different areas of scientific authority.

However, the few bridges built between cohesive groups can be considered as proof of the initiation of an integration process which will deserve to be followed over time. This initiation is carried out by collaborations between authors belonging to distinct areas of authority, those that we have called connectors, whose works remain less recognized in citations than the contributions located at the centers of the sub-communities. This low degree of integration is also confirmed by patterns of collaboration marked by the domination of assortative behaviors within each community. This implies a strong tendency of the most recognized authors, those we called stars, to interact with each other on the central topic of each cohesive group. We nevertheless observe that this trend is partially reduced by some contributions from authors with non-assortative behavior, contributions which have been plotted in Figure 1.5. These contributions, which result from collaborations between authors who seem more peripheral within each community, play a crucial role in the initiation of this process of social and scientific integration. In summary, the socio-semantic network analysis approach confirms a low degree of social integration between theoretical approaches and semantic fields contributing to the DEEs conceptual landscape. These first signs of integration can only be confirmed in the future if the knowledge produced by the connectors gives rise to new collaborations at the frontiers of the areas of authority.

Beyond this general result, other more detailed lessons can be drawn, in particular on the scientific issues that will face the community as a whole for the years to come. First, we showed the existence of semantic fields common to pairs of communities. This means that some common scientific issues are addressed by distinct and poorly connected communities. This is particularly the case on the geographical dimension of the links between digital ecosystems and entrepreneurial ecosystems, or even on the role of academic entrepreneurship in the development and growth of entrepreneurial ecosystems. Should this observation be interpreted as network failures (Vicente, 2017), or conversely does this coexistence of common topics in distinct communities promote scientific advances? Depending on the answer, this opens the question of the type of incentives to support scientific collaborations. Supporting research consortia composed of researchers from distinct rather than already highly cohesive communities could promote both integration and scientific advances within the same field. Here again, the socio-semantic approach can be useful because it can serve as a basis for proposing and selecting collaborative research projects.

Second, and more paradoxically, we observe that one of the two largest communities, that on the Economics of networks and technological standards, although directly connected to three of the four other communities, does not have any common semantic markers. A few connector authors exist, but the flows of knowledge have not led to a common language or scientific issues identifiable within each pair of communities. This is even more noteworthy as this result concerns the pair composed of the two largest communities and therefore the two most dominant approaches within the overall community. In terms of scientific progress on DEEs, this means that between the cohesive group centered on platform ecosystems (and its challenges in terms of technological standardization, and innovation strategies in new intermediation business models), and that on holistic approaches to institutions supporting the development of entrepreneurial ecosystems (including all the determinants of entrepreneurial incentives), we do not observe any distinctive markers which would confirm the emergence of a semantic corpus specific to a program of research on DEEs, as promoted by Sussan and Acs (2017). However, according to (Acs et al., 2017, p.1), the integration of these two theoretical blocks is one of the natural "lineages of the entrepreneurial ecosystem approach", as for (Autio et al., 2018, p.91) according to whom "there is a need for future research that examines the nature and effectiveness of such platform-specific entrepreneurial ecosystems and the boundary conditions associated with this new phenomenon". As shown by Balland et al. (2013) and Bessagnet et al. (2021), industrial and regulation strategies on technological standards impact the extent of entrepreneurial opportunities and success, as their geography. Such issues highlight the need to strengthen collaborations between these two cohesive groups to bring about a denser and shared conceptual framework within a more integrated community. Here again, the socio-semantic analysis sheds light on the gaps to be filled for upcoming research and outlines the nature of the collaborative incentives to be defined for the future.

To conclude, our analysis is not free of limitations. We restrained ourselves to a socio-semantic approach based on a network of scientific publications, and not on the network of their authors. The choice was justified by the need to semantically characterize the research outputs on DEEs, and not the knowledge bases of their authors. However, if each of these contributions produces concepts, the latter are constructed from knowledge, ideas, methods, data, provided by each of their contributors and constructed by their past scientific experience. In this sense, deepening the analysis of the structuring of the field of DEEs would require investing in the network of co-authors, which, even if it would certainly present similar characteristics (we tested it), would make it possible to enrich the semantic corpus by the sources of knowledge they brought to the contributions. This would be done, for instance, by affiliating to each node, this time the authors, the conceptual bases of their publications prior to their entry into the DEE network. Enriching the analysis with the network of co-authors would also make it possible to test the role of the institutional affiliation of the authors on the emerging semantic fields and the structural properties of the network. In particular, university affiliation (location) may play a role in collaborative attachment mechanisms, since public incentives for collaborative research are often limited to institutional and geographical areas. These extensions remain perspectives to explore.

Chapter 2

Unraveling the multi-scalar and evolutionary forces of entrepreneurial ecosystems: A historical event analysis applied to IoT Valley

Entrepreneurial Ecosystems (EEs) have attracted growing attention in the academic world as well as in policy spheres during this last decade. The internal and systemic mechanics of EEs are now based on solid theoretical and empirical foundations. However, few analyses have addressed how the structure and development of EEs are affected by and affect, in turn, the underlying competitive and regulatory dynamics that play out globally. To fill this gap, first, we use a multi-scalar framework where EEs are defined as local micro-organizations which are embedded both in regional contexts and in global market dynamics. Second, we suggest using the building blocks of EEs as the key components of a historical event analysis applied to the case of the IoT Valley in Toulouse (France), a digital EE dedicated to Low Power Wide Area Network (LPWAN) Internet of Things (IoT) technologies, from 2009 to 2019. This allows us to discern how events and scales work together over time and to offer a more complete and robust view of how EE dynamics result from the kinetics between entrepreneurial forces, regional context, and the worldwide battle between business ecosystems developing IoT platforms.

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In this chapter, my responsibilities were allocated as follows:

- Paper design and writing: 50%
- Empirical design and findings discussion: 70%
- Data collection and cleaning: 100%

2.1. Introduction

The *entrepreneurial ecosystem* (EE) concept has attracted increasing attention in the social sciences (Isenberg, 2010; Spigel and Stam, 2018), where the ecological metaphor has been used to link the systemic dimension of entrepreneurial processes with the opportunities offered by digital technologies (Song, 2019) as well as to renew research efforts on the sources of regional growth (Autio et al., 2018). As the literature on this subject grows (Acs et al., 2014, 2017; Alvedalen and Boschma, 2017; Malecki, 2018; Audretsch et al., 2019a; Stam and Van de Ven, 2021), some key elements have emerged that better delimit what an EE actually is, even if considerable variability exists in the empirical literature as to the scope of the EE (Cavallo et al., 2019a).

The academic literature on EEs can be broadly divided according to two methodological approaches. On the one hand, several empirical studies have used regressions to capture the drivers of EEs, including holistic and contextual components (Acs et al., 2014; Audretsch and Belitski, 2017). On the other hand, some well-documented monographs have contributed to providing a more precise picture of EEs through in-depth studies of their interacting components (Cohen, 2006; Cukier et al., 2016; Motoyama and Knowlton, 2017; Spigel, 2017; Thompson et al., 2018). Both approaches have identified EEs as the missing link in cross-country or regional differences in economic growth. Nevertheless, they generally fail to capture how the structure and development of EEs are affected by and affect, in turn, the global technological market dynamics in which EEs are involved.

Hence, our goal is twofold. First, we believe that this limitation can be overcome by determining the conditions and the channels through which technology and market dynamics stimulate or hinder the development of EEs; and what strategies are used by their players to deal with these conditions and channels so as to succeed in the competition between ecosystems. Addressing this issue by connecting the micro and macro scales to understand technological diffusion is not new in itself, and many past research studies on the geography of innovation have proven its relevance (Arthur, 1990). But concerning EEs, a salient characteristic of the macro-dynamics in which they are involved is the *platformization* of markets (Sussan and Acs, 2017; Hannah and Eisenhardt, 2018), and because it changes the organization of markets and facilitates the entry of new participants (the digital entrepreneurs) (Song, 2019), it also strongly modifies the very nature of regional growth sources (Audretsch and Belitski, 2017; Stam and Van de Ven, 2021). This *platformization* is concomitant with the development of EEs (Autio et al., 2018) and constitutes a particular competitive context where many EEs emerge but also can fail, depending on their ability (and that of the actors which are part of them) to engage in the battle of digital business models and of the technology standards they rely on (De Reuver et al., 2018; Teece, 2018).

Second, we propose a *historical event analysis* (HEA) (Van de Ven and Garud, 1993), it being a suitable methodology to grasp the nature of these interacting scales, i.e., the micro dimensions of EEs and the macro-dynamics of digital platforms. We apply this methodology to the IoT Valley, located in Toulouse (south of France), from 2009 to 2019. This EE is known as one of the top places worldwide for the Internet of Things (IoT) because of the location of Sigfox Inc., a network operator which, with its LPWAN (Low Power Wide Area Network)[1] technology called *Sigfox*, is one of the key players in the current worldwide battle occurring among different LPWAN standards and platforms (Mekki et al., 2019). Within the EE, Sigfox Inc. is surrounded by a myriad of local entrepreneurs developing LPWAN solutions for new business opportunities (Sestino et al., 2020). To undertake our HEA, we collected multi-scalar data on the LPWAN industry to reference and code a set of events. These events could be related to the main components of our specific EE or larger global events and cover aspects such as standards, regulations and formal rules, industrial alliances and networks, M&A and private financing, patenting, physical amenities, collaboration and deployments, products and services, and business ownership. We show that by combining qualitative and quantitative elements in a HEA, a more complete and robust view may be obtained about how the kinetics between local entrepreneurial forces, regional context, and the worldwide battle over technology standards and platform designs can lead to the emergence, growth or decline of an EE.

The paper is organized as follows: section 2.2 focuses on the EE literature to delimitate our case study and pinpoint the fundamentals of EEs. On this basis, we develop an original multi-scalar approach and position our case study within this framework. Section 2.3 presents the HEA methodology and explains in detail the process of gathering the data on events and of categorizing, cleaning, and coding them. Through this procedure, we created an original database containing more than 4800 events. Section 2.4 delves deeper into the case study by presenting the multi-scalar context related to *(i)* the initial conditions of the LPWAN entrepreneurial ecosystem of Toulouse, *(ii)* the main features of the regional environment in which the EE develops, and *(iii)* the worldwide technology and platform dynamics at work around LPWAN solutions and markets. Section 2.5 offers the results according to complementary event and scale representations underlining the EE's past and current trajectories and their driving forces. Section 2.6 concludes with analytical feedback and provides possible avenues for future research, including policy issues.

[1]LPWAN (Low Power Wide Area Network) technologies are described in Section 2.4.1

2.2. Entrepreneurial ecosystems: positioning of the concept in an event-based research approach

In a period where policymakers' enthusiasm for EEs is growing, if lessons are to be drawn from case studies, particular attention needs to be paid to how they are framed, theoretically and methodologically. Thus, given that our research priority is to frame the study of the IoT Valley, we first (2.2.1), need to formulate the EE concept in terms of its organizational boundaries, and in what respect it interacts with the concept of *business ecosystem* (BE), the very nature of its objectives, and how it differs from other concepts such as technological clusters or innovation networks. Secondly (2.2.2), it should be noted that an EE does not emerge from scratch, but rather it is usually born in a local context with which it continues to interact over time. And when it evolves, its development depends on its ability to impose its technology on global markets. What is needed, therefore, is a multi-scalar analysis, which is the second framing of our case study.

2.2.1. Matching the theoretical and empirical frontiers of an EE

2.2.1.1. Distinctions and interactions between business and entrepreneurial ecosystems

The *business* and *entrepreneurial ecosystem* concepts belong to two fields in management that are rarely connected in the literature as they refer to different scales and purposes. While the former refers to the global strategies of tech companies, the second relates to local entrepreneurship dynamics (Spigel and Harrison, 2018). More than reconciling the two approaches, where each has its *raison d'être*, our objective is to show that the dynamics at work within an entrepreneurial ecosystem interact with those at work within a business ecosystem, particularly for EEs hosting a blockbuster, i.e., a key player in global markets. Furthermore, the analysis of these interactions is all the more necessary as these markets rely on digital technologies, which question the borders of EEs (see Sussan and Acs (2017) on "the digital EEs" and the critique and reconfiguration of this concept by Song (2019)) and BEs (see Nachira et al. (2002) on "the digital BEs") emphasizing their interdependence.

On the one hand, the theory of business ecosystems, initiated by Moore (1993), postulates that the key to success for a firm depends on all the alliances it will build to promote its development. The entangled questions of technological standardization and business model are crucial for designing a dominant technology platform. To disseminate their standards, companies must rely on players such as suppliers, customers, or supporters. All the players linked to a certain standard and their interrelationship will constitute the business ecosystem (Iansiti and Levien, 2004), and actors involved in the field forge partnerships to create effective ecosystems (Cusumano et al., 2008). On the other hand, the theory of the entrepreneurial ecosystem developed by Isenberg (2010) is modeling the conditions that facilitate the development of productive entrepreneurship within a territory. By local entrepreneurial ecosystem, (Brown and Mason, 2017, p.14) mean *"a set of interconnected entrepreneurial actors, entrepreneurial organizations, institutions and entrepreneurial processes which formally and informally coalesce to connect, mediate and govern the performance within the local entrepreneurial environment"*. The idea is to promote a place of dialogue between the different stakeholders of entrepreneurship. As such, infrastructures, universities, funders, mentors, deal makers, social networks, and societal and cultural standards form a whole, like in the case studies referenced in the introduction, from Cohen (2006) to Thompson et al. (2018), or in the study by Spigel and Harrison (2018), where they are profoundly analyzed as actor and process categories.

Capturing the interdependencies between *entrepreneurial ecosystems* (EE) and *business ecosystems* (BE) involves researching how one or two blockbuster(s) of an EE organize the development of their platform by benefiting from the local entrepreneurial forces that they have themselves encouraged to fuel the uses of the platform, such as technological innovations and business models for connected objects, the improvement of sensors, or the optimization of interoperability protocols. Hence, they arrive well positioned globally in the competition between platforms and can build the necessary alliances to increase network externalities and the variety of uses in the market. In this sense, the worldwide alliances with local network operators should be recalled, as well as those with service providers wishing to benefit from digital technology to improve their business models. In other words, BEs develop through the integration of "the valves and fluids that make up the pipes" of the platform developed by the blockbuster(s) within the EE, thus reinforcing their position through their strategic interaction (Gawer and Cusumano, 2014).

2.2.1.2. Entrepreneurial ecosystems as drivers of digital platform development

To demarcate our particular EE under study properly, we consider it to be at the crossroads of the EE features that Song (2019) identified as being more representative of the key dimensions of digital EEs and the study by Autio et al. (2018), who accurately demonstrated how the exploitation of digital affordances, i.e., business models and innovation practices created by new digital opportunities, is what differentiates EEs from clusters. In fact, there is consensus between these two contributions that the development of EEs is directly related to the entrepreneurial opportunities opened up by the digitization and *platformization* of markets.

This consensus taken as a given, Song (2019) specifies the four key dimensions that help us differentiate EEs according to their weight. Among these dimensions, two are relevant for our case: *(i)* the *"digital technology entrepreneurship"* dimension, because our case focuses on the opportunities of LPWAN technologies that support IoT platforms efficiently, technologically speaking; and *(ii)* the *"digital multi-sided platform"* dimension, since the main objective of the EE entrepreneurs is to develop services supported by LPWAN technologies in a competitive way, economically speaking. This competition dimension relates, in our case, to the ability of the LPWAN platforms to attract providers and users to subscribe to efficient IoT solutions. Each one aims to reduce transaction costs and intermediaries' rents in markets like transport management, security and insurance, or earth observation, where the collection, treatment, and transmission of data matter for value creation.

Autio et al. (2018) delimit what EEs actually are according to a set of distinct features that enable us to clarify the confusion created previously in the literature about the difference between EEs and clusters. In doing so, they offer a relevant framework to delimit case studies. First, on one side, EEs are systems in which players benefit from digital affordances to develop stand-up, start-up, and scale-up activities, as largely developed by Elia et al. (2020), for whom digital technologies influence the interactions among actors and their capacity to identify resources and partners in the entrepreneurial processes. On the other side, clusters are more often viewed as structures benefiting from spatial affordance, i.e., thanks to spatial proximity, collaborative behaviors offer opportunities to manage voluntary knowledge spillovers through strategic R&D collaborations in the innovation value chain (Iammarino and McCann, 2006; Vicente, 2018). The EE in Toulouse clearly supports the development of "stand, start and, scale-up" processes that occur around the provision of services delivered by the LPWAN platform. Second, even if the initial conditions of many EEs can, to a large extent, be found in spatial affordances, EEs develop especially from the ability of actors to use digital affordances to explore new competitive business models and find a global niche for their product (Giones and Brem, 2017). This is typically the case for our EE under study, which differs from the local cluster dedicated to product innovation and not to exploring new business models. Third, EEs stand out from clusters through their ability to exploit digital affordances to seek out network effects external to clusters. These advantages are obtained most often on a global scale, where competition between platforms is played out (Nambisan, 2017). Here again, our case study enables us to isolate this specific EE dimension: the strategies of the Toulouse LPWAN EE's leading actors consist in searching for global network effects in the worldwide competition among LPWAN platforms. Nevertheless, these three characteristics do not exclude interactions and reciprocal feedback between EEs and clusters, particularly when local experiments of new business models come from a request by cluster actors to solve a specific problem (Auerswald and Dani, 2017; Qian, 2018; Ryan et al., 2021). However, confusing the two notions undermines the understanding of how EEs contribute to the dynamics of entrepreneurship and what drives competition between EEs and their platform models at the global level.

2.2.2. Placing the EE analysis in a multi-scalar context

2.2.2.1. General context

Designing a good EE monograph, i.e., a comprehensive qualitative case study, requires considering the effects of context. However, while national and regional contexts have been taken into account in many monographs as well as in several empirical studies using regressions, conversely, the global technology and market context in which EEs develop has barely been considered. To bridge this analytical gap, as we begin depicting the nature of the events to be collected, we suggest that the analysis of EEs is based on the interactions between *(i)* the EEs internal micro-organization and dynamics, *(ii)* its embeddedness in a larger urban or regional context, and *(iii)* the global business ecosystem features in terms of competition and regulation. Figure 2.1 summarizes our general multi-scalar framework.

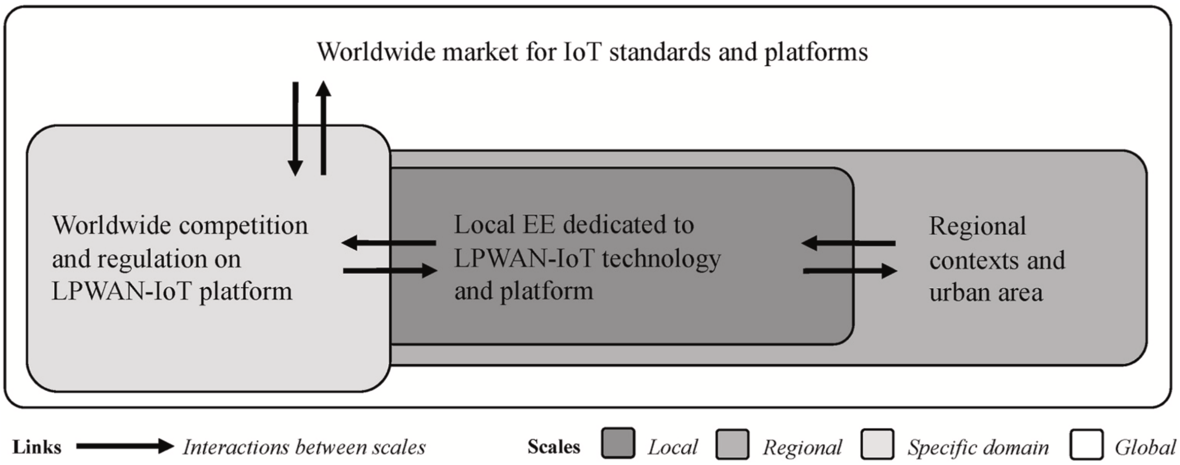


Figure 2.1: LPWAN-IoT Entrepreneurial Ecosystem embeddedness: general framework

EEs are systems that bring together interacting start-ups and entrepreneurs – leader and follower ones Feld (2012) – involved in new-to-the-world markets. On the one hand, these ecosystems do not start from scratch but emerge from local contingencies related to the region's technological and business history, where also incumbent firms are involved (Brown and Mason, 2017). Therefore, understanding EE growth dynamics requires analyzing, through a multi-scalar perspective, how their micro-organization affects and is affected by the business, institutional and technological dynamics at work within the region. On the other hand, at a global level, in particular as far as digital technologies are concerned (Sussan and Acs, 2017; Song, 2019), standard and dominant designs arise from the competition between different network technologies or platforms. According to Arthur (1990), the battle of standards and the battle of places (i.e., the places where these early competing technologies originate and develop) can influence each other (Suire and Vicente, 2014). This is particularly true for the growing economy of digital platforms whereby several EEs are emerging over the world and whose actors' strategies are confronted with the need to capture network externalities on the consumer side. This brings about competition and cooperation strategies, which depend on interoperability issues between the competing technologies and the integration of different complementary building blocks within reliable and complete systems (Adner and Kapoor, 2010; Hannah and Eisenhardt, 2018). It also depends on the institutional framework designed at different scales to regulate the competition between technology standards in general (David and Greenstein, 1990) and IoT platforms in particular (Mansell and Steinmueller, 2020), and on the ability of EE's main actors to influence the evolution of these contexts of nested regulation (Audretsch et al., 2019a,b).

2.2.2.2. IoT Valley elements and interactions between scales

Concerning our analytical framework, and before we expound on empirical considerations, the elements and interactions of IoT Valley are explored in greater depth to better target the content of the events we aim to collect. Figure 2.2 summarizes the contents of these elements and the interactions between them. In this study, we do not consider all interactions and feedback loops because some have a stronger relevance than others for our EE drivers and trends. We will focus mainly on the reciprocal influences between the internal dynamics of IoT Valley and the worldwide competition and regulation context of LPWAN technologies and platforms, and on the one-way impact of the urban and regional system on the local LPWAN-IoT EE. We do not consider the reciprocal influence between the EE and the regional system since it is out of the paper's scope, even if it is an important topic, in particular when considering the role played by nascent EEs in regional diversification and renewal (Spigel and Stam,

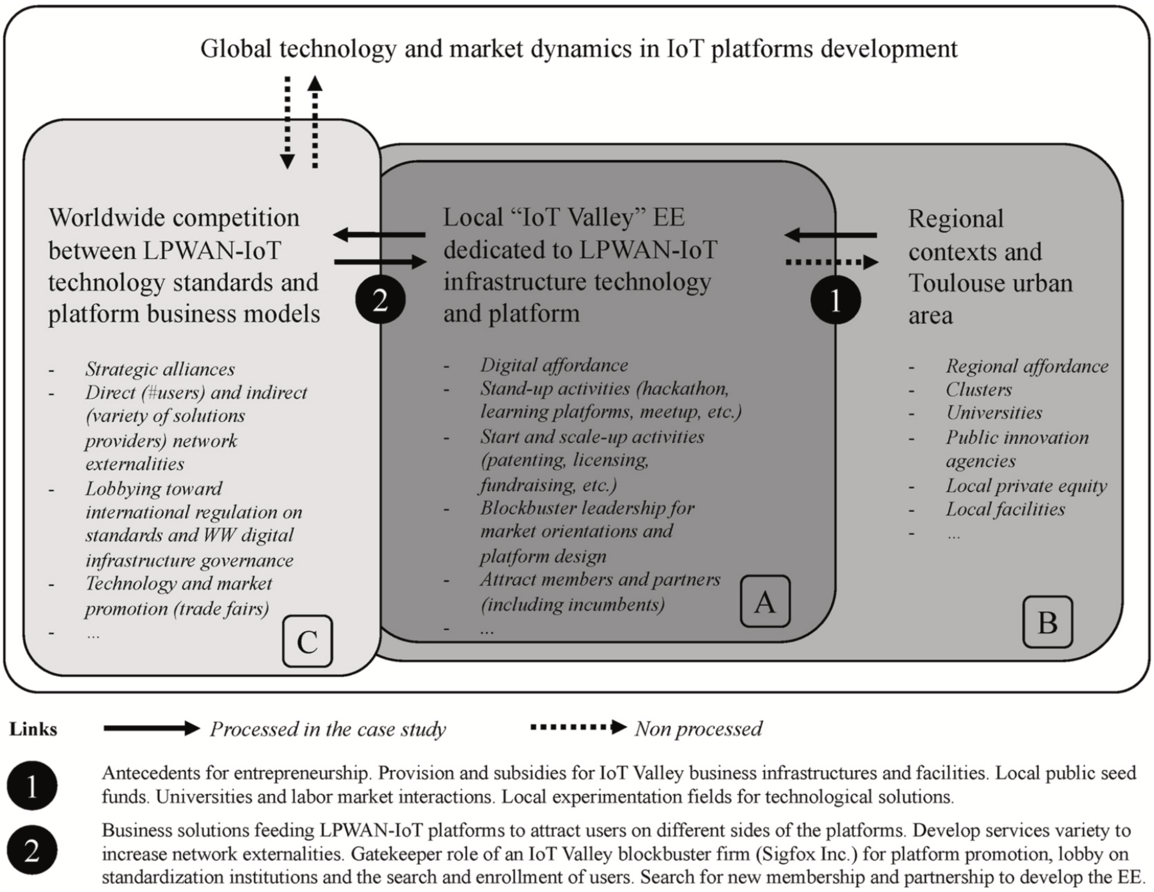


Figure 2.2: IoT Valley elements and scales interactions

2018; Spigel and Vinodrai, 2021). By the same token, except for research perspectives, we do not explore either the reciprocal influences between the specific low range IoT technologies and the worldwide competition among all alternative IoT systems.

Let us start with the elements. First (box A in Figure 2.2), the IoT Valley matches the key features on which the EE literature has reached a consensus. On the one hand, the IoT Valley is a structure consisting of – and hosting – entrepreneurs whose common objective is to create digital business opportunities to render the LPWAN platform more efficient by feeding one of its sides (users) with software and IoT solutions. On the other hand, the structure is directly connected through its governance system to one of the worldwide blockbuster LPWAN companies, which is a salient feature of growing EEs (Mason and Brown, 2014; Belitski and Godley, 2020). Besides facilitating social interactions within the EE, the EE governance aims are to develop partnerships with incumbents (Feld, 2012; Qian et al., 2013; Mason and Brown, 2014). Members interact through typical digital EEs stand-up and start-up activities, which are largely promoted to attract venture capital, partners, and users for the other side of the platform (providers) (Song, 2019). Patenting, licensing and business model exploration activities to facilitate scaling-up processes are also at the heart of the EE managing structure (Teece, 2018).

Second (box B), the IoT Valley is a formal organization that is part of a larger regional system with which the managing team maintains institutional and business relationships. The IoT Valley is acknowledged by local public institutions and funding agencies as an essential organization for regional renewal, while relationships between the IoT Valley entrepreneurs, clusters, and universities rely on local social networks developed over time (Nicotra et al., 2018).

Third (box C), the development and diffusion of LPWAN technologies occur in a global business ecosystem in which different LPWAN sponsors compete. The Sigfox technology created by the local EE blockbuster competes with two others (LoRaWAN and NB-IoT), and each of them aims to become a world standard. Undeniably, standardizing a new technological domain is crucial for the development of nascent EEs (Rice and Galvin, 2006) since it *(i)* facilitates interoperability and business deployment through alliances (Rosenkopf and Tushman, 1998; Sestino et al., 2020), *(ii)* plays a role in the demand side, and *(iii)* helps to gain market acceptance through normalization (Aldrich and Fiol, 1994; Song, 2019). Furthermore, as Shapiro and Varian (1999) found, firms or industrial alliances developing incompatible technologies compete for dominance in technology standards. Consequently, the main challenge for the players of each competing EE is to obtain increasing returns to adoption generated by direct network effects (numbers of users on one side of the platform) and indirect ones (variety of services on the other side of the platform) (Sussan and Acs, 2017; De Reuver et al., 2018).

Let us now turn to the interactions in Figure 2.2. First (link 1), it should be pointed out that, from the start, most digital EEs miss the opportunities and avoid the constraints of geography and agglomeration (Autio et al., 2018; Song, 2019). But many EEs also emerge and grow through regional affordances. In fact, antecedents can be found in their regional contexts, in particular, when, as is the case for IoT Valley, business opportunities are directly related not only to innovation in the digital business model (how to turn "things connected" into economic value) but also to technological innovation (how to connect "things" through low-power networks). Entrepreneurial businesses operate locally or regionally and are, therefore, subject to local or regional contextual influences (Nicotra et al., 2018). The regional aspects that shape the environment for would-be entrepreneurs are cultural and also resource-centric, i.e., they depend on the possibility of accessing critical resources. This last dimension is thus regional context dependent in terms of the technological and human resources and the region's research and business facilities and infrastructures. Moreover, experimentation opportunities for technological solutions, prior to them being launched as business solutions, are more easily found at the local level and can be supported by local public seed funding or even local private equity funds.

Second (link 2), the interactions between the IoT Valley and the worldwide competition among LPWAN technologies and platforms are the key issues to understand the IoT Valley trajectory over time. These interactions mainly rely on the local blockbuster's behavior and strategy, which could be acting as a central gatekeeper (Morrison, 2008) between the dynamics of local EE micro-organizations and the ongoing battle among technology and platform standards. In terms of the industrial organization of digital platforms (Rochet and Tirole, 2003; De Reuver et al., 2018), their quality of software and cloud offering and ability to provide business solutions to attract a wide range of users on the different sides of the market are crucial to the design of competitive strategies. Therefore, the blockbuster position is affected by the level of creativity achieved within the local EE in which it is involved. The better IoT Valley entrepreneurs perform in all dimensions, the better the blockbuster will perform in the competition among the technologies supporting digital platforms, which, logically, will have a positive impact on the EE's growth.

Positive feedback can also be obtained when the gatekeeper develops strategic alliances and effective network interoperability, both these strategies being suited for diversifying the range of potential users and reaching the necessary critical mass to strengthen the EE blockbuster monopolistic position (Adner and Kapoor, 2010; Hannah and Eisenhardt, 2018; Song, 2019). In terms of platform promotion and attractiveness, the visibility of the EE blockbuster in global trade fairs, the media, and elite political spheres does matter. And it matters not only for its own competitive position in the battle among platforms but also for the whole entrepreneurial community which gravitates around it. Finally, concerning the digital political economy and standard regulations, the multilateral geopolitical relationships present in the governance of digital infrastructures, technology standards, global interoperability, cloud computing, and data sovereignty (Mansell and Steinmueller, 2020) can have a strong influence on the growth trajectory of an EE. Here again, the gatekeeper role of the owner of an alternative technology standard and its ability to lobby governments and adapt its technology to the evolving rules of the digital infrastructure governance would also provide positive feedbacks to that EE.

