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

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

Keywords: Digital Entrepreneurial Ecosystems; State-of-the-art review; Socio-semantic networks, scientometrics.

1. Introduction

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

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

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

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

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

The paper is organized as follow: Section 2 introduces the research by analyzing the multiple origins of DEEs and presenting the methodological caveats of scientometrics for community detection and socio-semantic analysis. Section 3 presents the primary database of publications, the protocol for filtering scientific contributions, and the construction of the socio-semantic network. Section 4 offers an analysis of the social dimension of the network, focusing on the global structural properties of the network. Section 5 links the structural and semantic dimensions, through an analysis of the semantic specificities within and between communities. Section 6 discusses all the results.

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

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

2.1.1. *Entrepreneurial Ecosystems* (EE)

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

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

2.1.2. *Digital Entrepreneurial Ecosystems* (DEE)

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

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

2.1.3. Are EEs not digital?

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

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

Therefore, the way of apprehending the concept of EE and its evolution towards that of DEE differs between the research in Industrial Organization and Business Strategy and the research in Geography of Innovation. Contributors to the former understand EEs as forms of partially regulated markets whose sponsors promote both entrepreneurial action and transactions between distinct groups of users. They more specifically use the notion of DEE to highlight the key role of innovation in the digital industry, what Autio *et al*. (2017) call "digital affordances". In a certain sense, for this research, efficiency analysis has moved *upward*, from the level of the organization of the firm to that of the ecosystem and its orchestration (Helfat and Raubitschek, 2018; Bejjani *et al*., 2023). On the other hand, the contributors in Geography of Innovation maintain a more global level of analysis by considering EEs as local communities with more blurred organizational boundaries. Within these communities, actors and institutions with shared aspirations interact to promote entrepreneurial opportunities (Stam and van de Ven, 2021; Wurth *et al*., 2023), but the use (of) or the innovation (in) digital technologies are not at the center of the analysis as they are in the previous disciplines mentioned. The focus remains on what Autio *et al* (2017) call "spatial affordances", i.e. the different positive externalities favored by proximity, previously central in research on clusters (Vicente, 2018). This time, the movement of the analysis of efficiency is *downward*, moving from clusters to EEs. As researchers and policymakers had grasped that regional growth issues had shifted from boosting collaborations between firms and research institutions to fostering entrepreneurial behaviors and context, research on EEs developed to complement those on clusters or regional innovation systems (Rocha and Audretsch, 2022).

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

2.2.1. Opportunities: DEE network properties as markers of field structuring

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

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

DEEs as scientific field also raise the question of the semantic dimension of the network. If the members of the DEE research community share the same scientific interest at the intersection between the concepts of EE and DE, these concepts can be related to distinct scientific underpinnings that are not necessarily homogeneously distributed across all the network's sub-communities. When the co-authorship game shapes social islands of dense collaborations within the network, it may shape distinct cognitive islands if the sharing of scientific underpinnings come first among all the motives that drive collaboration, including prior to spatial and institutional ones (Katz and Martin, 1997; Hoekman *et al*., 2010). Therefore, adding and connecting a semantic dimension to structural properties of the DEE network becomes a fundamental issue for understanding how a new topic arises from collaborations between relatively distinct knowledge or disciplines. For that, a scientometric methodology inspired of Rafols and Meyer (2010) and Raimbault (2019), which consists in analyzing how the diversity of knowledge brought by each actor is distributed through collaborations, can help to study whether the structure of co-authorship goes with a semantic specialization within sub-communities or with an integrative process of ideas through the entire network. It can also help to assess if network fragmentation corresponds to failures in the collaboration pattern that reduce the integrative ambition of the concept defended in the literature. As we have seen in section 2.1, given the many sources of scientific topics that have contributed to DEEs, applying socio-semantic network analysis should make it possible to better understand through which semantic and/or social channels the bridging and integration of knowledge occurred.

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

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

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

3. Data and methodology

3.1. Data collection

To analyze the socio-semantic structure of DEE scientific community, we use the *Web of Science* (WOS) *Core Collection* database. Three queries are formulated to obtain papers that use in their *Title* or *Abstract* fields certain Boolean combinations of words that are consistent with a relevant overarching representation of DEEs. They have similar structure and require the generic term “ecosystem*” that we associate (AND operator) in each query with “digital*”, “entrepreneur*” and “platform*” respectively. Moreover, to increase the accuracy, we apply a set of additional filters: we restrain only to papers written in English, published (or being in press) by a journal indexed by the *Social Science Citation Index* (SSCI). Contrary, we do not introduce any chronological filter, so the period considered ends up in March 2023 (with in press papers affiliated to this year). Thus, after aggregating the results of the three queries and deleting duplicates, we get a dataset of 1882 papers, resulting from an almost balanced numbers of papers in each query. For each paper we have information about the authors and their affiliations, the journal of publication, the date, the title, abstract, keywords, and citation counts. *Figure 1* shows the aggregate counts of papers in our dataset, including the count of papers overlapping categories.

