Doctoral Program in Innovation for the Circular Economy

XXXVII Cycle

Essays on Innovation and Entrepreneurship Ecosystems

by

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This Thesis was the culmination of a journey.

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1. Introduction

1.1 Overview

This Thesis covers the Candidate's journey during his PhD in Innovation for the Circular Economy, started at the University of Turin in November 2021 and completed in October 2024. During this time, the Candidate participated in multiple academic endeavors, teaching activities, and third-mission projects. They include a diverse collection of book chapters (Paper 6), conference papers (Papers 1, 3, 7, 8, 10), and journal articles which have been published or are currently under review (Papers 2, 4, 5, 9). They range from technology and innovation management (e.g. Paper 6), innovation (e.g. Paper 4), entrepreneurship (e.g. Paper 5), and system design (e.g. Paper 10) as well as the intersects between them. Dissemination on these topics has been significant with guest lecturing at the University of Turin and IULM University, as well with the participation in major national and international conferences. To name a few, those organized by the Italian Association for Information Systems (*ItAIS*, 2023), by the Italian Journal of Management and the Società Italiana di Management (*Sinergie-SIMA*, 2023), and by the European Academy of Management (*EURAM*, 2023). Moreover, as part of his third mission, the Candidate engaged with nationally relevant projects aimed at fostering innovation and entrepreneurship from an ecosystem perspective: one being CTE Next, where he supported startups in the definition of their business model (*CTE Next*, n.d.); and another one being NODES Spoke 2, for which he developed a prototypical system for actors' match-making (*NODES Spoke 2*, n.d.), also co-supervising a Bachelor's thesis in computer science for this purpose.

1.2. Motivation

This Thesis adopts a meso-perspective to study complex socio-economic phenomena at the intertwine of innovation and entrepreneurship, with an eye for sustainability and the identification of novel data sources for research and practice. Over the last 70 years the human population has grown from 2.5 to more than 8 billion, the percentage of city dwellers shifted from only 29% to roughly 56%, and nominal GDP raised nine-fold from about 9 trillion to more than 80 trillion US dollars (Steffen et al., 2015). In this time we got to the Moon and back, we invented numerous ways to potentially extinct our own species, and developed drugs to fight and win the battle against almost all diseases that had plagued us in the previous 10,000 years. Yet, as a result of this exponential growth of human capabilities, we have also tweaked with the natural environment in many ways: from increasing the concentration of greenhouse gases causing climate change, to driving one of the largest extinctions in the planet history, to overconsuming or polluting the available water, air, and soil, on which our very existence still depends (Brolin & Kander, 2022; Steffen et al., 2015). Moreover, our impact on the environment has affected the lives of fellow humans seriously and unevenly, with most of the responsibilities in the hands of advanced economies and most of the hurdle on the shoulders of the remaining global population (Weiming Chen et al., 2021; Chen et al., 2020).

Accordingly, the last few decades have seen an unprecedented rise of sustainability discussions, widespread awareness, and political commitment to preserving the environment while achieving higher human prosperity for future and current generations alike (Visser & Brundtland, 2013). Though multiple conceptualizations and strategies have been proposed to achieve more sustainable societies (Riedy, 2020), however, for the moment only one trajectory seems politically feasible to square the circle. Assuming that economic output and environmental harm can be decoupled, and fast, the idea of a Green Growth requires to further pushing on the accelerator of technology innovation to preserve and restore the environment, improve the quality of life for billions, and keep the economy going (de Jong & Vijge, 2021; Hickel & Kallis, 2020; Young et al., 2017).

Though the ultimate success of this strategy will be judged by the next generations (Biermann et al., 2022; Hickmann et al., 2022), at least some positive evidence suggest that innovation and entrepreneurship might achieve this goal at the expenses of further increasing inequality and (temporarily) environmental degradation (Herman, 2023; S. Wang et al., 2021). Hence, from businesses, governments, and research organizations alike an entrepreneurial mindset is believed fundamental to actively drive this transformation (DiVito & Ingen-Housz, 2021; Mazzucato, 2024). Even more so as the increasing complexity of problems that humanity faces requires the participation of different actors capable of combining resources, knowledge, and competences in always novel combinations (Bertello et al., 2022; Carayannis et al., 2012; Matteo Spinazzola & Cavalli, 2022).

1.3 Background

Drawing from the Quadruple/Quintuple Helix model (Carayannis et al., 2012, 2018), innovation and entrepreneurship are complex and emergent phenomena at the crossroad of five subsystems: the environment defines boundaries for human activities and, as already mentioned, many of the challenges that we are called to solve (Carayannis & Campbell, 2010); government and civil society, on the other hand, interactively identify, legitimize, and act upon political priorities (Etzkowitz & Leydesdorff, 2000); last, generally aligning with such visions and constraints, research organizations explore the frontier of our knowledge and capabilities, leaving for businesses to further develop them into scalable products and services (Carayannis & Campbell, 2020). In this perspective, actors coordinate their activities to achieve complex goals by distributing discrete and complementary functions among themselves. Hence, the structure of their network relations significantly affects their opportunities to access knowledge and resources, coordinate other actors, and develop solutions. This incredibly complex phenomenon is multi-nodal and multi-level, and amounts to the collective problem-solving capacity of a society (Brusoni & Prencipe, 2013; Carayannis et al., 2012, 2018).

The concepts of Innovation Ecosystem (IE) and of Entrepreneurship Ecosystem (EE), further discussed in chapter Theoretical Landscape, are both situated in this understanding of socio-economic dynamics as complex systems. While IEs have the development of complementary processes, services, and products as their primary focus, EEs have the birth and growth of enterprises as their own (Stam & van de Ven, 2021; Suominen et al., 2019). Yet, the two concepts have been long intertwining (Kurz, 2012) to investigate technology-driven high-growth enterprises and territories (Bahrami & Evans, 1995; Pique et al., 2018), and under specific conditions may be interpreted as two sides of the same phenomenon (hereafter, IEE). While the papers here summarized employ only one of the two concepts at a time, accordingly, whenever possible the Thesis itself refers to the concept of IEE to identify ecosystems where innovation and entrepreneurship processes are strictly connected.

When discussing IEEs, special attention is deserved by Knowledge-Intensive Entrepreneurs (KIEs). As entrepreneurs highly focused on interacting with their social environment, KIEs recombine resources to develop high-growth technology-driven firms (Malerba & McKelvey, 2020). Given their propensity for the creation of new relations, not only they increase the internal connectedness of IEE but also the connectedness between IEEs (Chen et al., 2015). Hence, these relations impact the opportunities available to individual KIEs while determining the emergence of unpredictable and complex phenomena at the aggregate level which have long eluded investigation (Depret & Hamdouch, 2010; Ritala et al., 2022).

1.4 Research gap and foci

Acknowledging this difficulty, equally complex research and management approaches have been developed to orchestrate IEE and KIEs behavior (Srigiri & Dombrowsky, 2021; Stein et al., 2018). Overall, they aim at steering societal actors and resources towards collective goals (Carayannis et al., 2018; Kattel & Mazzucato, 2018), but no result is guaranteed or easily predictable, so that ecosystems often result in asymmetrical and dysfunctional relations between actors, as well as ineffective or inefficient outcomes (Kyle et al., 2017; Lazonick & Mazzucato, 2013; Quitzow, 2015; Rikap, 2019). Hence, understanding how IEE develop and resources are brokered becomes crucial to assess and maximize opportunities for knowledge recombination, entrepreneurship and innovation (Bertello et al., 2022; Carayannis et al., 2018). This is particularly true for sustainability issues, as their intrinsic complexity often requires a more diverse combination of resources and knowledge. Accordingly, governments are working to initiate and nurture IEE where new ventures and established companies alike may tap in locally and globally produced knowledge converting it into commercial solutions (Gifford et al., 2021; Hockerts & Wüstenhagen, 2010). Crucially, this includes the development of complex arrangements and strategies for technology-transfer (Del Giudice et al., 2017), public-private partnership (Lassen et al., 2015; Nissen et al., 2014), and participatory governance (Enkel & Gassmann, 2010; Romero & Molina, 2011; Scuotto, Del Giudice, et al., 2017).

Though potential research topics in this area are countless, the Candidate focused on three major and interrelated objectives for his PhD. While the reader shall refer to the original works for a thorough discussion, they are now summarized:

- Objective 1: Exploring novel data sources for research and practice
- Objective 2: Investigating IEE's connectedness from KIEs activities
- Objective 3: Conceptualizing novel management systems for IEE actors

Starting from Objective 1, as the amount of available data and the capacity to use it expand, research and practice have been increasingly relying on them to identify, understand, and ultimately control socio-economic phenomena. While studies on IEs frequently employ patent and bibliometric information to gain a relational understanding of scientific and patenting activity (Xu et al., 2018), however, investigations of EEs have been slower in adopting quantitative methods for a lack of globally available relational data (Brown & Mason, 2017). Aiming to address this issue, Papers 1, 2, 3 and 5 explore the use of web data sources to track the activities of EE actors, and specifically KIEs.

Moving to Objective 2, limited literature has yet investigated the connectedness of IEs (Binz & Truffer, 2017) and almost never the connectedness of EEs. Yet, inter-IEE dynamics are likely to impact the competitiveness of individual ecosystems and their organizations, particularly in a time of major restructuring of economic and political collaborations (Gur & Dilek, 2023; Rikap, 2019). Hence, Papers 4 and 5 provide two empirical investigations on the role played by KIEs in connecting different IEEs, whether by participating in public-private-partnerships or by their own professional mobility across employers and regions.

Last, Objective 3 aims at transferring empirical insights into practically useful ones. While Papers 6 and 7 sketch novel data-driven management approaches to foster within-firm and between IEE innovation with big data and Artificial Intelligence (AI), Papers 8, 9, and 10 develop the relatively underexplored concept of Professional Social Matching (PSM) and sketch the design of recommendation systems for data-drive collaborations. These works provide conceptual and empirical investigations, and hopefully will contribute to innovating partnership matchmaking within and across IEEs (Archer & Zytko, 2019).

1.5 Structure

The remaining of this Thesis is structured into four chapters. First, the Theoretical Landscape further expands on the key concepts of this work, including IEs, EEs, IEEs, and KIEs. Then the Analytical Approach briefly summarizes empirical elements common to individual papers, ranging from the availability and collection of data, to the definition of adequate units of analysis, and the presentation of unique methodologies. Third, the Research Outputs is organized into three sections, each corresponding to one of the objectives just presented and summarizing individual papers within. Last, the Discussion and Conclusion addresses each objective attempting to distill key insights and opportunities that emerged from individual papers into a more coherent conclusive take-away. Given the limitations imposed by its structure, this Thesis only summarizes the common and most important aspects of the Candidate's PhD journey, inviting the reader to refer to the original papers for a thorough presentation and discussion of their contribution to the literature.

2. Theoretical Landscape

2.1 Innovation ecosystems

IEs are complex networks of actors, typically firms, universities, research institutions, government agencies, and other organizations that interact to develop, disseminate, and commercialize new products, services, and technologies (Suominen et al., 2019). Thought actors adopt a combination of collaborative and competitive behaviors, sometimes referred to as co-opetition (Carayannis et al., 2018; Iansiti & Levien, 2004), IEs are characterized by a high degree of interdependence and co-evolution among actors, from which their emergence, sustainability, and prosperity ultimately depends (Carayannis et al., 2018; Iansiti & Levien, 2004).

This concept has been approached from a variety of academic perspectives. Evolutionary economics, for example, focuses on the role of innovation in driving economic growth and change, and the evolving nature of IEs. Studies in this field have primarily investigated the composition and structure of IEs, particularly focusing on the identification of topologies, on longitudinal evolutions, and on the role of orchestrating actors, primarily governments and corporate players, in steering the evolution of IEs towards desired directions (Dedehayir et al., 2018; Mack & Mayer, 2016; Nelson & Winter, 2002). A similar approach has also been taken by the research on innovation systems, from which the concept of IEs largely descends. This literature stream studies the complex interactions and relationships between different actors within a specific setting, such as a region, a country, or an industry, and how these interactions cumulatively support innovation (Binz et al., 2014; Suominen et al., 2019).

Conversely, the literature on strategic management and entrepreneurship has approached IEs from the perspective of individual firms. One key antecedent is considered the concept of business ecosystem, in which companies interact to develop complementary products or services, and compete to capture value (Moore, 1993). This is particularly true in the case of business platforms, where generally one player orchestrates others to develop products and services complementary to its own (Foros et al., 2013), but applies also to government or university-sponsored IEs (Addo, 2022; Thomas et al., 2021), and particularly for the development of sustainability-oriented innovations (Quitzow, 2015). Indeed, this literature has been increasingly recognizing also the contribution of non-business actors, interpreting innovation and entrepreneurship as a distributed and collective activity, highly dependent on the availability of resources in the environment as the further subsection on EEs will describe (Marchesani et al., 2022; Theodoraki et al., 2018).

These resources are accessed thanks to existing relations with other organizations in the network, which businesses actively explore to identify complimentary assets to their own (Carayannis et al., 2018; Malerba & McKelvey, 2020). This is particularly salient for knowledge, as it constitutes the primal resource for any innovation, is extremely challenging to copy from competitors, but can be shared at almost no marginal cost (Chesbrough et al., 2014; Rohrbeck et al., 2009). On the one hand, in their search for resources, actors establish collaborations across geographical and industrial boundaries (Di Minin et al., 2019; Järvi et al., 2018; Nambisan et al., 2019; Scuotto, Santoro, et al., 2017). On the other, in scientific research and technology development, multidisciplinary teams collaborate from different countries to produce and share knowledge via the internet overcoming traditional barriers (Büttner et al., 2022; Alberto Di Minin & Bianchi, 2011; Marginson, 2022; Yang et al., 2021). Hence, knowledge networks increasingly transcend the confined spaces of institutions and regions, and these dynamics become increasingly global (Binz et al., 2014; Gertler & Levitte, 2005; Ritala & Almpanopoulou, 2017).

Drawing from the innovation networks literature, this web of relations is often multilocal and multiscalar, as organizations share resources across geographical boundaries and industrial or disciplinary communities, and aggregate in clusters of more closely connected organizations (Carayannis et al., 2018; Etzkowitz & Zhou, 2006; Xu et al., 2018). Since access to new resources depends on the connections that a specific organization has with others as well as on the connections that they have, not all organizations display equal opportunities for accessing and exploiting knowledge and other assets. This fact has determined an increasing interest in the study of networks, as key predictors of the opportunities available to each actor to access new resources and, to some extent, steer the ecosystem itself (Hurmelinna-Laukkanen & Nätti, 2018; Ritala et al., 2022).

As a result, the concept of IE has been increasingly employed by governments as a general paradigm to drive and support innovation and growth. On the one hand, governments are increasingly focusing their attention on sustainability-oriented technologies, products, and services. As they try to address complex and wicked challenges for which uncertainty abounds and no clear understanding is available, engaging actors with the widest range possible of expertise and assets becomes crucial (Carayannis et al., 2012). Moreover, these actors would be responsible not only for developing a new technology, but also for adopting and scaling it up quickly so as to avoid potential mismatches between available technologies and industry or societal needs (Adner, 2006). Last, as the ecosystem concept highlights, these actors would not only provide complementary resources and provide opportunities for iterative development and use of technologies, but also co-evolve over time organizing themselves in fruitful and complementary relations (Carayannis et al., 2018; Gifford et al., 2021). However, favoring the collaborations that would best achieve these objectives while preserving the competitive advantage of local ecosystems remains challenging.