Turning the above-conceptualized elements into events, given that we have only positioned them empirically so far, would help us unravel, for our case study, how these elements play over a time sequence and precisely at which scale they interact in order to stimulate the development of the EE. The multi-scalar framework developed here would then allow us to understand how this trajectory unfolds in the EE's nested system of scales where many feedbacks occur due to the global competition among LPWAN technology platforms, the entrepreneurial stimuli within the EE, and the regional context. An EE trajectory cannot be appreciated solely by its internal dynamics nor by purely exogenous and holistic factors. Thus the challenge is to develop a methodology that enables us to capture this feedback so as to offer a view that is as-robust-as-possible of the kinetics between these events' and scales' interactions and the different channels through which an EE can be built, as well as to identify its developmental capabilities.

2.3. Data and methods: historical event analysis

To carry out empirical research on the IoT Valley EE, and to be able to capture this multi-scale kinetics, we use what is known as historical event analysis, as developed by Van de Ven and Poole (1990), Van de Ven and Garud (1993), and Poole et al. (2000), and often applied by the technological innovation systems (TIS) literature (e.g., Negro et al. (2008)) to study the innovation and development processes of new technologies.

The HEA method provides the basis for systematically collecting and treating qualitative historical data. The central analytical unit is the event, defined as "what central subjects do, or what happens to them" (Poole et al., 2000, p.40). Each event contains information on the what, the who, the when, and the where. This information is then classified into relevant analytical categories. The classified set of events can be used for counting the events per relevant category and in chronological order, and also to create sequences of interrelated events that link multiple dimensions, with various scales and multiple actors in which the meaning of each event is conditional on its position in the sequence (Van de Ven and Poole, 1990). Therefore, it is an appropriate tool to study the co-evolution of multi-dimensional and multi-scalar processes, as well as to identify salient events or the sequence of events that are relatively more important than others (Sewell, 1996).

We built a raw data sample collecting events about LPWAN development, its technological varieties, and its establishment in Toulouse. These data were collected from diverse sources. First, we relied on articles in newspapers and magazines from 2009 to 2019 to identify pertinent events by using Boolean combinations of keywords (LPWAN, IoT, LoRa, LoRaWAN, Sigfox, NB-IoT, Toulouse). We used Europress as a source for the generic press, which was completed with three IoT specialized press sites (Lembarqué, M2 Communication, VIPresse) and a press releases database (Business Wire). Second, we used two structured databases to obtain information on firms' fundraising: Crunchbase and Dealroom. Finally, we also relied on the Trade and Companies Register for corporate entities, specialized reports, interviews with actors involved in different steps of the value chain, and direct field observation, either within the EE or through the attendance at trade congresses in that field.

By means of this procedure, we obtained a raw database with more than 13,000 events. This information was then manually cleaned, deleting non-pertinent results produced during the keyword search and the duplicated events that had been reported several times by various sources. This way, we ended up with a database containing 4859 events. Next, we further enriched the data by classifying the events into categories and subcategories of EE components they related to and according to the geographical scale and the corresponding technological platform[2]. The classification of events into EE components was inspired by the consensus reached in the literature on the building blocks and critical components of EEs and industrial infrastructures for technological innovation (Van de Ven and Garud, 1993; Isenberg, 2010; Stam, 2015; Stam and Van de Ven, 2021). However, in comparison with this literature, our classification was not an exhaustive one. Indeed, the selection process was recursive; starting from the consensual components identified in the literature, we adapted them to the set of events obtained from our keywords search. Then, we excluded the categories that had no events. This was the case for the cultural context category, which was used in Stam's model (Stam, 2015). Finally, three analytically distinct categories of events were identified related to *(i)* changes in and the creation of supporting institutions (regulations and network affiliation), *(ii)* the development of fundamental resources (financial, knowledge, and infrastructures), *(iii)* and business development activities (commercial agreements, production, and firm creation). The descriptions for each category and subcategory are given in Table 2.1. These classified events allow us to unravel how they play out over time and at what scale they interact.

However, our set of events represents neither the whole population nor a random sample of occurrences (Van de Ven and Garud, 1993) connected to the EE and technological development. Moreover, data completeness was constrained for three reasons: human feasibility, secrecy and confidentiality of certain information and decisions made by the actors, and no press coverage of all events. To eliminate the constraints and bias created by this "incompleteness," we established several control procedures. First, we triangulated the collected data, our requirement being that at least two sources accepted the occurrence of an event. Second, the events' cleaning and classification processes were checked with various experts from the sector. Their feedback and recommendations allowed us to verify that no key events were missing and to correct certain events' classification. Thus, although some events data was not complete, the set was sufficiently broad to provide us with a better understanding of how the EE has

[2]The dataset and the analysis of the links between the events that support the findings of this study are available from the corresponding author on request.

Category	Subcategory	Description	Metrics	Events	Illustrations of events	# events
Supporting institutions	Regulations	Policy ground upon which firms assume their economic activities	New rule, law, norm, decision issued by regional agencies, States, firms or standard-setting bodies that impact global technology development	(a) Standard regulation and formal rules events	*09/11/2006*: Decision by the 121 Commission (2006/771/EC) on the harmonization of the radio spectrum for use by short-range devices *11/10/2017*: LoRaWAN specification 1.1 - Final release. The LoRa Alliance sets up roaming between LoRaWAN networks.	121
	Network affiliation	Firms that gather together in a group in order to distort the process of technological maturation	Affiliation of a new firm to an existing industrial alliance or network	(b) Industrial alliances and networks events	*19/04/2016*: Oceasoft joins the LoRa alliance and launches its first LoRaWan compatible sensors. *02/07/2016*: GreenCityZen Become a Sigfox Partners Company.	1295
Fundamental resources	Financial backing	Firms' private funding including acquisition and merger deals	New acquisition of a firm or investment in a firm for equity or debt loan	(c) M&A and private financial events	*30/05/2014*: GDF SUEZ acquires Ecova via Cofely. *23/09/2016*: Connit, specialist in the supervision of industrial connected objects, raises 3M€.	247
	Research and knowledge	Creation and protection of use of difficult-to-imitate commercial and industrial knowledge asset	New patent assigned to a private or a public organization	(d) Patenting events	*31/03/2015*: Patent titled as "Method and module for estimating frequency bias in a digital-telecom. system" granted to Sigfox Inc. *17/06/2017*: Patent titled as "Control-less Data Transmission for Narrow Band IoT" granted to Mediatek Inc.	617
	Infrastructures	Material conditions that enable business activities	New physical amenities available in local context	(e) Physical amenity events	*08/10/2015*: Opening of 574, the 24 SNCF accelerator in the IoT Valley 16/03/2017: IoT Campus: Sicoval holds 50,000 square meters for IoT Valley & Sigfox Inc.	24
Business mechanisms	Commercial agreements	Commercial agreement between two firms	New partnerships or deployments	(f) Collaboration and/or partnership events	*19/09/2016*: Silicon Controls & Thinxtra partner to connect 1 M devices for oil & gas industry withSigfox. *15/11/2016*: Senet and Paige Ag partner to deliver smart irrigation solutions with LoRaWAN.	1143
	Production	Established or entrepreneurial firms' commercializing innovations	New product or service pushed by a firm on the market	(g) Product or service events	*10/01/2018*: Sierra Wireless "AirPrime WP77" modules certified to operate T-Mobile's NB-IoT network. *24/10/2018*: NTT DoCoMo introduces IoT-driven temperature-monitoring service in U.S. based on LoRaWAN.	1320
	Firm creation	Firm demography	Number of new EE firms registered by official authorities	(h) Business ownership events	*03/09/2009*: Sigfox Inc. *22/02/2019*: MerciYanis	92

Table 2.1: Overview of events structuring an EE embedded in a macro-industrial organization of technologic field

developed over time. We also identified the most relevant ones (salient events). This selection was followed with the same protocol used in the events data analysis, i.e., we identified the inflections that introduced a shift in the trajectory of the EE and/or of the LPWAN industry. Their relevance was then confirmed through interviews conducted with industrial and local experts, such as Toulouse economic development officials and managers of acceleration facilities and knowledge-intensive business services (KIBS) active in the domain.

2.4. Spatio-temporal and technological context of the IoT Valley in Toulouse

2.4.1. LPWAN-IoT technology for IoT platforms

The Low Powered Wide Area Network (LPWAN) is part of what is commonly known as the Internet of Things (IoT) communication protocols. IoT is a system that enables devices to communicate with each other to carry out certain tasks in an autonomous way and at a distance (Sestino et al., 2020). IoT transforms physical objects into digital ones emitting information such as location, usage, stage, etc. This information is processed and then sets in motion a coordinated action of the emitting objects and/or other objects relying on this input. Thus, the IoT value chain can be divided in four steps: *(i)*the generation of information, *(ii)* its transmission from the device to the cloud, *(iii)* the processing of this information in the cloud, and *(iv)* the use of the information in multiple applications and services.

LPWAN technology connects objects to the cloud, so it mostly concerns the second step *(ii)* of the IoT value chain. There is no one-size-fits-all solution, but several alternative technologies can make that connection, either cellular-IoT (LTE-M, 5G) or short-range (wi-fi, Blue- tooth, etc.). However, the particularities of LPWAN as compared to other communicating technologies are the following: *(a)* given that it has a very long operating range, the development of the network is easier and cheaper (fewer antennas), *(b)* its power consumption is lower, and *(c)* linked to the previous two, the amount of data it can transfer is smaller (Sanchez-Iborra and Cano, 2016; Mekki et al., 2019). Thus, through the conjunction of these three particularities, LPWAN technology is well adapted to any situation where objects are dispersed across space and where the information they have to provide is very punctual. As a result, this technology is particularly suited for business opportunities where low-range information transmission constitutes a strategic differentiation for the development of IoT platforms dedicated to digital markets on the third and fourth steps of the IoT value chain (*iii* and *iv*).

Within LPWAN, three main similar technological alternatives are being broadly adopted: Sigfox, LoRaWAN, and NB-IoT. They constitute three competing digital global business ecosystems and are considered competing technologies because they focus on use case categories that partially overlap into the “low data rate” and “high range capability” quadrant (Figure 2.3). Sigfox and LoRaWAN are both proprietary technologies and use unlicensed frequency bands, while NB-IoT is not a proprietary technology and uses licensed LTE frequency bands. As a consequence, they have adopted different business models. On the one hand, Sigfox, controlled by Sigfox Inc. (Toulouse, France), follows a “network as a service” model. Users either create from scratch or buy their device and pay to connect it to the Sigfox network. Network deployment takes place through alliances with local companies in each country. On the other hand, in the case of LoRaWAN, which was first patented by Cycleo (Grenoble, France) and since 2012 has been controlled by Semtech, users need to buy sensors and gateway that contain a LoRa chipset (Semtech indirectly charges a fee on them); the network service is, however, free and promoted by the LoRa Alliance. Finally, NB-IoT follows a model similar to mobile-phone technologies, i.e., users have to pay a fee to access the network, but no specific chipset is required. Huawei, together with Deutsche Telekom and Vodafone, are the main companies that push for this model.

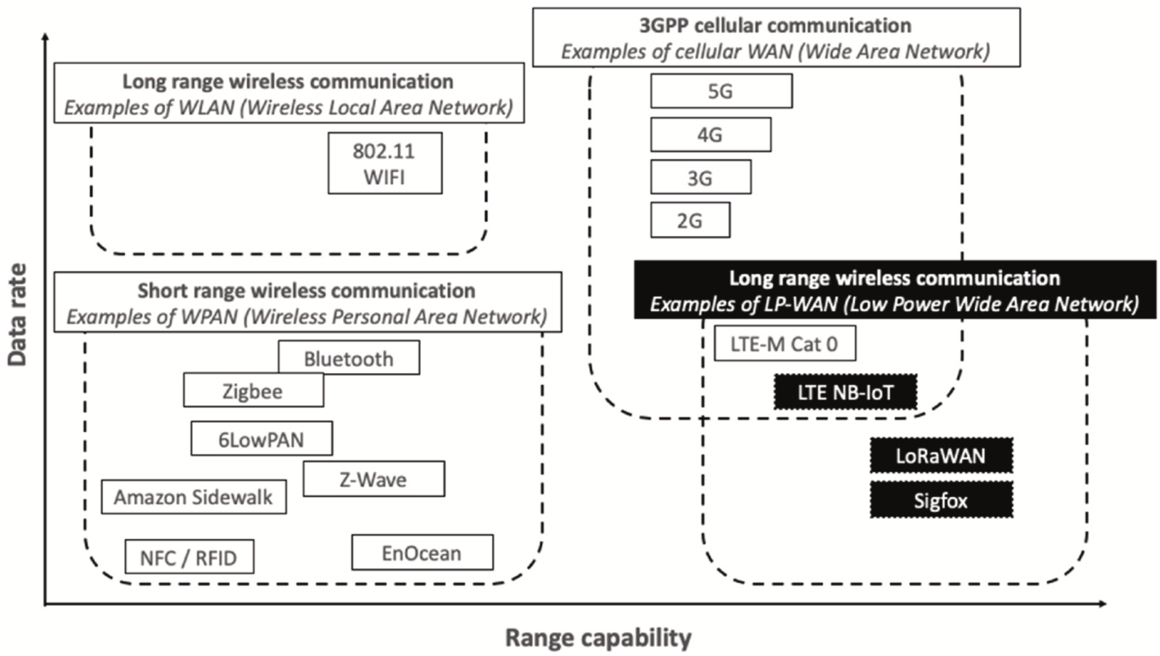


Figure 2.3: Required data rate vs. range capacity of radio communication technologies: LPWAN positioning. Adapted from Mekki et al. (2019)

2.4.2. The place: the Toulouse region and its entrepreneurial ecosystem

Sigfox was founded in Toulouse, where its headquarters are. The region is a dynamic one, specialized in several knowledge-intensive sectors (Talbot, 2000; Niosi and Zhegu, 2005; Zuliani, 2008; Porter and Takeuchi, 2013; Levy and Talbot, 2015) such as aeronautics, with the Airbus headquarters, product development labs and assembly lines, aerospace, with the National Space Agency, two satellite builders, and numerous SMEs dedicated to data management, positioning, and imagery. Historically, Toulouse has also been active in the electronics sector that emerged in the 1970s with the arrival of Motorola and CII, and in the 1990s with semiconductor production activities oriented towards R&D, and diversified towards embedded systems for transports and new mobilities (Continental, Actia, Hella, Renault). Since the 2000s, it has gone through an important re-organization with several mergers, acquisitions, and spin-off cascades.

Sigfox Inc. emerged from entrepreneurs immersed in this regional context. Sigfox Inc. was founded in 2009 by Christophe Fourtet, Thierry Bailleul and later joined by Ludovic Le Moan. Fourtet was a developer of radio technologies employed at Freescale in Toulouse, who brought with him and patented the technical innovation for low power communication. Le Moan is a serial entrepreneur in Toulouse, mainly working on the M2M and IT domain. Backed by his success at Anyware Technologies, Le Moan brought with him the business model for Sigfox Inc.'s foundation. Shortly after its birth, the company began to grow rapidly because its communication technology had the potential to become a highly innovative building block for the LPWAN platform, a domain whose growth expectations were very high (Saarikko et al., 2017). As a consequence, Sigfox Inc. entered the worldwide battle among LPWAN platforms, and to compete in it, it started constructing its own business ecosystem with partners from all over the world and across all stages of the value chain.

This study focuses on the birth and development of the IoT Valley in Toulouse, an EE dedicated to LPWAN and IoT activities, and its interplay with the global industrial organization of the LPWAN domain. The IoT Valley is an association that locally gathers entrepreneurs involved in IT and IoT technologies. It seeks to promote IoT technologies for digital markets and develops a large package of activities helping entrepreneurs to stand, start and scale up their LPWAN-based activities. The association's goal is twofold: *(i)* to attract members for the exchange of technical and business knowledge in shared facilities; and *(ii)* to attract partners by acting as a key interface between start-up and established firms interested in adopting IoT solutions and feeding sides of the emerging LPWAN platform. However, from its foundation, the IoT Valley has been tightly linked to Sigfox Inc. because this blockbuster company was a founding member of the association. Sigfox Inc. actually integrated the IoT Valley as part of its global business ecosystem from the very beginning. Through this linkage, the evolution of the IoT Valley EE has become dependent on the evolution of the LPWAN domain.

2.5. A historical event analysis of the EE multi-scalar driving forces

2.5.1. EE dynamics

The first steps towards the configuration of an LPWAN based EE in Toulouse were taken around 2009, when four entrepreneurs created an association to build an entrepreneurial friendly environment. They decided to co-locate their activities to share rental costs and entrepreneurial experiences (1)[3]. To do so, they reached an agreement with local authorities to be hosted in a business incubator with subsidized rents and with advantageous access to high-speed broadband internet (2, 3). And from that seed the TIC Valley was officially launched in 2011 (4). This was a step forward regarding the willingness of the founders to structure and formalize an EE. The TIC Valley's foundation saw an increase in the number of digital start-ups, in particular thanks to the launching of an acceleration program ("Le Camping") (5), and moving to a dedicated building. The new building had two effects on the evolution of the EE: a real one in terms of square meters to host more start-ups, and a symbolic one, in terms of the feeling of identification and belonging to a local entrepreneurial community.

The next turning point in the EE's development came in 2015 when the TIC Valley was re-founded as the IoT Valley (6). This transformation was tightly linked to the evolution of Sigfox Inc., the blockbuster startup of the EE, and its involvement in the worldwide battle among LPWAN platforms. Sigfox Inc. was strongly embedded in the EE from the very beginning because Le Moan, CEO of the firm, was also one of its founders in 2009. Until 2014, Sigfox Inc. had been in a start-up mood, mostly focusing on R&D activities and local experimentation with low range communication for connected objects and getting funds through relatively small fundraising rounds. However, in 2015, to scale up its project, Sigfox Inc. planned the geographical expansion of its network and succeeded in raising EUR 100 M in a funding round, followed by another one of EUR 150 M from private and public investors in the following year (7). As a result, Sigfox Inc. could increase its number of employees and expand its network geo-

[3]The numbers in parentheses refer to the salient events integrated in Figures 2.4 and 2.5. In these figures, letters (a)–(h) refer to the types of events developed in Table 2.1.

graphically[4] and its customer portfolio connected to its platform. It quickly became one of the leading companies in LPWAN infrastructures with extraordinary growth expectations. This positioning, the figures of its record fundraising for a French/European start-up, and the subsequent large media attention contributed to creating a strong legitimacy and reputation among local entrepreneurs, IoT entrepreneurs around the globe, and local and national policymakers (8).

To maintain the momentum, Le Moan participated in the refoundation of the EE, whose emphasis then shifted from entrepreneurship in *generic* IT to IoT-*specific* entrepreneurship. From then on, the association focused on entrepreneurial stand and start-ups based on digital solutions for improving the quality and potentialities of the platform. In this way, the scope of the EE became aligned with the fields of interest of its blockbuster start-up. Following the re-foundation, the "Le Camping" program was rebranded as the "Connected Camp" to accelerate IoT-related projects (9). Moreover, the EE broadened the scope of services offered via e-learning platforms (10), the development of tools to enhance interactions within the EE to solve technical and entrepreneurial problems (11), and the affiliation of established companies (12) to strengthen the link between IoT entrepreneurs and big companies looking for IoT solutions and, as a consequence, to feed the two sides of the Sigfox platform. With its expanded menu of tools and services, the EE sought to favor entrepreneurial processes all along its stages of opportunity discovery, start-up, and scale-up. Finally, the business model of the IoT Valley itself also changed. In TIC Valley times, resources were obtained from local institutions, renting activities, and funding partners (13), but during the IoT Valley stage, funding was obtained from contributions made by corporate partners and give-back payments from successful start-ups (14).

Figure 2.4 shows the evolution of funding raised by Sigfox Inc. and its impact on the EE. The shift sought to build positive bi-directional synergies between the EE and the Sigfox Inc. trajectory in the LPWAN battle. First, by defining a niche area close to its blockbuster's domain of specialization, the EE exploited the image of Sigfox Inc. to build a new industrial identity or geographical charisma for the region. This charisma and regional identity contributed to attracting new entrepreneurs and established firms in the field and related ones via a cascade localization process and network effects. It also allowed the EE to attract additional funding for new entrepreneurial activities based on its reputation (15, 16). Thus, while the entrepreneurs that enrolled in the first editions of acceleration programs were mostly from the Toulouse region (e.g., Citymeo, Capturs, etc.), the entrepreneurs in later editions came from all over the globe (e.g., Wearhealth, Zenodys, etc.). Similarly, there was also an increase in the number of big

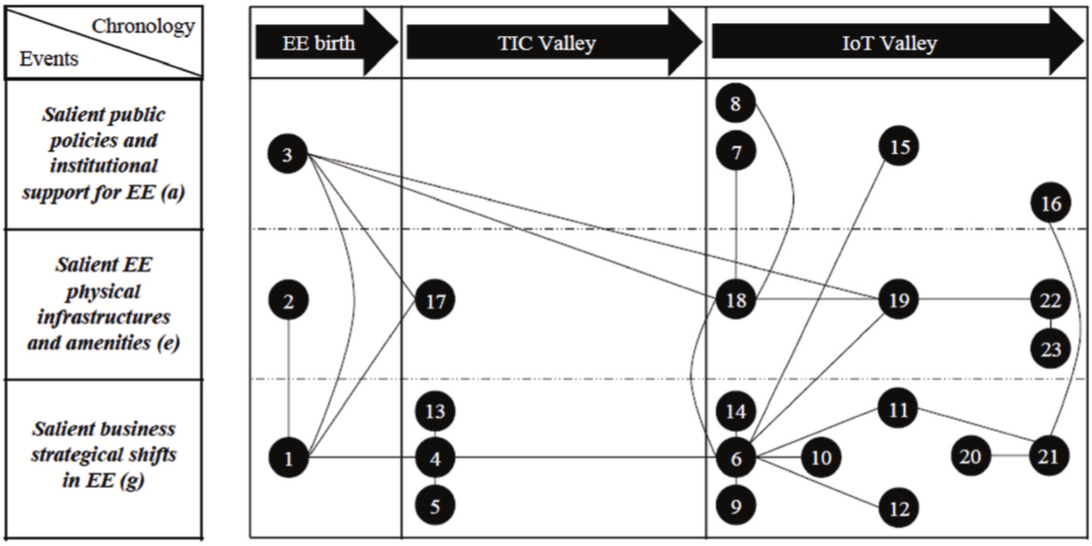
[4] Number of countries covered by Sigfox's network: 2012–2014=1; 2015=5; 2016=27; 2017=41; 2018=57; 2019=65.

partners affiliated to the EE, often from elsewhere in France (e.g., DXC technology, 4Mod, Locam, etc.).

Second, Sigfox Inc. exploited its reputation as an innovator and potential world leader in a new and growing sector, and as a source of power and legitimation to interact with regional and national policymakers. At the national level, this was important for networking and further attracting established firms (both technical and industrial partners) to become affiliated to the EE (e.g., Samsung Semiconductor, PTC, etc.). At the regional level, the growth of Sigfox Inc. and other firms in the EE, in terms of employment, was used as bargaining power to improve physical amenities in their favor (specific buildings and communication infrastructures) (17, 18, 19).

Third, to achieve global coverage for its network, Sigfox Inc. privileged the construction of a global network of partnerships rather than own overseas investments. Partnerships in that global network included both local companies in various countries to deploy the network itself and numerous firms in many unrelated sectors, such as insurance and civil security, climate observation, global shipping, etc. From a local micro-cluster in LPWAN antennas created by Sigfox Inc., the IoT Valley rapidly achieved the characteristics of a digital EE, as a specific LPWAN platform that was capable of changing market relationships in a wide range of areas of economic activity. Through its gatekeeper position, Sigfox Inc. connected the buzz in the EE with the global market in various ways. By expanding its markets, Sigfox Inc. also expanded the markets and potential contacts for entrepreneurs in the EE. Moreover, identifying new business opportunities across sectors and regions in a growing technological domain fed the EE and stimulated new entrepreneurial ideas locally. Thus, in 2019, the IoT Valley enlarged its acceleration program by creating a start-up studio whose aim was to push entrepreneurial projects that provided IoT solutions to problems and needs identified by partners affiliated to the IoT Valley (20, 21). However, as the blockbuster became a dominant firm in its international market ("first-mover advantage"), a natural hierarchy at the EE level was established. As a consequence, the blockbuster capitalized more on national and international resource control, resources that the other start-ups also benefited from.

Fourth, Sigfox Inc.'s engagement in the development of the local EE was also part of its strategy to compete in the worldwide LPWAN battle by increasing its installed base of users. Dominance in this arena depends not only on the network's geographical coverage but also on the variety and intense use of services offered to achieve direct and indirect network externalities. Thus, the performance of the Sigfox technological alternative in the LPWAN battle was influenced by the alignment of the EE's field of action and its blockbuster firm, and the creation of a vibrant local EE where new products, services, or solutions using LPWAN technologies were developed to feed



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
# of employees in IoT Valley (EE)	34	53	69	148	194	238	336	532	587	657	687
# of employees in Sigfox (in EE)	3	9	15	34	44	62	140	203	230	288	290
# of employees in IoTeam (in EE)	0	0	0	0	0	4	6	10	14	28	34
# of EE startups - LPWAN-based	1	2	2	5	6	7	7	10	12	14	16
# of EE startups - ICT-based	3	4	5	11	16	22	23	26	28	26	25
# of IoT Valley partners	0	1	3	3	3	7	6	14	19	20	21

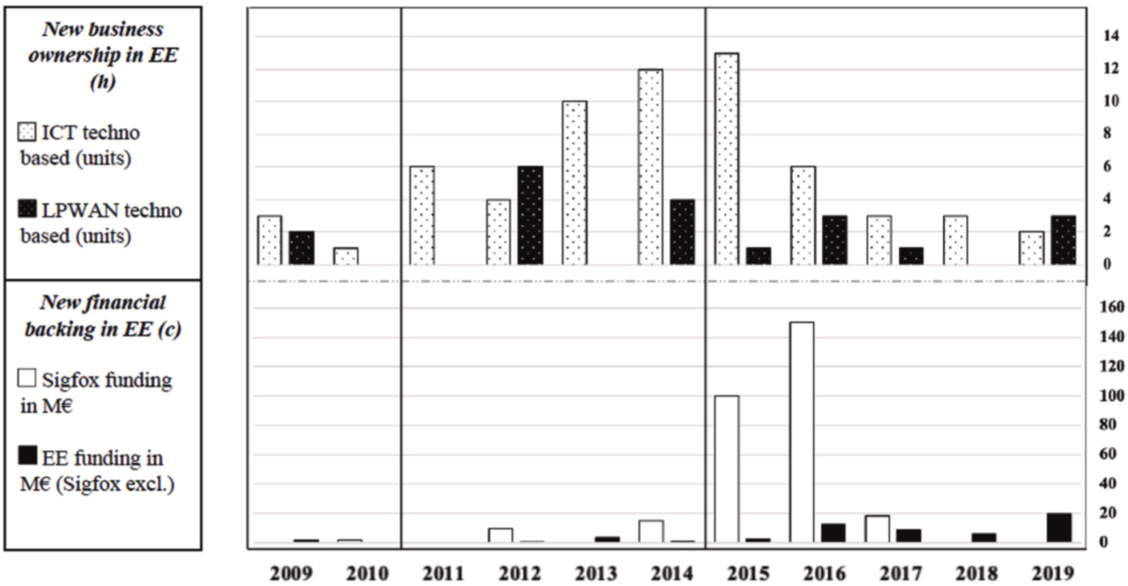


Figure 2.4: Interpretative historical event analysis of the EE - IoT Valley, from 2009 to December 31, 2019.

the platform. In some cases, products and services are available across technological alternatives because of technical gateways or other compatibility solutions, thereby increasing the number of potential users for all the alternatives. In other cases, since products and services are developed for a single technology, the potential new users are then circumscribed to that one, and this entails significant network externalities that become crucial in the battle between platforms. Additionally, to speed up the number of connected objects to the network, Sigfox Inc. formed partnerships with large industrial companies whose potential demand for these objects is much more intense. In some cases, there have been direct partnerships with companies (e.g., Michelin, Airbus, PSA, Louis Vuitton, etc.), while in other cases, partnerships were built through affiliation to the local EE (e. g., SNCF, Liebherr Aerospace, GA buildings, etc.).

Moreover, the IoT Valley's development was also affected by the regional context in several ways, i.e., the conditions and factors of the Toulouse region. First, the regional industrial specialization in electronics and embedded systems, and the existence of a solid knowledge system, provided strong cognitive bases upon which to build an IoT specialization. Second, the presence of important industrial actors in the vicinity, often involved in a transition towards industry 4.0, provided an essential playground for IoT Valley's entrepreneurs to test and develop solutions for the Sigfox LPWAN platform. Thus, numerous encounters between entrepreneurs of the IoT Valley and regional industrial actors were organized between 2016 and 2019. Third, regional policymakers have accompanied, although with punctual tensions, the birth and growth of the EE by building the necessary amenities such as specific buildings (e.g., IoT Campus) (22) or transportation (e.g., a metro extension) (23). In return, the EE and Sigfox Inc. have contributed to regional development. They have created new employment opportunities and have diversified the economy towards a new technological domain with multiple applications that are closely related to existing regional competences. Moreover, they have contributed to creating a positive image and reputation for the region regarding IoT, innovation, and entrepreneurship, which may generate spillover effects for the region's future development.

2.5.2. The LPWAN-IoT battle

Within the LPWAN, three principal technologies compete (Sigfox, LoRaWAN, and NB-IoT). Although technically different, they share the same main features and largely overlap in use cases and market opportunities, sometimes competing and other times complementing one another. The evolution of these technological alternatives is conditioned by a complex regulatory framework involving multiple scales, together with two typical interdependent features of network technologies: uncertainty and network externalities.

On the one hand, given that many connectivity solutions require global coverage, the regulatory frameworks they deal with are complex because global interoperability has to align with country-specific requirements. The three alternatives need national legal certification to connect devices. Sigfox and LoRaWAN use license-free frequency bands. In Europe, these frequency bands were standardized from 1997 to 2006 by the ETSI, the CEPT, and the European Commission[5], and were then adopted by national authorities[6]. In the USA, these frequencies are defined by the Code of Federal Regulations (27), while in China, the Ministry of Industry & Information Technology (MIIT) and its agencies (BRR and SRMC) are in charge of the radio regulation. However, the NBIoT uses licensed bands, and thus there is no specific rule because telecommunication operators can emit on the frequency band they buy from the national authority. The 3GPP was highly important for the NB-IoT standardization (releases 13, 14, and 15) (28, 29, 30) since it gathers together world telecom standardization organizations to produce and publish technical specifications for connectivity networks.