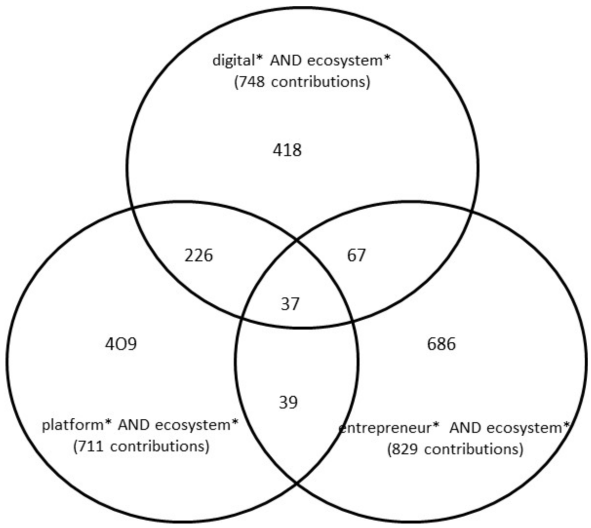

Figure 1: # papers for each query and their overlap

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

3.2. Data cleaning and papers' filtering

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

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

This first visualization reveals that part of the network is poorly or not connected, and therefore would not contain the most significant contributions. Following the scientometric literature which shows that the degree of embeddedness in co-authorship networks is positively correlated with citations, we could only consider the giant component of the network (316 articles). However, this would leave aside a significant part of the semantic depth of the scientific field. This is all the truer if we consider that isolated articles by a single author, particularly the early published ones, could have influenced the semantic content of the knowledge dynamics at work in the giant component. After calculating the average of annual citations for the entire network and for the giant component (3.57 citations per year outside the giant component, 9.5 citations per year inside), we use a double non-exclusive criterion to select the most relevant papers of the domain: all the papers of the giant component and the papers among the isolates that have received, on average since their publication, 10 or more citations per year. This way to proceed allow selecting for the socio-semantic analysis 8.3% of the isolates, i.e. the top of the distribution of the most influential papers. In the end, 447 papers will be selected, 71% being part of the main component, with a significant higher value for the "entrepreneur*" AND "ecosystem*" query as regard the two other queries (See *Table 1* for descriptives statistics and *Figure 2* for the distribution of papers per year).

	Total	**Share of selected contributions**	**Share of contributions in the main component**
Digital* AND	748	19,9% (149)	57,7% (86)
Entrepreneur* AND	829	32% (265)	84,2% (223)
Platform* AND	711	20,8% (148)	59,5% (88)