2.2 Entrepreneurship ecosystems

Though discussed since the Nineties, only in the last decade the concept of EE has seen empirical diffusion and advancements in theorization (Cavallo et al., 2019). As for other strictly connected terms such as business ecosystem (Iansiti & Levien, 2004; Moore, 1993), or IE (Zahra & Nambisan, 2011), it expands the focus from the heroic entrepreneur to its environment, thus including also the entrepreneur's relationship with peers and other diverse actors. Accordingly, the concept points to the major relevance that communities, culture, and interactions have on the chances of entrepreneurial success, and constitutes a highly contextual, evolutionary, and nonlinear perspective on entrepreneurship (Feld, 2020; Stam & Spigel, 2016). In these terms, it has been used to investigate different contexts and levels (Spigel, 2017; Tsvetkova, 2015).

The key elements of EEs were introduced in the Nineties referring to the Silicon Valley (Bahrami & Evans, 1995) and the entrepreneurial productivity deriving from the cumulative interactions between actors within a same region (Spilling, 1996). Different theories on the emergence and persistence of EEs (Thompson et al.,

2018) focus on clustering (Delgado et al., 2010), government support (Erkko Autio & Thomas, 2018), bonds among actors and institutions (Mack & Mayer, 2016; Spigel, 2017), and value co-creation (Adner, 2017). Nonetheless, they generally agree on recognizing EEs as an evolutionary and spatially bounded phenomena (Brown & Mason, 2017), each undergoing different phases in which they rise, grow, decline, and regenerate (Alvedalen & Boschma, 2017; Cantner et al., 2021). The concept presents major similarities to IEs, innovation systems, and industrial clusters (Alvedalen & Boschma, 2017; Brown & Mason, 2017). What ultimately distinguishes them is considering entrepreneurship – rather than innovation or economic productivity at large – the engine behind their lifecycle, and the birth and growth of new enterprises as their primary output (Alvedalen & Boschma, 2017; Brown & Mason, 2017).

Drawing from the recent work of Stam and van de Ven (2021), an EE could be analytically organized into three main institutional pillars, and namely Formal institutions, Culture, and Networks, each contributing to the ecosystem with endowments such as Physical infrastructure, Demand for products or services, Service intermediaries, Talents, Knowledge, Leadership, and Finance. These are the equivalent of abiotic resources (e.g. nutrients, water, rocks) available in a natural ecosystem to the multiplicity of species that inhabit it (Stam & Spigel, 2016). As living beings metabolize these resources to grow and replicate, so do entrepreneurs and enterprises, as they combine them to generate innovations, compete with each other, and scale up, and often contribute back to their ecosystem with additional knowledge, talents, and funding, or other resources (Carayannis et al., 2018; Stam & van de Ven, 2021).

In this environment, diverse actors including corporations, small and medium enterprises, startups, but also governmental bodies, universities, research centers, and customers interact, both in competitive and collaborative ways (Carayannis et al., 2018; Cavallo et al., 2019; Theodoraki et al., 2018). Accordingly, as for other types of ecosystems, EEs are significantly dependent on the availability of sufficient resources and functionally complementary actors, hence justifying the focus on local contexts (Colombelli et al., 2019; Stam, 2015). In this perspective, material and immaterial assets, and particularly knowledge, are similar to abiotic resources available in natural ecosystems (Stam & Spigel, 2016). As natural species metabolize these resources to develop and replicate, so do organizations in EEs as they combine them to generate new knowledge, products, and services, which ultimately nurture back the local humus (Carayannis et al., 2018; Stam & van de Ven, 2021). While mere spatial distance are likely to be of less relevance in the future due to the progressive expansion of business and innovation networks as well as to digitalization (Z. J. Acs et al., 2017; Florida et al., 2017), context still remains of great relevance as entrepreneurship emerges from a combination of global as well as local forces (Bereznoy et al., 2021; Del Giudice et al., 2017).

Indeed, multiple voices in academia have been recognizing that the concept of EE has often received simplistic usage in empirical research. On the one hand, most studies have assumed the scale of EEs to be fixed and corresponding to administrative boundaries of cities, regions, and less frequently countries (Cao & Shi, 2021; Fischer, Meissner, et al., 2022), neglecting that different economic processes happen at different levels and in different places (Bailey, 1983; Carayannis et al., 2018). On the other, there has been an excessive focus on the composition of EEs and less on their structure and relations (Brown & Mason, 2017; B. Carlsson & Stankiewicz, 1991; Ferrary & Granovetter, 2009). In particular, research has neglected the relationships between actors from different locations, furthering the analytical understanding of EEs as disconnected entities (Fuller-Love & Akiode, 2020). Thus, this perspective has often overlooked the actual multiscalarity of many processes in EEs (Carayannis et al., 2018; Fischer, Meissner, et al., 2022).

2.3 Innovation and entrepreneurship ecosystem connectedness

IEEs are complex networks of actors, notably firms, universities, and governments, that collaboratively produce and share new technical knowledge to develop new products and services (Brown & Mason, 2017; Suominen et al., 2019). Despite adopting a combination of collaborative and competitive behaviors, they feature a high degree of interdependence and co-evolution between participating actors (Adner, 2006; Iansiti & Levien, 2004).

Researchers have examined the intricate links and interactions between actors in a same region, country, or industry (Suominen et al., 2019; Thomas et al., 2021), but more recently also in a global perspective. Indeed, the production of scientific and technical knowledge has been increasingly globalized in the last decade, particularly for the expanding reach of universities and multinational companies (Conlé et al., 2023; Ervits, 2020). As organizations started collaborating across borders to access specialized knowledge, the network of their cumulative interactions has led to the emergence of IEEs beyond the boundaries of individual regions and countries. Since local interactions have not stopped, the result are multi-local and multiscalar ecosystems, in which actors simultaneously interact in different locations and at different spatial scales (Carayannis et al., 2018; Dewald & Fromhold-Eisebith, 2015).

This topic has been often investigated relying on network theory. At the local level, networks of organizations and individuals are analyzed to understand the flow of resources and knowledge between them. This can include analyzing the density and centrality of different nodes within the network, as well as the types of connections and collaborations that exist (Del Vecchio et al., 2017; Schuurman et al., 2016). At the regional level, the focus often shifts to understanding the relationships and interactions between different local networks, and how they contribute to regional innovation. This may involve analyzing the degree of connectivity between local networks, as well as the types of organizations and institutions that bridge them (Gallié et al., 2013; Parida et al., 2019). Lastly, at the national or global level, the focus converges towards the overall structure and dynamics of the IEEs, including the role of government policies, international collaborations, and global networks (Binz et al., 2014; Del Giudice et al., 2017). Despite different levels of analysis tend to focus on different topics, the nature of multiscalar dynamics inevitably offers to account for micro, meso, and macro factors and patterns simultaneously (Carayannis et al., 2018). Accordingly, some researchers have adopted network theory to identify key actors also in global dynamics, and to understand how they influence the transfer of knowledge and technologies with their local and global collaborations (Rikap, 2019; Zhong et al., 2022).

Not all organizations exhibit equal opportunities for obtaining and utilizing knowledge and other assets, since access to new resources depends on the connections that a particular organization has with others as well as on the connections that they have (Burt, 2001). This feature has led to a rising interest in the study of ecosystem networks, which serve as important indicators of actor's chances to acquire new resources and, to a certain extent, control the ecosystem itself (Hurmelinna-Laukkanen & Nätti, 2018; Ritala et al., 2022). Inevitably, actors possessing many and diverse collaborations have improved opportunities to access and recombine knowledge (Malerba & McKelvey, 2020). For instance, actors deeply ingrained in the network are ideally positioned to orchestrate others or benefit from spill overs (Gudmundsson & Lechner, 2006; Kadushin, 2002). Conversely, actors joining otherwise distinct clusters serve as bridges, effectively gaining control over the flow of knowledge between the clusters and benefitting from a wider range of resources (Burt, 1995; Hoegl & Schulze, 2005). While bridging positions would be more attractive for knowledge exploration, more central positions would offer an advantage for knowledge exploitation (Burt, 2001; Grenfell, 2008; Wang et al., 2020).

Accordingly, the structure of the collaboration network becomes crucial to determine the opportunities of individual organizations to access valuable resources in the ecosystem, as well as to determine the evolution of the ecosystem itself (Rikap, 2019; Xu et al., 2018). This is frequently the outcome of transnational partnerships interwoven by universities or multinational corporations, making them crucial players in the emergence of multiscalar and multilocal IEEs (Conlé et al., 2023; Del Giudice et al., 2017), and ultimately motivating researchers to adopt a multiscalar perspective (Binz et al., 2014; Carayannis et al., 2018). These brokering positions serve as intermediaries between various places and give organizations access to more diversified information to be recombined into new innovations (Malerba & McKelvey, 2020). While it may ultimately be advantageous for all connected ecosystems (Chen et al., 2015; Ritala et al., 2022), in times of harsh technological competition it may also lead to undesired spillovers or dependencies towards foreign actors (Gulo & Dwiastuti, 2022; Quitzow, 2015).

2.4 Knowledge-intensive entrepreneurship

The concept of knowledge-intensive ecosystems combines Schumpeterian economics, evolutionary economics, and IE literature to delineate a peculiar form of innovation, in which *"Knowledge-intensive innovative entrepreneurs* (KIEs) *are involved in the creation, diffusion, and use of knowledge; introduce new products and technologies; draw resources and ideas from their innovation system; and introduce change and dynamism into the economy"* (Malerba & McKelvey, 2020, p. 503; Sousa & Silva, 2019). Accordingly, KIEs are risk-taking organizations that, whether by discovering or creating them, exploit opportunities to recombine knowledge in new and useful ways (Alvarez & Barney, 2007; Kurz, 2012). This recombination destroys pre-existing products, services, processes, and models, hence perturbating their market, creating competition between incumbents and innovation-carrying ventures, and opening new opportunities (Bo Carlsson et al., 2013; Metcalfe, 1998; Nelson & Winter, 2002). This "creative destruction" is a fundamental process in the economy, as incumbents and new businesses interact with each other and other societal actors, learn and co-evolve, ultimately innovating their offer as well as themselves and existing institutions in non-equilibrium and non-linear processes (Lundvall, 2007; Metcalfe, 2001; Moore, 1993; Murmann, 2003; Nelson, 1994). Ultimately this fosters new knowledge generation, innovation, competitiveness, and economic growth, and increases the overall problem-solving capacity of organizations and societies (Carayannis et al., 2018; Malerba & McKelvey, 2020; Orton & Weick, 1990)

Though typical of new innovative enterprises and start-ups, this type of behavior may be adopted also by established actors such as governments, universities, corporate incumbents, and non-governmental organizations. They may launch new internal or external ventures designed specifically for this goal, or reform themselves by adopting a novel strategy and business model, by reconfiguring the internal organization, or by significantly redefining offered products and services (Kuratko et al., 2015; Malerba & McKelvey, 2020; Rohrbeck et al., 2009). Indeed, innovative and entrepreneurial behaviors are fundamental for the survival of any business as wealth and competitiveness is increasingly associated with accessing, producing, and recombining knowledge from the surrounding ecosystem (Del Giudice et al., 2017; Malerba & McKelvey, 2020). Most typically, KIEs access knowledge from peers via alliances and platforms, as well as from universities, research centers, and governments (Dooley, 2019; Karamanos, 2012; Zahra & Nambisan, 2011).

Drawing from innovation networks literature, this web of knowledge relations is often multimodal and multiscalar, as organizations share knowledge across geographical boundaries and disciplinary silos, and aggregate in clusters of more closely connected organizations (Carayannis et al., 2018; Etzkowitz & Zhou, 2006; Xu et al., 2018). Since access to knowledge depends on connections that a specific organization has with others as well as from the connections that they have, not all organizations display equal opportunities for accessing and exploiting knowledge. While multiple taxonomies of network brokering positions exist (Hurmelinna-Laukkanen & Nätti, 2018; Ritala et al., 2022), two have been most prominently considering in this Thesis. First, brokers at the center of the network and strongly embedded in it have the highest chances of orchestrating activities from other organizations as well as accessing knowledge produced within the network via knowledge spillovers (Gudmundsson & Lechner, 2006; Kadushin, 2002). Second, brokers connecting otherwise separate clusters may work as bridges. This would give them access to more diverse knowledge than if deeply embedded in the network, as well as control over knowledge flow between the clusters (Burt, 1995; Hoegl & Schulze, 2005).

Both brokering roles may be interpreted for more selfish or selfless goals: businesses are more likely to seek brokering positions that give them opportunities for accessing and exploiting knowledge while other, often public, actors may be interested in solely facilitating knowledge flow to achieve larger societal benefits (Benneworth et al., 2009; Chesbrough et al., 2014; Ma et al., 2019; Pugh et al., 2016; Rohrbeck et al., 2009). In the first scenario, bridging positions would be particularly beneficial in the early stages of the development of an innovation and for knowledge exploration, while more central positions would be advantageous during its more mature development for knowledge exploitation (Burt, 2001; Grenfell, 2008; Wang et al., 2020). Conversely, in the case of selfless brokers, bringing positions would be ideal for connecting otherwise distant actors and favor technology transfer, while orchestrating positions would be best for steering the innovation process also by distributing resources and labor across organizations (Chen et al., 2015; Oinas & Malecki, 2002; Thomas et al., 2021; Wright et al., 2008).

However, only few studies have openly conceptualized the role operated by relocating entrepreneurs in connecting multiple locations (Duan et al., 2022; Fuller-Love & Akiode, 2020). As KIEs move between IEEs, in each new location they build new social relations thus indirectly connecting organizations from different EEs (Fuller-Love & Akiode, 2020). Moreover, via their embeddedness in multiple ecosystems (Duan et al., 2022), they also connect EEs to one another leading to the emergence of proper mobility networks which favor further relocations and exchanges between EEs (Elo & Servais, 2018; Nogle, 1994). This is a similar phenomenon to that underlying the emergence of global innovation systems (Binz et al., 2014; Binz & Truffer, 2017) and, as it has been already suggested (Del Giudice et al., 2017; Knight & Liesch, 2016; Mainela et al., 2014), could be a crucial mechanism by which EEs increase their connectedness and acquire multiscalar features (Alvedalen & Boschma, 2017; Binz & Truffer, 2012; Coe & Bunnell, 2003).

3. Analytical Approach

3.1 Traditional and novel data sources

Works from this Thesis leveraged a multiplicity of highly granular data sources. Bibliometric and patent data from common repositories such as Scopus, Web of Science, and Google Patents have long been used to map knowledge and innovation relations at different levels (Rikap, 2019; Xu et al., 2018), and were employed in Papers 4, 9, and 10. Next to these traditional sources, the Candidate collected original data from a major professional social network (Te et al., 2022; Zhu et al., 2018). These include information on individual organizations to map their engagement with novel technologies (Paper 1) and sustainability issues (Paper 2); published job posts to capture the demand for green talents in different globally relevant EEs (Paper 3); and, last, information on individual KIEs and their mobility (Paper 5). The first-hand collection of data constituted a major burden on these research activities, and required significant effort for the combined use of multiple techniques in computer science, from web scraping to Natural Language Processing. However, it enabled to generate unique insights on the phenomena of interest.