On the other hand, LPWAN alternatives, as a building block of the IoT infrastructure and platform, offer high growth expectations because they represent a step forward in the current connectivity paradigm. Therefore, the opportunities to innovate and the diversity of potential uses are significant. However, like every emerging technology, they are also characterized by a high uncertainty regarding technical specifications and possibilities, the modes of value creation and appropriation, and users' and consumers' preferences and adoption behavior. Moreover, since the LPWAN field is subject to increasing returns to adoption, the intrinsic features of an LPWAN variety are balanced by direct and indirect network externalities. Consequently, an alternative gaining a lead may appeal to a larger proportion of potential adopters and become the dominant one on the market.

These uncertainties and network externalities leave room for the three technological alternatives to adopt different strategies to play within the LPWAN field, all of which aim at increasing the number of users and connected objects to their network. First, as often happens in digital EEs, technological battles are coupled to business model battles, and so LPWAN contenders have adopted different business models. While Sigfox Inc. charges final customers per connected object and operator customers for buying antennas, LoRaWAN provides gateways in addition to a free network service as long as the customer uses his/her own chipset. By contrast, in the NB-IoT business model,

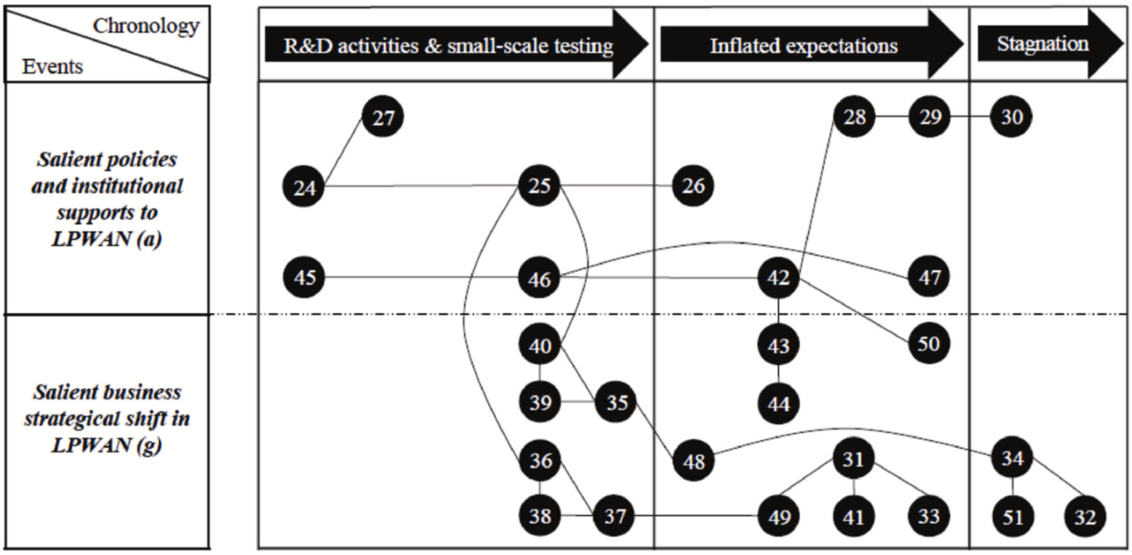
[5] In particular, the ERC/REC/70-03, the 1999/5/EC, the 2006/771/EC and the EN 300 220-2 norm (24) - all regularly updated at the UE level.

[6] In France, the norms are the 2012-0612 (25) and the 2014-1263 (26).

customers can develop and use their own chipset, but they have to pay a subscription to access the network. Second, they have tried to expand their networks' geographical coverage to grow in the number of connected objects on their platform. While Sigfox first entered European markets and then expanded to America, LATAM, and Asia, focusing on asset tracking, LoRaWAN developed its network in Europe and then in Asia through smart city use cases. Unlike the first two, NB-IoT was developed only recently in Europe and Asia and focused on public services use cases such as smart gas and water management. On the one hand, this increases the base of potential users. On the other hand, with broader geographical coverage, it becomes possible to develop new services or solutions that have no sense in limited geographical areas, since the objects connected are sometimes ones that move over large geographical scales (e.g., shipping containers). All this brings the battle to a global level, although it is fiercer in Europe, North America, and China, the first markets the three LPWAN alternatives have tried to conquer. This relates to the third relevant strategy that consists in increasing the number of different services in transversal businesses using LPWAN technologies. The variety of services offered and sectoral markets served is a valuable competitive tool in that it enlarges the base of potential connected objects, gateways, and users. Moreover, it generates opportunities for complementarities and bandwagon effects among them, as well as helping gain experience to improve the network. Thus, the sponsors of the three technological alternatives try to foster the development of new applications and uses by third actors progressively. To this end, in the case of the two non-cellular varieties, the LoRa Alliance released its specifications in open-source code in 2016 (31), and Sigfox Inc. did so in 2019 (32).

They also created tools to enhance and accompany the development of new applications via the "Design Partner Program" for LoRaWAN (33), or the "hacking houses" and "Sigfox agencies" for Sigfox (34), engaging big hardware manufacturers that focused on fast adoption and big contracts. This is even more relevant since the three LPWAN technologies are not always compatible, and hence, application developers or service providers on one side of the LPWAN platform have to either choose one of the three technologies or develop their own multitechnology products. As such, IoT devices and IoT projects may combine several LPWAN technologies in order to meet user needs and constraints.

Figure 2.5 shows new partnerships or deployments as well as new products or services for the three technological alternatives (left axis) and their combinations (right axis) from 2009 to 2019. By analyzing the "S" shape of the three curves and the characteristics of the actors involved in these events, it is possible to distinguish three phases. The first stage included R&D activities and small-scale testing (2009–2013), in particular for Sigfox and LoRaWAN.



# of patents in Sigfox (d)	0	1	2	3	0	9	22	35	52	86	111
# of patents in LoRaWAN (d)	1	0	0	0	2	0	0	3	16	43	97
# of patents in NB-IoT (d)	0	0	0	0	0	0	0	0	130	319	409
# of affiliations to LoRa Alliance (b)	0	0	0	0	0	0	135	272	461	505	592
# of affiliations to Sigfox network (b)	0	0	2	11	15	102	113	129	412	625	703

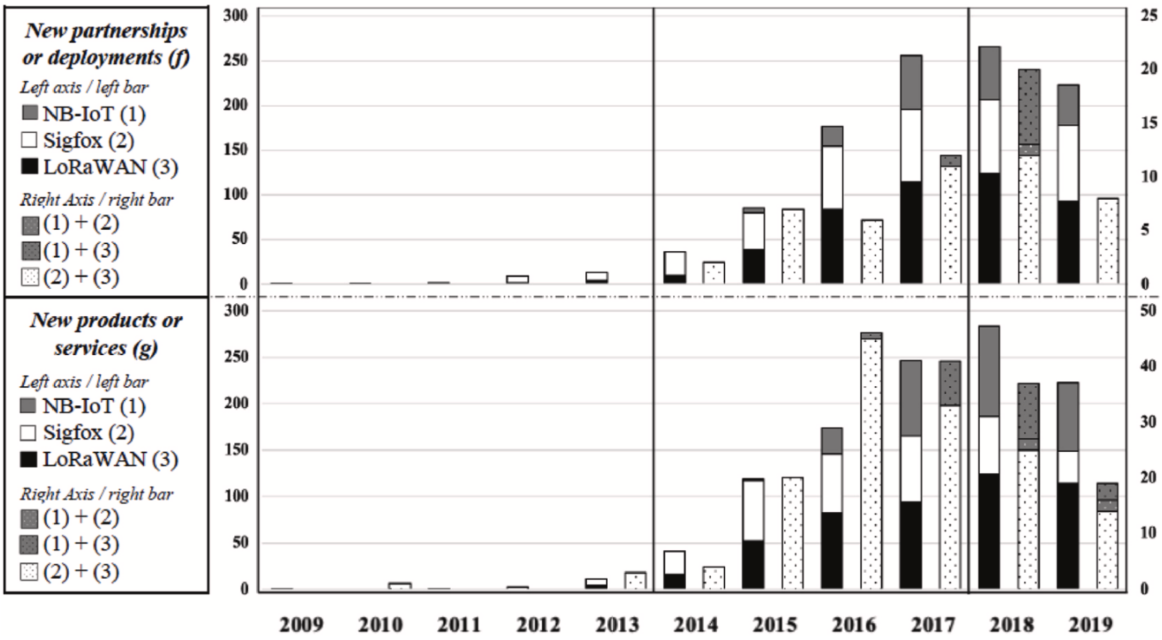


Figure 2.5: Interpretative historical analysis of the LPWAN-IoT worldwide battle of standards - from 2009 to 2019.

This period saw the patenting of essential specifications of each technological alternative and the launch of several research projects for experimentation in specific locations, such as E-pasto for Sigfox (35) or Sense-T for LoRaWAN (36). During this testing period, Sigfox and LoRaWAN already had made local and global partners. The first private contracts were executed in 2012; for LoRaWAN, they were related to "street lighting" and "smart metering" (37), as Semtech bought Cycleo in 2012 to concentrate on the AMR market (automatic meter reading) (38), while for Sigfox, contracts were signed in the areas of insurance and parking (39).

The second stage concerns the commercial launching and coincides with a period of inflated expectations about LPWAN possibilities (2014–2017). Although the first commercial offer in the market was launched by Sigfox in 2012 (40), the first to achieve full nationwide coverage was LoRaWAN in 2016 (41). Moreover, NB-IoT only entered the game in June 2016 after a battle within 3GPP won by Huawei, which imposed his specification process (42). The first NB-IoT devices were designed by China Unicom (43), and the first NB-IoT network in Europe was set up in Germany by Deutsch Telekom (44). In terms of partnerships or deployments, Sigfox network started expanding a bit earlier but was overtaken by LoRaWAN around 2016. That same year, NB-IoT began its commercialization with rapid growth in terms of partnerships or deployment contracts, allowing it to partially make up for its later entry. This growth was boosted by the support of the Chinese government that launched the "Sensing China program" (45), followed by the 5-year development plan issued by the MIIT, with a focus on 5G – NB-IoT (46), and China's announcement of targets and guidance (47) in order to promote NB-IoT through the state-owned company China Mobile, or China Telecom and China Unicom firms, though fiscal stimulus and policy support.

The growth of all three technological alternatives corresponds to a period of great expectations about the growth of the domain, both in terms of services and applications feeding the platforms on their two sides (providers and users), and in terms of key supportive technology to achieve further automation of production and distribution processes. In this context, the three technological alternatives tried to structure their own industrial alliances as a competitive tool (48, 49, 50). At that time, the market was highly segmented and still did not propose end-to-end solutions. Therefore, to reduce this fragmentation and enhance the development and adoption of IoT solutions, the sponsors of the three technological alternatives started to build industrial alliances and platforms with all actors involved in the IoT value chain and related to their own LPWAN technology, from the sensor and chipset builder to the provider of final services[7]. The rationale behind this is that bigger and less fragmented networks make

[7]**LoRa Alliance network** (in 2015) was made up by the following: components (MicroSemi, Freescale, Microchip, etc.), network modules and hardware (Multi-tech, Sagemcom, Kerlink, etc.),

it easier to develop LPWAN solutions with appropriate partners, increasing direct and indirect externalities of adoption. In order to further boost up their own expectations and network, they organized regular conventions and trade fairs to show off their latest offers and discredit their competitors (Sigfox Connect, LoRa Alliance Summit, and NB-IoT Eco Connect).

From 2018, the number of partnerships or deployments for all three technologies stagnated or decreased. There are four non-exclusive explanations for this. First, it may have been a side-effect of the battle itself. Faced with the uncertainty generated by competition, the user's side of LPWAN platforms may have decided to delay their adoption decisions to avoid betting on a losing alternative, consequently delaying the incentives to offer new dedicated solutions from the other side of the platforms. In this regard, the expectations in the early 2010s about the number of LPWAN connected objects that would be reached by 2019 are far from being met. Second, since the development and deployment of IoT solutions (LPWAN or others) involve a *hardware* part, they are more complex than other IT technologies. Third, as the technology and industry structures mature, fewer small contracts and larger ones with higher value may have been signed, lowering the event count. Fourth, there may be some bias in the event count due to shifts in the media coverage as the technology matures. As IoT techs progress in the hype cycle curve, media devote more attention to new "hot" technologies and underreport events on the LPWAN domain. In that stagnation context, the three alternatives engaged in a race for users' adoption. As a result of that, we can observe, on the one hand, a convergence of the commercial offers of the three alternatives (e.g., Sigfox Inc. launched a private network service and promoted bi-directional specifications for its network (51), thus starting to compete directly with LoRaWAN use cases). On the other hand, an intensification of their efforts can be observed towards the development of new uses and applications by releasing specifications and creating supportive tools to boost indirect network externalities through an increase in the variety of applications supported by their platform.

However, the evolution of the IoT Valley EE and the LPWAN battle influence each other, although not in a symmetric way. On one side, IoT Valley hosts and pushes forward start-ups that develop new products and services, usually for the Sigfox alter-

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services and software (Loriot, Actility, IBM, Cisco, Microsoft, etc.), operators dedicated to M2M (Strataggem, The Things Network, FastNet, etc.), and traditional telecoms operators from several countries (Bouygues Telecom, KPN, Proximus, etc.).

Sigfox network (in 2015) was formed by: components (Silicon Labs, TI, STMicroelectronics etc.), network modules and hardware (Adeunis, ATIM, Axsem, etc.) and services and software (Intent Technologies, SalesForce, OVH, etc.).

NB-IoT network (in 2017) consisted of: components (Huawei, Sequans, HiSilicon, etc.) network modules and hardware (U-blox, Telit, Altair Semiconductor, Quectel, etc.) services and software (Ericsson, Cisco, Microsoft, etc) and traditional telecoms operators from several countries (AT&T, Verizon China Telecom, etc.).

native, to make the platform more attractive than the two others by greater integration of complementary solutions. Similarly, IoT Valley start-ups and established partners, who have entered into one or several of the Sigfox, LoRaWAN, and NB-IoT alliances, contribute to reducing the network fragmentation and enhancing the development of new solutions within that network. In both cases, EE members contribute to altering the relative strength of the three LPWAN contenders in some of the key dimensions of the competition. Obviously, since the competition is worldwide, the marginal impact of those decisions made by EE actors is small on average, but it can become relevant in specific niches where a start-up may achieve worldwide success and attract many users and thus more connected devices (e.g., tracking goods in the shipping sector).

On the other side, Sigfox Inc. is the blockbuster start-up of the EE and the main builder of the Toulouse region's reputation around LWPAN. This tight relationship can be seen through the partnerships or deployments and products or services developed by firms in the EE. In fact, as shown in Figure 2.6, the Sigfox technological alternative is over represented.

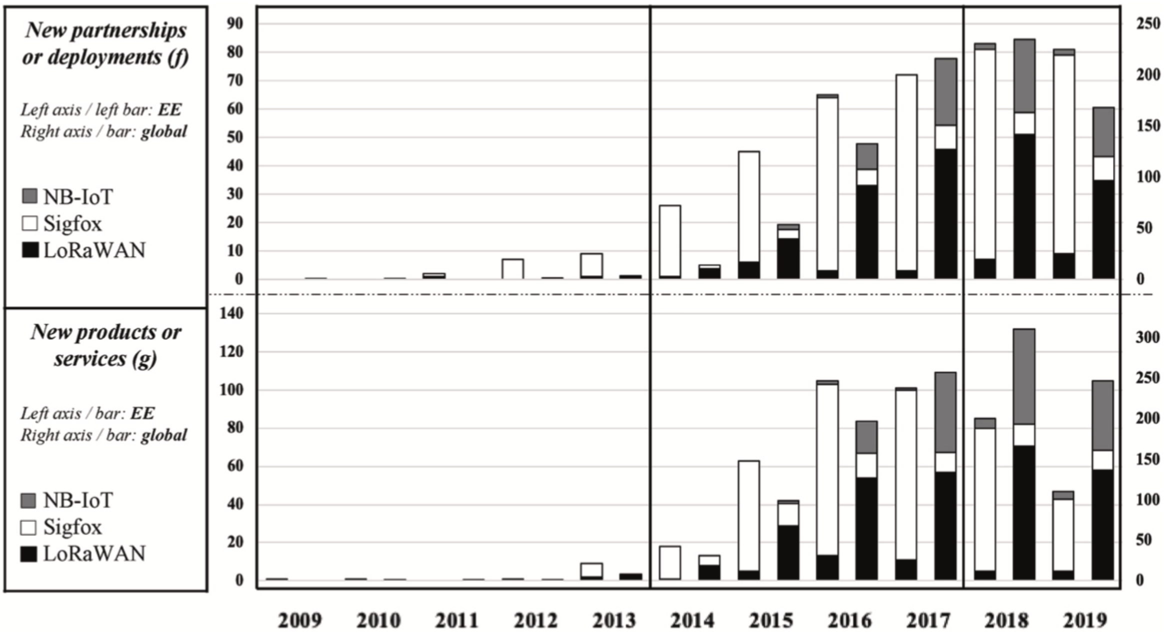

Figure 2.6: EE vs Global: new partnerships or deployments and new products or services events in the LPWAN-IoT worldwide battle of standards - from 2009 to 2019.

However, this relation greatly conditions how the EE evolves with respect to the performance of the Sigfox alternative in the LPWAN-IoT battle. Consequently, this tight link between Sigfox and the EE is a double-edged sword for the EE. The positive effects for the EE's development (i.e., reputation spillovers, knowledge flows, bargaining power) will continue as long as the Sigfox technological alternative is still a player in the LPWAN battle and it maintains its strategy of engaging with the EE because of the benefits it obtains from that relationship. Yet this tight link may also compromise the survival of the EE in several ways. First, there is a risk that if the Sigfox technology does not survive the battle, its decline drags the whole EE down with it. Second, given the role of knowledge gatekeeper played by Sigfox Inc., the EE is at risk of overlooking valuable business opportunities in the LPWAN domain by aligning too much with the strategic focus areas of Sigfox Inc. Finally, to succeed in the LPWAN battle, there are forces that push Sigfox Inc. to reduce its engagement in the IoT Valley EE. The LPWAN battle is a global one, and innovative ideas appear *everywhere*, but the capacity to attract them all to the IoT Valley remains limited. For this reason, Sigfox Inc. has created “hacking houses” over the world, which are programs opened to digital entrepreneurs aiming at solving problems for sponsor customers with IoT technologies. Additionally, Sigfox Inc. has invested in other EEs worldwide (e.g., Taiwan, San Francisco, etc.). As a consequence, in the near future, there is the risk of seeing a decrease in the reputation spillovers and knowledge inflows that the IoT Valley receives from Sigfox Inc., which should be taken into consideration.

2.6. Discussion and conclusions

Three main interrelated lessons can be drawn from this research. First *(i)*, conceptually, we have considered the development of EEs as being directly related to the entrepreneurial opportunities opened up by the *platformization* of markets (Autio et al., 2018; Song, 2019) and enhanced by business ecosystems (Iansiti and Levien, 2004). Such an approach, which connects EEs to digital platforms, opens up a new perspective to better understand the challenges, channels and scales used by a blockbuster firm embedded both within a local EE and a regional context to compete globally for dominance in multi-sided platforms. Second *(ii)*, empirically, we have tried to demonstrate that if global technology dynamics, in which EEs are involved, are excluded when searching for their critical factors of evolution, it can lead to an important lack of understanding of how EEs evolve over time. Third *(iii)*, methodologically speaking and despite some limitations and the need for further development, our study shows that the Historical Event Analysis (HEA) method can bring relevant aspects to light that fill the gap between fieldwork analysis and systematic regressions on EEs. These three lessons are discussed below in more detail.

(i) The ecosystem concept has been used alternately in two fields of management science, with one field focusing on “strategy,” as in business ecosystem studies, and the other one being centered on “entrepreneurship,” e.g., in EE studies. In this study, we start by exploring how a digital blockbuster tries to impose its technology and business model globally on multi-sided digital platforms to show that these two conceptual anal-

yses can, to some extent, be reconciled. Furthermore, we demonstrate that, rather than taking them all apart, one by one, the interactions between EE components at different levels do matter, of which we find the following three: the micro-organizational level (i.e., entrepreneurial and ventures), the meso-level (i.e., regional industry structure and institutions), and the macro-level (i.e., global market dynamics and business ecosystems). By doing so, we avoid using a "static perspective," which has been a recurring criticism in the EE literature (Alvedalen and Boschma, 2017). As such, we unravel the multi-scalar and evolutionary forces of EEs by relating the internal dynamics of an EE to the worldwide competition and regulation context of LPWAN technologies and platforms and to the influence of the regional context. This analysis thus offers the first steps of an approach to EEs, interpreted as complex adaptive systems (Roundy et al., 2018), or the basis of a more in-depth evolutionary analysis of the interactions between EE components according to business life cycles (Auerswald and Dani, 2017; Ryan et al., 2021). Additionally, we provide arguments on the extent to which development on both sides of a platform new services and users occurs through the actions of blockbusters (here Sigfox) in an EE (IoT Valley). On the one hand, to disseminate its network, the blockbuster offers its solution to multiple partners, constituting the business ecosystem, which includes the IoT Valley in our case, and also formally forging the alliance and feeding it with innovative devices (Iansiti and Levien, 2004). On the other hand, to become a technological standard and a "platform," the blockbuster first relies on a set of actors who can be suppliers, customers, or supporters, including the EE, which is its base camp. Second, it strives to enter a virtuous circle of self-reinforcement created thanks to the increasing returns from adoption and network externalities that result from its position as a "digital platform" (Gawer and Cusumano, 2014). Its main challenge is to attract actors capable of providing all the technological building blocks necessary to implement a complete operational application, from the device itself to the software in the cloud. Hence, it is imperative that actors in the field forge partnerships to create effective ecosystems (Cusumano et al., 2008).

(ii) The IoT Valley trajectory can be explained by some typical components of successful EEs identified in the literature, such as the presence of a blockbuster, some advantageous initial conditions in terms of related activities supported by local incumbents, an entrepreneurial spirit embodied in collective stand-up and start-up activities, and the patronage of local public institutions in terms of incentives and infrastructures. Until the mid-2010s, the IoT Valley kinetics were primarily driven by regional affordance for the development LPWAN-based infrastructures and market solutions. In fact, the Sigfox technology and other LPWAN alternatives were then mostly in an exploration stage. Sigfox Inc. was in a start-up mood of business, testing activities with partners of the regional knowledge-intensive economy and a few start-ups directly

related to the Sigfox network.

However, since 2015 the year when Sigfox Inc. raised two successive mega-rounds of funding, launched its network expansion, and entered the worldwide battle over LPWAN standards, the EE kinetics have no longer been able to rely solely on regional affordance. The EE started to be largely driven by the global competition among the business models of three sponsors of digital LPWAN platforms and by the reciprocal influences between these sponsors and the different regulation and standardization agencies. Because LPWAN platforms perform through network externalities, and thanks to the ability of sponsors to attract and balance the different sides of the market, the IoT Valley has developed by dint of the incentives of Sigfox Inc. that supported local entrepreneurs by offering innovative and reliable solutions for a variety of services and attracting users from different industries. The S-shaped curves of Sigfox Inc. in sales, partnerships, and network deployment contracts, as well as the growth in start and scale-up activities in the IoT Valley, illustrate this co-evolving process from the competition for the digital platform business model to the development of the EE.

Nevertheless, our analysis shows that a large part of how its trajectory is expected to evolve over the next few years depends on what is going on globally between competing digital platforms. As indeed, most of the future of EE's LPWAN is now being shaped at the international level through the main player's market strategies and the global regulations for setting the standards, which depend on complex geopolitical relationships and influences. But this does not mean that local factors no longer matter. They mattered a great deal in the early stage of the EE development in that they helped Sigfox Inc. to reach global markets and a central position in the monopolistic competition for LPWAN technologies. In the current "stagnation" phase, the future of the EE depends both on how the worldwide battle of standards unfolds from now on and on the ability of IoT Valley to continue with the diversification and diffusion of IoT based solutions to compete with other EEs emerging over the world, in which the main players are also involved. Undoubtedly, the ongoing battle over standards between the three LPWAN technology alternatives is based on a competition between three global business ecosystems that affect the development of local EEs.

Our analysis sheds light on what (Arthur, 1990) already highlighted earlier at the end of the last century, namely that behind a global battle over technological standards, there is also a hidden battle between places. In the case of digital platforms, competition between *business ecosystems* goes largely hand in hand with competition between local *entrepreneurial ecosystems*. In our case study, although LPWAN technologies overlap in some use cases, each of the alternatives is sponsored by a company or group of companies, and each alternative is attempting to build a global business ecosystem around its own model, which will stimulate the emergence of other EEs throughout the world. But then again, this LPWAN battle is also a source of uncertainty for the IoT Valley. Specifically, a major concern for its survival is the window of opportunity associated with the 5G deployment's geopolitical issues. In fact, the technology roadmap of the Narrowband Internet of Things (NB-IoT), sponsored by Huawei, is linked to that of 5G, over which a battle of strategic interest between the United States and China is being fought. In that sense, the NB-IoT affiliation to the development program of the 5G may give it an advantage. Thus, through its initiative, Sigfox Inc. has proven its ability to exploit the advantages of a very "niche" marketing position in the LPWAN market, namely "0G" or low power consumption for IoT solutions. Nevertheless, since the IoT Valley is tightly linked to Sigfox's technology, there is a strong risk that the failure of the latter may bring with it the failure of the former. If 5G technologies were to spell the end of LPWAN networks, resulting in the withdrawal of Sigfox from global competition, the IoT Valley would then face a shock that other digital EEs have already experienced (Spigel and Vinodrai, 2021). However, this would lead to the acceleration of recycling entrepreneurial forces within local high-growth tech companies, as a driving force for their development and diversification. Finally, we can draw some implications from the effect of the close interrelationships between an EE, a sole blockbuster (Sigfox Inc.), and the business ecosystem in the context of global competition. Indeed, these links are a double-edged sword for the EE since they strengthen their mutual positions (Gawer and Cusumano, 2014), but the risks of a failure can also lead to its collapse. In particular, a positive implication of this interconnectedness is the development of the EE itself (i.e., repercussions for its reputation, knowledge flows, bargaining power), but the other side of the coin is that the EE's survival can be jeopardized in several ways, mainly because of its dependence on a technology (Sigfox) that could potentially decline, the scrambling of the blockbuster's strategies, and a potential decrease of reputational spillovers.

(iii) To capture this kinetics of interactions, the choice of a HEA method seems to have turned out to be relevant since it combines a high level of accuracy in the qualitative contents of each event with a quantitative approach to events occurrence at the aggregate level of each scale. This methodology is promising as a way to unravel the different drivers at work for a particular EE. In our empirical case, it allowed us to capture how the EE has influenced the global LPWAN market dynamics over the period and how these, in turn, have been influenced by it. Of course, the methodology could face difficulties and problems of tractability if it were applied systematically to the analysis of a larger context. At the scale of this paper, our "small" case required

the construction of a "big" dataset, as well as complex information coding and triangulation processes. If the methodology were to be generalized, it would require automatic data treatments, with the risk of omitting some critical events or overestimating others. In addition, the methodology could be improved in four different ways. First, it would be interesting to use an "event weighting" factor because not all events have the same effects on the dynamics under study. In our particular case, the differences in the volume of products sold can significantly influence the market dynamics. Second, the Boolean combinations of keywords could be further refined for a better selection of the events that belong to smaller contextual categories in a number of EE components found in the literature. In this study, the lack of events regarding the cultural context is a limitation. Third, we could improve the event classification methodology by grouping the types of events according to the company's life cycle and technology maturity. This would inform us of the strategic directions taken by the actors in each stage of the industry. Fourth, a classification of events according to their positive or negative effects on the trajectory of the EE could offer further insights. Clearly, an additional categorization would make it possible to distinguish the influence of each event's positive or negative loops on the development of the EE.

Finally, it seems difficult to draw policy implications from a single case study, even if this case has precisely shown the role played by policymakers at different stages and different scales. Indeed, no generalization is possible due to the idiosyncratic historical and technological trajectory of every single EE at the local level. However, by considering their local infrastructure provision and entrepreneurship incentives, and the need for national and international standards and regulations, the case illustrates how a nested system of public incentives and regulation can impact an EE trajectory over time (Audretsch et al., 2019b,a). Nevertheless, our policy implications are not so far from the ones that have been well documented in research in which policy support had to be designed according to the life cycle phases of clusters (Brenner and Schlump, 2011). Our analysis illustrates these findings since it shows that, following the "stagnation" phase, the future of the IoT Valley in Toulouse now rests more on strategic political decisions at the national or European level that will allow the Sigfox technology to win the battle of LPWAN platforms, than on local incentives for innovation and scale-up, or new infrastructures to attract new businesses to the field. In the context of uncertainty in which the global markets of LPWAN currently find themselves, local public institutions have to capitalize on the charisma of one of the worldwide "first-mover" places in the IoT industry in order to attract people and firms. They should capitalize, too, on the competencies created over the period in the EE itself to foster new collaborations within the whole regional innovation system in order to facilitate related diversification towards new markets.

Chapter 3

Does employees' functional diversity matter for new venture growth? Evidence from the digital industry in greater Paris

The relationship between diversity and new venture growth has increasingly become an influential topic within organizational science and strategic management. Despite significant attention on Top Management Teams (TMTs) diversity, the potential impact of other employees on venture growth, such as Middle Management Teams (MMTs) and Operating Core Workers (OCWs), at different firm stages, remains largely underexplored. This paper aims to clarify this relationship, with a specific focus on the varying impacts of functional skills diversity across different organizational levels and stages of a company's development. In our empirical research, we analyzed a linked employer-employee dataset from the digital industry in France, spanning from 2010 to 2020. Our sample comprises 296 VC-backed new ventures located in the Metropolis of Greater Paris. Through a problem-solving lens, we scrutinized the functional skills across various hierarchical levels, including 5,243 TMTs, 10,274 MMTs, and 29,306 OCWs. Our results indicate that placing exclusive emphasis on top-level managers could lead to incorrectly assigning diversity effects, as these are likely shared with lower organizational levels. In addition, we found that the growth-related effects of diversity vary based on a firm's funding stage, with diversity having a stronger impact in the early stages of financing. We conclude with research and practical implications and suggest directions for future research.

This manuscript has been submitted to a WoS journal.