Table 1: Descriptives of the network

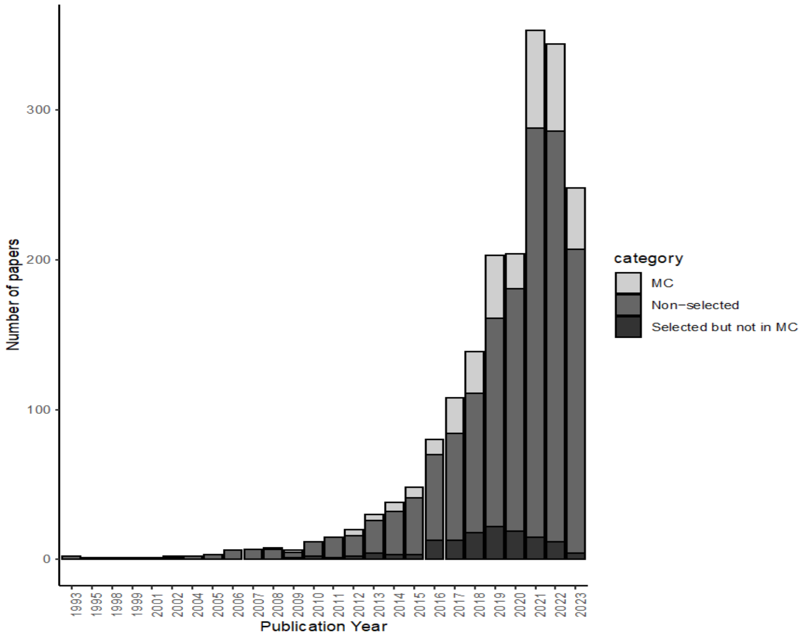

Figure 2: The annual distribution of DDE contributions

3.3. Sub-communities' identification

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

3.4. Words' filtering for semantic analysis

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

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

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

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

4.1. Network visualization

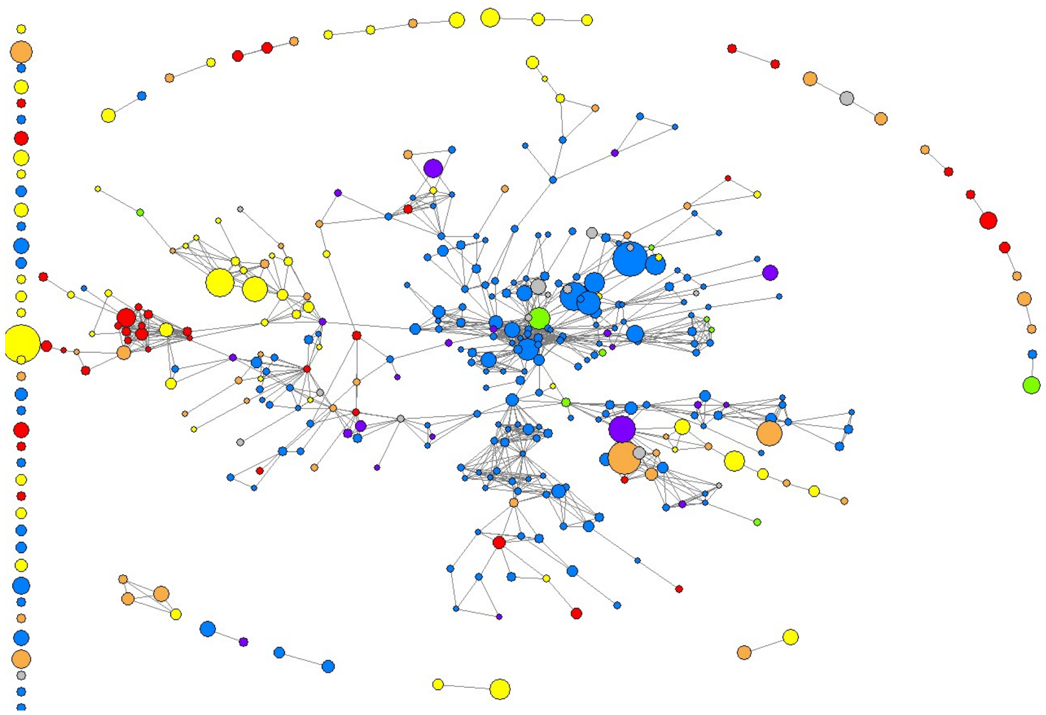

Figure 3: the DEE network (1)

(Nodes features: blue: Ecosystem & Entrepreneur*, yellow: Ecosystem* & Digital*, red: Ecosystem* & Platform*, green: Ecosystem* & Entrepreneur* & Digital; orange: Ecosystem* & Digital* & Platform*; purple: Ecosystem* & Entrepreneur* & Platform*; grey: Four terms. Size: average citation per year)*

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

We observe that even if there is a propensity of nodes to connect more to the nodes of the same initial semantic query, the structure of the giant component is not directly related to them, because we also observe that (i) the number of highly cohesive groups is largely superior to the number of queries; (ii) a same query gives rise to several cohesive groups poorly connected to each other; (iii) nodes mixing 2 or 3 requests irrigate many of the cohesive groups, and (iv) some highly cohesive groups host a balanced number of nodes from the three queries. It means for (ii) that scholars use and work on same pair of concepts in different social groups with few social relationships between groups. That is particularly the case for the "ecosystem* AND entrepreneur*" query that gives rise to more than four easily visible poorly connected cohesive groups. It is also the case that for the query "ecosystem* AND digital*" for which we observe two very distant social groups. But it also means for (iii) and (iv) that, in a few islands of the giant component, dense scientific relationships have mixed the digital and platform dimensions of ecosystems to its entrepreneurial dimension. That is particularly the case for two of the cohesive groups located at the right and left of the graph.