3.2 Units of analysis and methods

As already mentioned, these works investigated both within-ecosystem and between-ecosystem dynamics from a relational perspective. Individual organizations constituted the key unit of analysis in Papers 1, 2, 3, 4, 9, and 10. In Papers 5 and 7, however, organization-level information was aggregated to understand between-ecosystem dynamics, thus making individual IEEs the actual units. In line with the growing number of quantitative studies on IEEs, these papers primarily employed network analysis to understan ongoing dynamics between ecosystem actors or between ecosystems themselves (Isckia, 2009; Li, 2009; Xu, Hu, Qiao, & Zhou, 2020). Specifically, next to identifying typical network roles and configurations (Basole, 2016; Battistella, Colucci, De Toni, & Nonino, 2013; Panetti, Parmentola, Ferretti, & Reynolds, 2020; Xu et al., 2020), two specific techniques leveraging network analysis were employed.

A Stochastic Actor-Oriented Model was used to was used to investigate the factors influencing biotech KIEs mobility between EEs in Paper 5. This tool operates under the assumption that mobility dynamics are theoretically influenced by the unobserved behaviors of individual actors occurring in a continuous temporal framework between the observable waves in the empirical data, so that the dynamic network is considered the result of a continuous time Markov process (Ripley et al., 2020; Snijders et al., 2010). Enabling a distinction between node-specific exogenous factors (in this case EEs' elements) and network-specific factors (in this case the structure of the mobility network), this approach has been already used in migration studies at the national level (Leal & Harder, 2021) but never before at the subnational level or to study inter-EE mobility.

On the other hand, to perform a preliminary test of a PSM system, a descriptive picture of the global network of collaborations in photodegradation and photocatalysis technologies was constructed (Paper 9). Different strategies were conceptualized and tested to assess the consequence of applying different geographical boundaries when generating recommendations (Qi et al., 2022). Moreover, three alternative recommendation algorithms were tested and compared. On the one hand, the Preferential Attachment algorithm calculates the product of the degrees of the two nodes, hence favouring the connection between already well-connected nodes regardless of other structural aspects of the network (Liben-Nowell & Kleinberg, 2003). On the other, the Resource Allocation algorithm considers the number of shared neighbors between potential partners, thus favouring local clustering (Zhou et al., 2009). Last, the Within-Inter Cluster algorithm generates a score from the ratio of within-cluster and between-cluster common neighbors, thus further increasing the relevance of structural features in the network (Valverde-Rebaza & de Andrade Lopes, 2012).

4. Research Outputs

4.1 Objective 1: Exploring novel data sources for research and practice

Paper 1: Identifying Synergies and Barriers to the Adoption of Disruptive Technologies for Sustainable Societies – An Innovation Ecosystem Perspective

Authors

Matteo Spinazzola, Nicola Farronato, Veronica Scuotto, Marco Pironti

Executive summary

This paper contributes to the literature on the adoption of disruptive technologies for the transition to more sustainable societies by mapping businesses' uptake from the perspective of IEs. Disruptive technologies are believed fundamental to achieve more sustainable societies (Girardi & Temporelli, 2017; Kivimaa et al., 2021). For instance, 5G Networks and Artificial Intelligence are being used collect real-time data from environmental sensors, so as to regulate temperature in buildings with precision and reduce energy consumptions (Jo et al., 2013). The same technologies, integrated in Advanced Robotics, are being used to improve automation in factories and logistics to reduce carbon emissions, foster efficiency, and increase safety for workers (Cavalli et al., 2021; Nasiri et al., 2017). Similarly, Autonomous Drive is expected to significantly reduce noise and air pollution, as well as road traffic and accidents (Liet al., 2019; Stern et al., 2019). Comparatively, Drones are revolutionizing multiple sectors from air imaging, to agriculture, to the delivery of medical equipment in urban as well as remote areas (Ram Kumar et al., 2018; Tripicchio et al., 2015). Last, Blockchain technology is already employed to track environmental and social records to enable responsible supply chains, distributed energy production, and improved transparency (Corte et al., 2021; Di Vaio & Varriale, 2020; Imbault et al., 2017; Saihi, 2021; Upadhyay et al., 2021).

While multiple criticisms have targeted these technologies and particularly the environmental footprint deriving from the production and operation of their hardware, most academics and policy makers still recognize their overall positive contribution to society (Girardi & Temporelli, 2017; Hilty et al., 2014). Hence, the weak adoption of multiple disruptive technologies, including Artificial Intelligence, Robotics, and Blockchain in the European Union is particularly concerning: not only it would hinder competitiveness and growth, but also delay the social and environmental benefits that these technologies would provide (European Commission, 2021; Girardi & Temporelli, 2017). To support recommended policies aimed at enlarging the number of industries engaged with these innovations, at strengthening industrial synergies, and at fostering the uptake by Small and Medium Enterprises (SMEs), more research on the systemic nature of technology adoption and its relation with innovation is needed, particularly for lower geographical scales (European Commission, 2021; Radicic et al., 2020).

As a growing and successful approach, systematic IE mapping would is an ideal candidate for this task (Xu et al., 2018). However, because of the superior availability of scholarly and patent repositories, it has often focused on mapping the production of novel scientific and technological knowledge, leaving businesses' technology adoption to qualitative means (Rikap, 2019; Xu et al., 2018). Since only when businesses effectively adopt and commercialize existing technologies the ecosystem can flourish and the technologies' full benefits for sustainability can be leveraged, this is also a major gap in research.

To address the lack of knowledge on technology adoption dynamics at low geographical scales and of publicly available company information, it mapped the uptake of disruptive technologies by 17,000 businesses operating in the Italian region of Piedmont thanks to social network data (LinkedIn, n.d.). First, business information was analyzed with elementary text-mining techniques. 1,273 organizations from 115 different industries were found to have already engaged with at least one technology. Then, preliminary statistical analyses were performed and provided some initial but interesting results.

First, all six technologies were found to be already adopted by a small but considerable number of companies across a multiplicity of locations, organization sizes, and sectors. On the one hand, this confirms the applicability of this approach to map business actors in an IE. On the other, it supports only mild optimism on the diffusion of these technologies in Piedmont, as relative adoption numbers are still concentrated around high-tech businesses and overall behind the European average (European Commission, 2021). Indeed, these results confirm that some businesses face critical challenges in adopting novel technologies, particularly when located outside major metropolitan areas or small. This is possibly related to the lack of resources and institutional support that these companies face (Eller et al., 2020; Forman et al., 2005).

Considering the large number SMEs and their significant distribution in non-metropolitan areas, these findings confirm that the adoption of emerging and disruptive technologies could be meaningfully constrained in Europe (European Commission, n.d.-b). If this won't be addressed soon, it will hinder not only the competitiveness of companies and territories, but also the possibility to leverage these technologies to transition to more sustainable and smart societies (Hilty et al., 2014). This would imply less energy efficient and safe industrial activities, less transparent supply chains, no distributed energy production systems, as well as more air polluted and traffic congested cities (Girardi & Temporelli, 2017; Hilty et al., 2014).

While some technological innovations were clearly more relevant for specific industries (e.g. Autonomous Drive for Automotive and Drones for Aviation and Aerospace), these innovations reached also other sectors. There, synergies for technology adoption emerged as companies contributed with complementary products and services upstream and downstream of the value chain. This confirms the benefits of adopting an IE perspective to study technology adoption (Adner, 2006; Xu et al., 2018). However, similar results are only preliminary and further research is necessary to make them meaningful, for instance by comparing value-chain synergies across sub-ecosystems or geographies so to identify ideal patterns and benchmarks. One application may focus on European Smart Specialization Strategies and their contribution to competitiveness and sustainability (Morisson et al., 2020; Veldhuizen, 2020). Alternatively, a transition management perspective may focus on how disruptive innovations could be scaled up across industries, markets, and institutions to shift current sociotechnical regimes to more sustainable positions (Kivimaa et al., 2021). More data and advanced techniques, together with a geographically comparative perspective, will further strengthen these results and maximize the benefits of employing social networks as data sources. Nonetheless, this study already brings multiple contributions to science and practice.

It delivered first preliminary results on the synergetic adoption of disruptive technologies in Piedmont, confirmed existing evidences on the challenges faced by specific actors in uptaking new technologies, and provided a proof of concept for using a social network to map IEs. SMEs are the backbone of the European economy and yet are struggling to adopt key disruptive technologies. Provided adequate incentives, they may uptake them and easily scale up, involve more businesses and societal actors, and challenge existing less sustainable technological regimes (Kivimaa et al., 2021; Lasagni, 2012). However, to do that, they would have to be first embedded in solid ecosystems where they may acquire resources and develop synergies within value chains as well as across sub-ecosystems (Forman et al., 2005; Lasagni, 2012; Matt et al., 2021). This demands policy makers to create such incentives and entrepreneurs to engage with other businesses for their own and the collective good (European Commission, 2021). Thanks to its IE perspective, this work contributes to the understanding of this complex but crucial phenomenon and, hopefully, to leveraging the full benefits of these technologies for the transition to smarter and more sustainable societies (Kivimaa et al., 2021).

Paper 2: Anatomy of an Innovation Ecosystem: How Do Circular Economy and Social Impact Actors Interrelate? A Case Study on Catalonia

Authors

Cottafava, Matteo Spinazzola, Laura Corazza, Sònia Llorens i Cervera

Executive summary

This work contributes to the investigation of IE in management research by advancing ecosystem mapping with new data-intensive approaches and by proposing a novel Decision Support System (DSS) for practitioners and policy-makers to analyses emergent topic trends and potential convergence between sectors. Scholars from different literature streams such as on IE (Lynham, 2002), industrial clusters (Michael, 2003), and relational stakeholder theory (Patil et al., 2023), agree that innovation emerges from the interaction between different actors and often at the crossing between two, or more, sectors. While there has been a growing attempt to leverage and steer these interactions towards desirable ends (Addo, 2022; Jütting, 2024), the necessary quantitative assessments of IE actors has been lacking behind, particularly neglecting socio-cultural dimensions (Carayannis et al., 2018). Hence, this work contributes to IE literature by proposing a novel Information System (IS) for policy-makers to identify synergies and barriers between different fields in a regional IE. Drawing on Information Systems Design Theory, a three-step methodology was tested on the Catalan ecosystem by analyzing the description of more than 70,000 social network (LinkedIn, n.d.) webpages to identify the relationships between Circular Economy (CE) and the Social and Solidarity Economy (SSE). Thematic similarities, potential synergies and existing barriers between CE and SSE-engaged actors were highlighted via structural topic modelling.

Despite the current convergence between the two concepts in the scientific literature, what emerged from the mapping exercise is that, currently, the two concepts are still far from each other. In particular, entities working on SSE are mainly focused on branding, marketing and communication activities, on investment and funding, and on training and people's lifestyle. On the other side, entities related to CE are more focused on technical and industrial environmental-related activities. Accordingly, the convergence of the two paradigms should be supported by proper public policies or by ad-hoc entrepreneurial strategies at the ecosystem level (Carayannis et al., 2021; Panetti et al., 2020). This convergence may benefit both sectors, as SSE-focused organizations may overcome current critics related to the impact washing phenomenon by strengthening their activities to real actions while, on the other side, CE-related ones may improve their communication by strengthening their relations with social entities. Ultimately, this will foster the capacity of IEs to produce value and pursue sustainability (Findlay & Moran, 2019).

Beyond the specifics of the Catalonia case study, this paper shows that recent advancements in the automatic collection of web data, such as from organizations' websites and social networks, may provide great benefits to the mapping of IE (Rowley, 1997). Indeed, as long as potential limitations and risks concerning accuracy and legitimacy are taken into account and properly dealt with (Matteo Spinazzola & Cavalli, 2022), these data sources could reveal fundamental to go beyond techno-centric visions of innovation (Xu et al., 2020). Academically, this will enable to effectively test existing theorizations of the intricate interweaving that diverse actors and processes have with one-another, and particularly concerning the socio-cultural dynamics within the Quadruple and Quintuple Helices (Carayannis et al., 2018, 2021). More practically, this approach may support policymakers and practitioners. On one side, policy-makers may take advantage of the analysis of new trends at the ecosystem level in order to properly design new policies to facilitate the circular and the green transition of local territory (Rahul et al., 2018). On the other hand, practitioners, both from large corporations and SMEs or small NGOs may exploit this methodology to support their businesses. Large corporations may use the methodology to develop proper strategies by identifying shortcomings in a particular geographical area, while SMEs or small NGOs may take advantage of the results, if properly released in open data or public web platform, to have a more comprehensive vision of their territory (Cottafava & Corazza, 2021).

Learning from this study, further research could combine social network data with more traditional data sources provide a much more comprehensive picture of IE (Xu et al., 2020) or expand its geographical scope beyond regional or national boundaries (Binz & Truffer, 2017). Moreover, once the fundamental data and algorithms are in place, the academic research could expand its objectives to investigate new questions both in terms of thematic complementarity (Panetti et al., 2020) as well as of how this complementarity influences actors' interactions (Cai et al., 2019). Last, addressing emergent issues concerning the efficient use of existing information, a next-generation information system could go beyond providing on-demand policy analyses, and rather turn to predicting or even recommending adequate policy strategies (Kinne & Axenbeck, 2020; Olsson et al., 2020). The use of big data and our ability to learn from it are massively expanding. Despite the contributions of this work, we are but at the beginning of the systematic use of data and algorithms to understand and steer complex societal processes.

Paper 3: Entrepreneurial Ecosystems' Transition to Sustainability: Exploring the Demand for Green Talents in 20 Global Cities

Authors

Matteo Spinazzola, Nicola Farronato, Veronica Scuotto, Marco Pironti

Executive summary

EEs are growing in terms of quantity, diversity, and relevance to the economy and society (Theodoraki, Dana, et al., 2022). Based on the 2022 global report issued by Startup Genome, at least 300 emerging ecosystems can be identified globally, each with unique characteristics, compositions, resources, and specializations (Startup Genome, 2022b). The composition of EEs is enriched by different entities such as corporations, SMEs, startups, and incubators, across a variety of emerging technologies and sectors (Cavallo et al., 2019; Theodoraki, Messeghem, et al., 2022). Specifically, entrepreneurs and their startups' prosperity increasingly derives from the health, richness of resources, and interconnectedness of the local ecosystem, as innovation and entrepreneurship increasingly rely on distributed, complementary, and complex functions (Feld, 2020). Moreover, they contribute back to their ecosystem by providing infrastructure, financial resources, and human capital that foster local innovation and development, thus sustaining a virtuous cycle and the birth of more startups (Acs & Armington, 2004; Kasturi & Subrahmanya, 2014). As they enlarge, EEs have impacts beyond the local boundaries, and increasingly so due to the digitalization and remotization of the economy (Cukier & Kon, 2018; Dabić et al., 2020).

Yet, EEs and their local actors are currently challenged by the urgency to transform their practices, processes, and products to reduce their detrimental impact on society and the environment (Audretsch et al., 2019). This is also relevant in light of the United Nations' 2030 Agenda: as governments fall short in pursuing the Sustainable Development Goals (SDGs) and dealing with their complexity (Biermann et al., 2022; Hickmann et al., 2022; Matteo Spinazzola & Cavalli, 2022), bottom-up innovation and entrepreneurship may be fundamental to drive the achievement of multiple SDGs, including SDG 4 – Quality Education, SDG 8 – Decent Work and Economic Growth, SDG 9 – Industry, Innovation, and Infrastructure, SDG 11 – Sustainable Cities and Communities (Cordova & Celone, 2019; P. P. Walsh et al., 2020). Hence, scholars have attempted to analyze the importance of sustainable EEs (DiVito & Ingen-Housz, 2021; O'Shea et al., 2021; Pankov et al., 2021; Theodoraki, Dana, et al., 2022).