In this chapter, my responsibilities were allocated as follows:

- Paper design and writing: 100%
- Empirical design and findings discussion: 80%
- Data collection and cleaning: 60%

3.1. Introduction

Numerous leading new digital ventures have recently decided to incorporate non-monetary objectives into their guiding principles, specifically highlighting the benefits of diversity. This focus is partly due to the belief that diversity exerts a favorable influence on new venture growth, among other aspects. For instance, companies such as Revolut or Uber have embarked on a narrative that, precisely, aims to harness the potential of diversity. For example, in 2022, Revolut global head of HR Alexandra Loi said that *"Revolut values the skills, abilities and creativity that diversity brings to a business"*. In the same vein, Uber's CEO Dara Khosrowshahi announced in 2021 that *"diversity will be used as one key metric to assess performance"*. This consensus among many of the world's leading new ventures is intriguing, especially given the inconclusive findings of academic studies on the effects of diversity on venture performance. Indeed, diversity effects are known to vary depending on many factors such as contextual elements or even methodological approaches (Joshi and Roh, 2009; Lidström and Vanyushyn, 2023; Roberson, 2019; Van Knippenberg and Mell, 2016).

In order to make sense of the inconclusive empirical estimations, researchers have underscored the concurrent presence of both benefits and drawbacks associated with diversity (Harrison and Klein, 2007; Williamsky, 1998). In a nutshell, while diversity grants a group enhanced access to unique knowledge and confers a sustainable competitive edge to a firm (Page, 2007; Marco et al., 2023), on the other hand, insights from cognitive and social psychology suggest that diversity in a group may lead to a detrimental reduction in the exchange of information within the team due to the ensuing divergence of perspectives (Nooteboom et al., 2007; Stasser et al., 2000; Williamsky, 1998).

To differentiate the unfavorable repercussions from the advantageous outcomes, researchers have suggested distinguishing the various facets of diversity, anticipating positive performance outcomes for task-related diversity aspects such as functional diversity (Bunderson et al., 2002; Glick et al., 1993). Nevertheless, despite examining multiple contexts, methodologies and moderating factors, extant meta-analyses have failed to substantiate the positive impacts of functional diversity on firm performance (Jin et al., 2017; Bell et al., 2011; Horwitz and Horwitz, 2007; Webber and Donahue, 2001). Moreover, even when specifically examining performance in terms of sales growth and return on assets, results are still inconsistent. For instance, based on the informational diversity–cognitive resource perspective, Certo et al. (2006) found a (small but significant) positive effect of Top Management Teams (TMTs) functional diversity on return on assets (ROA) and sales growth. However, (Haleblian and Finkelstein, 1993) reported a negative relationship between TMT functional diversity and firm performance measured as a composite measure including ROA, return on sales (ROS), and return on equity. On their side, (Cannella Jr et al., 2008) discovered no significant main effect of TMT (dominant) functional diversity on ROA.

Hence, despite the efforts made by scholars to integrate moderating and contextual variables in an attempt to clarify this relationship (see e.g., Hmieleski and Ensley (2007)), a lingering debate persists regarding the ability of the informational diversity perspective to produce robust estimations. In this article, we argue that a more refined interpretation of the informational diversity framework is necessary and can be achieved by incorporating variances in the organizational structure configurations of teams. Specifically, we argue that the disproportionate emphasis on TMTs in the literature (see e.g., (Aboramadan, 2021; Boone and Hendriks, 2009; Finkelstein et al., 2009; Eesley et al., 2014)) may lead to inconsistencies, given the growing evidence highlighting the deep influence wielded by middle level managers and *Operating Core Workers* (OCWs) (i.e., non-managerial employees at the base of the organizational power hierarchy) on firm performance, across various stages (Andries and Czarnitzki, 2014; Floyd and Wooldridge, 1992; Mollick, 2012; Mintzberg and Waters, 1985). Therefore, we argue that the inconsistencies observed in the diversity literature may stem from overlooking the underlying multi-layered organizational structure configurations of teams.

Drawing on the problem-solving perspective (Graesser et al., 2018; Grant, 1996; Hong and Page, 2001; Nickerson and Zenger, 2004), we propose that organizations need a wide range of skills and knowledge to effectively solve valuable problems. In essence, this perspective implies that a diverse pool of individuals can bolster a firm's problem-solving capacity, thereby promoting new venture growth. To address the limitations in existing literature outlined in the previous paragraph and extend the literature, we propose a multi-layered theoretical framework that links functional skills diversity at the TMT, MMT, and OCW levels to new venture growth. We argue that taking into account the functional skills diversity within these different organizational levels is fundamental in shaping a firm's problem-solving capacity, and consequently, its growth. Further, acknowledging that a firm's financing stage shapes the nature of problems encountered, we distinguish between early and late funding stages. This distinction allows us to account for the variations in the intensity of the relationship between functional skills diversity and new venture growth at different maturity stages. By following the problem-solving perspective, we anticipate the impact of functional skills diversity to be stronger in the early than in the late financing stage.

We empirically evaluate our propositions by using a sample of 296 VC-backed new ventures utilizing digital business models, based in the Metropolis of Greater Paris, and by drawing on data pertaining to the functional skills of 5,243 TMTs, 10,274

MMTs, and 29,306 OCWs from 2010 to 2020. We argue that our contribution is significant as it, firstly, investigates how the organizational level of top, middle, and non-managerial teams can influence the anticipated effects of diversity, a facet largely overlooked by diversity literature that focused primarily on the effects of diversity in TMTs (Boone and Hendriks, 2009; Finkelstein et al., 2009; Eesley et al., 2014). Our findings suggest that focusing solely on the top managers risks misattributing the effects of diversity, some of which are likely attributable to lower organizational levels. Second, in line with a substantial literature that has long informed the organizational growth processes throughout stages and over time (Phelps et al., 2007), we provide evidence that contextual factor such as early and late funding stages plays a crucial role in the diversity-growth relationship.

The paper is structured as follows. Section 3.2 reviews the literature on the diversity-performance relationship and the problem-solving perspective. Section 3.3 explains the data and methods used, and Section 3.4 presents key findings. Finally, section 3.5 concludes by discussing implications for theory and practice, noting the limitations of this study.

3.2. Theoretical framework and hypotheses

3.2.1. Diversity and new venture growth

While the theoretical benefits of diversity are well-established in the literature, empirical findings present a more nuanced picture (Joshi and Roh, 2009; Lidström and Vanyushyn, 2023; Roberson, 2019; Van Knippenberg and Mell, 2016). The inconsistent findings can be traced back to the dual aspects of diversity. On one hand, diversity limits agents' communication effectiveness and exacerbate issues of unshared information due to induced divergence of perspectives (Stasser et al., 2000). On the other hand, diversity enhances access to a wider range of information and ultimately increases cognitive and behavioral repertoire, such as problem-solving abilities (O'Reilly III et al., 1989; Page, 2007). In more detail, insights from social categorization theory and cognitive and social psychology suggest that diversity within a group, in terms of world views, mental models, and decision-making routines, can trigger a variety of dynamics. These differences may ultimately lead to a decrease in the flow of information within the team, primarily due to the induced divergence of perspectives. Such divergence can further ignite conflicts, erode team cohesion, and ultimately, undermine overall organizational efficiency and effectiveness (Nooteboom et al., 2007; Stasser et al., 2000; Williamsky, 1998). Conversely, diversity is believed to bolster an organization's problem-solving capabilities (Hong and Page, 2001), enhance its learning potential, and fortify its resilience in the face of environmental instability (Page, 2007). This is primarily because a diverse team provides the organization with a larger endowment of information and thus a more diverse set of perspectives and capabilities (Kilduff et al., 2000). As a result, diversity ensures that team members examine an issue from various perspectives (Eesley et al., 2014), thereby enhancing the quality of the decision-making process and, ultimately, enhancing new venture growth.

In recent years, substantial intellectual disputes have arisen over the complex process of integrating the perspectives of information variety and induced divergence of perspectives. Notably, research proposes that diversity in terms of functional backgrounds exerts a positive influence on firm performance (Bunderson et al., 2002; Glick et al., 1993). Functional background diversity focuses on the different functional experiences of team members, and more precisely on the extent to which team members differ in their functional backgrounds (Bunderson et al., 2002).

On one hand, functional backgrounds diversity is intricately tied to the tasks executed by a team (Smolinski et al., 2020), thereby directly influencing the benefits derived from information (Sulik et al., 2022). Indeed, education and experience endow individuals with crucial skills and knowledge for new venture growth (Marco et al., 2023), forming a cognitive and functional structure that assists in discerning valuable information and its application (Marvel et al., 2016; Unger et al., 2011). Diverse functional backgrounds allow teams to access a broader range of cognitive perspectives, thereby increasing the likelihood of finding innovative and creative solutions (Smolinski et al., 2020). For instance, Taylor and Greve (2006) demonstrates that diverse knowledge domains within a team foster novel combinations of knowledge that increase the variability of product performance, and extensive experience contributes to higher average performance. Therefore, while diversity might generate challenges such as communication issues and potential conflicts, with effective management, these can be converted into opportunities for further enhancement of team performance, thus forming a robust case for diversity in teams.

On the other hand, functional diversity — unlike diversity in age, gender, or race — is less easily observable, reducing the likelihood of individuals categorizing their team members into “similar” or “dissimilar” groups (O'Reilly III et al., 1989). Moreover, functional diversity may be less likely to raise issues of unshared information compared to other task-related dimensions, such as work experiences, which reflect the variety of roles individuals fulfill within a firm (Patrício and Franco, 2022). It is crucial to note that induced divergence of perspectives, often driven by easily observable characteristics, can lead to biases, stereotypes, and intergroup conflict, potentially affecting team dynamics and productivity. However, the less tangible nature of functional diversity can, therefore, foster a more open-minded, unbiased, and harmonious work environment, thereby enhancing team collaboration and productivity. The contact hypothesis further supports this idea, suggesting that increased exposure to diverse functional backgrounds can reduce prejudices and promote cooperation among team members (Paluck et al., 2019).

Contrary to what one might initially presume, the empirical relationship between functional diversity and new venture growth is not straightforward and often produces varied results. Some studies found that functional diversity enhances individuals' cognitive capacity, behavioral repertoire, and problem-solving abilities (Hong and Page, 2001; Krieger et al., 2022; Page, 2007). For instance, Certo et al. (2006) identified a small but significant positive effect of TMT functional heterogeneity on ROA and sales growth. Similarly, Nielsen and Nielsen (2013) detected positive main effects on firm performance. Buyl et al. (2011), who explored the moderating role of CEO characteristics on the relationship between TMT functional diversity and firm performance, also discovered a positive relationship. However, the presence of functional diversity within a team can also provoke conflicts and misunderstandings, which can negatively impact new venture growth. Indeed, diversity based on functional background can amplify the occurrence of unshared information due to the ensuing divergence in perspectives (Stasser et al., 2000), thereby hindering new venture growth. For instance, Haleblian and Finkelstein (1993) observed a negative correlation between TMT functional heterogeneity and firm performance, a metric incorporating factors such as ROA, return on sales (ROS), and return on equity.

Furthermore, there are arguments for a *curvilinear* relationship, based on the theoretical premise that functional diversity can impair communication effectiveness among agents due to the cognitive distance between their mental models (Mathieu et al., 2000; Nooteboom et al., 2007). For example, by using a sample from privately-held medium and large high-tech companies in Italy, Sarto and Saggese (2022) provided evidence of a *curvilinear* effect in their study of industry expertise diversity. However, despite advocating the notion that functional diversity fosters new venture growth, Cannella Jr et al. (2008) found no significant primary effect of TMT (dominant) functional diversity on ROA. The complexity of this relationship may stem from the multifaceted interpretation of functional diversity. For instance, Bunderson et al. (2002) conducted an analysis on the implications and performance outcomes of dominant function diversity (the assortment of functional specialists within a team) and intrapersonal functional diversity (the cumulative functional spectrum of team members). Their findings show a negative impact of dominant function diversity and a positive one of intrapersonal functional diversity on information sharing and overall unit performance. This research suggests that different types of functional diversity can have markedly contrasting effects on team processes and performance.

In this article, we suggest that the inconsistent findings from the informational diversity perspective focusing on functional diversity may originate from an incomplete understanding of how growth-related tasks are distributed across the hierarchical layers of a firm and the stage-dependency aspect of the funding stage under examination. Indeed, we argue that the allocation of tasks carries implications on how functional diversity within the entire organizational structure (TMT, MMT, OCW) affects new venture growth. Specifically, we hypothesize that hierarchical layers other than top management also have a significant impact on new venture growth. Furthermore, we suggest that this influence is contingent upon a crucial contextual factor: the stage of funding maturity. Yet, no studies to our knowledge have incorporated such a contextual factor with a multi-layered theoretical framework that links diversity at TMT, MMT, and OCW levels to new venture growth, thus resulting in significant uncertainty in elucidating the mechanisms governing the relationship between functional-background diversity and stage-dependent new venture growth.

3.2.2. Positioning the impact of the multi-layered organizational approach on the diversity-growth relationship in a problem-solving perspective

The starting point of this paper is the observation that the exploration and resolution of organizational problems constitute both the daily operations and the driving force behind a firm's growth. This distinction highlights the varying roles of management and operational teams in conceiving, designing, and implementing effective problem-solving strategies (Graesser et al., 2018; Hong and Page, 2001; Nickerson and Zenger, 2004). The problem-solving perspective is rooted in the knowledge-based view or knowledge-based theory (KBT) of the firm (Grant, 1996). Within the KBT framework, the problem-solving perspective plays a pivotal role, fostering the growth and evolution of an organization. Advocating for a systemic, multi-layered approach to this perspective, we propose a dynamic organizational structure in which strategic and operational levels collaborate to conceive, design, and implement effective problem-solving strategies that promote new venture growth.

Following Mintzberg (1980), in this multi-layered approach, each central layer of the organization - the operational core workers (OCW), the middle management team (MMT), and the top management team (TMT) - assumes a distinct yet interconnected role in the creation, integration, and application of knowledge to solve problems (Nickerson and Zenger, 2004). Firstly, OCWs possess a significant amount of both implicit and explicit knowledge. Acquired through direct task execution and in-depth procedural engagement, this knowledge forms a crucial component of a firm's human capital

(Grant, 1996). These non-executive employees are anticipated to identify opportunities, generate actionable solutions and bolster organizational performance (Mintzberg and Waters, 1985). As evidence, empirical work on large established firms (e.g., Smith et al. (2005)) confirms that the human capital of non-managerial workers positively influences the firm's knowledge creation capabilities. Secondly, MMTs act as pivotal junctions within the knowledge management structure (Wooldridge and Floyd, 1990; Wooldridge et al., 2008). In industries characterized by creativity, innovation, and extensive knowledge utilization, Mollick (2012) show that the attributes of middle managers significantly affect firm performance. Their role is twofold: enabling the exchange of knowledge amongst operational workers and synthesizing insights from diverse areas for more extensive organizational distribution. They are tasked with reconciling operational knowledge with the firm's strategic aims, guaranteeing a synergy between bottom-up input and top-down guidance. Consequently, they play the fundamental role of communication facilitators that contribute to new venture growth (Grimpe et al., 2019; Kanter, 1982). Thirdly, TMTs are known to drive the direction and strategy of the firm (Hambrick and Mason, 1984). The human capital of top managers is posited to influence firm performance in both direct and indirect manners. On one hand, diverse top management teams are poised for high performance in competitive commercialization contexts (Eesley et al., 2014). On the other hand, the knowledge possessed by top managers is beneficial in resource acquisition (Patzelt, 2010). Additionally, managers who project confidence and contentment regarding entrepreneurial ventures boost employees' entrepreneurial initiative and consequently firm performance (Brundin et al., 2008).

Therefore, as the resolution of problems serves as the key driver of the problem-solving framework, and because every hierarchical layer is involved in the process of identifying valuable problems, conducting efficient solution searches, and implementing the solutions at their own level, it is in an organization's best interest to effectively structure knowledge flows across these layers, supporting the ongoing creation and application of knowledge. Furthermore, problems have a life cycle: an issue in one phase may not persist into another phase. Therefore, a dynamic problem-solving framework aligns with the evolving nature of firm challenges, making the approach pertinent for new venture growth over funding stages.

3.2.3. Hypothesis

As outlined in the previous paragraphs, the problem-solving perspective highlights the essential role of TMTs in making strategic decisions and detecting solutions to problems which could benefit the organization and promote new venture growth. As the overarching choice to pursue growth usually represents a decision of higher organizational layers, we argue that functional diversity in TMTs positively affects the ability to identify valuable problems, thereby also raising the likelihood of fostering new venture growth. First, the general argument made for the positive impact of functional diversity on firm performance is that having diversity in functional backgrounds ensures that the TMT has the full range of skills and abilities needed to manage the organization (E. Randel and Jaussi, 2003). This argument is also consistent with Roure and Keeley (1990) study of new ventures that reported team completeness (the degree to which key positions were staffed by members of the founding team) was associated with firm success. Second, having functional diversity represented on the team also makes a new venture more attractive to external stakeholders as it signals that the management team has the requisite skills and capabilities to make the firm successful by solving various valuable problems. For example, in contexts of high entrepreneurial rates, Kaiser and Müller (2015) show that founders' functional skills variety explains the performance differences between ventures. Third, functional diversity has positive effects on team creativity, which may help TMTs to perceive new applications of existing internal capabilities, find solutions to persistent and valuable problems (Milliken et al., 2003). Similarly, Boone and Hendriks (2009) find that in contexts of the high-tech sector, top managers with a high functional background diversity make better quality decisions and ultimately better organizational performance.

An argument against a uniformly positive relationship between TMT diversity and new venture growth is the presumption that exceedingly high levels of diversity may lead to additional costs, predominantly due to the increased need for communication and coordination among highly diverse team members. Nonetheless, we propose several circumstances where these curvilinear effects may be less pertinent, thus enabling us to emphasize more on the potential advantages of functional diversity in TMTs. Primarily, the industry's character can determine how diversity influences new venture growth. In sectors driven by innovation, like software or creative domains, a multitude of functional backgrounds within TMTs can stimulate a more extensive array of ideas and perspectives, frequently resulting in more performance outcomes. Hence, within such contexts, the curvilinear effects might be less of a concern as the rewards of diversity may counterbalance potential coordination or communication issues. Secondly, the firm's geographical location can also play a crucial role. Indeed, new ventures based in multicultural cities or regions renowned for cultural diversity may possess an enhanced capacity to leverage the advantages of workforce diversity. In these locations, employees might have mastered the art of dealing with cultural and professional variations, thereby mitigating potential communication or coordination hurdles tied to diverse teams. Our empirical investigation focusing on new ventures based in Paris, a significant global city, might decrease the emphasis placed on irregular effects. Lastly, the firm's age can also affect how diversity impacts firm operations. Newly established or relatively young firms often demonstrate more flexible and adaptable work cultures, which might be more efficient at handling the difficulties associated with a diverse team. These new ventures might adopt contemporary management practices and norms, which can streamline communication and coordination among diverse team members, thereby diminishing the influence of any fluctuating effects. Consequently, our empirical setting leads us to think that the curvilinear effects might be less of a worry. We therefore assume that TMTs functional diversity increases the firm's likelihood to experience growth.

H1*: There is a positive relationship between TMTs' functional diversity and new venture growth*

The role of middle management in organizational processes and new venture growth has been less frequently explored, often with an emphasis on their distinctive contributions and roles within the organization (Wooldridge and Floyd, 1990). Indeed, their unique position, granting access to both high-level managerial insights and operational perspectives, defines them as crucial intermediaries bridging an organization's strategy and operational implementation (Floyd and Wooldridge, 1992, 1999). For instance, empirical studies suggest that middle managers often serve as facilitators for innovation and communication (Grimpe et al., 2019; Kanter, 1982). Specifically, within knowledge-intensive industries, Mollick (2012) demonstrated that the influence of middle managers on firm performance is significant and that individual differences among middle managers may have a more substantial impact on firm performance than organizational factors.

The value of perceiving middle managers' role through the lens of the problem-solving perspective and functional diversity is interesting for at least two reasons. First, due to their unique positioning within the organizational structure, middle managers serve as key conduits, connecting different parts of the organization such as the top-level and operational teams (Floyd and Wooldridge, 1999). Therefore, middle management with broad functional diversity can better synthesize the managerial and operational approach to identify and solve organizational problems and therefore foster new venture growth. Second, research implies that middle managers are more likely than Top Management Teams (TMTs) to investigate the complex causal relationships between a firm's capabilities and its financial performance (King and Zeithaml, 2001). Consequently, they could potentially wield a more substantial influence than their superiors in areas pertaining to capability development and problem-solving, thereby influencing new venture growth. Based on this, we propose that the functional diversity of middle management teams (MMTs) positively correlates with the firm's likelihood to experience growth.

***H2**: There is a positive relationship between MMTs' functional diversity and new venture growth*

Fewer studies have explored the impacts of non-managerial employees' structure and their characteristics on firm performance, focusing on elements such as qualifications and diversity (O'Reilly III et al., 1989). However, recent studies show that a firm's strategic direction is not solely driven by top management because non-managerial employees are often expected to solve first-order valuable problems and identify opportunities (Mintzberg and Waters, 1985). For instance, empirical studies on large established technology firms substantiate that non-managerial employees' human capital positively influences the firm's knowledge creation capability (Smith et al., 2005). Further examination of technology start-ups firms by Koch et al. (2013) has revealed how initial worker and job characteristics, such as qualifications and workload, impact post-entry employment growth. Finally, Andries and Czarnitzki (2014) further emphasizes the critical role of non-managerial employees' ideas, skills, and knowledge in driving innovation in small firms. Non-managerial employees with functional diversity may therefore enhance a firm's ability to respond and adapt to external shocks by providing a wider range of capabilities to handle various problems (Milliken et al., 2003). Consequently, new ventures with more diverse non-managerial employees may outperform those with more homogeneous employees due to the broader array of external resources accessible through functional diversity and the potentially limited effect of unshared information.

Furthermore, in a recent study, Shah et al. (2021) suggests that conflicts arising from agents' diverse opinions or expertise do not necessarily propagate throughout the organization or negatively impact overall performance. For instance, it was found that conflicts stemming from diversity seldom spread within organizations and that performance can actually be boosted by dissent between one or two individuals. Hence, even if conflicts arise during problem-solving processes because of a divergence of perspectives, functional diversity within the team might positively affect the performance of firms. For all these reasons, we therefore hypothesize that OCWs functional diversity increases the firm's likelihood of experiencing growth.

***H3**: There is a positive relationship between OCWs' functional diversity and new venture growth*

Making informed decisions is crucial for problem-solving and subsequent new venture growth, rendering the quality of decisions a powerful determinant of a firm's success. However, the nature of problems evolves based on whether a firm is in its early or later stages. To put it differently, problems have a lifecycle: an issue in one stage may not persist into another stage and therefore may require a different kind of resources (Sirmon et al., 2011; Gompers, 1995).

This distinction is well-documented in the literature, notably by differentiating between early and late funding stages (Gompers, 1995; Hsu, 2010). It has been documented that in the early funding stage, new ventures predominantly focus on survival, developing core technologies, and establishing business processes (Ratzinger et al., 2018). At this point, the new ventures' operational scope is usually limited, restricting the ability of its employees to develop functional specialization, consequently reducing opportunities to fully leverage human capital (Sirmon et al., 2011). Moreover, new ventures in the early funding stage, particularly those in dynamic markets, engage in experimental processes, seeking feedback from the market to ascertain an optimal fit based on a hypothetical deduction process, allowing individuals to evaluate if the product aligns with a target market. Conversely, in the later funding stages, the firms' focus transitions to managing the complexities that accompany growth (Cavallo et al., 2019b). The scope of operations during this stage broadens, enabling individuals to develop functional specialization (Shepard, 1969). Furthermore, recent research indicates that late funding stages are characterized by the hyper-specialization of the firm's offerings, which, while enhancing efficiency, may limit future exploration of new opportunities as firms become overly focused on what has previously proven successful (Giustiziero et al., 2021). Hence, in these later stages, decisions are targeted towards sustaining scaling efforts (Piaskowska et al., 2021).

Given these nuances, and aligning with the problem-solving perspective, we contend that functional diversity's influence on new venture growth may oscillate across maturity stages (Hong and Page, 2001). We expect functional diversity to exert a greater impact in the early rather than the late financing stages because in early-stage firms, individuals tend to lean more on the knowledge of individual employees due to the lack of developed organizational routines, while in larger and more established firms, individuals place more reliance on organizational routines (Grillitsch and Schubert, 2020). Hence, functional diversity in teams may be more pronounced in new ventures.

H4: *The magnitude of the positive relationship between TMTs, MMTs and OCWs' functional diversity and new venture growth differs depending on firms' funding stages maturity*

3.3. Methodology

3.3.1. Data sources and collection process

To test our hypotheses, we constructed a dataset incorporating information at both organizational and individual levels of VC-backed new ventures utilizing digital business models for their innovation. Table 3.1 delineates our empirical variables, their definitions, and their sources. The following discussion outlines the data collection process.

Variable name	Description	Data source
Firms characteristics		
1. Efficient user base growth	Dummy variable resulting from the difference between user base and headcount acceleration growth signals defined as ($P = \int_w U_a \; - \; H_a$)	Desktop research
2. Age	Number of years since firm's foundation	Crunchbase
3. Size	Number of headcounts in the firm	LinkedIn, Dealroom, BPI France
4. Cumulated	Total amount raised in euros (EUR) in previous funding rounds	Crunchbase, Dealroom, BPI France
Independent variables		
5. *Diversity_TMT_skills*	diversity score consisting of the composition of skill differences in the Top Management Team	Linkedin
6. *Diversity_MMT_skills*	diversity score consisting of the composition of skill differences in the Middle Management Team	Linkedin
7. *Diversity_OCW_skills*	diversity score consisting of the composition of skill differences in the Operating Core Workers	LinkedIn
Controls (individual-level)		
8. *Experience_TMT*	Number of years of previous job experience in the Top Management Team	LinkedIn
9. *Experience_MMT*	Number of years of previous job experience in the Middle Management Team	LinkedIn
10. *Experience_OCW*	Number of years of previous job experience in the Operating Core Workers	LinkedIn
Controls (firm-level)		
Funding stage	Dummy variable. Equals 1 when firm had raised equity equal or superior than a Series A (late stage funding stage), 0 when firm had raised equity inferior than a Series A (early funding stage) (Cavallo et al., 2019b)	Crunchbase, Dealroom, BPI France
Amount raised	Total amount raised in euros (EUR) by a firm in a funding stage	Crunchbase, Dealroom, BPI France

Table 3.1: Variable description and data sources

First, we used Crunchbase, Dealroom, and BPI France databases to gather organizational data. The first two track the development of global firms receiving venture capital financing, while the third, a French state database, registers innovative, French-based start-ups backed by private investors. These resources provide data on the company's headquarters, founders' names, fundraising stage, business models, and founding dates. We collected this data between February and March 2020. Our selection criteria specified new ventures that *(i)* were established between 2010 and 2018, *(ii)* had procured venture capital financing in at least one funding round, *(iii)* had their headquarters in the Greater Paris Metropolis (France), *(iv)* were independent (not subsidiaries), and *(v)* utilized a digital business model for their innovations. These initial criteria yielded a list of 347 new ventures. For the fourth and fifth filters, we manually visited each firm's website to verify whether their offerings included hardware devices and whether they were dependent on a parent company. These checks resulted in the exclusion of 41 new ventures (34 new ventures with hardware business propositions and 7 subsidiaries).

In choosing to investigate new ventures that leverage digital business models (software-as-a-service, marketplaces), we encountered several challenges. The first challenge arises from the fact that there is no consensus in the literature on how to accurately measure firm performance (Delmar et al., 2003). In the context of digital business models, however, user base growth emerges as a vital metric. While this does not directly contribute to revenue, efficient user base growth is a primary determinant of commercial success (Huang et al., 2017; Sun et al., 2004). Consequently, unlike traditional firms that typically measure growth through profitability, sales volume, and market share (McKelvie and Wiklund, 2010), firms operating under digital business models accord high priority to user base growth, recognizing its instrumental role in facilitating international expansion. Furthermore, in stark contrast to conventional software licenses requiring installation, digital business models operate on the cloud, necessitate minimal infrastructure, are accessible via a web browser, and delivered over the internet, following either a subscription-based or alternative revenue logic. Consequently, these business models exhibit *scalable* characteristics that set them apart from traditional ones, making them ideal candidates for user base expansion through innovation (Huang et al., 2017). Moreover, we selected the period 2010-2018, coinciding with the widespread adoption of cloud technologies across various established markets. Such technologies have radically transformed the software industry across various sectors, including supply chain, finance, accounting, human resources, and customer relationships, rendering it a matter of interest across diverse industries. We focused on the Greater Paris Metropolis (France) due to its status as a significant global city, boasting labor and financial capital reserves, and a nearby client base. The financial and business landscape of the Greater Paris Metropolis, particularly its venture capital market, ranks among Europe's largest, most structured, and dynamic. For instance, between 2016 and 2020, SaaS-based and marketplace-based firms comprised 55% of the total capital raised in France, 75% of French fundraising rounds in Paris, and over 85% of the value (BPI, 2020). Lastly, we chose to examine firms that received VC funding during early and late funding stages. External funding significantly alters a company's internal organization and functioning (Davila et al., 2003), thus providing an interesting case to investigate the effect of functional diversity within TMTs, MMTs, and OCWs on new venture growth across early and late funding stages.

Second, between March and June 2021, we manually collected data points for new ventures' user base and headcount. New ventures user base data were primarily gathered through desktop research, utilizing a variety of resources such as press releases, magazines, specialized reports, and credible company websites. When public data were not readily available, we conducted semi-structured interviews with the founders of the respective new venture. This was applicable in about 24 instances. These interviews were conducted following a meticulous protocol to maintain the accuracy and validity of the data collected. The interview protocol involved preparing a set of open-ended and closed-ended questions aimed at understanding the new ventures' user base size and demographics. To ensure consistency, the same interview guide was used across all founders, but flexibility was granted to explore pertinent points that may arise during the conversation. Moreover, to confirm the trustworthiness of the data obtained, we adopted a two-step verification process. We first requested founders to furnish documentary evidence supporting their claims whenever possible. The remaining, where evidence could not be provided, were treated with a higher degree of skepticism and required further verification. In the second step, we cross-referenced the collected information with other sources such as third-party analyst reports or sector-specific data. This multi-source corroboration helped mitigate any potential concerns about the accuracy of the data, providing us with a comprehensive, validated data set[1]. For a new venture to be included in our sample, it had to have at least three annual user base data points from its inception date. As for the firms' monthly headcount data points, we utilized LinkedIn, the world's largest online business networking service. LinkedIn's platform features employment histories for over 600 million users across more than 200 countries, including 21 million French users. This indicates that a significant portion of the French workforce uses LinkedIn[2]. Consequently, new venture growth is mea-

[1]We acknowledge that trust is an integral component of this data collection process. However, rigorous measures have been implemented to ensure their validity. These include insisting on documentary evidence where possible, and cross-verifying the information using multiple reliable sources.