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

4.2. Some salient structural properties of the DEE network

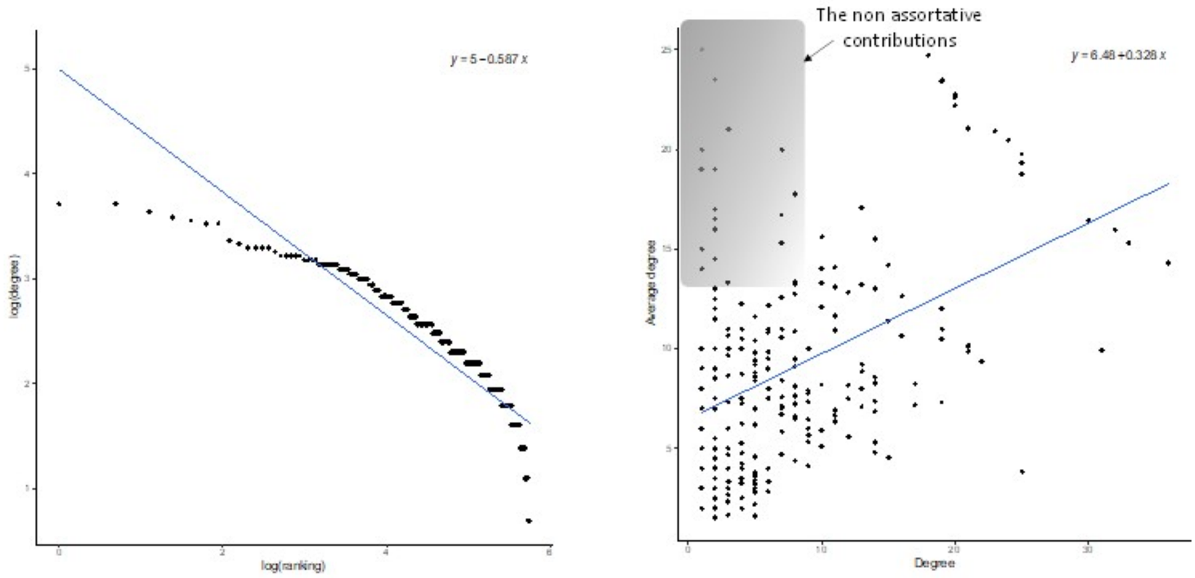

Figure 4: Structural properties of the DEE network. a: degree distribution; b: degree correlation

At a strictly structural level, collaboration patterns within the giant component can be analyzed through the distribution and correlation of node degrees. First, *Figure 4a* shows the level of hierarchy in the degree distribution, signifying a continuum of strongly to very weakly connected nodes. This is illustrative of the presence of very productive authors who diversify their portfolio of co-authors within the field, and of the existence of peripheral contributions from either young authors with their first co-authrd publications or established researchers in other scientific communiteis entering the DEE field. This hierarchy of degrees is typical of a *preferential attachment* mechanism (Barabasi and Albert 1999) which leads to the existence of reference contributions in the community, whose authors are attractive for any new collaboration, and whose ideas structure the scientific field.

Second, the correlation of degrees provides additional elements on collaboration patterns. *Figure 4b* shows a positive correlation: high (low) degree nodes have a stronger propensity to connect to high (low) degree nodes, indicating an assortative network (Newman, 2002). This means that the authors with high (low) degrees tend to co-write with authors who are themselves central (peripheral), such that the status of the authors appears to be a central determinant of collaboration choices. Assortativity in the matching of collaborations is generally associated with strong relational conformism in knowledge production (Ahuja *et al.*, 2012). For Crespo *et al.* (2014), this assortativity reveals a weak capacity of the community to experiment with collaborations with new entrants, whether they are young researchers or experienced researchers providing knowledge from other scientific fields. However, we observe in *Figure 4b* a very strong dispersion of the nodes on either side of the regression line, which shows that the assortative pattern at the aggregate level of the network hides a non-negligible number of nodes with a significant non-assortative behavior. This is typically the case in the top left part of the graph where very low degree nodes concentrate their collaboration with high degree nodes. This suggests the entry of fresh knowledge towards the core of the network. This may be explained by the burgeoning scientific cross-fertilization between the digital and entrepreneurial dimensions of ecosystem research from which the field of DEE arises, even if this observation must be accompanied by a contribution-by-contribution verification to be confirmed.