To develop more sustainable EEs, additional and specific resources would need to be acquired, ultimately aiming to initiate self-reinforcing dynamics within EEs (Carayannis et al., 2018; Pelinescu, 2015; Stam & van de Ven, 2021). Crucially, these would include the recruitment of Green Talents possessing adequate knowledge, skills, abilities, attitudes, behavior and awareness to drive this transformation to sustainability (Cabral & Lochan Dhar, 2019; Glen et al., 2009). Hence, public and private actors are moving to understand and nurture the provision and attraction of Green Talents (ESCO, 2022; European Training Foundation, 2022), and some initial studies in this regard have been produced, specifically on sectors such as construction (Hamzeh et al., 2019), e-waste management (Bozkurt & Stowell, 2016), and education (McGrath & Powell, 2016). Nonetheless, there is still a lack of systemic understanding on necessary need for talents possessing green skills and knowledge, particularly at the level of EEs (Carayannis et al., 2018; Odugbesan et al., 2022; Ogbeibu et al., 2022, 2021)

To fill this gap, the present paper assessed the demand for Green Talents in city EEs, exploring recurring patterns, and ultimately identifying predicting factors. First, it was designed drawing on the

Quadruple/Quintuple Helix Framework and from multiple streams in evolutionary economics, regional development, and entrepreneurship (Carayannis et al., 2012, 2018). Then, after identifying 20 leading city EEs from the most recent Startup Genome report (Startup Genome, 2022b), almost 3.5 million online job vacancies (OJVs) published in in the month of November 2022 were retrieved and quantitatively analyzed with descriptive and inferential statistics (European Training Foundation, 2022; Lovaglio et al., 2018).

The preliminary analyses revealed that only 1.53% of all OJVs were aimed at Green Talents, but interesting patterns could be observed: they confirmed that employer-specific factors as well as EE-specific factors significantly influence the demand for Green Talents. Specifically, Construction, Mining and oil, Utilities, and Corporate services were confirmed to be in the first line to acquire these talents, while Finance and banking, Technology, and Legal were found to be lagging behind (LinkedIn, 2022; Sern et al., 2018). Moreover, the demand for Green Talents results higher for Manufacturing, Analytical, and Business jobs than to other types, coherent with the relevance of technical and analytical skills and the leading role played by the heavy sectors (Cabral & Lochan Dhar, 2019; ESCO, 2022). Additionally, local EE factors appear to influence the demand for Green Talents via OJVs, whether negatively such as EE Performance and green Talent availability, or positively such as availability of green Knowledge, Funding, or EE Focus on green enterprises. These results are only partially aligned with the literature on ecosystems, which would primarily expect positive relations to manifest (Carayannis et al., 2018; Stam & van de Ven, 2021). Further research is necessary to fully understand the motives of these negative influences.

Though this paper could leverage almost 3.5 million OJVs, of which more than 50,000 directed to Green Talents, dependence on a single source of data significantly limits the validity of this research. Similarly, Startup Genome Cleantech report is a valuable and accurate source of information on EEs and startups but provided already aggregated data that were not originally intended for this purpose. Accordingly, integrating additional data sources, including data on already employed personnel with green skills and traditional data sources on talents, would certainly strengthen these results and constitute the next step of this work.

Nonetheless, these analyses already contribute to the literature with first empirical results on the demand for Green Talents in EEs and confirm existing theories on ecosystem entrepreneurship at the city level. Moreover, they highlight the importance of employer-specific and EE-specific factors, despite hinting at previously undetected negative feedback in EEs. Being crucial for the growth of ecosystems and their transition to sustainability, further research is certainly necessary to investigate them (Carayannis et al., 2018; Theodoraki, Dana, et al., 2022). These results also contribute to informing key actors, and namely businesses, universities, and governments, in city ecosystems. They provide first insights on the current demand for Green Talents, which may be further used to explore future scenarios in the prosecution of this work. Specifically this data could be used for benchmarking between cities and sectors (Startup Genome, 2022a) and to support data-driven policies for the acquisition of Green Talents, the launch of new subsidiaries, or the design of synergetic training and industrial programs (Carayannis et al., 2018; Del Giudice et al., 2017; Hausmann et al., 2014). Indeed, previous research has shown that bottom-up approaches underpinned by local ecosystems could be crucial to complement governmental top-down policies and meet the SDGs (Cavalli et al., 2022; Cillo et al., 2020; Palumbo et al., 2021). To achieve this, EEs and organizations within them need to acquire additional and specific resources, including by attracting and employing workers with adequate knowledge and skills (Pelinescu, 2015; Stam & van de Ven, 2021). By shedding light on the demand for Green Talents in 20 leading city EEs, this work aims to support their transition (Carayannis et al., 2018; Theodoraki, Dana, et al., 2022).

4.2 Objective 2: Investigating IEE's connectedness from KIEs activities

Paper 4: A Knowledge-intensive and Innovation Network Perspective on Global Knowledge Brokering - An Explorative Study on Sustainable Aviation Fuels

Authors

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Executive summary

This explorative article contributes to the literature on knowledge-intensive ecosystems and innovation networks by combining the two perspectives to investigate global knowledge brokering in the Sustainable Aviation Fuels (SAFs) sector. Knowledge is a fundamental resource for innovation, entrepreneurship and competitiveness (Del Giudice et al., 2017; Malerba & McKelvey, 2020). Growing research on knowledge-intensive ecosystems (E. Autio & Thomas, 2014; Sousa & Silva, 2019) is showing how accessing and brokering knowledge is reshaping the source of competitive advantage (Borgh et al., 2012; Bart Clarysse et al., 2014) and moving companies to adopt novel strategies and business models (Karagouni, 2018; Muscio et al., 2016). This includes the use of open innovation approaches, platforms, and complementary product development, so that companies may more easily access and recombine knowledge in novel products or services (Malerba & McKelvey, 2020; Nambisan et al., 2019; Rohrbeck et al., 2009).

More than in the past, organizations draw from internal as well as external knowledge to produce innovation. Where small enterprises and new ventures search knowledge externally to compensate for their lack of internal resources (Scuotto, Santoro, et al., 2017), large corporations and incumbents set up platforms to internalize diverse and dispersed knowledge compensating for their own lack of flexibility (Rohrbeck et al., 2009; Zahra & Nambisan, 2011). To this aim, businesses actively engage with peers, governments and universities (Del Giudice et al., 2017; Guerrero & Urbano, 2017; Secundo et al., 2017). What results is a network of reciprocal connections, in which the opportunities to access and recombine knowledge significantly depend on the participation in multiple networks and on the role of brokering organizations that enable knowledge flow between actors, industries, and domains (Ritala et al., 2013; Ritala et al., 2022; Zahra & Nambisan, 2011; Zhang et al., 2018). Under specific circumstances, these networks bring to the emergence of IEs in which different societal actors entertain complex cooperative as well as competitive interactions, pursue shared and individualistic goals, and co-evolve under the drive of intentional design and emergent behaviors (Moore, 1993; Ritala et al., 2013; Ritala & Almpanopoulou, 2017).

In line with this, governments are working to initiate knowledge-intensive IEs in which new ventures and established companies alike may tap in locally and globally produced knowledge to convert it into commercial solutions (Gifford et al., 2021; Hockerts & Wüstenhagen, 2010). Crucially, this includes the launch of public-private partnerships (PPPs) for sustainable technologies and processes as a typical instrument to implement mission-oriented policies (Lassen et al., 2015; Nissen et al., 2014). While this is expected to effectively steer societal actors and resources towards collective goals (Carayannis et al., 2018; Kattel & Mazzucato, 2018), it may be ineffective or result in asymmetrical and dysfunctional relations (Kyle et al., 2017; Lazonick & Mazzucato, 2013; Quitzow, 2015; Rikap, 2019). Hence, understanding how knowledge is brokered in this global network would be crucial to assess and maximize opportunities for knowledge recombination, entrepreneurship and innovation, but has not been approached from the perspective of knowledge-intensive ecosystems yet (Bertello et al., 2022; Carayannis et al., 2018).

An exemplary case of this phenomenon is the development of SAFs. Burning oil-based aviation fuels is responsible for as much as 2% of global GHG emissions every year, a number expected to massively increase as passengers are on the way to double (ATAG, 2017; IATA, 2018). Hence, decoupling aviation from oil constitutes a key priority for mitigating climate change and improving the environmental and business sustainability of this sector (Chiaramonti & Goumas, 2019). For an immediate reduction of GHG emissions, SAFs' research and development (R&D) has been focused on drop-in fuels that could be compatible with existing jet systems and aviation infrastructures, and produced by thermo-chemically converting crop and waste feedstock into biofuels (Chiaramonti et al., 2014; Chuck & Donnelly, 2014). While existing literature provides a comprehensive picture of the technological and supply chain readiness of SAFs conversion processes (Chiaramonti et al., 2014; Doliente et al., 2020; Ebrahimi et al., 2022; Gutiérrez-Antonio et al., 2017), as well as of their environmental and economic performances (Prussi et al., 2021; Ringsred et al., 2021; Wei et al., 2019), little is known about the underlying innovation dynamics. Indeed, these technologies have been developed with significant policy, monetary, and research support from major national governments and research institutions, as well as by globally reaching international organizations (e.g. ICAO and IATA), aircraft manufacturers (such as Boeing and Airbus), airlines (e.g. Air France- KLM, Lufthansa, etc.), and biofuel producers (such as Neste Oil, UOP Honeywell, etc.) (ICAO, n.d.; Ng et al., 2021).

Hence, SAFs conversion processes constitute a perfect case for applying the perspective of knowledge-intensive ecosystems and provide first explorative evidence on how actors broker knowledge in global innovation networks. This was achieved by systematically retrieving scholarly articles and patents on SAFs conversion processes from large databases (Web of Science and Google Patents) to assess the production of scientific and technological knowledge by individual organizations, as well as to map funding, co-authoring, and patenting collaborations, both intranationally and transnationally. Moreover, the effect of public-private partnerships on network structure and knowledge brokering was assessed.

As with any scholarly publication, external contingencies and deliberate choices determined several limitations afflicting this article. Yet, some key insights could be derived. Results show that governments, universities, and businesses, both established and entrepreneurial ones, collaborated to produce scientific and technological knowledge on SAFs. Interestingly there was no manifest participation of civil society to this endeavor. While civil society doesn't necessarily participate in knowledge production, lack of engagement may be a lost opportunity to inform and legitimate existing research and development, specifically since the production of SAFs from edible crops has some significant ethical implications. This partially contrasts with what would be expected of sustainability-related ecosystems (Binz & Truffer, 2017; Carayannis et al., 2012; Chiaramonti & Goumas, 2019).

Scientific knowledge production was dominated by USA, European, and Brazilian organizations, with governments primarily as financers and universities as articles co-authors; conversely, Chinese organizations, and particularly universities, were cumulatively the most active producers of technological knowledge via patents. These results confirm the high political interest in SAFs (Chiaramonti and Goumas 2019; Ng, Farooq, and Yang 2021) and possibly the sector's dependence on public funding (Rennings 2000). Since China is the largest patenting country in the world with a strong incentive system for patent-publishing universities as well as the largest and most growing market for civil aviation, a similar contribution isn't surprising (Fisch et al., 2016; WIPO, 2022; World Bank, n.d.). Last, though the cumulative output from entrepreneurial businesses was marginal, companies form the USA and Europe, and namely UOP Honeywell, Neste Oil, Standard Alcohol Co. of America, and Boeing contributed significantly to both forms of knowledge production, possibly indicating their crucial role within the network and as brokers between scientific and technological knowledge (Clarysse et al., 2014; Xu et al., 2018).

Once collaborations were mapped, Chinese organizations were found to be mostly disconnected from the network while two major components, and namely a USA-Europe and a Brazil-Europe one, could be identified. Since the network structure changed significantly due to PPPs, their effect on brokering was also separately presented. Overall, when global networks are considered, incumbents may occupy better positions for brokering compared to new ventures, and even broker between them and the emergent network. Hence, despite geographical distance can be easily overcome by digital technologies (Scuotto, Santoro, et al., 2017; Trimi, 2008), lack of material and relational resources may still prevent entrepreneurial businesses from engaging in global collaborations (Karamanos, 2012; Reypens et al., 2016). Since the digitally-enabled globalization of knowledge and innovation is well-recognized (Binz et al., 2014; Di Minin et al., 2019; Yang et al., 2021), this may be explained by the intrinsically non-disruptive nature of drop-in biofuels, which sustain existing technological regimes (Hockerts & Wüstenhagen, 2010; Kivimaa et al., 2021), and the capital-intense and oligopolistic features of the aviation sector, which inevitably limits competition (Friedman, 1982; Knoll-Csete & Kárász, 2021). Accordingly, incumbents may be able to sustain their competitive advantage (Kuratko et al., 2015; Rohrbeck et al., 2009) while resource restriction and consolidated market structures may force entrepreneurial businesses to settle in niches (Kivimaa et al., 2021; López-Nicolás & Soto-Acosta, 2010; Rikap, 2019), possibly hindering the process of creative destruction (Alvarez & Barney, 2007; Kurz, 2012; Metcalfe, 1998)

This would confirm the possibility of synergetic dynamics between entrepreneurial ventures and incumbents. Though, in principle, both groups may act as KIEs (Kuratko et al., 2015; Malerba & McKelvey, 2020), the first is more likely to focus on producing specialized and innovative knowledge and solutions while the second provides the material and relational resources necessary to scale and diffuse them (Hockerts & Wüstenhagen, 2010; Orton & Weick, 1990; Rohrbeck et al., 2009). Moreover, since many industries fundamental for the transition to more sustainable economies, such as energy, transportation, and heavy industry, are both capital-intense and oligopolistic (Rissman et al., 2020; Yomogida, 2008), it isn't surprising that governments are attempting to initiate such synergies with major attention on the revitalization of these traditional sectors and their sustainability transition (Kattel & Mazzucato, 2018; Walravens et al., 2014). However, this study shows that while governments launch PPPs to stimulate the local emergence of knowledge-intensive ecosystems (Gifford et al., 2021), multinational businesses may disproportionately capitalize from that knowledge (Hockerts & Wüstenhagen, 2010; Lazonick & Mazzucato, 2013). Particularly if they were to occupy crucial bridging positions in the global network, as in the case of SAFs, they may be tempted to indulge in opportunistic behaviors detrimental to innovation and the societal transition to sustainability (Arel-Bundock, 2017; Granovetter, 2005; Lazonick & Mazzucato, 2013; Zhang et al., 2018)

Accordingly, this explorative study contributed to the literature on knowledge-intensive ecosystems in multiple ways. First, it rigorously combined the two emerging streams of knowledge-intensive ecosystems and global innovation networks, which have never been openly blended despite their common foundations in evolutionary economics and complex systems (Binz et al., 2014; Malerba & McKelvey, 2020; Ritala & Almpanopoulou, 2017). Second, this novel approach enriches existing literature with preliminary evidence on peculiar dynamics of knowledge brokering in global innovation networks, and specifically of asymmetries between incumbent and entrepreneurial businesses and between businesses and governments. Though they have already been assessed in the past (Lazonick & Mazzucato, 2013; Rikap, 2019), never before a knowledge-intensive perspective had been. Hence this work expands existing literature on knowledge brokering (Rohrbeck et al., 2009; Scuotto, Santoro, et al., 2017; Zahra & Nambisan, 2011), and provides highly needed insights on the dynamics underlying the transition to sustainability of traditional industrial sectors (Bertello et al., 2022; Gifford et al., 2021; Hockerts & Wüstenhagen, 2010). Thus, recommendations may be derived for policymakers and managers in the SAFs sector and possibly in others. To favor competitiveness and innovation, governments may dedicate particular attention to involving new ventures in their mission-oriented policies and not only in a subsidiary position (Gifford et al., 2021; Hockerts & Wüstenhagen, 2010). Additionally, entrepreneurial business may spend their limited resources to reach and bridge knowledge from distant actors, which would make them more important to the network and mitigate potential asymmetries (Burt, 1995; Rikap, 2019).