[2]As of May 2020, LinkedIn had 21 million users in France, accounting for 70% of the active workforce out of a total working population of 29.8 million, as per INSEE French National statistics. On LinkedIn, individuals working in professional services and the technology and software sector are

Part A : Firms sectors classification

Sector	Number of firms	% total
Business Intelligence and Analytics	51	17.2
Customer Relationship Management	13	4.3
Developers - IT - Infrastructure	31	10.5
Finance and Legal	42	14.2
Human Resources	41	13.9
Marketing	69	23.3
Productivity and Collaboration	49	16.6
Total	296	100

Part B : Firms size categories

Headcount range size	Number of firms	% total
2-10	43	14.6
11-50	154	52.1
51-100	50	16.8
101-250	38	12.8
251-500	8	2.7
501-2000	3	1
Total	296	100

Table 3.2: Distribution of sample firms by firms' sectors classification and size

sured on a monthly basis with a maximum of 120 observations for growth rates. We used linear interpolation to determine a firm's efficient user base growth. We integrated these two measures into a firm-level performance metric, defined as an increase in the number of users registered for a digital innovation between two points in time without proportionately additional resources, i.e., with "human-capital-light growth" as described by Piaskowska et al. (2021). Ultimately, we excluded 51 out of 347 firms due to unavailable yearly user base data points, leaving 296 VC-backed new ventures in the sample. Table 3.2 presents the general statistics and distribution across various sizes and sectors. Table 3.3 provides descriptive statistics of the fundraising activities of the 296 VC-backed new ventures[3].

Thirdly, we use LinkedIn to collect functional background data (diplomas, work experiences, biodata, skills) and specific occupations of all the individuals who worked in these 296 VC-backed new ventures, representing a total of 44,823 individuals, including

overrepresented, comprising more than 40% of users. This first argument supports a satisfactory coverage rate for professionals in the software industry. Second, we performed differential margin of error tests by comparing the employees we recorded with the number of employees listed on BPI France, Crunchbase, and Dealroom's open platforms. Excluding new ventures that received substantial funding in the year after data collection, we found a 97% completeness rate.

[3]Part A of Table 3.2 provides an overview of the number of fundraising rounds per year. In total, 296 new ventures received 650 investment rounds, which indicates that all new ventures have raised capital from investors at least once, and some have undergone multiple investment rounds. Part B of Table 3.2 displays the number of financing rounds according to the new ventures' founding date. Lastly, Part C details the investment categories of new ventures and rounds. We note that 553 new ventures participated in 650 rounds, suggesting that some new ventures may have conducted two or more seed or series A rounds.

Part A : Number of fundraising rounds per years

		Amount in millions of euros				
Fundraising years	Rounds	Mean	Median	Min	Max	SD
2010	2	0.433	0.433	0.066	4.500	0.519
2011	7	0.549	0.200	0.025	12.500	0.614
2012	15	0.989	0.400	0.090	3.200	1.024
2013	27	0.709	0.500	0.060	20.000	0.968
2014	53	1.746	1.000	0.025	15.910	2.232
2015	91	2.310	1.000	0.023	47.000	3.631
2016	94	3.016	1.100	0.015	30.000	5.019
2017	123	4.531	1.800	0.050	51.000	8.049
2018	93	7.406	3.250	0.020	88.600	12.266
2019	112	13.433	4.000	0.050	205.000	27.931
2020	33	12.252	5.000	0.500	104.000	19.928
Total	650	5.841	1.700	0.023	205.000	14.546

Part B : Fundraising per founding date

			Amount in millions of euros				
Fundraising years	Firms	Rounds	Mean	Median	Min	Max	SD
2010	18	50	4.681	1.975	0.066	28.000	5.892
2011	24	63	3.914	1.500	0.050	62.000	8.376
2012	26	63	6.073	1.300	0.060	100.000	14.794
2013	40	97	9.701	2.500	0.023	150.000	21.298
2014	40	104	7.390	1.750	0.080	205.000	21.208
2015	44	91	5.348	1.800	0.060	70.000	10.578
2016	57	112	4.810	1.500	0.050	104.000	11.278
2017	30	48	2.677	1.500	0.050	10.800	2.913
2018	17	22	2.717	1.850	2.500	20.000	4.136
Total	296	650	5.841	1.700	0.023	205.000	14.546

Part C : Fundraising categories

			Amount in millions of euros				
Categories	Firms	Rounds	Mean	Median	Min	Max	SD
Grant	9	11	0.398	0.072	0.050	2.500	0.746
Dept	7	10	1.776	0.765	0.100	1.200	3.612
Seed	250	318	0.912	0.615	0.023	12.000	1.058
Series A	192	216	4.980	3.650	0.500	23.000	4.084
Series B	69	69	15.514	11.000	1.000	53.700	11.614
Series C	23	23	48.852	30.000	4.000	205.000	44.966
Series D	2	2	32.500	32.500	30.000	35.000	35.355
Series E	1	1	150.000	150.000	150.000	150.000	*nan*
Total	553	650	5.841	1.700	0.023	205.000	14.546

Table 3.3: Descriptive statistics of the distribution of fundraising activities of the 296 VC-backed new ventures

5,243 top managers (including 1,052 founders), 10,274 middle managers, and 29,306 core workers at lower hierarchical level.

LinkedIn provides granular information on individuals' professional trajectories and users have an incentive to keep their profiles current since the website is valuable for professional networking: many employers use it to recruit new employees, either by posting job ads or through direct headhunting.

Virtual skill endorsement (i.e. skills endorsed and validated by peers on LinkedIn) is a socially constructed online reputation and is a way of self-presentation through which job seekers brand themselves to potential recruiters (Rapanta and Cantoni, 2017) considered as a piece of valuable information for entrepreneurial studies (Gasiorowski and Lee, 2022; Piazza et al., 2023). Indeed, using LinkedIn skill endorsements data has proven its relevance in recent entrepreneurship studies because it provides detailed individual-level data not available through more traditional sources. For example, Reese et al. (2020) use LinkedIn information about founders, especially their "*Skills & Endorsements*" section, to measure founders' human capital and Sako et al. (2020) used LinkedIn skill endorsement section too in order to identify the skills of individual start-ups founders. While we utilize skill endorsements on LinkedIn as a measure of skill variety, we acknowledge the potential for bias given their public nature and the elements of performativity and reciprocation.

Variables	Mean	SD	Min	Max
Firms characteristics				
1. Efficient user base growth	0.21	0.40	0	1
2. Age	7.22	2.18	2,83	11.75
3. Size	30.34	39.41	2	442
4. Cumulated	3,149,312	5,158,914	23,000	262,000,000
Independent variables				
5. *Diversity_TMT_skills*	0.57	0.52	0	1.90
6. *Diversity_MMT_skills*	0.53	0.49	0	1.87
7. *Diversity_OCW_skills*	0.68	0.40	0	1.92
Controls (individual-level)				
8. *Experience_TMT*	0.56	0.97	0	9.70
9. *Experience_MMT*	0.61	1.08	0	10.48
10. *Experience_OCW*	0.43	2.20	0	44.24
Controls (firm-level)				
Funding stage	0.36	0.48	0	1
Amount raised	2,647,329	4,236,516	23,000	45,000,000

Table 3.4: Descriptive statistics

However, our study assumes that while this potential bias exists, it does not invalidate the overall indication of skill variety as these endorsements are widely accepted and used as a metric in the professional world. Data on functional backgrounds were gathered from LinkedIn, encompassing 44,823 unique individuals who endorsed a total of 866,638 skills (45,449 unique skills). Table 3.4 list the descriptive statistics of all variables (means, std dev, min, max).

3.3.2. Dependent variable

There is no agreement in the literature concerning how to measure firms' performance. Performance has been operationalized in many ways, such as growth (in terms of sales, employment, revenue), profitability, survival, innovativeness, or initial public offering (IPO) (Delmar et al., 2003). However, in a digital context, since it assigns weight and legitimacy to a new digital service or product, user base growth is a central point for any firm (Sun et al., 2004). Indeed, building in an efficient way a user base is a precondition for creating a customer base. While users do not directly contribute to the revenue of a firm, a significant amount of users is necessary for making a commercially successful firm (Huang et al., 2017; Liu et al., 2019). Therefore, *efficient user base growth* has been considered as the measure of growth, and hence, it represents our dependent variable.

Efficient user base growth occurs when the user base and headcount of a firm increase with opposite dynamics, i.e., the former accelerates faster than the latter, for a "human-capital light" growth as described by Piaskowska et al. (2021). We, therefore, characterize firms' *efficient user base growth* by computing user base and headcount dynamics; we derive their growth signals twice over time, interpreted as accelerations of the user base $U_a(t)$ and headcount $H_a(t)$.

Let $U_a(t)$ be the acceleration (second derivative) of the user base growth signal defined as follow:

$$U_a(t) = \frac{d^2u}{dt^2} \tag{3.1}$$

Let $H_a(t)$ be the acceleration (second derivative) of the headcount growth signal defined as follow:

$$H_a(t) = \frac{d^2h}{dt^2} \tag{3.2}$$

To calculate *efficient user base growth*, we integrate the difference between the two signals in a *window of interest* w computed from an *offset* o (see details for in the next section *Timing and hyper parameters*).

Let P be the difference between the user base acceleration growth signal noted $U_a(t)$ and the headcount acceleration growth signal noted $H_a(t)$, within a *window of interest*

w defined as follow:

$$P = \int_w U_a \ - \ H_a \tag{3.3}$$

A positive value of P in a period of time t in a *window of interest* w means that the $U_a(t)$ is growing at a higher rate than $H_a(t)$, meaning in that case that the firm issued an $efficientuserbasegrowth$ event. Consequently, the firm was allocated a value of 1 if $P > 0$, and 0 otherwise.

3.3.3. Timing and hyper-parameters

Besides time lags between causes and effects, one of the most direct consequences of firms receiving a private VC investment is the rapid increase in available resources and, thus, the potential to experience an *efficient user base growth* event. Indeed, this surplus of financial resources acts as a stimulus that precipitates the turnover of team members through hiring and attrition, alters the configuration of teams in terms of functional skills, and changes how a firm organizes (Sirmon et al., 2011). For example, Davila et al. (2003) indicated how VC fundraisings stimulate the mean change in the number of employees around the month firms receive investments from VCs.

By following this rationale, we restricted our analysis to the months when we expected the impact of fundraising to be most significant to the firm's growth. To do so, we determined two different sliding windows, called *offset* and *window of interest*, that distinguish the acceleration change in headcount and user base. The first sliding time window is noted o, for *offset*, and is defined as the period around the month when firms receive external VC funding, precisely between when $U_a(t)$ increase and when $H_a(t)$ stabilize. This period happens before the *window of interest* period, and we set the hyper-parameter o at the month of the funding event and two months after: month 0 (fundraising), month 1, month 2. The second sliding time window is noted w, for *window of interest*, and is defined as the period after firms receive external funding when $H_a(t)$ stabilizes. This period happens after the *offset*, and we set the hyper-parameter w at +3 to +5 months after the funding event: month 3, month 4, month 5.

3.3.4. Independent variable

Since our focus is on the impact of different hierarchical level functional diversity on new venture growth, the main independent variable of our econometric model is *functional diversity* of TMTs, MMTs, and OCWs. In line with Bunderson et al. (2002), we define functional diversity as *"the different functional experiences of team members [...], the extent to which team members differ in their functional backgrounds"*. To operationalize *functional diversity* measure for each hierarchical level of each firm, first, we assigned each individual a score in 10 functional areas, namely: strategy, marketing, entrepreneurship, sales, software development, product, finance, management, human resources, and design. To create the main functional areas and assign a score, we utilized a bottom-up hierarchical clustering approach with Kruskal's minimum spanning tree algorithm, therefore considering skill occurrences and co-occurrences between individuals (Kruskal, 1956). As such, the similarity between any pair of skills is naturally defined by their "intersection over union." We thus determined an individual's affinity to any skill cluster in the tree by measuring the shared skills. Instead of assigning an individual to the cluster with the highest affinity (hard clustering), which would not account for their versatility (for instance, the Blau or Teachman index), we represent an individual by their set of affinities to the skills of interest (fuzzy clustering). Second, we aggregated the individual's functional diversity scores at different hierarchical levels - TMT, MMT, OCW - and, similar to Bunderson et al. (2002), we operationalized *functional diversity* and use Cosine and Euclidean distance to compute the average shortest distance between each team member and every other team member across all relevant functions.

3.3.5. Controls

We used firm-level control variables.

Cumulated amount raised: we control for the cumulated capital, i.e., the total amount raised in euros (EUR) by a firm in previous funding rounds. Indeed, the amount of financial capital fundraised is known as an antecedent of a firms' survival and future growth.

Age: age is the time since firm founding. We control for age as a proxy for firms' stage of development.

Size: firm size, measured as the headcount of each firm, is a proxy for smallness. We also use size as a moderating factor in the team's functional diversity - new venture growth relationship.

We used individual-level control variables.

Experience: we leverage LinkedIn data to quantify an individual's experience, aiming for a broad perspective on their career progression. We classify individuals' hierarchical positions as either top, middle, or lower, relying on their declared job titles (see next section "classification of hierarchical levels in firms"). Notably, our assessment includes all listed professional experiences, irrespective of their relevance to the individual's current role. Recognizing that past experiences in unrelated fields may not directly impact an individual's current role proficiency, we still argue that it is an indicator of their professional adaptability. In line with Becker's human capital theory and Harrison's elaboration, we view experience as a "variable linked to time," with the duration spent in a function facilitating the accumulation of job-specific knowledge and therefore the capacity to solve problems. Given that an increase in skills correlates with longer tenures, individuals tend to make improved decisions, solve complex problems more effectively, and develop superior strategies with accumulated experiences. Thus, investing time in gaining experience enhances an individual's problem-solving performance. For the purposes of this study, we define experience as the total years of an individual's past professional experience. The aggregated results present a three-tiered view: experience at the TMT ($Experience\_TMT$), MMT level ($Experience\_MMT$), and OCW level ($Experience\_OCW$). To compute this, we consider the sum of all professional experience. For instance, an individual with three different job experiences, each lasting four years, would be assigned a total experience of 12 years. By doing so, our approach allows us to calculate the average total years of job experiences, providing a holistic view of each individual's career journey.

3.3.6. Classification of hierarchical levels in firms

In line with prior studies (e.g., Lee (2022)) we categorized each individual's job title into one of 12 levels (i.e., "Owner", "President", "VP", "CEO", "C-Suite", "Director", "Head", "Manager", "Producer", "Lead", "Supervisor", and "Other") and affiliate it to a specific occupation (TTMs, MMTs, OCWs) (Mintzberg, 1980). Specifically, we leveraged Lee (2022) methodology to classify each individual's job title into one of 12 distinct levels. This classification is achieved by applying Rules 1 through 12 from Table 3.5 sequentially until a match is identified — essentially, if a job title contains terms applicable to a specific level. The list of pertinent terms (as seen in the fourth column of Table 3.5) encompasses abbreviations (for instance, "vp" stands for vice president) and typographical mistakes often found in the LinkedIn database. Finally, after classifying all job titles into these levels, we affiliate the hierarchical levels with top management teams ("Owner", "President", "VP", "CEO", "C-Suite", "Director"), middle management teams ("Head", "Manager", "Producer", "Lead", "Supervisor"), and core operational workers ("Other"), as seen in the third column of Table 3.5.

3.3.7. Classification of early and late funding stages

Funding types are differentiated based on their stage of maturity as outlined by Gompers (1995). Within the domain of venture capital-backed firms, the literature categorizes firms past the seed stage as being in the early VC funding stage and those entering Series A or higher as being in the late VC funding stage (Gompers, 1995; Hsu, 2010). The principle behind this classification is that once a firm overcomes

Rule	Hierarchical Level	Affiliation	If the specific occupation includes any of these terms	Examples
1	Owner	TMT	owner, founder, chairman, creator, created, or made	"cofounder", "fondateur", "co-fondateur", "co-fondateur", "cofondateur", "fondatrice", "co fondatrice", "co-fondatrice"
2	President	TMT	president or presidente (but not vice)	"President", "Président", "President and CEO" "President & CEO", "President, North America"
3	VP	TMT	vp, evp, avp, svp, snrvp, vice president, or vice presidente	"Vice President", "Vice Président", "Vice President of Marketing", "VP of Marketing", "Senior Vice President"
4	CEO	TMT	ceo or any combination of {chief or cheif} and {executive, exec, exective, or executiver}	"CEO," "Chief Executive Officer"
5	C-Suite	TMT	cco, cdo, cfo, cho, cio, clo, cmo, coo, cpo, cso, cto, or both chief and officer	"COO," "CFO," "Chief Marketing Officer", "Chief Operating Officer"
6	Director	TMT	director, directo, diercto, dir, or dierctor	"Art Director," "Director," "Technical Director," "Creative Director", "Directeur", "Directeur général", "Directrice", "Directrice général"
7	Head	MMT	head	"Head of Production," "Studio Head," "Head of Marketing," "Head of Development"
8	Manager	MMT	manager, mgr, or gm	"Project Manager," "Product Manager," "QA Manager," "Production Manager"
9	Producer	MMT	producer	"Producer," "Executive Producer"
10	Lead	MMT	lead or leader	"Lead Programmer," "Lead Artist," "Lead Tester," "Lead Designer"
11	Supervisor	MMT	supervisor	"Supervisor," "QA Supervisor," "Music Supervisor," "Test Supervisor"
12	Other	OCW	(includes none of the above)	"Business developper", "commercial", "employé polyvalent"

Table 3.5: The rules to categorize each employee's specific occupation into a hierarchical level. Inspired by (Lee, 2022)

a problem-solving situation at an early venture capital stage, it encounters a different challenge and transitions from one stage to another by securing additional funds, thereby signifying potential internal organizational transformations. Consequently, the distribution of new resources within the organization may influence the efficiency and pace of decision-making regarding problem-solving (Sirmon et al., 2011). For instance, Cavallo et al. (2019b) contends that firms progress from an initial stage where they are still learning and validating their product and business model to a more advanced stage, demonstrating traction metrics (having attracted €1 million or more in VC funding).

As such, we introduced a binary variable to differentiate between the early and late VC funding stages, assigning 1 to firms that have raised equity equal to or greater than a Series A throughout their history (i.e., late funding stage), and 0 otherwise (i.e., early funding stage).

3.3.8. Model specification

Finally, integrating all the parameters, we run the following equation for each organizational echelon (TMT, MMT, OCW), each type of funding stage (early and late) and each parameter (offsets and windows of interest). We propose below the equation of our logit regression.

$$y_s = \epsilon.C + \sum_p \beta_p.V_p \tag{3.4}$$

Where y_s is whether efficient user base growth occurred in the studied window, C are the control variables including firm size, firm age, cumulated capital and average job experience level in the organizational echelon, V is the functional diversity score of the organizational echelon, S is the type of funding stage, and p the hierarchical level, one of : top management, middle management, operational core workers.

We chose to use logistic regression in this study because it enables us to ascertain the odds of a certain event happening (i.e., experiencing an efficient user base growth event) given a set of predictor variables at a specific point in time. It is this snapshot-like quality of logistic regression that we found valuable for our particular research question. It allows us to isolate the variables influencing a firm's ability to attract VC investment at a particular funding stage, irrespective of their past success or failure. Furthermore, logistic regression affords us the flexibility to control for time-varying covariates, making it a robust choice in the presence of confounding variables. Nonetheless, we acknowledge the possibility of endogeneity in our model and the effect of prior funding success on subsequent rounds. Consequently, we performed several robustness tests to ensure the quality of the analysis (see robustness tests section).

3.4. Results

3.4.1. Descriptive statistics and correlation matrix

Table 3.2 and Table 3.4 present the descriptive statistics of the sectors comprising firms and their size categories. They also provide descriptive statistics for various attributes related to these firms.

Table 3.2 shows that our dataset is composed of 296 VC-backed new ventures, each categorized into one of seven industry sectors. The most represented sectors include Marketing (constituting 23.3% of total firms), Productivity and Collaboration (16.6%), and Business Intelligence and Analytics (17.2%). Conversely, sectors such as Customer Relationship Management and Developers - IT - Infrastructure account for a smaller proportion of firms, at 4.3% and 10.5% respectively. With regard to firm size, measured by the number of employees, over half (52.1%) of the firms in our dataset have a workforce ranging from 11 to 50 individuals. A lesser percentage of firms have a headcount exceeding 100.

In Table 3.4, we outline the various attributes of the firms in our sample, which include independent variables and other characteristics. On average, firms in our sample have been operating for approximately 7.22 years and employ around 30 people. The "Efficient user base growth" variable indicates that about 21% of firms in our sample have experienced rapid growth. We also present data related to the functional diversity of skills among top management teams - $Diversity\_TMT\_skills$, middle management teams - $Diversity\_MMT\_skills$, and operational core workers - $Diversity\_OCW\_skills$, with average values of 0.57, 0.53, and 0.68 respectively. Additional key variables considered in our study include funding stage and amount raised, with the average amount raised being approximately 2.65 million.

Table 3.6 presents the correlation matrix for our dataset, illustrating the relationships between the various attributes of our firms. Notably, the "Size" variable shows a moderate positive correlation with "Cumulated" ($\rho = .56$), suggesting that larger firms tend to have higher cumulative values. Furthermore, $Diversity\_MMT\_skills$ exhibits a moderate positive correlation with both "Size" ($\rho = .20$) and "Cumulated" ($\rho = .21$), suggesting that an increase in firm size and cumulative values is associated with a broader diversity of middle management team skills. Conversely, variables representing job experience, specifically $Experience\_TMT$, $Experience\_MMT$, and $Experience\_OCW$, generally exhibit negative correlations with other variables. For instance, *Experience_TMT* has a moderate negative correlation with both "Size" (ρ = -.08) and "Cumulated" (ρ = -.12), implying that job experience within top management teams tends to decrease as firm size and cumulative values increase.

		1	2	3	4	5	6	7	8	9	10
1.	Efficient user base growth	1									
2.	Age	0.09	1								
3.	Size	-0.02	0.16	1							
4.	Cumulated	-0.08	-0.01	0.56	1						
5.	*Diversity_TMT_skills*	0.07	0.06	0.10	0.12	1					
6.	*Diversity_MMT_skills*	-0.01	0.07	0.20	0.21	0.06	1				
7.	*Diversity_OCW_skills*	0.04	-0.01	0.16	0.17	0.10	0.13	1			
8.	*Experience_TMT*	0.02	-0.16	-0.08	-0.12	-0.23	-0.01	-0.07	1		
9.	*Experience_MMT*	0.11	-0.04	-0.14	-0.19	-0.01	-0.40	-0.04	0.01	1	
10.	*Experience_OCW*	-0.02	-0.05	-0.06	-0.07	-0.06	-0.07	-0.20	0.03	0.02	1

Determinant of the correlation matrix: 0.403

Table 3.6: Correlation Matrix

The determinant of the correlation matrix is 0.403, indicating that our dataset does not exhibit perfect multicollinearity. Further statistical tests, such as variance inflation factors, affirm the absence of severe multicollinearity in our data.

3.4.2. Regression results

Table 3.7 presents the results for our main logit regression. Table 3.8 presents the results for the logit regression on early VC funding stage and table 3.9 presents the results for the logit regression on later VC funding stages.

Regarding Hypothesis **H1**, it is suggested that there is a positive relationship between the functional diversity of TMTs (Top Management Teams) and new venture growth. This is validated by the significant coefficients of *Diversity_TMT_skills* across all months and for both all and start-up funding stages. The coefficients are positive and significant at the 5% and 1% level, which provides strong evidence for Hypothesis H1. The odds ratios associated with these coefficients ranging from 1.170 to 1.262 further indicate the strong effect of TMTs' functional diversity on new venture growth.

	Offsets									Windows of interest								
	Month 0 (fundraising)			Month 1			Month 2			Month 3			Month 4			Month 5		
Variables	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR
Theorical																		
Diversity_TMT_skills	0.157**	(0.063)	1.170	0.191***	(0.063)	1.211	0.235***	(0.063)	1.265	0.183***	(0.058)	1.201	0.199***	(0.059)	1.220	0.233***	(0.059)	1.262
Diversity_MMT_skills	0.129*	(0.069)	1.137	0.167**	(0.070)	1.182	0.061	(0.069)	1.063	0.107*	(0.064)	1.113	0.108*	(0.064)	1.114	0.116*	(0.065)	1.123
Diversity_OCW_skills	0.064	(0.064)	1.066	0.196***	(0.068)	1.217	0.215***	(0.069)	1.240	0.119**	(0.060)	1.126	0.137**	(0.060)	1.147	0.129**	(0.061)	1.137
Controls (individual-level)																		
Experience_TMT	0.191***	(0.058)	1.210	0.147**	(0.059)	1.158	0.071	(0.062)	1.074	0.124**	(0.057)	1.132	0.113**	(0.057)	1.119	0.111*	(0.058)	1.117
Experience_MMT	0.271***	(0.062)	1.311	0.257***	(0.061)	1.294	0.222***	(0.059)	1.249	0.285***	(0.063)	1.33	0.278***	(0.063)	1.321	0.283***	(0.063)	1.327
Experience_OCW	-0.034	(0.089)	0.967	-0.004	(0.087)	0.996	-0.002	(0.087)	0.998	-0.031	(0.083)	0.969	-0.023	(0.080)	0.977	-0.023	(0.082)	0.977
Controls (firm-level)																		
Age	0.236***	(0.064)	1.266	0.222***	(0.063)	1.249	0.239***	(0.063)	1.270	0.277***	(0.059)	1.319	0.230***	(0.059)	1.259	0.243***	(0.059)	1.275
Cumulated	-0.181**	(0.089)	0.834	-0.210**	(0.090)	0.811	-0.274***	(0.093)	0.760	-0.222***	(0.082)	0.801	-0.266***	(0.085)	0.766	-0.291***	(0.087)	0.747
Headcount	0.016	(0.077)	1.016	-0.003	(0.079)	0.997	0.031	(0.079)	1.031	0.014	(0.072)	1.014	0.032	(0.073)	1.033	0.043	(0.073)	1.044
Constant	-1.244***	(0.063)	0.288	-1.293***	(0.063)	0.274	-1.275***	(0.063)	0.279	-0.920***	(0.058)	0.399	-0.965***	(0.058)	0.381	-0.975***	(0.059)	0.377
R2	0.034	0.034	0.034	0.038	0.038	0.038	0.040	0.040	0.040	0.040	0.040	0.040	0.039	0.039	0.039	0.043	0.043	0.043
Observations	1545	1545	1545	1590	1590	1590	1605	1605	1605	1574	1574	1574	1574	1574	1574	1574	1574	1574
Number of firms	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296

Notes: (Coef.) = Coefficients; (OR) = Odds Ratio. Robust standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Table 3.7: Logistic regression with efficient user base growth as the dependent variable. Results include early and late funding stages

	Offsets									Windows of interest								
	Month 0 (fundraising)			Month 1			Month 2			Month 3			Month 4			Month 5		
Variables	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR
Theorical																		
Diversity_TMT_skills	0.129*	(0.077)	1.137	0.159**	(0.077)	1.172	0.178**	(0.076)	1.195	0.149**	(0.072)	1.161	0.167**	(0.073)	1.182	0.189***	(0.073)	1.208
Diversity_MMT_skills	0.201**	(0.085)	1.223	0.231***	(0.085)	1.260	0.052	(0.085)	1.053	0.141*	(0.079)	1.152	0.152*	(0.079)	1.164	0.152*	(0.079)	1.164
Diversity_OCW_skills	0.184**	(0.081)	1.202	0.354***	(0.085)	1.425	0.397***	(0.087)	1.488	0.269***	(0.076)	1.309	0.298***	(0.077)	1.347	0.281***	(0.077)	1.324
Controls (individual-level)																		
Experience_TMT	0.181**	(0.074)	1.199	0.118	(0.074)	1.126	0.061	(0.074)	1.063	0.110	(0.071)	1.116	0.089	(0.072)	1.093	0.095	(0.072)	1.100
Experience_MMT	0.252***	(0.076)	1.286	0.226***	(0.075)	1.254	0.195***	(0.074)	1.215	0.245***	(0.075)	1.277	0.246***	(0.075)	1.279	0.257***	(0.076)	1.293
Experience_OCW	-0.080	(0.150)	0.924	-0.042	(0.144)	0.959	-0.050	(0.159)	0.951	-0.091	(0.152)	0.913	-0.077	(0.145)	0.926	-0.084	(0.149)	0.920
Controls (firm-level)																		
Age	0.281***	(0.079)	1.324	0.284***	(0.077)	1.328	0.330***	(0.077)	1.391	0.366***	(0.074)	1.441	0.323***	(0.074)	1.382	0.323***	(0.074)	1.381
Cumulated	-0.189*	(0.104)	0.828	-0.150	(0.096)	0.861	-0.171*	(0.098)	0.842	-0.149*	(0.089)	0.861	-0.183**	(0.092)	0.833	-0.186**	(0.093)	0.830
Headcount	0.089	(0.076)	1.093	0.081	(0.074)	1.085	0.104	(0.074)	1.110	0.091	(0.074)	1.096	0.101	(0.074)	1.106	0.112	(0.074)	1.119
Constant	-1.021	(0.078)	0.360	-1.052	(0.078)	0.349	-1.042	(0.078)	0.353	-0.658	(0.072)	0.518	-0.689	(0.073)	0.502	-0.690	(0.073)	0.502
R2	0.044	0.044	0.044	0.057	0.057	0.057	0.058	0.058	0.058	0.055	0.055	0.055	0.056	0.056	0.056	0.056	0.056	0.056
Observations	915	915	915	950	950	950	965	965	965	939	939	939	939	939	939	939	939	939
Number of firms	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296

Notes: (Coef.) = Coefficients; (OR) = Odds Ratio. Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: Logistic regression results with efficient user base growth as the dependent variable. Results include only early funding stages

	Offsets									Windows of interest								
	Month 0 (fundraising)			Month 1			Month 2			Month 3			Month 4			Month 5		
Variables	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR	Coef.	Std.Err.	OR
Theorical																		
Diversity_TMT_skills	0.272**	(0.125)	1.312	0.354***	(0.133)	1.425	0.460***	(0.137)	1.583	0.333***	(0.118)	1.395	0.365***	(0.122)	1.440	0.455***	(0.125)	1.576
Diversity_MMT_skills	0.127	(0.125)	1.135	0.212	(0.136)	1.237	0.311**	(0.136)	1.364	0.222*	(0.121)	1.249	0.199	(0.123)	1.220	0.226*	(0.125)	1.253
Diversity_OCW_skills	-0.112	(0.108)	0.894	-0.093	(0.113)	0.912	0.006	(0.124)	1.006	-0.097	(0.105)	0.907	-0.104	(0.107)	0.902	-0.082	(0.108)	0.922
Controls (individual-level)																		
Experience_TMT	0.312***	(0.109)	1.367	0.299**	(0.116)	1.348	0.164	(0.147)	1.178	0.238**	(0.111)	1.269	0.256**	(0.112)	1.292	0.251**	(0.117)	1.285
Experience_MMT	0.333***	(0.102)	1.395	0.346***	(0.107)	1.413	0.188*	(0.105)	1.207	0.334***	(0.102)	1.397	0.283***	(0.101)	1.327	0.232**	(0.102)	1.261
Experience_OCW	0.319***	(0.099)	1.376	0.332***	(0.101)	1.394	0.492***	(0.108)	1.635	0.390***	(0.094)	1.477	0.424***	(0.095)	1.528	0.421***	(0.096)	1.523
Controls (firm-level)																		
Age	0.285**	(0.122)	1.329	0.265**	(0.123)	1.303	0.236*	(0.124)	1.266	0.299***	(0.112)	1.348	0.237**	(0.114)	1.267	0.281**	(0.115)	1.324
Cumulated	0.279**	(0.128)	1.322	0.321**	(0.127)	1.379	0.215*	(0.129)	1.239	0.272**	(0.118)	1.312	0.252**	(0.121)	1.286	0.228*	(0.122)	1.256
Headcount	-0.111	(0.124)	0.895	-0.114	(0.127)	0.893	-0.070	(0.127)	0.933	-0.092	(0.115)	0.912	-0.063	(0.117)	0.939	-0.056	(0.118)	0.946
Constant	-1.715	(0.117)	0.180	-1.863	(0.124)	0.155	-1.872	(0.126)	0.154	-1.465	(0.108)	0.231	-1.553	(0.111)	0.212	-1.580	(0.113)	0.206
R2	0.059	0.059	0.059	0.072	0.072	0.072	0.091	0.091	0.091	0.077	0.077	0.077	0.078	0.078	0.078	0.083	0.083	0.083
Observations	630	630	630	640	640	640	640	640	640	635	635	635	635	635	635	635	635	635
Number of firms	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296	296

Notes: (Coef.) = Coefficients; (OR) = Odds Ratio. Robust standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Table 3.9: Logistic regression results with efficient user base growth as the dependent variable. Results include only late funding stages

For Hypothesis **H2**, the relationship between the functional diversity of MMTs (Middle Management Teams) and new venture growth is also significantly positive, as shown by the $Diversity\_MMT\_skills$ coefficients. However, the results show somewhat less consistency, with the coefficients being significant only at the 10% and 5% levels across various months. Nonetheless, the corresponding odds ratios (between 1.063 and 1.182) also suggest a moderate effect of MMTs' functional diversity on new venture growth, supporting Hypothesis H2.