When linked to the volume of citations, as measure of recognition and dissemination of ideas, the socio-structural analysis reveals the most cited papers have a central positioning in each of the cohesive groups. This observation is in line with the literature on the relational determinants of scientific impact, which recurrently shows that the degree centrality of authors in co-authorship networks is significantly correlated with citations (Yan and Ding, 2009). This is explained by the social capital built by the authors as far as the number of co-authors increases. But second, the literature emphasizes the same correlation with betweenness centrality. Recall that the betweenness centrality of a vertex measures the number of shortest paths between other vertices passing through it. Papers with strong betweenness are then those co-authored by scholars collaborating with other authors who are little or not connected to each other, giving the former a leading position for bridging between different cohesive groups, or, to say in other words, those without which the giant component could be split into several disconnected components. As their contributions are produced by authors from different communities, the potential for dissemination and citation is broader.

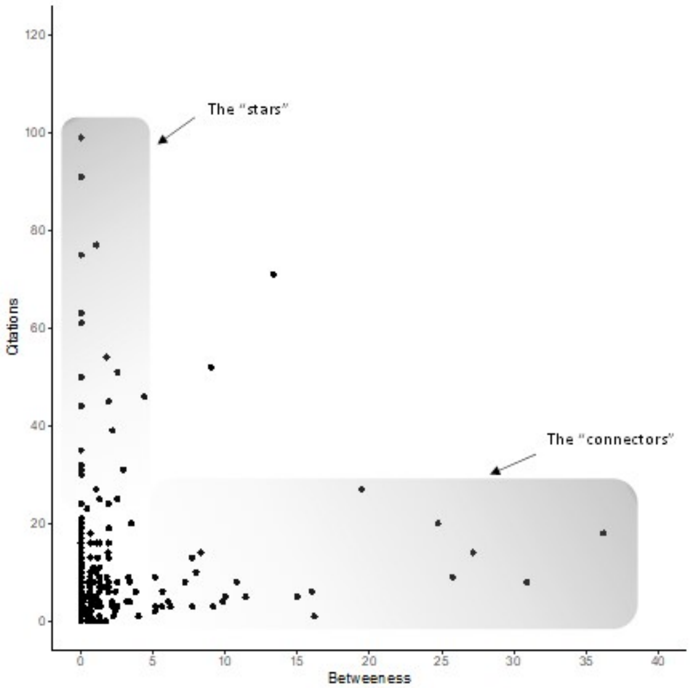

Figure 5: betweenness centrality and citation count

As shown in *Figure 5*, this recurring pattern is not verified. Alongside a majority of papers from the giant component having received few citations and having a low betweenness score (at the bottom left of the graph), two groups of contributions appear that are significantly distinct and of important size. The *stars* group on the top corner left is made up of highly cited contributions with a zero or low betweenness score. These are key papers that are highly recognized within sub-communities, but whose authors have not or only rarely established collaborations with authors from distant sub-communities. The *connectors* group at the bottom right has a roughly equivalent number of contributions and a strict inversion of scores. Here, the papers come from scientific collaborations between authors belonging to very distinct communities, i.e. research combining scientific expertise developed in poorly connected social groups. The fact that these groups are distinct does not mean *a priori* that the knowledge mobilized is also necessarily distinct, in accordance with the distinction we have made between the analyzes of citation networks (diffusion and absorption of knowledge) and those of collaboration networks (production of new knowledge). But this means when we focus only on the structural dimension that the production of new knowledge is based on collaborations never or very little explored during the period. These are collaborations between scholars involved in groups whose other members have little explored an equivalent strategy of collaboration outside their own group, which can suggest the emergence of innovative scientific results, but which however remain little recognized.

4.3. Is the DEE network a small world?

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

So why are these contributions less recognized when citations are considered, even though they would potentially contribute more strongly to scientific advances within the field? The explanations are twofold. First, by the propensity of "connector" contributions to be interdisciplinary or inter-domain research. As shown by Wang *et al*. (2015), the recognition delays for these contributions are much longer, and can increase after several years, including when citations to mono-disciplinary papers start to decline. As the field of DEE emerged at the end of the 2010s with the reference contributions of Sussan and Acs (2017) and Song (2019), we cannot exclude that *connector* contributions will become the *star* ones in a few years, after having been *sleeping beauties* during a long period. This negative correlation between citation and betweenness centrality would then be the mark of the emerging dimension of the field rather than the one of an intrinsic fragility. Secondly, as shown by Biscaro and Giupponi (2014), the status of the authors being a determining factor in the number of citations, we can infer that the risk-taking of exploring collaborations at the frontiers of communities is carried out mainly by researchers whose level of recognition has not yet reached that of the most recognized authors within their sub-communities. If such a conjecture was verified, it would then confirm, with the small world property, the ongoing structuring of a DEE community from diverse and previously unconnected origins. However, we observe in *Figure 5* that two contributions stand out by the combination of a high citation score and a betweenness score which is well above the median. These two contributions (Acs *et al*., 2017; Autio *et al*., 2018), when we go into their detail, have two characteristics in common: they were published in the same period (2017 - 2018), and both promote the need to bring together research on EEs and that on platform and digital ecosystems. Following Newman (2009), these two contributions connecting authors from previously poorly connected communities benefit from a *first mover advantage* which can confirm that the field of DEEs is in its early phase of development.