Paper 5: Connectedness of Entrepreneurial Ecosystems: Evidence from the Mobility of Knowledge-intensive Entrepreneurs

Authors

Matteo Spinazzola, Veronica Scuotto, Marco Pironti, Manlio Del Giudice

Executive summary

The concept of EE has emerged to describe the economic, social, and technological interactions sustaining and driving entrepreneurial productivity, frequently at the city or regional scale. Highlighting the dynamic, cumulative, and complex features of these interactions, it aims at explaining why some territories are better than others at attracting and growing businesses, and how such interactions evolve over time (Brown & Mason, 2017; Cantner et al., 2021; Mack & Mayer, 2016). These dynamics concentrate key actors and resources in the same geography. There, in the presence of a positive entrepreneurial culture and regulatory environment, the flow of capital, knowledge, and talents is highly facilitated, thus favouring the birth and growth of enterprises (Acs et al., 2014; Stam & van de Ven, 2021).

Given the density of resources and connections, EEs are ideal environments for KIEs to emerge and thrive (Bertello et al., 2022; Nicotra et al., 2018). This concept identifies the strategic behaviour of entrepreneurs actively acquiring resources (most notably knowledge) by interacting with other organizations, and recombining them into original innovations to obtain a competitive advantage in the market (Malerba et al., 2015; Moraes et al., 2023). Previous studies have specifically investigated how ecosystem features impact the development of such enterprises (Fischer, Salles-Filho, et al., 2022; Siqueira et al., 2023) and hinted at the role played by KIEs in dynamizing their local ecosystem (Malerba & McKelvey, 2020; Sousa & Silva, 2019) but research on the role of KIEs in connecting different ecosystems is still in its infancy.

Since KIEs actively search for resources beyond ecosystem boundaries, they are often ready to relocate (Bosetti et al., 2015; Elo & Servais, 2018). If, at the individual level, it can be interpreted as a maximization choice and has already been investigated multiple times (Stephens et al., 2019), the systemic consequences deriving from the relocation of KIEs have been rarely taken into account (Schäfer & Henn, 2018), particularly from a network perspective (Leal & Harder, 2021). Though this used to be a problem also for the investigation of IEs (Binz & Truffer, 2017), the EE literature has been slower to address it, probably for a lack of adequate data and a tendency to focus on spatial dimension at the expenses of more relational approaches (Audretsch & Belitski, 2017; Ferrary & Granovetter, 2009). Overall, this limited consideration for the connectedness of EEs hinders the multiscalar usage of the concept (Alvedalen & Boschma, 2017; Brown & Mason, 2017; Theodoraki & Messeghem, 2017) and, for the specific topic of interest in this paper, from a full understanding of the factors influencing the mobility of KIEs.

To address this gap, the present data-intensive study investigates KIEs' mobility providing empirical evidence at support of EEs' connectedness (Fischer, Meissner, et al., 2022). The model proposed by Stam and van de Ven (2021) to explain the functioning of – implicitly – isolated EEs was revised to account for the connectedness between EEs and explain the mobility of KIEs between them (Alvedalen & Boschma, 2017; Binz & Truffer, 2017; Carayannis et al., 2018). The starting EEs' framework is organized into three structurally nested components (Van De Ven, 1993). Productive Entrepreneurship is where resources are effectively recombined into New Enterprises, and can be interpreted as the key output of EEs as well as their engine (Blackburn et al., 2018). Next, the Resource Endowments component includes the assets available within EEs, while the Institutional Arrangement component constitutes the overarching landscape in which EEs emerge (Stam & van de Ven, 2021).

Moreover, to account for EEs' connectedness, the Network Structure component was added to the original model. Previous studies have shown that mobility flows between location pairs can be best understood when the dynamics between other locations are taken into account, thus requiring the adoption of a network perspective (Fawcett, 1989; Nogle, 1994). Within the context of this study, it implies that the mobility of KIEs is at least partially dependent on the structure of existing relocation flows between EEs. Though the topic doesn't seem to have received much attention from the literature on EEs yet (Alvedalen & Boschma, 2017; Walsh, 2019), in country-level studies it was found that migration networks see the emergence of multiple and sometimes balancing dynamics resulting from their structure.

Hence, the professional history of 3,897 biotech KIEs across 32 European countries over a 15-year time was analyzed. Though EEs are not necessarily thematic (Stam & van de Ven, 2021), KIEs' need for specialized knowledge motivates focusing the biotechnology industry from the perspective of within-sector concentrations and externalities (Depret & Hamdouch, 2010; Marshall, 1890). After an initial descriptive assessment, a Stochastic Actor-Oriented Model (SAOM) was employed to identify the key determinants attracting KIEs from one EE to another (Leal & Harder, 2021; Ripley et al., 2020). Crucially, this analysis included both location-specific variables for every EE (Stam & van de Ven, 2021), as well as the dynamics of the inter-EE mobility network itself (Leal & Harder, 2021).

This paper demonstrated that both local EE characteristics and inter-EE network features influence KIEs mobility, and that - at least at the regional level - they operate as self-reinforcing mechanisms for KIEs aggregation (Depret & Hamdouch, 2010; Malerba, 2014). As a result, biotech KIEs mobility across European EEs is characterized by multiscalar dynamics (Depret & Hamdouch, 2010; Motoyama & Knowlton, 2016), with a predominance of regional-level mobility. However, the "strength of weak ties" should not be overlooked (Granovetter, 1973). Further research should investigate the evolution of this "network of ecosystems" in different sectors (Hamdouch, 2008; Nicotra et al., 2018) and countries (Binz & Truffer, 2017), as well its implications for individual EEs. On the one hand, network positioning may influence resource recombination and productive entrepreneurship (Cooke, 2005; Depret & Hamdouch, 2010), as some EEs could be characterized by more endogenous entrepreneurial processes while others might be more dependent on exogenous ones (Binz & Truffer, 2017; Stephens et al., 2019). On the other, complementarity between closely connected EEs might emerge (Balland & Boschma, 2021; Rikap, 2019), and the role of EE super-connectors between regional networks would certainly require investigation (Saxenian, 1996; Waxell & Malmberg, 2007).

While policy makers can invest in creating ideal local conditions for the emergence of EEs, previous studies on the biotech sector have shown that network dynamics are harder to instantiate ex-novo (Orsenigo, 2001). Accordingly, while providing the necessary EE conditions, policy makers should also invest in attracting KIEs which – thanks to their multiple embeddedness (Duan et al., 2022) – could be major catalyzers of innovation and entrepreneurship (Harima et al., 2021; Lerner, 2010). This could be particularly relevant for Europe and the European Union, where policies directed at KIEs mobility would be fundamental to increase innovation and productivity in a non-zero sum logic (Ejermo et al., 2006; Liagouras, 2010; Lopes et al., 2021). Thought not focused on KIEs, the concept of inter-regional Smart Specialization could be the ideal policy ground to experiment in this direction (Balland & Boschma, 2021; Kruse & Wedemeier, 2022).

Ultimately, this study supports a more relational understanding of EEs and their processes at large (Brown & Mason, 2017). Thus, it provides an example of how mobility data might sustain this empirical and policy endeavor (Gluckler, 2007; M. Spinazzola, Farronato, Murray, et al., 2023), also favoring a convergence with existing literature on IEs and global innovation networks (Alvedalen & Boschma, 2017; Binz et al., 2014; Carayannis et al., 2018).

4.3 Objective 3: Conceptualizing novel management systems for IEE actors

Paper 6: Business Model Innovation with AI

This work summarizes key aspects of integrating AI in companies' business models, including the opportunities that this integration offers, as well as the challenges that need to be addressed for the adoption of this technology to be realized in the most sustainable way.

Since its initial proposition in the Nineties, the concept of business model has been widely used among academics and practitioners interested in providing a holistic description of company processes, canonically divided into the four pillars of Value Creation, Value Proposition, Value Distribution, and Financial Structure (Teece, 2010; Zott et al., 2011). To a large extent, this interest stems from the awareness that the business model significantly determines an organization's ability to be competitive and achieve good economic results (Zott & Amit, 2010). This has therefore led to underlining the importance of emulating the most successful business models by innovating companies in their internal logic (Doz & Kosonen, 2010; Mitchell & Coles, 2003). As a result, business model innovation has also become a topic of great scientific and practical attention (Foss & Saebi, 2017). This is generally understood to mean a non-trivial and intentional change, initiated by the highest levels of company management, of the fundamental elements of the company or of the links between them. Therefore, innovation can individually concern aspects such as the relationship with customers, partners and suppliers, the creation of value, and the distribution channels (Giesen et al., 2007; Koen et al., 2011), but also the overall architecture that holds these elements together (Amit & Zott, 2012; Santos et al., 2009).

Drawing from the existing literature (Faggella, 2021; Sena & Nocker, 2021; Steininger, 2019), from the integration of AI into its pillars four macro-types of business models can be identified. The first and most common pillar for the adoption of AI, as with most digital technologies, is that of Value Creation. Excluding, for the moment, relationships with partners, it is the use of AI in operational processes, mainly in automation activities and in order to reduce costs, both through the installation of specialized hardware or software, and through the purchase of solutions from third-party companies (Gusikhin et al., 2007; Naskos et al., 2021; Rychtyckyj et al., 2007). This type of use improves efficiency but does not constitute a radical transformation of the business model and can be adopted by most industries. It is therefore called "AI-Facilitated Business Model" and offers a competitive advantage mainly in terms of cost reduction (Steininger, 2019; Zott & Amit, 2010). This business model can be adopted by emerging companies not strictly related to the AI sector. At the same time, this improvement creates discontinuities in the market by forcing incumbent companies to adapt, potentially adopting AI in order to reduce their costs and prevent a migration of value (Sena & Nocker, 2021).

The second pillar of major application of AI is that of Value Distribution, including the relationships with customers, suppliers, and other stakeholders, in order to achieve customization, co-production, and integration. This type of use not only improves the efficiency of these interactions, but also determines the possibility of new relationships and, therefore, radical transformations of the business model and is potentially pursued by many sectors (Scuotto, Santoro, et al., 2017; Sigala, 2012; Solakis et al., 2022). It is called "AI-Mediated

Business Model" and offers a competitive advantage not only in cost reduction but also through the creation of additional value and, as mentioned above, potential stakeholder loyalty (Florez Ramos & Blind, 2020; Soni et al., 2019).

The third pillar of application of AI is that of Value Proposition through the integration of artificial intelligence into products, services, and solutions (Grigorescu et al., 2020; Maghded et al., 2020; Soni et al., 2019). This type of use determines the possibility of offering products and services that would not otherwise be possible and, consequently, radical transformations of the business model. In addition to companies specializing in the development of Artificial Intelligence solutions, this business model can potentially be adopted by companies in any sector that integrate AI solutions into their offer (Grigorescu et al., 2020; Maghded et al., 2020). It is called "AI-Bearer Business Model" and offers a competitive advantage by creating additional value and potential stakeholder loyalty (Steininger, 2019).

Finally, AI can be integrated into all three pillars at the same time, thus innovating both the structural and production elements, the relationships with the various stakeholders, and the value offer. This constitutes a radical innovation of the business model and leads to a competitive advantage over both cost and quality, and can potentially affect any industrial sector although it can manifest itself more easily in sectors related to the IT world (Katsamakas & Pavlov, 2019; Steininger, 2019). It is therefore called "Fully AI business model".

Intuitively, these four business models can be interpreted as levels of progressive maturity in the use of AI in a company (Faggella, 2021; Sena & Nocker, 2021; Steininger, 2019). However, greater maturity inevitably requires greater investments and therefore must be sought only when it can determine an advantage over the competition. What is most important, in fact, is the consistency between the AI tools used and the business model, in particular for the development of adequate synergies that AI can determine.

Explicitly, indeed, the concept of business model adopts a holistic complex system perspective to the study of organizations (Foss & Saebi, 2017; Osterwalder et al., 2005). This concept, originally proposed for the understanding of biological models such as bacterial cells, animals, and superorganisms, has subsequently been applied to the social context, both to describe the macroscopic functioning of entire societies and to present the functional dynamics of specific organizations (Ladyman & Wiesner, 2020; Simon, 1991). In this perspective, the four pillars of the business model can be interpreted as the set of subsystems of the human body (e.g. musculoskeletal, cardiocirculatory, nervous, endocrine, etc.). Each performs primary functions for the survival of the entire organism, each is in turn made up of multiple organs responsible for specific activities (e.g. liver, heart, kidneys in the human body; in the company human resources division, sales division, and production division) and internal dynamics between them. Above all, the various subsystems of the human body and pillars of the business model are constantly interconnected with each other, both in synergistic and competitive dynamics, and the prosperity of the organism/organization ultimately depends on the ability of these subsystems to coordinate thanks to an effective exchange of information (Brusoni & Prencipe, 2013; Kaufmann et al., 2021).

For this reason, as just mentioned, there is no "right" business model for the implementation of AI, and rather it is important to focus on achieving an organic integration within each business area, within each pillar, and between the pillars of the model itself (Brynjolfsson & Mcafee, 2016). To this end, as for the understanding of other complex systems, it has been proposed to adopt causal loop diagrams to represent the relationships between the different components of a business model, both traditional and related to the AI world. Studying the business model of Google Search, Katsamakas and Pavlov have shown some of the complex synergies that exist: the number of users (Value Proposition) has a positive effect on the accuracy of search algorithms (Value Creation), which in turn positively influences the number of users. At the same time, more users bring in more advertising customers (Value Distribution), which ensures increased revenue (Financial Structure) which in turn has a positive effect on the company's ability to invest in the development of effective algorithms (Katsamakas & Pavlov, 2019).

These examples show the importance of developing synergies in any business model. However, these become particularly important in the integration of digital technologies and especially AI. as it favors the collection, flow, and accumulation of information in real time within each and between the pillars of the business model (Steininger, 2019). This not only allows for more efficient processes and better products to be developed (Steininger, 2019), but also to increase the integration of the business model by establishing new virtuous circles and speeding up existing ones. On the other hand, AI makes it possible to further exploit this information, not only to generate insights, predictions, and decisions, but also to improve the processes of data collection, flow, and use, thus generating a stronger integration between the pillars of the business model (Element AI, 2019; Ransbotham et al., 2020). An example of this is the ability of AI to increase the value delivered to each customer by offering them a personalized product or service from the collection of data from that same customer, which guarantees better loyalty and therefore a better offer (Sena & Nocker, 2021; Soni et al., 2019). Another example is the personalization of the price at which a product or service is sold, based not only on the customer's willingness to spend, but also on the real-time maximization of the price (Calvano et al., 2020; Ezrachi & Stucke, 2016).