Hypothesis **H3**, positing a positive relationship between the functional diversity of OCWs (Operational Core Workers) and new venture growth, is also supported. This is evident from the significant positive coefficients of $Diversity\_OCW\_skills$. The relationship is particularly strong during the start-up funding stages where the coefficient is significant at the 5% and 1% levels, suggesting a crucial role for functional diversity among OCWs during the start-up phase. The respective odds ratios reinforce this implication (from 1.066 to 1.240).

Finally, for Hypothesis **H4**, the strength of relationships indeed varies depending on the maturity of the firm's funding stages. For instance, the $Diversity\_TMT\_skills$ coefficients are higher during the start-up stage than in the overall sample, suggesting that functional diversity in the top management team has a greater impact during this stage. Similarly, the impact of functional diversity among OCWs is also stronger during the start-up phase, as indicated by the higher $Diversity\_OCW\_skills$ coefficients. This differential impact, as evidenced by differing odds ratios, provides support for Hypothesis H4.

In terms of control variables, the job experience of TMT and MMT both positively relate to new venture growth, with significant odds ratios indicating these positive relationships. However, the job experience of OCWs does not show any significant relationship, as suggested by the corresponding non-significant odds ratio. The age of the firm also positively correlates with the firm's growth (OR from 1.324 to 1.391), and the accumulated funding received negatively relates to growth, as reflected in their respective odds ratios (from 0.680 to 0.823). Headcount does not show any significant relation to new venture growth.

3.4.3. Robustness tests

We performed several robustness tests to ensure the quality of the analysis. We tested our regressions in different sample sub-populations, categorized different skills functional areas through bottom-up hierarchical clustering, ran other functional diversity measures, and used multiple sliding observational windows. Results remained consistent. Because of spatial restrictions, we avoid displaying the tables here but they can be obtained from the authors if asked for.

Adjustment to team size: recent methodological study posited the most common measures used to operationalize diversity (such as the mean Euclidean distance) do not correct for variations in group size (Harrison and Klein, 2007; Biemann and Kearney, 2010). To adjust for this potential bias, we used measures advocated by Biemann and Kearney (2010) and reevaluated tables 3.7, 3.8 and 3.9. The key findings remained unaltered.

Sample sub-populations: we did not identify potential selection effect nor missing data because the empirical settings reduce *(i)* alternative explanations for skills requirements, *(ii)* desirable funding amounts at funding stages, *(iii)* geographical market comparison *(iv)* sample endogeneity issues. Also, as we focused on firms that were founded in the Metropolis of Greater Paris between 2010 and 2018, use a digital business model for their innovation in various sectors and do business in professional markets (business-to-business) in different sectors, we test for robustness across sub-populations sectors : we ran our regressions along the sub-populations identified. Results remained consistent.

Kruskal's minimum spanning tree algorithm: The categorization of skills into functional areas may be worth further discussion, especially on the applicability of bottom-up hierarchical clustering with Kruskal's minimum spanning tree algorithm (Kruskal, 1956). Indeed, specific skills, such as entrepreneurship, may be more or less critical at different organizational echelons. We ran the regressions and analyses for each hierarchical level with different categorization of skills, and the main results remained stable.

Alternative measure of diversity: One might argue that the Cosine distance does not have the same interpretation depending on firm size and skill cluster completion. To exclude the potential for bias in this respect, we estimated our regression model using the Euclidian distance instead of the Cosine distance (average distance per pair of individuals within a group) (Bunderson et al., 2002). Findings remained consistent.

Causality: in our theoretical propositions, we consider the functional diversity as being influenced by external factors, which is a strong assumption that may overlook the possibility of functional diversity being a product of earlier strategic decisions. In order to offset this potential bias, we implemented different sliding windows and hyper-parameters that have at least two virtues. First, this gives a timed sequential reference, as one period precedes another, thus arguably allowing us to offer causal interpretations of the effect under study. Second, it provides sliding data points computable simultaneously, supporting the robustness of the computation.

3.5. Discussion and conclusion

The relationship between diversity and new venture growth has become a focal point of crystallization in the organizational science and strategic management literatures. Indeed, academic studies show mixed results, with diversity benefits and drawbacks varying based on many contextual factors and methodologies. Indeed, the theoretical part of the literature suggests that diversity can result in enhanced unique knowledge access and competitive edge, but also potential reduction in information exchange due to diverging perspectives. Despite empirical research efforts, no consensus on the positive impacts of functional diversity on firm performance was found (Jin et al., 2017; Bell et al., 2011; Horwitz and Horwitz, 2007; Webber and Donahue, 2001). To fill this gap, by drawing on the problem-solving perspective (Graesser et al., 2018; Grant, 1996; Hong and Page, 2001; Nickerson and Zenger, 2004), we suggest the need for a more refined interpretation of the informational diversity framework. More precisely, we propose considering the impact of diversity at different organizational levels, not just at the top management level as traditionally done (see e.g., (Aboramadan, 2021; Boone and Hendriks, 2009; Finkelstein et al., 2009; Eesley et al., 2014)). Indeed, MMTs and OCWs also have significant influences on new venture growth (Andries and Czarnitzki, 2014; Floyd and Wooldridge, 1992; Mollick, 2012; Mintzberg and Waters, 1985). Therefore, we propose a multi-layered theoretical framework that links functional diversity at top, middle, and bottom levels to new venture growth, therefore arguing that functional diversity at all hierarchical levels is crucial to shaping a firm's problem-solving capacity and consequently its growth. Moreover, we suggest that a firm's financing stage, being early or late, should also be considered as it impacts the problems encountered (an issue in one stage may not persist into another stage) and therefore the nature of diversity's effect. We test this multi-layered theoretical framework across firms' maturity stage using a sample of 296 VC-backed new ventures in the Greater Paris area and find a positive relationship between functional diversity within TMTs, MMTs, and OCWs, and new venture growth measured in terms of user base, with the correlation strength varying with funding stages' maturity. This claim holds substantial relevance from multiple perspectives.

First, the inconclusive results originating from the study of informational diversity, particularly focusing on functional diversity, may arise from a limited comprehension of how tasks associated with growth are apportioned across the different hierarchical levels of an organization and the stage-specific characteristics of the funding phase. The existing literature often overemphasizes Top Management Teams (TMTs) (see (Aboramadan, 2021; Boone and Hendriks, 2009; Finkelstein et al., 2009; Eesley et al., 2014)), which might result in inconsistencies, especially considering the mounting evidence underscoring the profound influence Middle Management Teams (MMTs) and the Operating Core Workers (OCWs) exert on firm performance. As such, the inconsistencies observed in diversity studies may be attributed to a neglect of the inherent multi-layered configurations of organizational structures. Indeed, the conclusions derived from our study infer that an exclusive concentration on top management teams (TMTs) could potentially be overemphasized, especially when other hierarchical levels are disregarded or merely considered as secondary factors. Second, our research offers evidence that the delineation between early and late funding stages (Gompers, 1995; Hsu, 2010) plays a crucial role in the diversity-growth relationship. Indeed, the challenges a firm faces are dynamic and evolve based on its lifecycle stage, emphasizing the temporality of issues. Indeed, in line with a substantial literature that has long informed the organizational growth processes throughout stages and over time (Phelps et al., 2007), problems experienced in one phase may not persist into the next, thus necessitating different resources (Sirmon et al., 2011; Gompers, 1995). However, no studies, to our knowledge, have incorporated such a contextual factor within a multi-layered theoretical framework that ties diversity at TMT, MMT, and OCW levels to new venture growth, thus leaving significant gaps in clarifying the mechanisms steering this relationship. While it remains uncertain to unequivocally claim the universality of our findings, the exhaustive validity tests conducted suggest a high degree of resilience to changes in methodological approaches. This includes alterations in diversity metrics and considerations of potential endogeneity bias.

Nonetheless, our study is not without limitations, paving the way for future research opportunities. Firstly, the size of the firm and the experience of individuals serve as a moderating factor, indicating that our theory is contingent on specific factors. The scope of our current work limits the exploration of all potential contingencies, hence future research could go into these in detail. For instance, our dataset, comprised of secondary sources, fails to account for internal team dynamics. Evidence suggests that numerous aspects of a firm's organizational structure, such as networks or alliances, can impact performance (Grimpe et al., 2019; Lee, 2022; Mintzberg, 1980; Schubert and Tavassoli, 2020).

Second, we utilize LinkedIn skill endorsements data as a measure of individual-level functional diversity. This socially constructed online reputation forms a significant part of self-presentation, as job seekers leverage these endorsements to present their skill sets to prospective employers (Rapanta and Cantoni, 2017). This approach has become invaluable in recent entrepreneurship research due to its ability to provide detailed individual-level data not typically available through traditional sources. Previous research has considered social endorsement as a piece of valuable information for entrepreneurial studies (Gasiorowski and Lee, 2022) and studies like that of Reese et al. (2020) and Sako et al. (2020), have successfully used information from the "skills and endorsements" section of LinkedIn profiles to examine founders' human capital and identify individual skills. We acknowledge that the public nature of LinkedIn skill endorsements and the elements of performativity and reciprocation inherent in them may introduce potential bias. However, we posit that despite this potential bias, the use of these endorsements as a measure of skill diversity remains valid given their wide acceptance and usage in the professional world. Furthermore, from a methodological standpoint, we have developed a fully reproducible and robust skills diversity classification using a bottom-up hierarchical clustering with Kruskal's minimum spanning tree algorithm Kruskal (1956). Therefore, while the emergence of these skills remains unclear (Rapanta and Cantoni, 2017), these data underline the challenges researchers face when attempting to understand new venture growth, due to the lack of detailed datasets exploring the characteristics of individuals across the power hierarchy in new ventures, from top managers to non-managerial employees. This paper illustrates the potential of LinkedIn skill endorsement data in addressing some significant limitations in diversity-related research in management and organizational science. It suggests a new way to explore and understand diversity within the professional landscape, offering fresh insights for future research.

Chapter 4

Online skill endorsements and start-up funding: Evidence from new digital ventures in the greater Paris

Securing financial capital from external stakeholders is crucial for the survival and expansion of start-up teams. Yet, accurately predicting the eventual success of these start-up teams remains a significant challenge for investors. Drawing from signaling theory, human capital literature, and cognitive psychology, this article analyzes the influence of "online skill endorsements" - peer-reviewed indicators of human capital available on professional social networks that signal a team's expertise - on the likelihood of securing funding from investors. By analyzing a dataset of 439 French digital start-ups, we discovered that start-up teams showcasing a high level of skill expertise across diverse domains do not fully exploit the benefits of their showcased varied skills. Our findings show that investors tend to favor start-up teams that either possess a high level of endorsed skills or a broad variety of them, but rarely both. Hence, our study enriches the academic literature surrounding the use of online skill endorsements as complementary human capital measures with signaling impacts on early-stage resource acquisition. In managerial terms, our findings offer valuable insights for entrepreneurs utilizing professional social networks for their fundraising activities.

This manuscript has been submitted to a WoS journal.

In this chapter, my responsibilities were allocated as follows:

- Paper design and writing: 100%
- Empirical design and findings discussion: 100%
- Data collection and cleaning: 100%

4.1. Introduction

Which start-up teams are funded and why are recurring themes in contemporary economic and entrepreneurial literature (Baum and Silverman, 2004; Beckman et al., 2007; Bernstein et al., 2017; Franke et al., 2006, 2008; Kaplan et al., 2009; Plummer et al., 2016; Shane and Cable, 2002). In entrepreneurship literature, start-up teams, defined as groups of individuals exhibiting attributes such as equity ownership, decision-making autonomy, and entitativeness (Knight et al., 2020), are recognized as essential agents for the development of cities, regions, and countries due to their role in firm creation and growth (Audretsch and Thurik, 2001; Autio, 2016). Acquiring financial resources is a key factor for their survival and expansion (Rosenbusch et al., 2013), thus making the determinants of attracting such resources of great interest to researchers, practitioners, and policy makers (European-Commission, 2015; Subramanian et al., 2022).

The literature has underscored the intricate relationship between start-up team composition and investor decisions (Ghassemi et al., 2020; Klotz et al., 2014; Jin et al., 2017). For instance, qualities of start-up teams, such as the founders' education, their prior work experiences (Errico et al., 2023; Shane and Cable, 2002; Hsu, 2007), and their relationships with investors and partners (Huang and Knight, 2017), serve as quality signals for obtaining financial resources. While these studies have provided significant insights, this approach is becoming less comprehensive because nowadays, investors rely on a wide array of other signals to evaluate the viability of investing in a start-up team, and start-up teams use other information channels to signal their expertise to investors (Piazza et al., 2023). For example, Banerji and Reimer (2019) found that the number of followers founders have on their LinkedIn profiles was the strongest predictor of the amount of funds raised by new ventures from private investors. Similarly, using data from the Kickstarter crowdfunding website, Mollick (2014) and Courtney et al. (2017) have shown that a founder's Facebook connections enhance equity crowdfunding success.

On professional social networks, the endorsement feature acts as a socially constructed online reputation metric and a means of self-presentation, allowing individuals to market themselves to potential recruiters or investors (Rapanta and Cantoni, 2017; Piazza et al., 2023). Several social networks, including LinkedIn and ResearchGate, have integrated the endorsement feature, permitting users to earn endorsements for specific skills that reflect authority and social credibility (Pérez-Rosés et al., 2016; Rapanta and Cantoni, 2017; Wu et al., 2018). On LinkedIn, the world's largest professional online social network (Wu et al., 2018), the "*Skills & Endorsements*" feature was introduced in 2012[1]. This feature enables users to associate themselves with topics

[1]https://blog.linkedin.com/2012/09/24/introducing-endorsements-give-kudos-with-just-one-click

that showcase their expertise, and to receive validation of their proficiency in these areas from their connections.

In this context, entrepreneurship scholars view the "*Skills and Endorsements*" LinkedIn feature as a valuable data source for entrepreneurial studies. It is useful not only for assessing the expertise of a founding team (Gasiorowski and Lee, 2022; Reese et al., 2020; Sako et al., 2020) but also to assist founders in enhancing their start-up's credibility and persuading early-stage investors to invest. For instance, a recent study by Piazza et al. (2023) highlights that while "*actual expertise*" is crucial, particularly in events like company sales or mergers, how founders present their abilities on social networks - termed "*expertise signaling*" - can be even more decisive when seeking investments. This emphasizes the importance of a start-up team's self-presentation in the pursuit of funding, reinforcing the role of online skill endorsements in the funding process.

However, researchers have yet to explore the signaling effects of the skill level and skill diversity of online endorsements within start-up teams on early-stage resource acquisition. This gap in the literature is noteworthy, particularly considering that entrepreneurial endeavors are primarily undertaken by groups of individuals (Klotz et al., 2014). Furthermore, the elevated levels of uncertainty and information asymmetry between the signal sender and receiver during early stages further amplify this need (Harrer and Owen, 2022; Matusik et al., 2008; Spence, 2002). Thus, any quality signals that provide an additional perspective and assist in triangulating start-up team data are highly valued by investors. After all, a new venture typically lacks a performance track record to reference, yet it still needs to establish its legitimacy with potential investors[2] (Becker-Blease and Sohl, 2015; Ko and McKelvie, 2018).

This study seeks to bridge this gap by examining the impact of the levels and diversity of online skill endorsements within start-up teams on early-stage resource acquisition. Drawing from signaling theory, human capital literature, and cognitive psychology, we posit that teams that provide investors with the perception of being highly skilled in diverse fields may not be fully leveraging the advantages of their diverse skills in fundraising efforts. To test our propositions, we use data from a sample of 439 French digital new ventures and human capital data on their start-up teams. We constructed a unique dataset that includes "human capital investments" (i.e., tra-

[2]It is key to note that in this study we are not suggesting that investors always check start-up teams LinkedIn profiles when deciding to invest. Instead, we believe that how start-up teams portrays their expertise on LinkedIn reflects their general tendency to promote their skills, given the platform's popularity among professionals and the increasing emphasis on making connections there. Consequently, because we are not able to definitively establish if investors consider start-up teams LinkedIn endorsements when making investment decisions, we propose in the last section of this paper further research avenues on that topic, especially given the significance of investment decisions.

ditional signals used by investors such as years of education, professional experience, and previous founding experience) and endorsed "outcomes of human capital" (i.e., skills, abilities, and knowledge) based on *Skills and Endorsements* data from LinkedIn (Marvel et al., 2016; Rapanta and Cantoni, 2017). We use the latter as our main independent variable and the former as moderating variables. We analyze our statement in two stages. First, we examine the relationship between the level of online skill endorsement of start-up teams and its impact on capital acquisitions in early-stage investment. Secondly, drawing from the cognitive distance model (Nooteboom et al., 2007) and the cybernetics principles of requisite variety applied to the entrepreneurship literature (Ashby, 1956; Harrison and Klein, 2007; Sundermeier and Mahlert, 2022; Villani et al., 2018), we assess the extent to which signals from start-up teams' online skill endorsement variety help the firm acquire capital. Following our claims, we find that investors favor start-up teams that have either a high level of endorsed skills or a high level of variety of endorsed skills, but not both at once.

This study aims to enrich the entrepreneurship literature from two distinct perspectives. First, we aim to extend past research is start-up team composition (Beckman et al., 2007; Jung et al., 2017). Despite the pervasive mention of team composition topic in the corpus of literature pertaining to start-up teams, there seems to be a lack of agreement on the precise process by which composition signaling influences outcomes, and the circumstances under which these effects might be significant (Klotz et al., 2014; Zhou and Rosini, 2015). Our endeavor is to offer fresh perspectives in the trade-off between homogeneity and heterogeneity regarding online skills endorsement in start-up teams (Sundermeier and Mahlert, 2022; Villani et al., 2018). Second, by building upon the literature on signaling and new venture financing (Colombo, 2021; Drover et al., 2017; Klein et al., 2020), this paper seek to expand upon previous investigations of the signaling effect of human capital on venture financing (Banerji and Reimer, 2019; Marvel et al., 2016; Mollick, 2014; Reese et al., 2020) by explicitly examining the impact of online skills endorsement on resource acquisition. We aim to demonstrate the utility of online endorsements data for research and venture capitalists, specifically to elucidate the dynamics of new venture signals in entrepreneurship literature (Pérez-Rosés et al., 2016; Gasiorowski and Lee, 2022).

The paper is structured as follows. Section 4.2 reviews the literature on signaling theory for early-stage resource acquisition and the interest in "online skill endorsements". Section 4.3 explains the data and methods used, and Section 4.4 presents key findings. Finally, section 4.6 concludes by discussing implications for entrepreneurship and new venture financing literature, noting the limitations of this study.

4.2. Theoretical framework and hypotheses

4.2.1. Signaling theory for early-stage resource acquisition

Literature on entrepreneurship has continually underscored the critical role of financial resources for the survival and growth of new venture (Cooper et al., 1994; Drover et al., 2017; Klein et al., 2020). However, securing funding from external investors is a challenging task, with investors having difficulty predicting which teams will come out on top (Ghassemi et al., 2020), notably due to the inherent information asymmetries between them and venture founders, or the lack of past financial results. In order to mitigate the information asymmetries, investors draw on quality-signals (Harrer and Owen, 2022; Ko and McKelvie, 2018; Subramanian et al., 2022), with signaling theory being particularly applicable in the uncertain entrepreneurial processes (Spence, 1978).

Signaling theory posits that two parties take conscious and voluntary steps to reduce asymmetric information and perceived uncertainty between them, and this is done by focusing on the signals available to them (Spence, 1974). This concept has been used in various disciplines to provide insight into social selection problems when there is an absence of perfect information (Connelly et al., 2011; Colombo, 2021). Entrepreneurship scholars have found this concept to be beneficial as particular signals can diminish uncertainty about ventures' quality in the eyes of stakeholders, such as prestigious government grants (Islam et al., 2018), the enthusiasm and passion of the founders (Chen et al., 2009), affiliations of the venture with other entities (Plummer et al., 2016), previous occupational characteristics and experiences (Wu et al., 2023), the composition of the founders' team (Ko and McKelvie, 2018) and signaling expertise (Piazza et al., 2023). Investors, similarly, use a variety of indicators to mitigate asymmetric information such as the founders' ties to others (Shane and Cable, 2002), communication tools (Harrer and Owen, 2022), endorsements (Courtney et al., 2017; Janney and Folta, 2006; Plummer et al., 2016; Gasiorowski and Lee, 2022; Piazza et al., 2023), social capital (Shane and Stuart, 2002) or human capital (Beckman et al., 2007).

In the context of early-stage ventures, human capital characteristics of the start-up teams are considered to be significant and prominent factors for investors to consider (Beckman et al., 2007; Ko and McKelvie, 2018; Matusik et al., 2008). This emphasis is due to the limited resources and the small number of people responsible for formulating and carrying out strategies. According to the organizational theory perspective applied to the entrepreneurship field, the human capital composition of the start-up teams is believed to have an imprinting effect on the processes and operations of the firm (Packalen, 2007). This concept implies that past experiences, and therefore the underlying skills and experiences acquired during those times, can shape the present and future performance (Wu et al., 2023). Extensive research has been conducted to explore the association between traditional human capital signaling and the acquisition of financial resources (see Connelly et al. (2011) and Colombo (2021) for a review). Though these studies offer valuable perspectives, their approach is increasingly seen as less comprehensive since investors currently rely on various other signals to assess the potential of investing in a start-up team, and these teams employ different information channels to showcase their expertise to potential backers (Piazza et al., 2023). Therefore, a remaining challenge is the examination of the signaling role of online skills endorsements used by start-up teams in their fundraising processes.

4.2.2. Online skill endorsements as a peer-reviewed measure of human capital and as a valuable tool for founders seeking to raise funds

Professional social networks have emerged as primary conduits of data, generating an extensive pool of information that, when harvested, analyzed, and refined, becomes a valuable resource used by organizations (Ponte et al., 2022). According to Urdaneta-Ponte et al. (2021), many companies have started incorporating this new source of data into their recruitment processes, with LinkedIn (which boasts over 650M+ users) being the top choice. On this platform, members reveal career-specific information, including occupation details, education, and skills. For Rapanta and Cantoni (2017), LinkedIn is one of the most influential web resource and social network for professional use.

The "*Skills & Endorsements*" feature of LinkedIn has led to a surge in research around the concept of endorsements. For instance, the study conducted by Yan et al. (2019) uses endorsements as a tool to assess the depth of skills, thereby deducing the professional expertise of LinkedIn members. Similarly, Drakopoulos et al. (2020) use endorsements to determine a user's skills, providing a measure of credibility for potential start-up candidates, and Constantinov et al. (2015) extract skills from LinkedIn and evaluate individuals' competency levels based on endorsements, thereby identifying a range of competencies demanded by the market. These competencies then form the foundation for curriculum construction. A similar perspective is also used by Wu et al. (2018), who suggest that firms use this information in their recruitment strategies to select the most suitable candidates for their vacancies. Closer to the subject of start-up teams showcasing expertise and resource acquisition, a recent study by Piazza et al. (2023) illustrates the importance of "*expertise signaling*" for founders seeking to raise funds, indicating that online skill endorsement can be as crucial as the start-up team's genuine background, if not more so. Indeed, the findings reveal that even less qualified teams, if they adeptly present themselves, can secure more funds than superior teams that do not manage well in "skill self-presentation". The authors attribute this to investors' reliance on gut feelings and, consequently, investors might occasionally allocate resources to teams that accentuate their potential over their actual readiness, overlooking teams with capability but who are less assertive in their self-presentation.

However, the abilities mentioned on a LinkedIn profile might not truly reflect someone's skill level. Therefore, there is a risk in exaggerating since LinkedIn does not check if users genuinely have the skills they claim. Mostly, people list skills to shape how others see them, based on the idea of creating a good image - what Zott and Huy (2007) and Fischer and Reuber (2014) call *symbolic management*. So, start-up teams keen on creating a positive impression for investors might claim more skills than others less focused on their online image. These factors make LinkedIn's "*Skills & Endorsements*" section a handy way to see how people show off their expertise, separate from their real skills and background.

In all the research mentioned above, LinkedIn's "*Skills & Endorsements*" is viewed both as a peer-reviewed measure of human capital and a useful tool for founders seeking to raise funds. The endorsement feature allows individuals to associate themselves with domains while their network validates these claims by endorsing the member's proficiency in the chosen domains (Pérez-Rosés et al., 2016). As a result, investors - who often claim that their primary focus is "the team" - assess the quality of the firm through human capital attributes of start-up teams, such as traditional human capital indicators like prior professional experiences and academic qualifications, and also the skills exhibited on founders' LinkedIn profiles (Gasiorowski and Lee, 2022; Piazza et al., 2023). In the following section, we leverage this body of work to examine the signaling effect stemming from the proficiency level and diversity of skill endorsements within start-up teams.

4.2.3. Signaling effects from start-up teams' level and diversity of skills endorsement

Entrepreneurship researchers have extensively explored which start-up teams' characteristics enable them to access external funding (Roure and Keeley, 1990). The focus on start-up teams stems from the fact that most entrepreneurial initiatives are run mainly by groups of individuals rather than by lone individuals (Klotz et al., 2014). Such characteristics include the team's demographics and size (Eisenhardt and Schoonhoven, 1990), the team's match with an investor's characteristics (Aggarwal et al., 2015), the industry environment (Townsend and Busenitz, 2015), and the investor's experience (Franke et al., 2008). However, in the context of early-stage ventures, "human capital outcomes" (i.e. agents' "observable applications or know-how related to a domain"

(Becker, 1964; Marvel et al., 2016)) of the start-up teams are maybe the most significant and prominent factors for investors to consider as investors focus mostly on "picking the right people" (Beckman et al., 2007; Ko and McKelvie, 2018; Matusik et al., 2008).

Conformed to the human capital literature applied to the entrepreneurial field, we postulate that start-up teams with higher levels of skills endorsement have a greater propensity to reach specific entrepreneurial milestones, elicit greater investor confidence, and have a greater likelihood of attracting external financial capital. There are several reasons for such a claim. First, it has been shown that a high level of "expertise signaling" can help entrepreneurs to obtain resources complementary to their financial resources, which are an issue for many firms in the early stages of development (Beckman et al., 2007; Piazza et al., 2023). Moreover, studies find that higher levels of skills enable founders to take greater risks and demonstrate proactive behavior (Becherer and Maurer, 1999), allowing them to optimize business opportunities (Shane and Venkataraman, 2000; Chandler and Hanks, 1994). Additionally, the acquired skills enable entrepreneurs to make full use of the available technological tools (Nambisan, 2017), enabling them to better understand and differentiate their offerings through the introduction of new technologies and disruptive products (Marvel and Lumpkin, 2007). Finally, developing skills and knowledge is a prerequisite for further entrepreneurial learning and helps entrepreneurs acquire additional skills and knowledge that will help the firm to grow (Hunter, 1986).

Therefore, we propose that a high level of skills endorsement within a start-up team enhances the quality of the signal intended for investors looking to engage financially in the early stages. The investors are alerted by this signal because it suggests that higher skill levels may translate into future success. Thus, we hypothesize the following:

H1*: Start-up teams with greater skills endorsement levels will get more funding from investors.*

In this study, we consider not only the level of skills endorsement but also their diversity at the team level (Harrison and Klein, 2007; Sundermeier and Mahlert, 2022). Diversity is a concept in line with the information / decision-making perspective, which posits that diversity of task-relevant resources increases the potential for developing synergistic solutions that are superior to those attainable by homogeneous groups with a more limited pool of resources (Williamsky, 1998). In our perspective, online skills endorsement diversity in a start-up team matters because the success of entrepreneurial initiatives is often the result of teamwork and collective endeavors, which require the combination of knowledge, the synergy of abilities, and the collaboration of multiple individuals analyzed by investors (Klotz et al., 2014). Therefore, we argue that start-up teams with a wide range of skills endorsement have a greater chance of acquiring investors due to two key reasons.

The first reason relates to the decision-making process. The underlying argument is that groups with various skills make better decisions because they have access to more information (Hong and Page, 2001). Therefore, the solutions to new issues encountered during entrepreneurial cycles might result from recombining existing knowledge in new forms. A meta-analysis conducted by Jin et al. (2017) suggests that an entrepreneurial team endowed with a varied skill set is more likely to use various market entry, internationalization, or innovation strategies. This implies that start-up teams with diverse skills are in a better position to make high-quality decisions, thus increasing their chances of success. Consequently, investors may interpret start-up teams' skills endorsement diversity as a signal to assess their future performance, which can significantly impact the probability of receiving investments.