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

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

What are precisely these origins, and how do they fit into collaboration patterns? Section 2 provided us with a first vision of the diversity of these origins, from upward approaches developing DEEs as a move beyond theories of the firm towards platform ecosystems supported by the development of digital technologies, to downward approaches gradually shifting from innovation systems to the determinants of entrepreneurship within ecosystems. Beyond these two movements, a variety of methods and ideas also appeared. Numerous works have relied on methods and ideas from the economics and geography of innovation, to capture the effects of geographical and institutional context on entrepreneurship. Others developed new theoretical ideas from industrial organization and strategic management to explain and demonstrate the nature of organizational changes and market strategies supported by the deployment of digital platforms. The aim now is to see how the ideas are articulated in the social structure of collaboration, and through which knowledge and cognitive content the scientific field progresses.

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

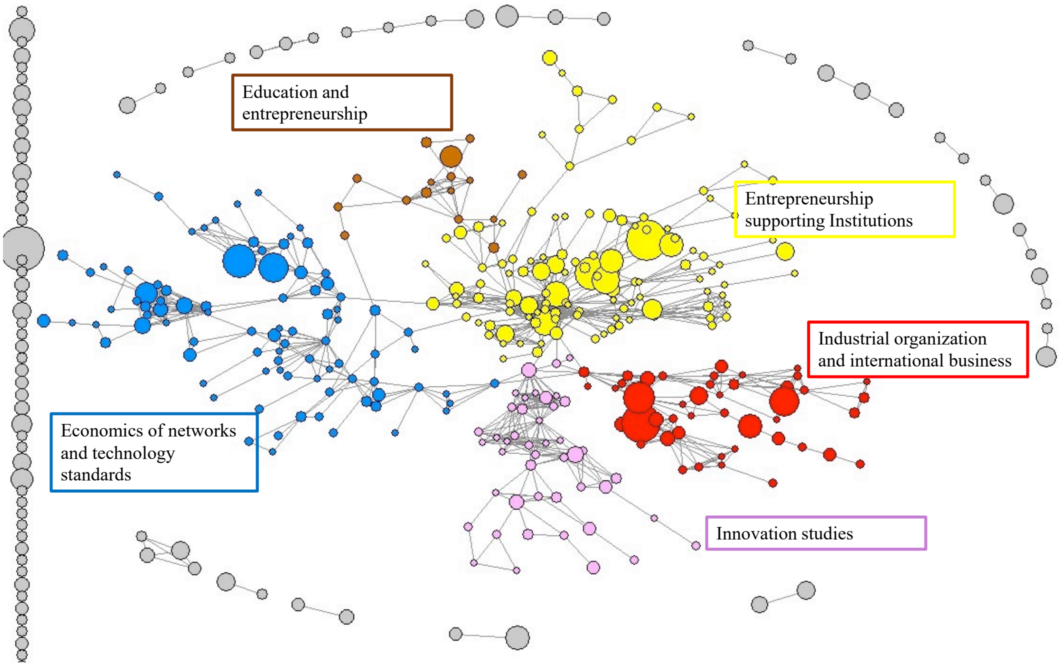

Figure 3: the DEE network (2)

Figure 6 represents the same network as previously, but now nodes' colors reflect the affiliation to a community according to the Girvan-Newman algorithm. We set the detection algorithm to 5 communities and focus on the search for non-predefined words and expressions which emerge from cohesive substructures. Communities' size ranges from 16 to 119 nodes within the giant component, while the isolated, dyads and triads are grouped within a sixth community of 126 contributions. As the 5 communities belong to the giant component, there always exists a path between two contributions taken randomly regardless of the community they belong to. But if some of the communities are connected directly to each other, by authors having published at least one paper in at least two of the communities, other pairs of communities are only connected through contributions from a third community, therefore without authors in common.