Given these synergies, in order to fully benefit from them, it is therefore necessary for companies to integrate AI into their processes as soon as possible to ensure that they have sufficient time to produce fruit (McKinsey, 2018). Moreover, given the high costs of implementing this technology and its dependence on large volumes of data, these synergies are in turn linked to dynamics of scale (Metelskaia et al., 2018). Together, these two characteristics create a significant competitive advantage for those companies that are not only able to develop and adopt AI solutions first but also manage to quickly capture a significant share of the market (Gregory et al., 2021; Himan, 2002; Varian, 2014). This is also because, as already mentioned, the high level of customization of AI solutions acts as a deterrent to the migration of customers from one provider to another (Farrell & Klemperer, 2006). Such dynamics constitute major opportunities for first movers, condemning the others to a situation of systemic disadvantage that is difficult to recover. This trend, which cuts across multiple sectors involved in the adoption of AI, is particularly pronounced among those players involved in the development of this technology. Already today, in fact, the market for AI solutions is dominated by a few large global players (e.g. Google, Amazon, Facebook, more recently Open AI) capable of developing complex technologies, reaching diversified customers, providing multiple value propositions, and benefiting from the dynamics of scale just mentioned, and with the potential to absorb competition should it become too threatening (Gibbs, 2014; Gregory et al., 2021; Metelskaia et al., 2018).

Paper 7: Trans-city data integration platforms: an explorative study on Smart Dublin and Torino City Lab

Authors

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Executive summary

This paper contributes to the literature on living labs and IEs by exploring the use of trans-city data integration platforms as assets for the transformation toward smart and sustainable cities (Kalinauskaite et al., 2020; Pucihar et al., 2019). Research on living labs and IEs is growing with increasing interest in the urban scale and the development of smart cities. Indeed, for the density and interconnectedness of actors and resources, smart cities are believed the perfect ground for technological and social experimentation, and they may catalyze a new wave of participatory and sustainable innovations (Cillo et al., 2020; Zygiaris, 2013). This requires to systematically collect data from a multiplicity of local stakeholders (Pereira et al., 2017; Walravens et al., 2014). While research has already started to investigate the opportunities and challenges related to this data collection at the city level (Raghavan et al., 2020), almost no study has yet investigated the potential of aggregating and integrating data from multiple cities in the same platform, hence forming a trans-city data infrastructure (ATIS, 2018). This explorative study aims at addressing this gap. Focusing on the smart city programs of Dublin (Smart Dublin) and Turin (Torino City Lab), it aims at fostering the conceptualization of trans-city data integration platforms and verifying their applicability to two real-life living labs.

Smart city programs are expected to catalyze innovation via participatory co-creation processes so to deliver more sustainable, smart, and inclusive societies (Cillo et al., 2020; Vilariño & Karatzas, 2018). Crucially, this will be enabled by the growing availability of data on city processes resulting from the systematic use of IoT sensors to monitor water and air quality, energy use, road traffic, waste production and disposal, and so on (Allam & Dhunny, 2019; Byun et al., 2016; Veeckman & Temmerman, 2020). Provided to citizens, this data could be used to offer better services, customize services to their needs, optimize resource use, and improve circularity (Marchiori et al., 2021; Pereira et al., 2017). Moreover, data would become a new resource in its own and be potentially employed by local entrepreneurs to innovate and further improve existing services (Jussila et al., 2019; Kitsios & Kamariotou, 2022; Walravens et al., 2014). However, the predominant use of proprietary closed systems for IoT devices, of unstructured or semi-structured databases by governments and agencies, and the production of data in heterogeneous formats and semantics, currently impedes interoperability, portability, and integrability, hence hindering these developments (Ferraris Alberto & Grieco Cecilia, 2018; Raghavan et al., 2020).

To overcome this issue, in the coming years, significant evolutions in data collection are expected, moving first towards general-purpose open data platforms able to break within-city boundaries, and then to fully integrated and open platforms where data are shared also with other cities and administrative levels, potentially adopting decentralized system structures, standardized interfaces or APIs, and monetization strategies (ATIS, 2018; Braud et al., 2021). Specifically, integrating data from multiple smart cities may provide unprecedented benefits, including lowered experimental redundancy, improved diversity, and efficiency of scale. Additionally, by fostering coordination and knowledge recombination across geographies, thematic silos, and organizational boundaries, it would foster opportunities for knowledge recombination, innovation, and entrepreneurship (ATIS, 2018; Malerba & McKelvey, 2020; Scuotto, Santoro, et al., 2017). While there are already some speculations on the potential benefits of this type of platforms, no research has been yet conducted on real-life settings.

To further explore this possibility, the present study aims at reviewing the experimental projects promoted by the two cities in the period 2020-2021 to identify affinities that could justify trans-city data integration in the future. Publicly available material was retrieved from the Smart Dublin's and Torino City Lab's websites (Smart Dublin, 2020; TCL, n.d.) and analyzed via iterative and inductive cycles of qualitative content analysis (Kyngäs, 2020; Täuscher & Laudien, 2018). This enabled to group together the experimental projects implemented by the two cities, and to establish a first benchmark of thematic and technological similarities that could underpin future data integration.

Smart Dublin (Smart Dublin, 2020) brings together top international high-tech companies, academia, and citizens to transform public services and enhance the quality of life (Coletta et al., 2019). It has been founded by Dublin Local Authorities with the vision of tackling key challenges for society such as climate change, the digital divide, and social inclusion. Torino City Lab (TCL, n.d.) was launched by the Municipality of Turin, aiming to convert the city into an open urban lab for experimentation and build up a smart and better place to live in thanks to the collaboration of international and local stakeholders (Cillo et al., 2020). Both programs support experimentation and an open approach to innovation, thus being consistent with the definition of living labs employed in this paper. In both cities, large amounts of data have been produced by a rich and diverse IEs composed of corporations, small and medium businesses, start-ups and research organizations. Though both cities already possess open data platforms, neither of them is yet ready to integrate its data across departments or with other cities (Raghavan et al., 2020).

In 2020 and 2021, Smart Dublin and Torino City Lab developed 27 and 26 different experimental projects each, which the inductive qualitative content analysis categorized in a three-level framework. First, an overarching District/City level was identified to respectively collect 7 and 6 projects who were particularly large in their thematic and technological scope. Second, four thematic categories were identified, and namely Culture (0 projects from Smart Dublin and 1 project from Torino City Lab), Environment (4 and 0 projects), Mobility (10 and 9 projects), People (6 and 1 projects). Third, three technologically oriented projects were identified, and namely Urban Air Mobility (0 and 7 projects), Internet of Things (0 and 1 projects), and Security/Big Data (0 and 1 projects).

These initial results indicate significant overlaps between the two smart city programs, specifically concerning the development of overarching projects aimed at whole-district or whole-city smartness (District/ City), but also individual themes such as Mobility and People. Nonetheless, from these initial results it appears that the majority of projects did not have a counterpart in the other program, as the Environment was only openly addressed by Smart Dublin, and Culture, Urban Air Mobility, Internet of Things, and Security/Big Data only by the Torino City Lab. Of course, this doesn't necessarily mean that the abovementioned themes or technologies were not of concern or not used, but only that they were not targeted by dedicated projects. Hence, the prosecution of this work will deepen the analyses to look more in detail into the technical specifications as well as into the societal objectives directly and indirectly pursued by each project.

In the meantime, these results confirm that a trans-city data integration platform could be applied to Smart Dublin and Torino City Lab. Indeed, each smart city program could channel data from its experimentations into a shared digital infrastructure. There, data sourced from similar experimentations could be integrated to develop a critical mass sufficient to fuel advanced and data-intensive applications. Conversely, data from non-replicated projects could be used to provide initial insights into phenomena, lowering redundancy, and improving learning and efficiency (Allam & Dhunny, 2019; ATIS, 2018). This would make the best use of the two cities' infrastructures and resources, favoring coordination and resource use across distances and organizations(Scuotto, Del Giudice, et al., 2017). Accordingly, more and more diverse data may enable entrepreneurs to exploit scale to develop new innovations, improve existing services or invent new ones (Jussila et al., 2019; Kitsios & Kamariotou, 2022; Malerba & McKelvey, 2020). As both overlapping and complementary interests may provide opportunities for data integration in a common platform (Allam & Dhunny, 2019; ATIS, 2018), the prosecution of this study will necessarily deepen the analyses and explore use cases for data integration so as to answer the two remaining.

Nonetheless, this work already contributes to the existing literature by fostering the currently embryonic conceptualization of trans-city data integration platforms and providing preliminary evidence on their applicability to two real-life living labs. Such platforms would enable resource sharing as well as coordination between actors operating in different ecosystems and potentially across scales, hence fostering learning, entrepreneurship, and innovation from what already enabled by open data (Carayannis et al., 2018; Walravens et al., 2014). To achieve this, decision makers in the public sector and in businesses would have to implement policies to address the use of proprietary systems, closed communication languages, and unstructured data also beyond the local level. Moreover, this study may motivate them to adopt novel approaches to experimentation and open data that consider data integration across geographies, silos, and organizations since the design phase (Braud et al., 2021). Ultimately, this would contribute to smart cities and living labs by providing better data-intensive services, improve governments' transparency and accountability, and enable the active participation of citizens in developing solutions (Cillo et al., 2020; ENOLL, 2017).

Paper 8: Unlocking the Potential of Professional Social Matching in Innovation Ecosystems: A Conceptual Framework and Research Agenda to Foster Local Interactions in Global Networks

Authors

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Executive summary

This paper contributes to the literature on strategic management and entrepreneurship by conceptualizing the use of PSM systems to recommend and foster partnerships within IEs. Since innovation has progressively expanded beyond organizational boundaries (Chesbrough et al., 2014; Moore, 1993), academics and practitioners have displayed a growing interest in the role of ecosystems in the creation and diffusion of innovation (Amin & Roberts, 2008; Anderson & Tushman, 1990; Powell, 1990; Tsai & Ghoshal, 1998). Indeed, innovation is increasingly dependent on the interactions between heterogeneous actors (Suominen et al., 2019) spread across regional, national, and global networks (Binz et al., 2014). Hence, organizations are increasingly focused on accessing tangible and intangible resources dispersed across organizations and locations (Carayannis et al., 2018; Malerba & McKelvey, 2020). These dynamics have become particularly evident and problematic in the last few years, as the Covid-19 pandemic and the growing international uncertainty have exposed the intricacy of these global networks (Bathelt & Li, 2022; Mazutis et al., 2021). Moreover, accounting for them would be crucial to efficiently leverage all locally and globally available resources to address the most pressing sustainability challenges, and to foster the competitiveness of organizations and territories (Carayannis et al., 2018; Prainsack, 2012; Soderstrom & Weber, 2020).

In face of a similar managerial complexity, fostering valuable interactions between innovation actors becomes crucial, though challenging for several reasons. First, IEs often comprise a large and diverse range of actors, such as universities, firms, public organizations, and civil society groups (P. Kivimaa & Mattila, 2015; Martin, 2014). Second, they are often split into disciplinary or organizational communities who speak different epistemic languages (Markowski, 2022). Third, actors are located in different regions or countries, further increasing their distance in geographical, linguistic, culture, or normative terms (Binz et al., 2014; Mazutis et al., 2021; Prainsack, 2012). While this diversity often nurtures creativity and innovation, it is also an obstacle to the construction of new partnerships as distant actors have lower opportunities to interact and transactions costs are higher (Orsatti et al., 2020; Paula & de Macedo-Soares, 2022). Since actors in IEs possess different resources and capabilities that each organization is interested in capturing, two key aspects must be considered when choosing the right innovation partner: first, it should be sufficiently different and distant to provide complementary assets and, second, it should be sufficiently similar and socially close to enable easy collaboration (Amin & Roberts, 2008; Gallié et al., 2013; Powell, 1990). In doing so, organizations also strive

to maximize their absorption of external knowledge without losing excessive knowledge to competing organizations and territories (Quitzow, 2015).

Despite the increasing importance of effective collaborations, there is a gap in understanding how to best identify, cultivate and leverage them (Malerba et al., 2015; Prainsack, 2012). On the one hand, approaches to matchmaking and network formation are often ad-hoc and rely on personal relationships, homophily, and reputation, rather than systematic and data-driven methods (Gulati, 1995; Kogut & Zander, 1992; Olsson et al., 2020). On the other, not only individual organizations are interested in building fruitful collaborations with peers, but multiple public and private actors are increasingly interested in fostering local interactions and ecosystem's performance (Parida et al., 2019; Sternad et al., 2017; Thomas et al., 2021). Moreover, given the international uncertainty, these actors are increasingly concerned with avoiding that local knowledge spills over from their ecosystem to foreign businesses and countries (Binz & Truffer, 2017; The Economist, 2023a).To address these gaps, the purpose of the present conceptual paper is to review the most recent literature on the use of PSM in IEs and to draft an initial framework and a research agenda on the topic.

The concept of PSM has been around for several years, but it has become increasingly relevant with the rise of professional networking platforms such as LinkedIn. Nonetheless, from an academic perspective, it still remains largely under-theorized (Olsson et al., 2020). While only a few papers explicitly referencing the topic have been published, it is possible to find roots of this concept in existing literature streams. On the one hand, the concept relates to the problem of finding the right collaboration partner, typically for innovation or business purposes. On the other, and most importantly, the concept draws from the literature on social matching systems and, at large, on recommendation systems.

Recommendation systems have emerged in the last decades to address the overabundance of information and the impossibility to systematically review it all prior to taking decision (Terveen & McDonald, 2005). Recommendation systems have been used to recommend consumers with products such as books, movies, and items from shops on-line and streaming platforms for many years now, but widespread tools such as Google Search also fall into this category (Khan et al., 2022; Olakanmi & Odeyemi, 2021). First, they assume that people may be interested in products similar to those they already possess or have searched for and, two, they assume that people may be interested in products similar to those that other people are interested in as long as socially connected (Bobadilla et al., 2013).

Most recently, the focus has shifted from products to people, as social matching systems have emerged as a specific sub-category of recommendation systems largely used in social networks and dating apps (Nayak et al., 2010). What these two applications have in common is that they host personal pages for each user and employ information on them and on the structure of the network they are embedded in to recommend new connections (LinkedIn, n.d.; Tinder, n.d.). As for previous recommending systems, social matching systems are based on the idea that individuals are more likely to be compatible if they share similar interests or have shared connections, thus enhancing the social experience of users and improving the quality of online interactions. PSM constitutes a specific application of social matching systems to the vocational domain, and rely on a similar number of methodological approaches (Terveen & McDonald, 2005).