The second reason is related to the connection between start-up teams' skills diversity and their social capital. Evidence shows that the social capital of a start-up team has the capacity to act as control for information asymmetries. Indeed, Huang and Knight (2017) and Shane and Stuart (2002) posit that the presence of a social connection between start-up teams and investors can reduce the informational gap between them. In the same vein, Shane and Cable (2002) infer that social capital plays a role in connecting start-up teams to potential investors and facilitating fundraising. Additionally, Hoenig and Henkel (2015) suggest that the social capital of a start-up team is utilized by investors to triangulate the quality of the firm and the composition of start-up teams and their relationships (alliances) are used as indicators of quality by investors (Plummer et al., 2016; Semrau and Werner, 2014).

Following these rationales, if a start-up team's diversity of skills endorsement is the result of different social capital and given that this capital influences the start-up teams' ability to raise funds from investors, start-up teams with diverse skills might therefore raise more funds than less diversified ones. Thus, we hypothesize the following:

H2: *Start-up teams with greater skills endorsement diversity will get more funding from investors.*

The past rationales invite us to think that having both highly skilled individuals and a high level of diversity is beneficial for firm performance (Díaz-Fernández et al., 2020). However, past findings suggest that adding more human capital to a start-up team does not necessarily translate into greater success (Pierce and Aguinis, 2013; Sundermeier and Mahlert, 2022). This calls into question the positive relationship between diversity and performance, as diversity can introduce additional costs related to communication and coordination. Indeed, if empirical entrepreneurship studies evidence that a particular level of expertise stimulates the detection of new business (Shane and Venkataraman, 2000; Marvel et al., 2016), increases the likelihood of generating remarkably new and commercially viable services, and boosts the chances of obtaining external funding (Beckman et al., 2007; Marvel and Lumpkin, 2007), conversely, cognitive and social psychology findings indicate that highly skilled individuals across various fields tend to possess greater cognitive inelasticity and greater cognitive distance (Nooteboom et al., 2007). Cognitive inelasticity arises from the prolonged exposure to a specific field, which engenders a cognitive model that adheres to the prevalent logical pattern of that field. Although cognitive inelasticity can lead to greater determination, it can also diminish one's receptiveness to entirely distinct logics and approaches, hinder communication within a start-up team, and limit the team's exploitation of its knowledge. Therefore, the dangers of cognitive inelasticity are more probable and particularly menacing when two or more persons share a high cognitive distance. Cognitive distance denotes the degree to which two or more people have created distinct cognitive models or belief systems (Nooteboom et al., 2007). Therefore, high cognitive distance may create obstacles to communication and collaboration within a start-up team and limit openness to innovative business models, such as pivoting (Kirtley and O'Mahony, 2020). Furthermore, Franke et al. (2008) find that experienced VCs focus more on team cohesion, a concept directly related to how well a team communicates and collaborates.

Consequently, though any two individuals in a team inherently have some degree of cognitive divergence, those who share comparable abilities and fields of expertise tend to have lower cognitive distance, as they are more likely to be familiar with each other's cognitive models and therefore can establish the essential mutual trust for a social group's effective functioning. Conversely, those with completely different areas of expertise are more prone to possess divergent outlooks and knowledge, thereby increasing their cognitive distance. As a result, this may reduce the quality of their interactions, decisions, and ability to interact effectively. Since the adverse impacts of cognitive distance are more pronounced when group members have firmly established cognitive models and entrenched opinions and positions (i.e., when they are cognitively inflexible), start-up teams comprised of highly skilled individuals from different domains may not fully exploit the benefits of their varied endorsed skill sets, information, and social capital. Therefore, we put forth the following hypothesis:

H3: *Start-up teams' skill endorsement diversity impact negatively the positive effect of level of skill endorsement on the funds raised*

Our formal hypotheses (H1, H2, H3) conform with the proposed model presented in Figure 4.1

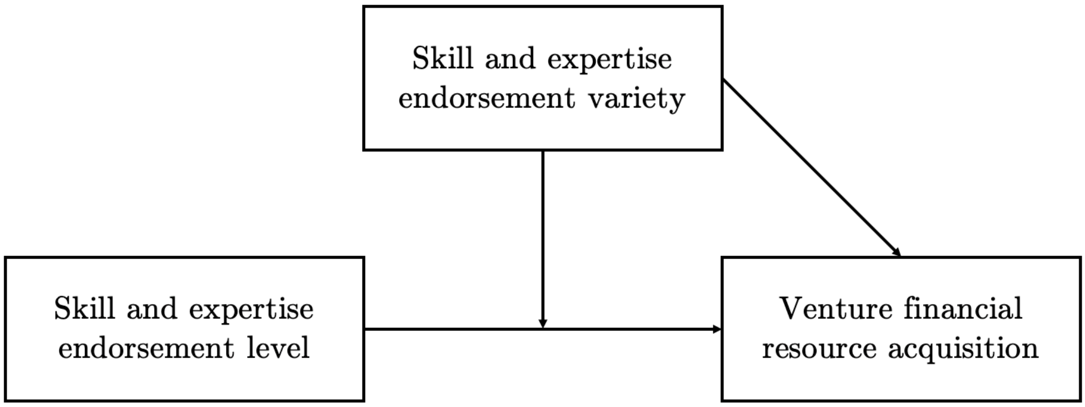

Figure 4.1: Research Model

4.3. Method

4.3.1. Sample and data collection

To test our hypotheses, we constructed a dataset incorporating information at both organizational and individual levels of start-up teams. Table 4.1 lists our empirical variables, definitions, and sources. Table 4.2 provides the general statistics and distribution across sectors. Table 4.3 provides the descriptive statistics of the fundraising activities of the 439 digital new ventures in our sample. We detail the collection process below.

Variable name	Description	Data source
Dependent variable		
1. *Capital Raised (log)*	Natural logarithm of the amount of investment provided by external investors in the first round [€]	Crunchbase, BPI
Independent variables		
2. *Skills level*	Ordinate variable ranging from 0 to 9 (0= min; 9= max). Each start-up team is assigned the highest median score associated with any of its members	Linkedin
3. *Skills field variety*	Blau index on the probability of finding a particular skill in a start-up team among the six fields identified (i.e., Finance, Product, Development, Management, Marketing, Entrepreneurship)	Linkedin
Control variables		
Human Capital control variables		
4. *Previous Prestigious University*	Number of graduations from one of the best French business, engineering schools or from the 10 universities worldwide. Each start-up team is assigned the maximum score associated with any of its members	LinkedIn
5. *Previous Founding Experience*	Number of unique ventures previously founded or cofounder. Each start-up team is assigned the maximum score associated with any of its members	LinkedIn
6. *Previous Working Experience*	Maximum number of years of work experience of a start-up team member. Each start-up team in our sample is assigned the highest score associated with any of its members	LinkedIn
7. *Previous Ph.D Degree*	Number of Ph.D graduations. Each start-up team is assigned the maximum score associated with any of its members	LinkedIn
New Ventures control variables		
8. *New Venture Age*	Number of years since new ventures' foundation	Crunchbase, BPI
9. *Team size*	Number of start-up team members	LinkedIn
10. *Industry*	Eleven industry dummies which take value 1 if the company is operating in *i)* Business Intelligence Analytics, *ii)* Customer Relationship Management, *iii)* Developers Software Infrastructure, *iv)* Education Human Resources, *v)* Finance Legal Insurance, *vi)* Healthcare, *vii)* Logistics Supply Chain, *viii)* Marketing and Media *ix)* Productivity Collaboration, *x)* Real Estate Construction *xi)* Retail Ecommerce	Crunchbase, BPI

Table 4.1: Variable definitions and sources

First, we collected firm-level data from Crunchbase, Dealroom, and BPI France databases between February and March 2020. We chose to draw on three distinct databases in order to triangulate information and confirm that the data is similar in the other two public databases. The first two databases follow the evolution of global firms benefiting from venture capital financing. The third is a French state database that lists French-based innovative firms. These databases provide information on the firm's headquarters, founders' names, fundraising activity, business models, and date of foundation. We only included digital ventures that *(i)* were founded between 2011 and 2018, *(ii)* had their headquarters in the Metropolis of Greater Paris (France), *(iii)* were independent (no subsidiaries), *(iv)* operated in business-to-business markets, and *(v)* used a digital business model in the digital industry. From these filters, we ended up with 439 firms.

We decided to study digital ventures with digital business models in the digital industry (i.e., software-as-a-service, marketplaces, and platforms) because digital business models echo the efficient, predictable, and repeatable systems that offer investors new opportunities due to the non-linear revenues of digital technologies (Nambisan, 2017). Therefore, we expect to observe more "funding events" in these ventures because unlike traditional software licenses that require installers, scalable business models are hosted in the cloud, require little infrastructure, are searchable using a browser, and are delivered over the Internet with or without a subscription-based revenue logic, providing financing forecast that investors favor most.

We chose the period 2012-2018 because it coincides with the mass adoption of cloud technologies in pre-existing markets, making it a topic of interest in various industries and investors. Indeed, these technologies have revolutionized the software industry in various markets, such as supply chain, financial, accounting, human resources, or customer relationships. For example, from 2016 to 2018, software-as-a-service, marketplaces, and platforms firms accounted for 55% of the total amount raised in France, 75% of French fundraising rounds in Paris, and more than 85% of the value (France-Digitale, 2023).

Finally, we limited the geographical location of the ventures because this factor can influence financial results, as pointed out in studies by Reese et al. (2020) and Beckman et al. (2007). The Metropolis of Greater Paris (France) is of particular interest because it is a significant global city with labor and financial capital pools and proximate clients. Furthermore, the Metropolis of Greater Paris' financing and business landscape, especially its venture capital market, is one of Europe's largest, most structured, and most dynamic ones, even though it is characterized by tight links between firms and the state and by powerful elite networks (Milosevic, 2018).

Industry	Number of firms	% total
Business Intelligence Analytics	38	8.7
Customer Relationship Management	25	5.7
Developers Software Infrastructure	50	11.4
Education Human Resources	59	13.4
Finance Legal Insurance	51	11.6
Healthcare	24	5.5
Logistics Supply Chain	27	6.1
Marketing and Media	56	12.8
Productivity Collaboration	48	10.9
Real Estate Construction	25	5.7
Retail Ecommerce	36	8.2
Total	439	100

Table 4.2: Distribution of sample : digital new ventures by industry classification

Second, to complement the firm-level data, we collected individual-level data of all the founders who worked in these 439 digital firms, representing a total of 1341 individuals. LinkedIn provides granular information on individuals' professional and academic trajectories, and users have an incentive to keep their profiles current since the website is valuable for professional networking (Pérez-Rosés et al., 2016; Rapanta and Cantoni, 2017; Wu et al., 2018). We collected previous job and academic experiences as they

Part A : Fundraising rounds per years	Amount in millions of euros					
Fundraising years	Rounds	Mean	Median	Min	Max	SD
2011	4	0.251	0.115	0.025	0.750	0.338
2012	7	0.977	0.700	0.100	2.500	0.878
2013	19	0.611	0.200	0.060	5.000	1.114
2014	30	0.752	0.370	0.055	8.000	1.457
2015	54	1.146	0.500	0.023	10.000	1.783
2016	56	0.942	0.400	0.060	12.000	1.689
2017	67	1.542	0.750	0.050	10.000	2.090
2018	44	1.796	1.000	0.090	15.000	2.544
2019	38	2.044	1.500	0.250	12.000	2.131
2020	11	2.410	1.000	0.500	14.500	4.073
Total	330	1.247	0.600	0.023	15.000	1.027

Part B : Fundraising per founding date	Amount in millions of euros						
Founding date	Firms	Rounds	Mean	Median	Min	Max	SD
2011	27	27	1.196	0.400	0.250	7.300	1.564
2012	36	29	0.834	0.450	0	4.000	1.040
2013	58	49	0.775	0.250	0	8.000	1.447
2014	65	49	1.415	0.300	0	15.000	2.864
2015	74	55	1.141	0.400	0	14.500	2.331
2016	85	67	0.067	0.500	0	12.000	1.856
2017	60	35	0.679	0.215	0	3.700	0.925
2018	34	19	0.828	0.550	0	4.000	1.035
Total	439	330	0.992	0.400	0	15.000	0.687

Table 4.3: Descriptive statistics of fundraising rounds

Variables	Obs	Mean	SD	Min	Max
Dependent variable					
Capital Raised (log)	439	10.009	5.872	0	16.524
Independent variables					
Skills level	439	6.215	2.186	0	9
Skills field variety	439	0.621	0.354	0	1
Control variables					
Human capital control variables					
Previous Prestigious University	439	0.827	0.766	0	3
Previous Founding Experience	439	1.230	0.981	0	4
Previous Working Experience	439	16.724	8.629	1	47
Previous PhD Degree	439	0.128	0.360	0	2
Firms control variables					
New Venture Age	439	5.205	1.950	2	9
Team size	439	2.590	0.785	2	8
Business Intelligence Analytics	439	0.087	0.282	0	1
Customer Relationship Management	439	0.057	0.232	0	1
Developers Software Infrastructure	439	0.114	0.318	0	1
Education Human Resources	439	0.134	0.341	0	1
Finance Legal Insurance	439	0.116	0.321	0	1
Healthcare	439	0.055	0.228	0	1
Logistics Supply Chain	439	0.062	0.241	0	1
Productivity Collaboration	439	0.109	0.312	0	1
Real Estate Construction	439	0.057	0.232	0	1
Marketing Media	439	0.128	0.334	0	1
Retail Ecommerce	439	0.082	0.275	0	1

Table 4.4: Descriptive statistics

are indicators frequently used in entrepreneurship studies as predictors of firm performance (see e.g., Colombo and Grilli (2005) or Delmar and Shane (2006)), and also all the data in the "*Skills & Endorsements*" section, considered as a socially constructed online reputation metric that is both a way of self-presentation and a valuable human capital data for entrepreneurial studies. For example, Reese et al. (2020) use LinkedIn information about founders, especially their "*Skills & Endorsements*" section, to measure founders' human capital, Sako et al. (2020) used this data in order to identify the skills of individual start-up founders, and Piazza et al. (2023) used it to understand the effect of genuine skills and experience of the founding team - that is, actual expertise — from how the founding team presents itself, which they label "expertise signaling", on venture financing. Table 4.4 lists the descriptive statistics of all variables (means, std dev, min, max).

4.3.2. Variables

4.3.2.1. Dependent variables

The success in entrepreneurship has many dimensions, and prior research has evaluated it using various methods. To avoid capturing only a single facet of it, in this study, we explore two measures related to venture funding. Indeed, empirical evidence indicates that attracting funding from an investor is a significant predictor of a firm's future survival and growth (Beckman et al., 2007), and inadequate financial resources are frequently cited as the leading cause of failure for new ventures at the onset of their lifecycle (Franke et al., 2008; Eddleston et al., 2016).

The first dependent variable is the logarithm of the first round of funding (*log fundraising*) for OLS linear regression. Some new digital ventures did not raise any funds during the observed period. As has been done in previous empirical studies, we include these observations as zero. However, instead of censoring the fundraising variables, we add a small constant to preserve information about the new digital firms. Therefore, the *log fundraising* variable ranges from 0,001 to a maximum value of 16,524.

Second, we aim to examine how online skills endorsement correlates with the performance outcomes of VC-backed digital ventures. Accordingly, and in line with previous studies, we use Logit as our main regression model (Ahlers et al., 2015; Islam et al., 2018).

4.3.2.2. Independant variables

Achieving success in entrepreneurship typically demands a broad skill set. Accordingly, we conceptualize start-up team *Skills level* and *Skills field variety*, our two main independent variables, based on a score calculated through a bottom-up hierarchical clustering approach with Kruskal's minimum spanning tree algorithm (Kruskal, 1956), taking into account the occurrences and co-occurrences of different online skills endorsed among individuals' profiles. We detail the process below.

In the first phase of data pre-treatment, because individuals usually have more than one skill endorsed on their profiles, with some of those skills being related (Pérez-Rosés et al., 2016), we defined critical cluster energy areas around six functional areas, namely Finance, Product, Development, Management, Marketing, and Entrepreneurship. To create the six functional areas, we made use of Kruskal (1956) and semantic web methodologies and, therefore, the similarity between any pair of endorsed skills is naturally defined as "intersection over union". Consequently, we determined an individual's affinity to any skill cluster in the tree by measuring the endorsed skills that individuals share. In other words, instead of assigning an individual to the cluster with the highest affinity (hard clustering) that would not account for their versatility, we describe an agent by their set of affinities to the skills of interest (fuzzy clustering). This supervised machine learning model is frequently used in entrepreneurship and management studies to build semantic web ontologies (Kaushal et al., 2021; Ponte et al., 2022). Building on such ontologies helps to standardize skills from social networks that are related (Pérez-Rosés et al., 2016) and helped us to develop these novel measures based on LinkedIn's "*Skills & Endorsements*".

In the second phase of individuals data pre-treatment, we followed the practices of entrepreneurship studies and standardized the scores of each individual to make them comparable across an ordinal variable (Harrison and Klein, 2007). Specifically, we assigned a ranking to the 1341 individuals from the 439 start-up teams for each functional area based on 10 quantiles, where the 0th quantile represented the lowest level and the 9th quantile represented the highest level of skill endorsement. We developed this variable as an ordinal one, as we contend that for each degree of online endorsement achieved, there is a commensurate effect on the ability to obtain financial resources. Thus, each level corresponds to an incremental advantage for start-ups seeking to secure funding.

From the pre-treatment data process used to generate individual scores, we now possess the necessary raw material to compute start-up team level scores for *Skills level* and *Skills field variety*. To measure the start-up team's *Skills level* score, we assigned the highest median score in the six functional areas associated with any of its founders. To measure the start-up team's *Skills field variety* score, we assigned a variable that captures the number of different fields of expertise of its founders. Following Harrison and Klein (2007, p.5), we interpret diversity as *variety* defined as *differences in kind or category, primarily of information, knowledge, or experience among unit members.*, in this case being the start-up team. Concretely, we compute the variable score based on Blau's index, where the variable is equal to $1 - \sum p_k^2$ where p is the proportion of unit members in kth category, ranging from zero to $k - 1/k$.

Last but not least, one might argue that the use of LinkedIn endorsements lacks a clear timestamp, making it difficult to determine the sequence of endorsements relative to funding events. This can result in potential reverse causality, with successful start-ups perhaps receiving more endorsements post-funding. To mitigate this risk, based on the nature of previous job experiences of each founder in the dataset, we manually check each profiles if the highest skill score is likely to have been developed or honed during the longest job experience period. For instance, if someone's prior job role was "Data Scientist" for 3 years, one can infer they might have developed skills in "Machine Learning" or "Data Analysis" during that tenure, therefore confirming a relatively high score in "Development". In other words, we make sure that the highest score in a given skill cluster is related to the skills that may be acquired in prior longest job experiences.

4.3.2.3. Control variables

We employ traditional controls used frequently in the literature to measure entrepreneurs' human capital quality-signals effects.

First, the variable *Previous Prestigious University* was included to take into account the institutionalized cultural capital of the start-up teams' members, as defined by Bourdieu (1979). The presence of such capital allows for the transmission of a quality signal to investors and is thus considered an important factor for start-up teams' success. For example, Ferrary (1999) empirically demonstrated that degrees from prominent institutions contribute to quality-signals. In more detail, this variable is constructed from a combination of the top 10 universities worldwide (ARWU 2022 ranking) and the best French business and engineering schools (Figaro Etudiant Ranking 2023). ARWU is not suitable for capturing the entrepreneurial elite graduating in France, due to the weight and attractiveness of French "Grandes Ecoles", poorly represented in ARWU-type international rankings based on Clarivate bibliometric data. The student Figaro ranking integrates the quality of faculty recruitment, relations with industry, and the salary of graduating students.

Second, we use *Previous Founding Experience* to control for the number of firms previously founded by the individuals, also known as serial entrepreneurship (Kirschenhofer and Lechner, 2012). Indeed, more extensive entrepreneurial experience can increase investor confidence, send a signal of competence, have an impact on the amount of raised funds (Hsu, 2007), and have a positive impact on growth aspirations of subsequent start-ups (Fuentelsaz et al., 2023).

Third, we control for *Previous Working Experience* to determine whether a start-up team member had any significant prior professional experience. Indeed, using human capital and signaling theory, Subramanian et al. (2022) investigated whether and how founders' human capital characteristics affect early-stage venture capital investment. They concluded that founders with extensive professional working experience attract higher initial investments than other founders.

Fourth, we control for *Previous Ph.D. Degree* as teams founded by Ph.D. holders are more likely to receive funding and higher valuations, suggesting a signal effect (Hsu, 2007).

Fifth, we use *New Venture Age* to control for the time in years since the founding date of a new venture to incorporate the new ventures' stage of development.

Sixth, we controlled for the *Team size* as a larger start-up team may naturally have more skill endorsements simply due to the greater number of individuals. Therefore, controlling for team size can help isolate the specific effect of skill endorsements on early-stage venture funding. Furthermore, investors often consider team size as one of the factors in their investment decisions. Larger teams may be perceived as more capable in terms of delivering on their proposed business plans (Harrison and Klein, 2007; Williamsky, 1998).

Lastly, as there can be confounding effects related to industry conditions in which start-ups operate, we controlled for the *Industry.* In more detail, 11 industry dummies were included which take a value of 1 if the firm is operating in *i)* Business Intelligence Analytics, *ii)* Customer Relationship Management, *iii)* Developers Software Infrastructure, *iv)* Education Human Resources, *v)* Finance Legal Insurance, *vi)* Healthcare, *vii)* Logistics Supply Chain, *viii)* Marketing and Media, *ix)* Productivity Collaboration, *x)* Real Estate Construction, and *xi)* Retail Ecommerce.

4.3.2.4. Models

To test the predictions of our model, we first ran an OLS linear regression with the logarithm of the first round of funding (*log fundraising*) as the dependent variable. Correlations among the variables are reported in Table . The statistical analyses were conducted with Statsmodels Release 0.13.0. The package is released under the open source Modified BSD (3-clause) license (Seabold and Perktold, 2010). Secondly, we use Logit as our main regression model. The dependent variable is a dummy variable that takes the value of 1 if the firm has raised a seed, 0 if not.

4.4. Results

As a first step, we ran an OLS model whose results are reported in Table 4.6. Model 1 includes only control variables; Model 2 contains only the first independent variable; Model 3 contains only the second independent variable; Model 4 contains the two independent variables; Model 5 comprises the full model with all the independent and moderating variables. We have also controlled for potential multicollinearity problems through a VIF test (James et al., 2013), and no issues of that nature are present.

In our first hypothesis, we propose that start-up teams with greater skills endorsement levels will get more funding from investors. Based on the econometric outcomes presented in Table 4.6, the *Skills level* variable in relation to the natural logarithm of funds demonstrates a positive and highly noteworthy value in Model 2 ($p < 0.01$), Model 4 ($p < 0.01$), and Model 5 ($p < 0.01$). Hence, we validate **H1**.

Subsequently, in our second hypothesis, we posited that *Skills field variety* among start-up team members would inspire more optimistic investor expectations concerning the future success of a start-up due to a range of mindsets, superior problem-solving abilities, greater social networks, and a higher probability that diverse organizational tasks would be competently executed. Thus, in our second hypothesis, we posited that diversity of skills fields among start-up team members would result in an increased capacity to obtain funding. As the *Skills field variety* coefficient is positive in model 3 and 4 but very significant only in Model 5 ($p < 0.01$), we find partial support for **H2**.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Capital Raised (log)	1																		
2	Skills level	0.142	1																	
3	Skills field variety	-0.018	-0.257	1																
4	Previous Prestigious University	0.213	0.031	0.020	1															
5	Previous Founding Experience	0.124	0.151	-0.079	0.065	1														
6	Previous Working Experience	0.073	0.260	-0.144	-0.046	0.163	1													
7	Previous PhD Degree	0.005	-0.148	0.080	0.089	-0.025	0.052	1												
8	Firm Age	0.189	0.241	-0.165	-0.013	0.034	0.273	-0.005	1											
10	Team Size	0.088	0.180	0.168	0.163	0.152	0.156	0.016	-0.122	1										
11	Business Intelligence Analytics	-0.033	-0.038	0.002	0.059	-0.122	0.025	0.026	0.130	-0.025	1									
10	Customer Relationship Management	-0.001	0.111	-0.135	0.004	0.033	0.038	-0.060	0.120	-0.047	-0.076	1								
11	Developers Software Infrastructure	0.050	-0.144	0.101	-0.022	0.004	0.157	0.112	0.040	-0.005	-0.110	-0.088	1							
12	Education Human Resources	0.023	0.082	-0.058	-0.068	-0.045	-0.078	-0.028	-0.100	0.053	-0.121	-0.097	-0.141	1						
13	Finance Legal Insurance	0.042	-0.076	0.067	0.045	0.125	-0.002	-0.069	-0.166	0.026	-0.112	-0.089	-0.130	-0.143	1					
14	Healthcare	0.070	-0.054	0.041	0.133	0.036	0.050	0.221	-0.041	0.049	-0.074	-0.059	-0.086	-0.095	-0.087	1				
15	Logistics Supply Chain	-0.009	0.053	0.049	-0.041	-0.041	-0.025	-0.012	-0.027	0.098	-0.079	-0.063	-0.092	-0.101	-0.093	-0.062	1			
16	Productivity Collaboration	-0.065	0.014	0.026	-0.026	0.037	-0.063	-0.104	-0.011	-0.112	-0.108	-0.086	-0.126	-0.138	-0.127	-0.084	-0.090	1		
17	Real Estate Construction	0.003	-0.062	-0.002	0.004	-0.068	-0.021	-0.087	-0.076	-0.034	-0.076	-0.060	-0.088	-0.097	-0.089	-0.059	-0.063	-0.086	1	
18	Marketing Media	-0.074	0.045	-0.014	-0.056	-0.006	-0.027	0.016	0.033	-0.044	-0.118	-0.094	-0.137	-0.151	-0.139	-0.092	-0.098	-0.134	-0.094	1
19	Retail Ecommerce	0.011	0.079	-0.100	0.013	0.031	-0.038	0.009	0.131	-0.055	-0.092	-0.073	-0.107	-0.118	-0.108	-0.072	-0.077	-0.105	-0.073	-0.114

Table 4.5: Correlation Table

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Theorical					
Skill level (SL)		0.250*		0.265*	0.547***
		(0.139)		(0.143)	(0.192)
Skill field diversity (SFD)			0.005	0.369	4.575**
			(0.810)	(0.831)	(2.104)
Interaction SL * SFD					-1.051**
					(0.484)
Controls					
Previous Prestigious University	1.509***	1.477***	1.509***	1.480***	1.478***
	(0.364)	(0.363)	(0.364)	(0.364)	(0.362)
Previous Founding Experience	0.527*	0.481*	0.527*	0.489*	0.463
	(0.286)	(0.286)	(0.287)	(0.287)	(0.286)
Previous Working Experience	-0.008	-0.021	-0.007	-0.020	-0.020
	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)
Previous PhD Degree	-0.374	-0.168	-0.374	-0.179	-0.256
	(0.780)	(0.787)	(0.783)	(0.788)	(0.785)
Firm Age	0.689***	0.637***	0.689***	0.638***	0.655***
	(0.152)	(0.154)	(0.152)	(0.154)	(0.154)
Team Size	0.451	0.346	0.451	0.308	0.213
	(0.363)	(0.367)	(0.370)	(0.377)	(0.378)
Business Intelligence Analytics	-0.741	-0.521	-0.741	-0.549	-0.650
	(1.317)	(1.319)	(1.322)	(1.322)	(1.317)
Customer Relationship Management	-0.309	-0.352	-0.309	-0.336	-0.347
	(1.466)	(1.462)	(1.468)	(1.464)	(1.458)
Developers Software Infrastructure	1.231	1.613	1.230	1.555	1.578
	(1.248)	(1.263)	(1.262)	(1.271)	(1.265)
Education Human Resources	1.298	1.269	1.298	1.261	1.320
	(1.209)	(1.206)	(1.211)	(1.207)	(1.202)
Finance Legal Insurance	1.350	1.583	1.349	1.537	1.478
	(1.256)	(1.259)	(1.264)	(1.265)	(1.259)
Healthcare	1.704	1.927	1.703	1.889	1.607
	(1.521)	(1.522)	(1.528)	(1.526)	(1.525)
Logistics Supply Chain	0.477	0.492	0.477	0.446	0.432
	(1.449)	(1.446)	(1.455)	(1.451)	(1.444)
Marketing Media	-0.610	-0.564	-0.610	-0.594	-0.625
	(1.206)	(1.203)	(1.209)	(1.206)	(1.201)
Productivity Collaboration	-0.633	-0.531	-0.634	-0.571	-0.696
	(1.249)	(1.247)	(1.255)	(1.252)	(1.247)
Intercept	3.109***	2.261	3.107*	2.018	0.481
	(1.610)	(1.673)	(1.666)	(1.762)	(1.891)
R-squared	0.119	0.126	0.119	0.126	0.136
R-squared Adj.	0.086	0.091	0.084	0.089	0.097
Observations	439	439	439	439	439

SEs are in parentheses
*** p < .001; ** p < .01; * p < .05

Table 4.6: Results of OLS Regression for Signals and Investment Outcome. Log of funds received is the dependent variable of the OLS linear regression.

Lastly, we developed a negative moderating effect of *Skills level* on the relationship between *Skills field variety* and funds raised by the start-up team. In order to arrive at this reasoning, we put forth the notion that team members in a start-up with advanced levels of skill are subject to cognitive inflexibility. Therefore individuals may struggle to interact effectively with other team members whose mental models differ from their own. Therefore, we conjectured that team members with advanced proficiency may have lower chances of providing constructive inputs to the start-up if their peers possess varied skill sets. Thus, we postulated that investors might show a diminished inclination to invest in start-ups where the members possess both extensive proficiency and a wide range of skill and expertise fields. The interaction term between *Skills level* and *Skills field variety* has negative and significant coefficients ($p < 0.01$) in Model 5, the comprehensive model, thereby providing support for **H3**.

As a second step, we estimated a logistic regression as a second regression model in which the dependent variable is binary (*Fundraising*), since it has been widely used in recent entrepreneurial finance research studies (Ahlers et al., 2015; Islam et al., 2018). Again, Model 1 includes only control variables; Model 2 contains only the first independent variable; Model 3 contains only the second independent variable; Model 4 contains the two independent variables; Model 5 comprises the full model with all the independent and moderating variables. Results are reported in Table 4.7.

The econometric analysis of the logit regression reveals that the *Skills level* variable exhibits a positive and statistically significant value in Model 2 ($p < 0.05$), Model 4 ($p < 0.05$), and most notably in Model 5 ($p < 0.001$). These findings lend credence to **H1**.