5.2. The semantic drivers of cohesive groups

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

Table 2: the semantic drivers and specificities of the cohesive blocks of the DEE collaboration network

Inspired by Roth and Cointet (2010) and Raimbault (2019), we first seek to determine whether cohesive groups exhibit specific semantic usage. If such specificities are confirmed, we obtain a first approximation of the content of the ideas which feed each of these groups, and of their scientific origin. To do this, we compute the RCA scores for each words-community pair. Then we define specificity thresholds to each community, both to portray them semantically and to assess the degree to which the words and expressions used distinguish them regarding the overall semantic landscape. The results are presented in *Table 2*.

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

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

For C3 (45 contributions), we also observe high RCA thresholds for several words and expressions (>2.5). The international and organizational dimensions of DEEs distinguish this community from others. The topics concern the international growth of digital companies and the development of new ventures. They also concern the problems of agencies and transaction costs. Due to a change in scale from the firm to the ecosystem, the analysis of new value chains as well as that of new patterns of distribution of authority and decisions becomes critical in understanding DEEs and the sources of their growth. The social cohesion within this group mirrors a semantic cohesion around the topics of *industrial organization and international business*. If we look at the position of C3 within the network, it may seem surprising to observe its social distance from C2. Only one contribution directly links both communities, while the economics of networks can be considered as a branch of industrial organization theories. C2 emphasizes more on strategic management of platform companies, with a strong focus on technology, while in C3 the emphasis is more focused on international development and growth. However, the question of the degree of dissociation between social and semantic dimensions will deserve our attention in the final discussion.

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

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

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

5.3. The transversal semantic drivers

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

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

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

Table 3: The transversal semantic drivers of the DEE collaboration network

Table 3 summarizes the search for semantic specificities crossing two communities. Note that previously we measured the semantic specificity of a word or an expression to a community by an RCA at least greater than 2, and at most less than 1.5 in another community. The same method makes it possible to search for semantic fields specific to two communities, i.e. transversal semantic fields whose social mirror effect can be discussed. To do this, we seek to identify for all pairs of communities the words and expressions having an RCA strictly greater than 2 in one community, and this time strictly greater than 1.5 in another.

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

Let's start with the pairs of communities that reveal common distinctive semantic markers. Among them, we note the pairs C1-C3, C1-C4, C3-C5. These three pairs have their own set of markers that distinguish them semantically from any other pair. We see that a majority of these markers within the three sets refer to issues relating to regional development and locational aspects. If the "geographic" marker did not appear in the semantic characterization of the cohesive blocks, it appears now in a salient manner when it comes to studying pairwise the semantic landscape, i.e. when we seek to identify scientific markers that go beyond the perimeter of separated small worlds of dense collaborations. Thus, issues on DEEs relating to local entrepreneurial dynamics, clusters or regional policies constitute topics which cross the communities working on institutional aspects (C1), on those on industrial organization and international development (C3), on those on innovation studies (C4), or those on education and entrepreneurship issues (C5). These common markers can in some cases translate into connections between communities, and sometimes not. We observe contributions published by authors who connect C1 to C3, and C1 to C4, and whose geographical dimension appears central in the title (see *Table 3*). But conversely, the sharing of common markers does not result in collaborative links for the pair C3-C4. We will return to this aspect of disconnection between the social and semantic dimensions in the final discussion.

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

We further note that the cohesive block C2 "behaves" very differently from its "neighbors". On the one hand, common semantic markers appear with C3, confirming the natural proximity between the economics of networks & technological standards and the economics of industrial organization. These markers refer to the issues of competition between digital platforms and their growth, in a digital industry typified by network externalities which push towards oligopolistic industrial structures. But on the other hand, what should attract our attention is the absence of common semantic markers with other communities in the network (despite a small number of social connections). So, we deduce that the second cohesive block in size does not yet seem to have constructed a distinctive semantic landscape with the other communities, except for its closest natural neighbor C3. This C2 block of contributions focuses on one of the most central aspects of the economic dynamics of platform ecosystems, namely what Nylund and Brem (2023) call “ecosystem-based standards”. This would then mean that the dynamics of collaboration on this theme would not have yet led to the construction of a common language and topics shared with institutional and holistic approaches (C1), with innovation studies (C4), or with research on education and entrepreneurship (C5).