Indeed, there are several quantitative methods for PSM in the information systems literature, mostly relying on the use of bibliometric and patent information as primal material (Qi et al., 2022). One approach is to develop synthetic indicators representative of organizations' propensity to innovation and collaboration, and then match potential partners according to priority rankings (Geum et al., 2013). Alternatively, citations and collaboration information have been widely used to map networks of collaborating organizations or individuals, drawing on link prediction algorithms and triadic closure principles to identify partnerships most likely to emerge in the future due to historical interaction (Wei Chen et al., 2021; Yan & Guns, 2014). Additionally, patents and scholarly articles have been mined with NLP techniques to extract insights from the content of these documents, and then use various algorithms to recommend collaborations according to content similarity (Jeon et al., 2011; Wang et al., 2017). Most recently, these methodologies have been combined to account for both the structure of the network, the thematic affinity of actors, and the different innovation roles that actors may play (Ding & Guo, 2021; Park et al., 2015). Since each of these methods has its own strengths and weaknesses the choice of method depends on the goals and constraints of the PSM system. Algorithmic matching, for example, may provide quick and efficient matches but may not consider personal preferences or cultural differences. Expert-based matching, on the other hand, may provide more accurate matches but may be more time-consuming and resource-intensive. While the choice of method should be based on a thorough analysis of the goals and constraints of the PSM system and the resources available to support it, it is increasingly acknowledged that effective systems should leverage a combination of these approaches (Qi et al., 2022).

Ultimately, this paper makes several contributions to the literature on strategic management and entrepreneurship by providing a concise and targeted review of the most recent literature and developing an original and framework for an IE Professional Social Matching System (IEPSMS). Following a strictly logical order, key features of the framework are now presented:

1. Continuous input of ecosystem's data: first, data from multiple publicly available sources is collected via automatic and semi-automatic processes, such as web scraping. Typical data sources include scholarly publications, patents, social networks, and public registries. Data is periodically collected to keep the system updated (Kinne & Axenbeck, 2020; Xu et al., 2018).
2. Data integration and analysis: then, this data is normalized, processed to overcome disambiguation, and integrated to link each actor to relevant material. This data is also analyzed with NLP and network analysis techniques to provide a first representation of the IE, accessible to the ecosystem orchestrator (Jeon et al., 2011; Kang et al., 2019; Xuefeng et al., 2015).
3. Input of actor's data: once an actor (hereafter Company X) is interested in exploring its positioning in the ecosystem or searching for a suitable innovation partner, it interacts with the front end of the IEPSMS (e.g. a public website) by providing key information about itself, such as the topics of

interests and existing collaborations. This enables to validate the preliminary representation of the ecosystem and to enrich it with additional data (Cai et al., 2019).

4. Actor-level options generation: subsequently, existing approaches to PSM, including NLP and network analysis, are combined to provide recommendation options to Company X. These options aim to maximize complementarity and efficiency (Qi et al., 2022). These options, however, are not yet shared.
5. Ecosystem-level optimization: at this point, the top options generated at the previous step are evaluated according to their impact on the structure of the ecosystem. For simplicity, ecosystem-level optimization may follow the same principles of actor-level recommendation, or rely on dedicated algorithms (Ionescu & Vernic, 2021; Kaufmann et al., 2021). It is worth noticing that the ecosystem orchestrator would be demanded to choose the boundaries of the ecosystem in order to identify the relations to optimize (Konietzko et al., 2020).
6. Actor-level options recommendation: at this point, a subset of options resulting from step 4 and step 5 would be provided to Company X, accompanied by estimations of the impact of a new collaboration on the structure of the ecosystem. This would enable Company X to consider all available information for a solid choice, avoiding black-box situations (Qi et al., 2022).
7. Expert recommendation: drawing on knowledge of the IEPSMS, of the ecosystem, and the specific sector, experts from the orchestrating organization would complement the automatically generated recommendations with a qualitative assessment and suggestions to Company X (Crupi et al., 2020).
8. Collaboration choice: at this point, Company X choses one or multiple potential collaboration partners. The IEPSMS provides reach-out contacts for each organization so as to monitor any in-platform communication. Nonetheless, it is most likely that communications would happen out of sight.
9. Follow-ups: at fixed times, data on the new collaboration launched by Company X as well as on the evolution of the ecosystem are collected, comparing them to the recommended collaborations. This allows to have updated data on Company X, to improve expert's recommendations, and to improve the ecosystem-level optimization, possibly with the implementation of machine learning instruments.

The IEPSMS framework enhances existing PSM approaches in a few ways. Firstly, by focusing on specific ecosystems, it enables the combination of various quantitative and qualitative data and methods (Qi et al., 2022), thus improving accuracy. Secondly, it builds upon the concept of actors' complementarity (Rodan & Galunic, 2004), addressing the need for PSM systems that overcome, rather than inherit, human biases from existing social matching systems and social flows (Olsson et al., 2020). Thirdly, the framework prioritizes the prosperity of the entire ecosystem, viewing recommendations as a cumulative and iterative process rather than one-time activities (Barabási & Albert, 2011; Olsson et al., 2020). This feature is crucial for translating on-paper concepts into real-world applications, as well as for enabling orchestrators to strategize local interactions within global innovation networks (Addo, 2022). Lastly, by continuously collecting data on the ecosystem's interactions and comparing them to its recommendations, the IEPSMS is itself capable of evolution and learning, thus providing better recommendations over time (Iansiti & Lakhani, 2020; Pironti & Spinazzola, 2022).

Accordingly, a research agenda for IEPSMS can be outlined. Key specific issues include the definition and measurement of complementarity and efficiency in collaborations (Qi et al., 2022), the conceptualization and study of ecosystems' complexity and evolution (Mack & Mayer, 2016; Nelson & Winter, 2002), and most importantly the definition of ecosystem-level optimizations (Ionescu & Vernic, 2021; Tran et al., 2016). Additionally, it is important to investigate the issues of trust and motivations of ecosystem actors (Terveen & McDonald, 2005), data availability and lawfulness (Huhtamäki & Olsson, 2018; Mancosu & Vegetti, 2020), which are fundamental for the adoption of PSM systems. By addressing these challenges and issues, researchers can further develop and improve the IEPSMS framework, which has the potential to be a valuable tool for fostering innovation and prosperity in various ecosystems.

Ultimately, this paper may motivate ecosystem orchestrators to invest in an IEPSMS. This would facilitate valuable interactions at the local level, as well as a prosperous evolution of the ecosystem within the global network of innovation relations. This would foster the competitiveness of organization and territories and their capacity to address complex sustainability challenges also in times of international uncertainty (Attig & Brockman, 2017; Bathelt & Li, 2022).

Paper 9: Professional Social Matching for Innovation and Technology Transfer in Multiscalar Innovation Ecosystems: A Conceptual Framework

Authors

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Executive summary

This paper offers a new approach to implement next-generation technology transfer strategies, policies and practices (Guo et al., 2022) by conceptualizing and testing the use of PSM systems to recommend new partnerships in multiscalar IEs and networks. Specifically, three alternative strategies and three recommendation algorithms were compared and evaluated by employing an original Professional Social Matching for Innovation and Technology Transfer (PSM4ITT) system. Management scholars have long been studying the value creation and capture strategies of innovative organizations. Since these processes have progressively expanded beyond the organizations' own boundaries (Chesbrough et al., 2014; Moore, 1993), however, they have displayed a growing interest in the meso-dynamics between organizations, and particularly in the role of ecosystems for the creation and diffusion of knowledge (Amin & Roberts, 2008; Anderson & Tushman, 1990; Guerrero et al., 2016). Indeed, innovation is increasingly dependent on the interactions between heterogeneous actors (Suominen et al., 2019) spread across regional, national, and global networks (Binz et al., 2014). Hence, organizations are growingly focused on accessing tangible and intangible resources dispersed across organizations and locations (Carayannis et al., 2018; Malerba & McKelvey, 2020), and particularly technical knowledge for the development of new products and services (Panetti et al., 2020).

These dynamics have sustained the growth of knowledge-driven enterprises and territories (Malerba & McKelvey, 2020; Nicotra et al., 2018). However, they have become problematic in the last few years, as the growing international uncertainty resulting from trade and technological confrontations has exposed the intricacy of these global networks (Bathelt & Li, 2022; Mazutis et al., 2021). Indeed, the current resurgence of protectionist policies, particularly in the United States (USA) (Dadush, 2022; Zw, 2022), could hinder the decades-long process of knowledge globalization (Del Giudice et al., 2017; Marginson, 2022). At the aggregated level, this may undermine the transfer of knowledge and technologies towards developing countries (Lewis, 2014; The Economist, 2023a). Conversely, at the meso-level, it may create additional barriers to organization interested in finding adequate innovation partners or traditionally reliant on international networks for the acquisition of knowledge (Ervits, 2020; Rikap, 2019). These developments are already influencing the structure and interactions of existing innovation networks at the global and local level, also impacting the dynamics of IEs and increasing the relevance of multiscalar dynamics (Bathelt & Li, 2022; Dewald & Fromhold-Eisebith, 2015; Zw, 2022). Ultimately, they may also hinder the adoption of green

technologies, slowing down the transition to more sustainable economies and affecting competitiveness (Goel, 2023; Lewis, 2014; The Economist, 2023b; Yu, 2019).

Despite the significance of productive collaborations in IEs and the challenge represented by the growing complexity and multiscalarity of innovation networks, there is a knowledge gap regarding how to best locate, nurture, and utilize them (Malerba et al., 2015; Prainsack, 2012). On the one hand, matchmaking is frequently dependant on interpersonal connections, homophily, and reputation rather than systematic and data-driven (Gulati, 1995; Kogut & Zander, 1992; Olsson et al., 2020). On the other hand, numerous public and private actors are increasingly focused on orchestrating local interactions and ecosystem to improve their performance. Typical actors include companies, national and regional governments, and universities (Parida et al., 2019; Thomas et al., 2021). These players are increasingly worried about preventing the transfer of local expertise from their ecosystem to foreign companies and nations and to nurture the development of local competencies and knowledge, particularly in key sectors such as green technologies (Binz & Truffer, 2017; The Economist, 2023a). Though these dynamics significantly impact the multiscalar nature of global innovation networks, their implications for building new collaborations have received little consideration (Cai et al., 2019). Aiming to address these challenges, the purpose of the current work is to draft and test a framework for a recommendation system suggesting partnerships for innovation and technology transfer by answering to two questions:

1. What design strategies best account for multiscalar information in a PSM system?
2. What recommendation algorithm works best with a multiscalar PSM system?

To answer these questions, the article first synthetized the literature on PSM and IEs to highlight synergies among the two constructs (Van de Ven, 1989). Then, relying on a creative and iterative approach (Weick, 1989), it connected the two literature streams in an original framework for a PSM4ITT system (Gilson & Goldberg, 2015). Third, it tested this framework on a collaboration network of 2,261 organizations innovating in photodegradation and photocatalysis as a key area for green chemistry (Wu et al., 2021). This was achieved testing three alternative design strategues for the system (Ex-ante, Ex-post, and Global) as well as three alternative recommendation algorithms (Preferential Attachment, Resource Allocation, and Within-Inter Cluster). After identifying adequate metrics to measure the effects of the PSM4ITT, they were used to compare alternative design strategies and recommendation algorithms, focusing on the USA for its recent wave of technology protectionism (Dadush, 2022; The Economist, 2023a).

Accordingly, some key insights could be provided. On the one hand, the Global strategy was expected to produce the least favourable results for the USA as collaborations with this country were treated as those of any other, thus being more likely to reproduce the status quo. Worse than that, this strategy strengthened Iran in particular, possibly as a result of the current under-connectedness of its organizations (Labi, 2008). Accordingly, if only the network structure was taken into account, a natural surge of this country in the global network would likely be imminent, and adopting the Global strategy within the PSM4ITT would speed it up. Hence, this result confirms that when trade, industry, or geopolitical tensions exist not adopting a multiscalar perspective in the use of a PSM4ITT system may do more harm than good (Quitzow, 2015). On the other hand, both the Ex-ante and the Ex-post strategy effectively improved USA's metrics. While the Ex-post strategy essentially worked by filtering and implementing the recommendations generated by Global strategy, however, the Ex-ante properly focused on USA's collaborations and generated recommendations specifically for this purpose. As a result, the number and accuracy of recommendations was higher, making the Ex-ante strategy the most effective to implement a scalar perspective in the PSM4ITT system, confirming that multiscalar perspectives need to be included since the design of the PSM system.

Moving the second research question, regardless of the metric used the Preferential Attachment algorithm consistently appeared as the least performing in improving USA's standing in the global network. As this tool favours already highly connected nodes it is likely to improve the positioning of individual organizations while only marginally improving that of the remaining organizations in the focus ecosystem (Liben-Nowell & Kleinberg, 2003). A better performance was registered for Resource Allocation, which is less hierarchical and closer to the natural behaviour of networks, and for this reason is also the most common approach in PSM systems (Qi et al., 2022). The Within-Inter Cluster algorithm, however, is even more effective in increasing USA's metrics, and particularly in combination with the Ex-ante strategy as it allowed to more precisely identify the communities within the USA's ecosystem, which it relies upon to generate recommendations (Valverde-Rebaza & de Andrade Lopes, 2012). Hence, the Within-Inter Cluster algorithm emerged as the most suited to account for network multiscalarity.

Particularly when a combination of and Ex-ante strategy and a Within-Inter Cluster algorithm were used, this study confirmed that a PSM4ITT system adopting a multiscalar perspective could be used to boost the positioning of specific countries. Though with differences in size, both Betweenness Centrality and Eigenvector Centrality were affected, thus implying that a scalar PSM4ITT system may improve opportunities for both knowledge exploration and knowledge exploitation (Almahendra & Ambos, 2015; Burt, 1995). While this is theoretically correct, however, the real-life consequences of using such a system may be less favourable for knowledge exploration: excessively closing in themselves, ecosystems may lose access to heterogeneous knowledge available in the global network. This possibility would be supported by the even larger increase displayed by Network Clustering and Network Density. Hence, increasing the connectedness of organizations within a delimited ecosystem would improve trust among ecosystem actors, further facilitating the emergence of fruitful collaborations and opportunities for spillover, but may also foster 'bubble effects' (Guerrero & Urbano, 2012; Guerrero et al., 2014; Suominen et al., 2019). The prosecution of this research should certainly account for this aspect as an extremely relevant one for PSM in general (Burt, 2001).

Moreover, when this combination of design strategy and recommendation algorithm is used, the PSM4ITT system affects the focus country almost exclusively. As this differs significantly from the consequences of using a Global strategy, for instance on Iran, it suggest that it might be less problematic than other protectionist policies (The Economist, 2023a).

Accordingly, this work provides several key contributions to literature. First, it contributes to the conceptualization of PSM in IEs. While current PSM systems already account for the structure of collaboration networks, they are rarely explicit on the complex and cumulative dynamics within (Del Giudice & Maggioni, 2014), thus making that of PSM for IEs a relatively new and undertheorized concept (Cai et al., 2019; Zytko & DeVreugd, 2019). In this regard, it also expands the use of PSM systems to generate recommendations not only for individual actors but also for ecosystem orchestrators (Olsson et al., 2020). Second, and strictly connected to the first point, this paper conceptualizes and tests the use of PSM from a multiscalar perspective. Indeed, the idea of organizations simultaneously interacting at multiple scales is relatively new also to the innovation system and ecosystem literature (Carayannis et al., 2018, 2016), but has only superficially been addressed by studies on PSM systems (Olsson et al., 2020). Therefore, this paper could support scholars interested in PSM systems to be more explicit on the scalar level of their analyses, and hence integrate scalar information in their models. This would make such models more accurate, and capable of dealing with the intrinsic complexity and multiscalarity of IEs. Third, specifically, this paper already provides an implementation of multiscalar perspectives, which could be a starting point for further methodological advancements.