As per Hypothesis 2, we proposed that *Skills field variety* would catalyze the fundraising process. While the *Skills field variety* coefficient displays a positive orientation in Model 4, it only achieves significance in Model 5 ($p < 0.05$), implying a partial endorsement of **H2**.

Lastly, we surmised a counteractive role of the *Skills level* in the association between *Skills field variety* and successful capital acquisition. Our assumption finds support in Model 5, where the interaction term between *Skills level*and *Skills field variety* reveals a negative and significant coefficient ($p < 0.05$), thus supporting **H3**.

4.5. Robustness tests

We performed several robustness tests to ensure the quality of the analysis.

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Theorical					
Skill level (SL)		0.105*		0.109*	0.224***
		(0.060)		(0.061)	(0.086)
Skill field diversity (SFD)			-0.005	0.135	1.801*
			(0.365)	(0.375)	(0.942)
Interaction SL * SFD					-0.424*
					(0.219)
Controls					
Previous Prestigious University	0.720***	0.705***	0.720***	0.704***	0.709***
	(0.179)	(0.179)	(0.179)	(0.179)	(0.180)
Previous Founding Experience	0.187	0.167	0.187	0.169	0.176
	(0.130)	(0.131)	(0.130)	(0.131)	(0.132)
Previous Working Experience	-0.015	-0.021	-0.015	-0.021	-0.022
	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)
Previous PhD Degree	-0.140	-0.071	-0.140	-0.074	-0.105
	(0.351)	(0.354)	(0.351)	(0.354)	(0.352)
Firm Age	0.371***	0.350***	0.371***	0.350***	0.366***
	(0.073)	(0.074)	(0.073)	(0.074)	(0.075)
Team Size	0.246	0.202	0.247	0.187	0.156
	(0.170)	(0.172)	(0.174)	(0.176)	(0.178)
Business Intelligence Analytics	-0.410	-0.298	-0.409	-0.306	-0.340
	(0.583)	(0.589)	(0.584)	(0.589)	(0.592)
Customer Relationship Management	-0.131	-0.128	-0.131	-0.122	-0.083
	(0.658)	(0.659)	(0.659)	(0.660)	(0.667)
Developers Software Infrastructure	0.652	0.822	0.653	0.802	0.850
	(0.582)	(0.591)	(0.586)	(0.594)	(0.597)
Education Human Resources	0.573	0.575	0.573	0.578	0.643
	(0.550)	(0.551)	(0.550)	(0.551)	(0.556)
Finance Legal Insurance	0.514	0.657	0.515	0.635	0.636
	(0.574)	(0.582)	(0.579)	(0.585)	(0.587)
Healthcare	0.941	1.113	0.941	1.108	1.055
	(0.784)	(0.800)	(0.785)	(0.801)	(0.809)
Logistics Supply Chain	0.179	0.203	0.180	0.185	0.212
	(0.648)	(0.652)	(0.650)	(0.654)	(0.658)
Marketing Media	-0.275	-0.227	-0.275	-0.241	-0.249
	(0.531)	(0.534)	(0.533)	(0.535)	(0.536)
Productivity Collaboration	-0.306	-0.255	-0.305	-0.271	-0.304
	(0.543)	(0.543)	(0.545)	(0.545)	(0.546)
Intercept	-1.989***	-2.350***	-1.987***	-2.428***	-3.104***
	(0.743)	(0.773)	(0.762)	(0.804)	(0.884)
Observations	439	439	439	439	439

SEs are in parentheses
*** $p < .001$; ** $p < .01$; * $p < .05$

Table 4.7: Results of Logit Regression for Signals and Investment Outcome. Fundraising is the dependent variable of the Logit regression.

Corrected Blau index: as varying group sizes in a sample affect the most common measures of group diversity (Biemann and Kearney, 2010), we use an alternative formula to get an unbiased estimation of within-group variety $(1 - \sum(N_i * (N_i - 1))/(N * (N - 1))$, where N_i is the absolute frequency of group members in the i^{th} category and N is the total number of group members). Results remain consistent.

Huber-White test: we utilized this test for heteroscedasticity using the het_white function of Statsmodels Release 0.13.0. (Seabold and Perktold, 2010). In our case, the p-value for the White test is 0.36. Consequently, we cannot reject the null hypothesis that the errors are homoscedastic. This infers that based on the test's results, there is insufficient evidence of heteroscedasticity in our data.

Kruskal's minimum spanning tree algorithm: there might be room for further discourse about the classification of skills into functional domains, specifically about the relevance of bottom-up hierarchical clustering with Kruskal's algorithm (Kruskal, 1956). Certainly, certain skills, like entrepreneurship, might be more or less pivotal for different start-up teams. We executed the regressions and assessments using different skills classifications, and the primary findings remain consistent.

Skills level scores: finally, we also allocated the highest maximum and mean scores of skills levels in the six associated functional areas to any of its founding members to the start-up team. The outcomes derived from utilizing alternate estimators align reasonably well with those shown here and can be provided by the authors upon request.

4.6. Discussion and conclusion

Research has highlighted the complexity of the effects of start-up team composition expertise signaling on investors' evaluations. Prior studies found that individual qualities of founding members, such as their education, work experience, and prior entrepreneurial endeavors (Shane and Cable, 2002; Hsu, 2007), as well as their social capital - the direct or indirect relationships that founding members have with investors, corporate partners, and other entities (Shane and Cable, 2002; Hsu, 2007; Huang and Knight, 2017) - act as signals of venture quality and are therefore determinants of financial resource acquisition. While these studies have provided significant insights, this approach is becoming less comprehensive because nowadays, investors rely on a wide array of other signals to evaluate the viability of investing in a start-up team, and start-up teams use other information channels to signal their expertise to investors (Piazza et al., 2023). Indeed, recent entrepreneurship research has, among other, identified online skills endorsement data as valuable information for entrepreneurial studies and a reliable criterion for judging an individual's knowledge (Rapanta and Cantoni, 2017; Reese et al., 2020; Sako et al., 2020). However, the potential signaling effects of online skills endorsement data on early-stage resource acquisition have been overlooked in the literature and previous empirical studies did not engage in efforts to assess the signaling role of skills levels and diversity used by start-up teams to influence a new venture's success in a digital context.

Drawing from signaling theory, human capital literature, and cognitive psychology, this study addresses this gap and explore how these socially constructed peer-reviewed measures of professional capabilities can influence the ability of start-up teams to acquire financial resources from investors. More precisely, in this article we develop and examine two human capital measures simultaneously (skills levels and skills field variety) computed from the LinkedIn's "*Skills & Endorsements*" data section, and focus on the dynamics of early-stage start-up teams and how these characteristics signal expertise to investors. Using a sample of 439 digital new ventures in the greater Paris, we demonstrate that, investors favor start-up teams that have *(i)* either a high level of skills endorsement, *(ii)* either a high level of variety of skills endorsement, *(iii)* but not both at once. Because of this, start-up teams that contain highly skilled individuals in related fields, i.e., the variety of their skills is low, receive more financial resources.

This research seeks to enrich existing works from two unique angles. First, despite the prevalent discussion of start-up team composition and its relation with fundraising (Beckman et al., 2007; Jung et al., 2017), there appears to be a noticeable absence of consensus on the exact modalities by which team composition expertise signaling impacts outcomes, and the conditions that render these impacts meaningful (Klotz et al., 2014; Zhou and Rosini, 2015). Therefore, we introduced new insights into the delicate balance between homogeneity and diversity in relation to endorsed skills within entrepreneurial teams (Sundermeier and Mahlert, 2022). Second, while many empirical studies looking at how start-up teams' composition affects investors' evaluations focused on indicators such as education (Franke et al., 2008), entrepreneurial experience (Beckman et al., 2007; Fuentelsaz et al., 2023), industry experience (Becker-Blease and Sohl, 2015), previous occupational characteristics and experiences (Wu et al., 2023) or leadership experience (Hoenig and Henkel, 2015), this article adopt a skill-based approach and derived an outcome-based human capital indicator which is considered a more direct measure of human capital and as one way of analyzing how skills affect firms' performance in a digital environment (Colombo, 2021; Drover et al., 2017; Klein et al., 2020; Marvel et al., 2016). In this study, we focus on the signaling role of "outcomes of human capital" (i.e. knowledge, skills and abilities) as a complementary measure to those related to "investment in human capital" such as education and experience. To do so, we make use of CrunchBase and Dealroom firm-level data and LinkedIn individual-level data and demonstrate the value of this information for research to understand the dynamics of signals in entrepreneurship literature.

Nonetheless, our study is not without limitations, paving the way for future research opportunities. The first limitation concerns the data of LinkedIn endorsements that lack a clear timestamp. While we mitigated the risk by checking for every profile that the highest skill score might have been likely to have been developed or honed during the longest job experience period, future research could use surveys or interviews to directly ask professionals when they believe they acquired certain skills. This primary data can then validate or correct the inferences made from LinkedIn data. Second, we have not been able to definitively establish if investors consider LinkedIn endorsements when making investment decisions. This assumption requires further qualitative work, especially given the significance of investment decisions in early-stage start-up teams. Finally, one might argue that the validity of LinkedIn endorsements as a reflection of genuine skills may be more of a reflection of one's network size and social capital. This poses a challenge when interpreting the real meaning behind the number of endorsements. Therefore, future research could control for the size of founders' LinkedIn network. By doing this, researchers can separate the effects of network size from the genuine skill endorsement.

Conclusion

Can *Digital Entrepreneurship* act as a catalyst for countries, regions, or cities aiming to establish or regain sustainable economic development? Central to this question is the idea that if certain places do not take the digital turn, their development will be determined by external forces. However, it is essential to emphasize that in a macroeconomic environment marked by unprecedented international tensions, promoting *Digital Entrepreneurship* is just one aspect of a broader development strategy through which policymakers can reassert their economic sovereignty and enhance the well-being of their citizens.

At the onset of this research, the prevailing sentiment was that Silicon Valley represented an unparalleled ideal for several compelling reasons. For instance, policymakers desired to nurture a Silicon Valley-like ecosystem initiative in their respective countries, regions, or cities to fuel economic growth. Entrepreneurs aspired to either be part of or draw inspiration from such a dynamic environment for their ventures. Venture capitalists were enthusiastic about investing in startups from these hubs, expecting significant returns, while academics pursued the elusive "magic formula" that might create such a flourishing place. However, this model often exacerbates existing regional disparities, favoring areas with abundant resources and sidelining others. Indeed, *Digital Entrepreneurship* is a very skewed phenomenon and, for example, even within a single country, clear disparities exist across regions, with a notable concentration of complex economic activities in urban centers, driven, among others, by entrepreneurial ecosystems (Leendertse et al., 2022) and innovative ventures (Balland et al., 2020). This leads to heightened spatial inequalities, challenges in housing accessibility, and more. Thus, when the rise of such technology hubs fails to coincide with inclusive growth, championing *Digital Entrepreneurship* "as a tool of local economic development" becomes contentious (Feldman et al., 2021).

The purpose of this thesis dissertation is to show how crucial it is to approach Digital Entrepreneurship with caution and show the necessity to approach both its systemic nature and the idiosyncratic micro characteristics of individuals and firms.

On one side, if we simply define entrepreneurs as individuals pursuing profit, it is unrealistic to consider the broader impacts of their activities on an economy's overall production. Therefore, viewing entrepreneurship through a holistic lens, shifting from a paradigm that centers on individual entities to one that emphasizes networked and interconnected actors, provides a more comprehensive picture. This systemic approach is both necessary when analyzing the very structure of academic literature of *Digital Entrepreneurial Ecosystems* (DEE) – as addressed in the first chapter – and from an empirical perspective in order to understand the multi-scale dynamics and underlying evolutionary forces of *Entrepreneurial Ecosystems* (EE) – the focus of the second chapter. In the first chapter, the socio-semantic system analysis confirmed a low degree of social integration between theoretical approaches and semantic fields contributing to the DEE conceptual landscape. Such insights enhance our understanding of DEE's origins and structuration, opening avenues for research and policy implications. In the second chapter, by employing a historical event analysis (HEA) to the case of the IoT Valley in Toulouse, we highlight how EE development stems from the interactions among local entrepreneurial initiatives, regional infrastructure, established entities, and global battles over technological standards and market *platformization*.

However, these researches come with their limitations. On one hand, the analysis of the structuration of the literature of DEE focused on the publications rather than their authors, leading to more potential explorations. Indeed, the aim was to highlight the research outputs on DEEs, not the authors' knowledge. Therefore, including the co-authors' network would enhance this analysis, especially assessing each author's contribution and the impact of institutional affiliations on the semantic field. Moreover, university affiliations, particularly geographical ones, deserve further exploration as they might influence collaborative research networks. On the other hand, the empirical analysis of the IoT Valley using HEA methodology presents several challenges, like the complexity of handling large databases and the risk of omitting or overestimating events. Furthermore, the application of this methodology to our case study is restricted by factors such as the lack of events related to cultural context and the challenge of generalizing from a single case. Yet, there are avenues for improvement, like weighting events based on their impact on EE development, refining keyword selection, grouping events by company lifecycle and technology maturity, and classifying them by their effects on EE trajectory. Such improvements could enrich the analysis and provide more nuanced insights for future research.

On the other side, this thesis considers the functional skills of individuals and their diversity as essential to the problem-solving activity inherent in the detection of digital opportunities and their successful realization. As such, human capital characteristics, honed through formal education, professional training and work experience, are therefore essential for advancing the understanding of *Digital Entrepreneurship*. This is true both if we look at the relationship between the growth of the user base of digital firms (across different stages of financing) and the skills diversity in different hierarchical layers – discussed in the third chapter – and if we looks at founder skills diversity as a signal of quality for fundraising – the theme of the fourth and final chapter. For instance, in the third chapter, the analysis shows the importance of examining the "skill variety" variable not just for Top Management Teams (TMTs) as often done in the literature, but also for Middle Management Teams (MMTs) and Operating Core Workers (OCWs). Indeed, the analysis reveals a positive relationship between functional diversity across these hierarchical layers and venture growth, with variations depending on the funding stage. In the fourth chapter, analyzing the implications of endorsed skill level and skill variety signaling role on investors has been found meaningful for both academic research and practitioners as the findings suggest that investors prefer start-up teams with either a high level of endorsed skills or a high variety of endorsed skills, but not both at the same time.

However, this research also has its limitations. On the one hand, the third chapter does not take into account internal team dynamics or other contingencies that could play an important role in firms' user base growth. Additionally, although we used LinkedIn skill endorsement data to measure individual functional diversity, this method may have biases, despite its broad professional acceptance and ability to provide detailed individual data, due to its public nature and its performative actions. As a result, addressing the issue of diversity still requires new ways of understanding human capital and guiding future research. On the other hand, the last chapter aims to enrich existing studies by focusing on start-up team composition expertise signaling and adopting a skill-based approach, using skill endorsements as a measure of human capital. While we recognize the potential biases inherent in using public LinkedIn data, a limitation of our study is the lack of exploration into how different combinations of endorsed skills can convey distinct signals to potential investors. Future research could go deeper into the nuances of the diversity literature, moving beyond the simplistic notion that "diversity is beneficial, but excess can be detrimental." A more in-depth analysis could focus on understanding how specific "bundles" of skills are perceived by investors and how they influence their trust levels.

In conclusion of this thesis dissertation, it seems legitimate and important to remember that without entrepreneurial endeavors, there might not have been any economic progress. Referencing Perez (2010), the innovations of our era, from semiconductor technology and AI to cloud computing, have led to many advancements. Digital ventures, as Steve Blank defines them, have thrived on these technologies born from state defense projects, but the challenge lay in building sustainable business models around these. However, given the fast-paced and ever-changing nature of *Digital Entrepreneurship*, questions arise about its future direction. Are we perhaps seeing the decline of digital startups as we know them? A look at the broader economic landscape prompts the question if the window of opportunity for *Digital Entrepreneurship* is slowly narrowing. Looking back, the decade from 2010-2020 was marked by strong investor enthusiasm for *Digital Entrepreneurship*. A key aspect of this euphoria was the affordable capital, leading investors to back innovative ideas rather than sticking strictly to traditional ROI metrics. The potential disruption by digital startups and market *platformization*, who could dominate markets and reshape pricing, justified these investments. But post-2020, as noted by Nicolas Colin, a French entrepreneur and essayist, we have seen a shift in the *Digital Entrepreneurship* environment, influenced notably by post-COVID-19 consolidation (Allaire et al., 2019). Factors like rising capital costs, geopolitical tensions affecting startup globalization, and decreased uncertainty in the digital venture space have reshaped the entrepreneurial scene. Business models that once seemed highly profitable are now appearing outdated and impractical. While Netflix aimed to revolutionize the movie industry, heavyweights like Disney resisted and maintained their position. In the music industry, even though traditional labels might have lost some visibility, the primary rights-holders continue to wield considerable influence in the market.

In this context of "technology backlash" full of unrealized potential, what is the future of entrepreneurship in the emerging global scenario? Because many digital-related challenges await us, it is legitimate to highlight the importance of *Digital Entrepreneurship* as a promising research area, and to pave the way for even more fascinating and urgent explorations.

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Extended abstract in English

The study of entrepreneurship in the digital age encompasses various realities depending on the perspective taken. This thesis aims to meticulously explore specific entrepreneurial realities within the realm of *Digital Entrepreneurship* (DE) and to explore two distinct yet complementary analytical dimensions: one of a systemic nature and the other rooted in the micro-behavioral characteristics of individuals and businesses. The systemic perspective, while essential for understanding, for instance, the development of a local Entrepreneurial Ecosystem (EE) embedded in institutional dynamics and technological market trends at the global level, can sometimes overshadow the microeconomic view centered on the individual, which emphasizes personal attributes and motivations that influence entrepreneurial success. Indeed, when analyzing the micro-characteristics of individuals or firms, factors such as academic education, skills, and professional experiences play a significant role in achieving their outcomes. Consequently, this thesis proposes four essays that discuss these two dimensions to understand the complex mechanisms of entrepreneurship in the digital age.

Through the systemic perspective, the first essay of this thesis offers an analysis of the structuring of academic literature on *Digital Entrepreneurial Ecosystems* (DEE) and sheds light on the link between co-author networks and the semantic content that shapes it. Using methodologies from scientometrics, this chapter aims to complement previous qualitative studies based on citation analysis. One of the significant findings of this study is that the scientific domain of DEE is characterized by a rich array of themes and disciplines, albeit with limited integration, as it is largely anchored on a narrow set of contributions connecting these various areas of authority. Furthermore, the analysis reveals common semantic zones among certain pairs of communities, indicating research themes shared by distinct and loosely connected communities. However, the two main communities identified, although they interact partially with others, do not share common semantic foundations. The conclusion of this first chapter, therefore, prompts questions about the future of this concept and whether this divergence results from a "network failure" or simply reflects the dynamic nature of scientific evolution.

The second essay, still from a systemic perspective, views EE as entities embedded within broader regional and global markets. It explores the development of the IoT Valley, an EE specialized in IoT (LPWAN) technologies, from 2009 to 2019. This second chapter applies and develops the so-called historical event analysis (HEA) methodology. It demonstrates that the evolution and growth of EEs can result from a blend of local entrepreneurial dynamism, regional contexts, and global phenomena such as standards battles or the platformization of markets. The findings indicate that overlooking the mechanisms of digital platforms when researching the critical drivers of local EE evolution can lead to misconceptions about their progression. Indeed, we illustrate that the development of a "*blockbuster*" firm linked to a local EE depends on various stakeholders across multiple geographical scales, especially in a global battle for technological standards, thus suggesting an underlying competition between places. Ultimately, this chapter reveals how the dynamics of an EE, steered by such a firms, can enter a virtuous cycle of self-reinforcement due to the increasing returns from adoption and the externalities stemming from its position as a digital platform.

The subsequent two essays analyse the micro-aspects of entrepreneurship in the digital age. The third focuses on the relationship between skill diversity across different organizational strata and company performance. In this chapter, we examine the role of functional skill diversity across three organizational tiers (executive teams, mid-level management teams, and operational workers) in the user base growth of digital businesses. The results indicate a positive correlation between functional skill diversity across different hierarchical levels of digital companies and their expansion. However, a secondary finding tempers this observation: the strength of this relationship varies based on the company's financing stage, paving the way for potential new research directions. A key contribution of this third chapter is the introduction of a classification methodology for skill diversity, which is entirely reproducible and robust, using an ascending hierarchical clustering with Kruskal's minimum spanning tree algorithm.

Finally, the fourth and last essay turns to applying signaling theory to entrepreneurial studies, suggesting that the level and diversity of online-endorsed skills of digital start-up teams can attract investors to invest in their business. In fact, by analyzing data from 439 Parisian startups, this research shows that investors favor teams that showcase either deep expertise (a high level of endorsed skill) or diversified skills (a high level of variety in endorsed skills within the company), but rarely both at once. Although this study has limitations, paving the way for future research opportunities, one of the unique aspects of this last chapter is the use of professional networking sites to gather online-endorsed skills of startup teams and the creation of human capital indicators based on these skills for statistical modeling.

In fine, this dissertation underscores how crucial it is to approach entrepreneurship in the digital age by both its systemic nature and the idiosyncratic micro-characteristics of individuals and firms. Essentially, it sheds light on the interactions of various factors frequently mobilized in forming the entrepreneurial narrative. Such a perspective paves the way for enriching academic discussions and better-informed practical applications in the realm of digital enterprises.

Résumé étendu en Français

L'étude de l'entrepreneuriat à l'ère numérique recouvre plusieurs réalités selon la perspective adoptée. Cette thèse vise à explorer minutieusement des réalités entrepreneuriales très spécifiques au sein du domaine de l'*Entrepreneuriat Numérique* (EN) et à approfondir deux dimensions analytiques distinctes mais complémentaires : l'une de nature systémique et l'autre ancrée dans les caractéristiques micro-comportementales des individus et des entreprises. La perspective systémique, bien qu'essentielle pour comprendre, par exemple, le développement d'un *Écosystème Entrepreneurial* (EE) local encastré dans des dynamiques institutionnelles et de marchés technologiques au niveau global, peut parfois éclipser la vue microéconomique axée sur l'individu, qui met en avant les attributs personnels et motivations qui influencent le succès entrepreneurial. En effet, au niveau de l'analyse des caractéristiques micro des individus ou des firmes, des facteurs comme la formation universitaire, les compétences et les expériences professionnelles jouent un rôle important dans l'atteinte de leurs objectifs. Dès lors, cette thèse propose quatre essais qui discutent de ces deux dimensions pour comprendre les mécanismes complexes de l'entrepreneuriat à l'ère numérique.

À travers la perspective systémique, le premier essai de cette thèse propose une analyse de la structuration de la littérature académique des *Écosystème Entrepreneurial Digitaux* (DEE) et met en lumière le lien entre les réseaux de co-auteurs et le contenu sémantique qui la façonne. En utilisant des méthodologies issues de la scientométrie, ce chapitre a pour objectif de compléter les études qualitatives antérieures basées sur l'analyse des citations. Un des résultats importants de cette étude est que le domaine scientifique des DEE se caractérise par une riche gamme de thématiques et de disciplines, bien qu'avec une intégration limitée, car largement ancré sur un ensemble restreint de contributions reliant ces différents domaines d'autorité. De plus, l'analyse montre des zones sémantiques communes entre certaines paires de communautés, indiquant des thèmes de recherche partagés par des communautés distinctes et faiblement liées. Cependant, les deux principales communautés identifiées, bien qu'interagissant partiellement avec d'autres, ne partagent pas de fondements sémantiques communs. La conclusion de ce premier chapitre invite donc à interroger l'avenir de ce concept et à déterminer si cette divergence est due à une “défaillance du réseau” ou si elle reflète simplement la nature dynamique de l’évolution scientifique.

Le deuxième essai, toujours dans une perspective systémique, considère les Écosystèmes Entrepreneuriaux (EE) comme des entités encastrées au sein de marchés régionaux et mondiaux plus larges. Il explore le développement de l’IoT Valley, un EE spécialisé dans les technologies IoT (LPWAN), entre 2009 et 2019. Ce deuxième chapitre met en application et développe la méthodologie dite de l’analyse des événements historiques (HEA). Il montre que l’évolution et le développement des EE peuvent être le résultat d’un mélange de dynamisme entrepreneurial local, de contextes régionaux et de phénomènes mondiaux tels qu’une bataille de standards ou la plateformisation des marchés. Les résultats démontrent que négliger les mécanismes des plateformes numériques lors de la recherche des éléments clés de l’évolution des EE locaux peut conduire à une mauvaise interprétation de leur évolution. En effet, nous illustrons que le développement d’une firme “*blockbuster*” liée à un EE local dépend de divers acteurs à plusieurs échelles géographiques, notamment dans une lutte globale pour les standards technologiques, suggérant ainsi une compétition sous-jacente entre les lieux. Finalement, ce chapitre révèle comment la dynamique d’un EE, piloté par une telle entreprise, peut s’engager dans un cercle vertueux d’auto-renforcement grâce aux rendements croissants d’adoption et aux externalités découlant de sa position de plateforme numérique.

Les deux essais suivants abordent les aspects micro de l’entrepreneuriat à l’ère numérique. Le troisième se penche sur la relation entre la diversité des compétences à différentes strates organisationnelles et la performance des entreprises. Dans ce chapitre, nous examinons le rôle de la diversité fonctionnelle des compétences de trois échelons organisationnels (équipes de direction, équipes de management de niveau intermédiaire et travailleurs opérationnels) sur la croissance des utilisateurs d’entreprises numériques. Les résultats montrent une corrélation positive entre la diversité fonctionnelle des compétences à différents niveaux hiérarchiques des entreprises numériques et l’expansion de ces dernières. Cependant, un deuxième résultat vient nuancer cette observation : la force de cette relation varie selon la phase de financement de l’entreprise, ouvrant ainsi la voie à de potentielles nouvelles directions de recherche. Enfin, un des apports de ce troisième chapitre est l’apport d’une méthodologie de classification de la diversité des compétences, entièrement reproductible et robuste, à l’aide d’un regroupement hiérarchique ascendant avec l’algorithme d’arbre couvrant minimum de Kruskal.

Enfin, le quatrième et dernier essai se tourne vers l’application de la théorie du signal aux études entrepreneuriales, suggérant que le niveau et la diversité des compétences approuvés en ligne des équipes de start-ups numériques peut attirer les investisseurs à investir dans leur entreprise. De fait, en analysant les données de 439 start-ups parisiennes, cette recherche montre que les investisseurs privilégient les équipes mettant en avant soit des compétences très approfondies (un haut niveau de compétence), soit diversifiées (un haut niveau de variété des compétences au sein de l'entreprise), mais rarement les deux à la fois. Bien que cette étude présente des limites, ouvrant la voie à de futures opportunités de recherche, l'une des originalités de ce dernier chapitre concerne l'utilisation des sites de réseautage professionnel pour recueillir les compétences des équipes de start-ups approuvées en ligne et la constitution d'indicateurs de capital humain basé sur ces compétences pour les modélisations statistiques.

In fine, cette thèse montre à quel point il est crucial d'aborder l'entrepreneuriat à l'ère numérique à la fois par sa nature systémique et par les micro-caractéristiques idiosyncrasiques des individus et des entreprises. En essence, elle met en lumière les interactions de divers facteurs souvent mobilisés dans la formation du récit entrepreneurial. Une telle perspective permet d'ouvrir la voie à des discussions académiques enrichissantes et à des applications pratiques mieux informées dans le domaine des entreprises numériques.

Quatre essais sur l'entrepreneuriat numérique :
développement de nouvelles entreprises et d'écosystèmes.

L'entrepreneuriat à l'ère numérique est une discipline aux multiples facettes, englobant à la fois des dynamiques systémiques et des micro-caractéristiques individuelles. Cette thèse examine de manière critique ces deux aspects à travers quatre essais qui mettent en lumière les subtilités de l'*Entrepreneuriat Numérique*. D'un point de vue systémique, cette thèse analyse la composition et l'interaction de la littérature académique sur les écosystèmes Entrepreneuriaux Digitaux (DEE), révélant une grande diversité thématique et une fragmentation potentielle. De plus, une analyse historique de la l'IoT Valley entre 2009 et 2019 montre comment les écosystèmes Entrepreneuriaux (EE) sont façonnés par un mélange d'initiatives locales, de contextes régionaux et de tendances mondiales, mettant en évidence le rôle essentiel des mécanismes des plateformes numériques. En se concentrant sur le micro-niveau, la thèse explore la corrélation entre la diversité des compétences à travers les hiérarchies organisationnelles et la croissance des entreprises numériques. Il est à noter que, bien que la diversité des compétences favorise généralement l'expansion, son impact varie selon le stade de financement de l'entreprise. De plus, une analyse de 439 start-ups parisiennes indique que l'attrait des investisseurs dépend de la profondeur ou de la diversité des compétences de l'équipe de démarrage approuvées en ligne, mais rarement des deux à la fois. En conclusion, comprendre l'entrepreneuriat à l'ère numérique nécessite un examen harmonisé des systèmes globaux et des facteurs individuels nuancés. Cette approche combinée promet des perspectives académiques plus riches et des applications pratiques plus perspicaces dans le domaine de l'*Entrepreneuriat Numérique*.

Mots clés: Ecosystème Entrepreneurial, Plateformes Numériques, Capital-Risque, Diversité du Capital Humain, Croissance de Nouvelles Entreprises, IoT Valley

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Four essays on digital entrepreneurship:
new ventures and ecosystems development

Entrepreneurship in the digital age is a multifaceted discipline, encompassing systemic dynamics and individual micro-characteristics. This thesis critically examines these dual aspects through four essays that highlight the intricacies of *Digital Entrepreneurship* (DE). From a systemic perspective, this thesis analyse the composition and interaction of academic literature on Digital Entrepreneurial Ecosystems (DEE), revealing both vast thematic diversity and potential fragmentation. Furthermore, a historical event analysis of the IoT Valley between 2009-2019 demonstrates how Entrepreneurial Ecosystems (EE) are shaped by a mix of local initiatives, regional contexts, and global trends, emphasizing the pivotal role of digital platforms. Shifting focus to the micro-level, the thesis explores the correlation between skill diversity across organizational hierarchies and digital business growth. Notably, while skill diversity generally augments expansion, its impact varies with the company's financing stage. Additionally, an analysis of 439 Parisian start-ups indicates that investor attraction hinges on the depth or diversity of start-up team endorsed skills, but rarely both. In conclusion, understanding entrepreneurship in the digital era necessitates a harmonized examination of overarching systems and nuanced individual factors. This blended approach promises richer academic insights and more astute practical applications in the *Digital Entrepreneurship* field of study.

Key words: Entrepreneurial Ecosystems, Digital platforms, Venture Capital, Human Capital Diversity, New Ventures Growth, IoT Valley