6. Discussion and conclusion

Where does the scientific community stand along the process of social (the collaboration network) and semantic (the conceptual and theoretical landscape) structuring of the field of DEEs? Recall that, while the research community on EEs reached a critical mass of contributions and a recognition within the scientific community and within the circle of policy makers at the middle of the 2010s, two important contributions (Sussan and Acs, 2017; Song, 2019) appeared a couple of years later to outline the framing of a new field dedicated to DEEs. At the same period, in a different way, Acs *et al.* (2017) and Autio *et al.* (2018) propose to better integrate the constituent of platform ecosystem theory into the framework of EEs and analyze more in depth the articulation of digital and spatial affordances in EE development, but without proposing a new and specific framework for DEE. While for the former, an autonomous recognition of the DEE field is expressed, it is not the case for the latter, who limit to the integration of some key elements relating to platform ecosystems in the existing EE research program. The socio-semantic approach developed here provides an interesting interpretation of these debates. While it cannot replace the rigor of a discursive analysis of the state of the art, it offers a rich complement based on objective data and reproducible methodology. Based on sections 4 and 5, we can now discuss how social and semantic dimensions interact.

At the first glance, the DEE collaboration network enters the category of small world networks (Moody, 2004). These are networks that are neither perfectly integrated nor perfectly fragmented (even if fragmentation remains outside the giant component). These are multi-cluster networks, representing different areas of cohesive scientific authorities, and connected to each other by a few connectors who play a role as a knowledge conduit within the overall structure. The analysis through the detection of communities and their semantic content made it possible to specify the scientific nature of these areas of authority. We thus identify two communities of significant size in terms of number of contributions (labelled as *Entrepreneurship supporting institutions* and *Economics of networks and technology standards*), whose semantic landscape of each reflects the two scientific dynamics considered by Sussan and Acs as those whose intersection defines the perimeter of the research program on DEEs. These two central communities also connect to three other smaller cohesive communities dedicated to the educational aspects of entrepreneurship, innovation studies and the international dimension of the industrial organization of the digital economy. The scientific field of DEEs is therefore marked by a thematic and disciplinary pluralism of approaches whose integration is still weak at this stage and based only on a small number of contributions connecting these different areas of scientific authority. However, the few bridges built between cohesive groups can be considered as proof of the initiation of an integration process which will deserve to be followed over time. This initiation is carried out by collaborations between authors belonging to distinct areas of authority, those that we have called *connectors*, whose works remain less recognized in citations than the contributions located at the centers of the sub-communities. This low degree of integration is also confirmed by patterns of collaboration marked by the domination of assortative behaviors within each community. This implies a strong tendency of the most recognized authors, those we called *stars*, to interact with each other on the central topic of each cohesive group. We nevertheless observe that this trend is partially reduced by some contributions from authors with non-assortative behavior, contributions which have been plotted in *Figure 4b*. These contributions, which result from collaborations between authors who seem more peripheral within each community, play a crucial role in the initiation of this process of social and scientific integration. In summary, the socio-semantic network analysis approach confirms a low degree of social integration between theoretical approaches and semantic fields contributing to the DEEs conceptual landscape. These first signs of integration can only be confirmed in the future if the knowledge produced by the connectors gives rise to new collaborations at the frontiers of the areas of authority.

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

Second, and more paradoxically, we observe that one of the two largest communities, that on the *Economics of networks and technological standards*, although directly connected to three of the four other communities, does not have any common semantic markers. A few connector authors exist, but the flows of knowledge have not led to a common language or scientific issues identifiable within each pair of communities. This is even more noteworthy as this result concerns the pair composed of the two largest communities and therefore the two most dominant approaches within the overall community. In terms of scientific progress on DEEs, this means that between the cohesive group centered on platform ecosystems (and its challenges in terms of technological standardization, and innovation strategies in new intermediation business models), and that on holistic approaches to institutions supporting the development of entrepreneurial ecosystems (including all the determinants of entrepreneurial incentives), we do not observe any distinctive markers which would confirm the emergence of a semantic corpus specific to a program of research on DEEs, as promoted by Sussan in Acs (2017). However, according to Acs *et al*. (2017), the integration of these two theoretical blocks is one of the natural *"lineages of the entrepreneurial ecosystem approach"* (p. 1), as for Autio *et al*. (2018) according to whom *"there is a need for future research that examines the nature and effectiveness of such platform-*

specific entrepreneurial ecosystems and the boundary conditions associated with this new phenomenon" (p. 91). As shown by Balland *et al.* (2013) and Bessagnet *et al.* (2021), industrial and regulation strategies on technological standards impact the extent of entrepreneurial opportunities and success, as their geography. Such issues highlight the need to strengthen collaborations between these two cohesive groups to bring about a denser and shared conceptual framework within a more integrated community. Here again, the socio-semantic analysis sheds light on the gaps to be filled for upcoming research and outlines the nature of the collaborative incentives to be defined for the future.

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

7. References

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