Additionally, this paper contributes to the emergent literature on entrepreneurial knowledge-driven IEs. On the one hand, it shows the value that a multiscalar PSM4ITT system may have for IEs. By increasing actors centrality in the global network as well as local interconnectedness, PSM4ITT systems would give actors improved opportunities for knowledge exploration and exploitation (Almahendra & Ambos, 2015; Burt, 1995; Rikap, 2019). In turn, local entrepreneurial organizations would exhibit improved opportunities to recombine knowledge into new innovations and gain competitiveness, which may then feed-back to nurture the local ecosystem (Malerba et al., 2015; Malerba & McKelvey, 2020; Theodoraki et al., 2018). Though tested at the country and global scales, this same methodology may be applied also at the subnational level to orchestrate the development of regional or city ecosystems (Carayannis et al., 2016), or at the supranational level with a focus on highly integrated areas such as the European Union (Butter et al., 2020), or for technology transfer between developed and developing countries (Al–Ghailani & Moor, 1995). Ultimately, PSM4ITT systems would strengthen the conceptualization of entrepreneurial and IEs and improve the applicability of this construct to real life situations.

At the practical level, this paper and the research that it aims to initiate could support both policymakers and corporate managers. Starting from the first group, they may be interested in developing PSM4ITT systems to more effectively orchestrate their IEs at the regional, national, or supranational level. On the one hand, it may support local orchestrating organizations, such as entrepreneurial universities, in establishing flourishing IEs by recommending actors with complementary capabilities (Guerrero et al., 2016; Thomas et al., 2021). On the other, it could foster the adoption of innovation and entrepreneurship driven policies, such as the European Smart Specialization Strategies (Balland et al., 2019), by recommending collaborations within and across regions depending on selected parameters and adequate scalar strategies such as those proposed in this paper

(Qi et al., 2022). Similarly, it could be employed to foster the collaborations between selected regions or countries (Cai et al., 2019), limiting spill over to competitors (Quitzow, 2015) while supporting transfer of green technologies to developing ones (Ockwell et al., 2008).

Conversely, managers from entrepreneurial organizations may focus on using a PSM4ITT system to access new knowledge. A PSM system could be beneficial for knowledge-intensive entrepreneurial organizations to understand their positioning in the ecosystem, plan adequate strategies, and select partners (Song et al., 2016; Zytko & DeVreugd, 2019). However, a multiscalar PSM4ITT system would enable them to make the multiscalar nature of their knowledge network explicit, thus gaining an improved understanding of the implications that every new collaboration would have on their opportunities for knowledge exploration and exploitation (Burt, 2001; Rikap, 2019). Ultimately, this would boost their capacity to access and recombine knowledge, maximising their innovativeness and entrepreneurship.

Crucially, this would require managers to undergo comprehensive training to effectively utilize collaboration recommendation tools. This training should encompass a deep dive into the tool's functionalities, including data input, algorithm explanations, and output interpretation. Managers should learn how to assess the reliability and relevance of the tool's suggestions based on their team's specific context and goals. Moreover, they should be equipped with skills to identify potential biases in the tool's recommendations and mitigate their impact (Adler, 1986; Leonidou et al., 2020). Crucially, training should emphasize the importance of human judgment in complementing the tool's output. Managers should be taught how to foster a collaborative culture, build trust, and effectively communicate the value of collaboration to their teams, leveraging the tool as a catalyst for innovation. Additionally, they should understand how to measure the impact of collaborative efforts and refine their approach based on data-driven insights (Olsson et al., 2020; Pironti & Spinazzola, 2022).

This study could validate the PSM4ITT framework on a single sector and only by simulating its repeated use for 100 recommendation rounds rather than on a real-life employment. Given its exploratory nature, this was inevitable and using a large and relevant sample of data improved the reliability of its findings. Yet, as different sectors may display different network topologies in different countries, further research should test the use of the PSM4ITT system under different conditions (Binz & Truffer, 2017).

Nonetheless, its findings enrich academia with first conceptualizations and results. On the one hand, they foster the investigation of multiscalar processes from a quantitative perspective (Cunningham & O'Reilly, 2018; Depret & Hamdouch, 2010). On the other, they advance the development of innovative strategies and tools to support policymakers in the identification of novel technology transfer processes and practices (Cottafava et al., 2024; Guo et al., 2022; M. Spinazzola, Farronato, Scuotto, et al., 2023). Hence, by balancing openness and protectionism, PSM4ITT systems could be fundamental to guarantee the competitiveness of organization and territories and the development of green technologies (Arora & Gambardella, 1994; Dewald & Fromhold-Eisebith, 2015).

Paper 10: Green Recommendation Systems for Smart and Sustainable Cities: a Proof-of-Concept on the City of Milan

Authors

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Executive summary

This work contributes to the study of Green Information Systems (GIS) as key assets for the transition to smarter and more sustainable cities, as well as drivers of innovation and entrepreneurship (Carayannis et al., 2018; Cillo et al., 2020). The literature on GIS, however, has primarily focused on the use of big data produced by sensors, neglecting the role of information systems to provide other types of data-driven services, such as knowledge or partnership recommendations (Addo, 2022; Corbett & Mellouli, 2017). To address this gap, the current paper offers a first conceptualization for the use of Green Recommendation Systems (GRS) and a first preliminary application to the Italian city of Milan. This was achieved by reviewing existing literature on GIS and recommendation systems and their potential value for smarter and more sustainable cities (Archer & Zytko, 2019; Olsson et al., 2020). Accordingly, an original framework presenting the functioning of a GRS for Smart and Sustainable Cities (GRS3C) was designed. This framework was then tested by simulating its usage for the City of Milan, focusing on the recommendation of relevant academic knowledge and actors specialized in the issue of air pollution. Drawing on the concept of Digital Urban Acupuncture (DUA) (Iaconesi & Persico, 2017a) and intellectual capital literature (Bertello et al., 2022), preliminary results show that a GRS3C may support policymakers and entrepreneurs in understanding the complexity of social, environmental, and economic issues, as well as in identifying local actors which may contribute to the development of adequate solutions.

The city of Milan was selected to offer a proof-of-concept of the GRS3C as it constitutes one of the most advanced smart and sustainable cities in the country (Cassinadri et al., 2019). First, a database was constructed collecting articles published on the topic of smart and sustainable cities. This was achieved by employing the Scopus' pre-made query for SDG.11 "Sustainable cities and communities", limiting results to English articles published in Italy since 2003. This leveraged a total of 19,956 articles ranging across physical, social, and life sciences (Pranckutė, 2021). Second, this dataset was cleaned and processed to extract key information on authoring organizations (Kathuria et al., 2021). Third, the state-of-the-art sentence-embedding model BERTopic was used to inductively identify 98 topics from the abstracts contained in the dataset (Sharifian-Attar et al., 2022). These topics were then clustered in a hierarchical form, to provide the hierarchical structure used in step 1, and a topic dissimilarity matrix was generated to inform the construction of the topic-correlation network which informed step 2 (Grootendorst, n.d.). Last, for every sub-topic, the list of the most active organization operating within the city of Milan was extracted, thus delivering the ultimate output required by step 3 (Qi et al., 2022; M. Spinazzola, Farronato, Murray, et al., 2023).

To test this proof-of-concept, the GRS3C's use was simulated from the perspective of a hypothetical policymaker interested in air pollution, and specifically on pm10.

The preliminary findings suggest that a GRS3C could assist decision-makers in better comprehending the complexities of social, environmental, and economic problems, as well as in locating actors who might contribute to the formulation of suitable solutions. Accordingly, by lowering exploration and interaction costs, a GRS3C could be fundamental to engage a multiplicity of local actors in the development of adequate solutions to the most pressing environmental challenges (Farronato et al., 2022; Huhtamäki & Olsson, 2018). This would facilitate the flow of tangible and intangible resources among actors, boosting innovation and entrepreneurship at the city level (Cillo et al., 2020; Matteo Spinazzola et al., 2022), by exploiting the relational dimensions of all actors within an local and punctual ecosystem. In this sense, the use of large dataset with a relational component – i.e., with information about collaborations, relationships, interactions – recalling the concept of DUA may facilitate the design of micro-interventions or policies (Cottafava, 2019; Iaconesi & Persico, 2017b). Accordingly, this paper contributes to the expansion of GIS and professional social matching concepts, opening for more research at the intersection of these two literature streams. Moreover, as a proof-of-concept it may motivate the development of actual GRS3Cs which could facilitate the development of innovative solutions for smart and sustainable cities, and support policymakers dealing with complex challenges (Matteo Spinazzola & Cavalli, 2022).

5. Discussion and Conclusion

5.1 Objective 1: Exploring novel data sources for research and practice

Bibliometric, patent, and registry data are unlikely to be supplanted by web ones. On the one hand, web scraping is a resource-intensive practice and presents significant legal and privacy challenges (Mancosu & Vegetti, 2020). Hence, though potentially global in scope, high costs might deter from fully scaling it or impose significant restrictions. In Paper 1 and Paper 2, for instance, it was decided to collect data for all organizations regardless of their sectors and size focusing on two regions only. To compensate for this, in Paper 3 specific global cities were chosen, but implied isolating them from their larger geographical context. As an alternative strategy, Paper 5 adopted a continental scope though only one sector could be chosen. Moreover, web scraped information might not possess the same accuracy of institutionally sourced data, and particularly so as social networks display different usage according to industry, country, and social status of its users (Zhu et al., 2018).

Despite such limitations, the present Thesis showed that web data can provide unique insights into innovation and entrepreneurship. This was achieved via web scraping and NLP techniques to retrieve and make use of different social network data (Zhu et al., 2018). Examples include the technological and sustainability characterization of businesses (Papers 1 and 2), the assessment of talents demand (Paper 3), and the identification of mobility patterns and determinants for KIEs (Paper 5).

These practices can support the identification and analysis of many real-life phenomena that until now eluded economic research, from the real-time identification of skills demand by the job market (Zhu et al., 2018) to tracking individual level activities of employees and entrepreneurs (Paper 5). Furthermore, this highly granular and timed data would be available for different countries in a relatively comparable fashion, thus fostering comparative and international research. As already mentioned, this seems particularly significant for EEs, which until now have suffered for a lack of relational sources (Fischer, Meissner, et al., 2022).

From a policy perspective, this increasing use of web data constitutes a potential threat to organizations and people (Mancosu & Vegetti, 2020). However, it may also constitute a necessary step to balance the current inequity in the availability and use of information between the public and private sector (*Social science one*, n.d.). Hence, the direction taken by the European Union to support research organizations appears aimed in the right direction (European Commission, n.d.-a) despite both regulatory bodies and research institutions should probably be more active in defining proper guidelines that enable this type of research (Mancosu & Vegetti, 2020).

5.2 Objective 2: Investigating IEE's connectedness from KIEs activities

Making inferences on the behavior of individual entrepreneurs and enterprises is extremely challenging. It is particularly problematic in quantitative studies that focus on registry-like information, and especially so without the possibility to interpret the findings with the entrepreneurs themselves (Javadian et al., 2020). Moreover, Papers 4 and 5 focused on specific industries such as SAFs and biotech, so further studies should certainly expand to different sectors to increase the generalizability of their findings (Schillaci et al., 2013)

Despite such limitations, however, this Thesis could investigate the role played by KIEs in connecting different IEEs. This required the collection and use of different sources of data, namely bibliometrics, patents, and social network ones, and the identification of different mechanisms for IEs and EEs connectedness. Though with major differences, both articles contribute to fostering the understanding of IEEs as connected entities and to highlighting the major role played by KIEs in this vein.

Specifically, Paper 4 showed that network positioning and brokering of KIEs have a major influence on the development pathways for local IEs. Indeed, previous research indicated that brokers play a fundamental role in knowledge transfer and technological catch up between countries as well as in determining unequal relationships in the global innovation networks (Binz & Truffer, 2017; Rikap, 2019). Hence, KIEs activity might deserve further scrutiny in a time of technological and trade wars (Gulo & Dwiastuti, 2022). Even more so as free-riding could deter investments in sustainability-purposed technologies (Binz & Truffer, 2017). Hence, further research should certainly focus on improving our knowledge of patterns and practices to manage international brokering to the benefit of all participants (Ritala et al., 2022).

Similarly, Paper 5 focuses on the mobility of KIEs. As one of the few studies openly addressing the topic of EEs connectedness, it confirms the value of web data and geography-agnostic approaches to the investigation of entrepreneurial processes. Though it was found that KIEs mobility is predominantly a regional phenomenon, the full implications of long-distance and weak ties remain to be investigated (Granovetter, 1973). Though in the most recent slowdown to globalization, the mobility of people within countries and economic blocks such as the European Union is likely yet to peak (Windzio et al., 2019). Hence, geography agnostic approaches would become increasingly necessary to fully grasp economic trends, allowing policy makers for better attracting KIEs as major catalyzers of innovation and entrepreneurship (Harima et al., 2021; Lerner, 2010).

5.3 Objective 3: Conceptualizing novel management systems for IEE actors

The conceptualizations and early prototypes presented require testing in real-life situations in order to confirm their adequacy to solve actual problems (Olsson et al., 2020). Moreover, factors intrinsic to data like gender, race, and socioeconomic status may bias existing algorithms (Li et al., 2016). Data-driven management systems and PSM systems in particular, hence, could end up creating excessively homogenous networks, thus reinforcing existing patterns rather than creating new opportunities (Olsson et al., 2020). Consequently, the creation of homogeneous 'bubbles' may provoke an extreme polarization and a lack of diversity, with detrimental consequences for both inclusion and innovation (Kubin & von Sikorski, 2021; Orsatti et al., 2020). On the user side, additional issues may emerge. Information systems often require sensitive personal and professional data, opening privacy and data security concerns. Cyberattacks, data breaches, and misuse can compromise trust, and privacy could be broken even if data is anonymized (Kalidien et al., 2010).

Despite these limitations, the present Thesis showed how further use of AI and recommendation systems could boost networking, collaboration, and innovation (Qi et al., 2022). Where Paper 6 focuses on the use of AI within organizational silos (Soni et al., 2019), Paper 7 outlined the possible development and benefits of data sharing platforms spanning beyond traditional geographical boundaries (Walravens et al., 2014). Moreover, Papers 8, 9, and 10 showed novel conceptualizations and tests of PSM prototypes (or components of prototypes). Though this topic remains significantly under-theorized, these works brought the discussion forward by identifying more specific features for the debate (Olsson et al., 2020). Yet, two main obstacles remain. First, examples of joint development of PSM systems together with actual users are lacking and very much necessary. Second, once the first PSM systems are commercially available, organizations would have to pick them up. Given the relevance of personal ties in identifying innovation and business partners, as well as the general presence of bias towards data-driven decisions, this outcome is everything but granted.

5.4 Concluding remarks

As humanity prosecutes on its path in the XXI Century, challenges become increasingly complex and wicked (Oksanen & Hautamäki, 2015; Steffen et al., 2015). Though beyond the aims of this Thesis to assess the effectiveness and equity of current strategies, it is very likely that the necessary solutions will require more data, a more efficient use of resources, and the collaboration of a wider variety of actors (Bertello et al., 2022; Spinazzola & Cavalli, 2022). Even marginally, this Thesis aims at contributing to this goal.

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