SCIENTIFIC ECOSYSTEMS AND DECENTRALIZED ORCHESTRATION: A SOCIAL NETWORK ANALYSIS OF THE CINET CONFERENCES

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ABSTRACT

This article addresses the orchestration of scientific ecosystems, which encompass a variety of competing and/or collaborating autonomous actors – including researchers, universities and industrial firms – which aim at developing theory. Scientific ecosystems are a very interesting subject to be studied because some of their features – specifically data building and sharing – are increasingly assuming importance for firms that post-COVID will have to cope with the 'new normal', which requires them to experiment on the basis of collectively gathered data in order to accelerate their learning "on the fly". Specifically, business ecosystems challenged by the 'new normal' can leverage on the experience that scientific ecosystems have always had regarding data building and sharing.
Considering conferences as decentralized orchestrating moments capable of pulling together dispersed resources/capabilities by ensuring knowledge mobility, and building on a social network analysis of the CINet conferences between 2014 and 2017, we aim at understanding the characteristics of the CINet scientific ecosystem in order to infer how well connected and close its researchers are and how effectively information is shared among them.

__Keywords__: Orchestration, Social Network Analysis, Evolution, CINet.

1. INTRODUCTION

COVID-19 has so rapidly and deeply challenged economies all over the world that firms, consultants and academics are wondering how to approach innovation for competing in the "new normal" to come. The newness of this scenario is so challenging that it is almost impossible to build on past lessons learned (Verganti, 2020). Everyone is required to learn "on the fly" how to compete through innovation – extensively experimenting new solutions and business models (Edmondson, 2018). Although experimenting in isolation is a viable way, experimenting in collaboration with partners seems to be more promising since it allows firms to build on the others' mistakes and achievements (Verganti, 2020). Hence, while leveraging on collective experimentation, firms are able to get most from their reciprocal experimental efforts and speed up their own learning (Verganti, 2020).

One way for collaboratively experimenting is putting in place the "learning by sharing" approach, which consists of sharing data and results between firms in order to learn as rapidly as possible (Verganti, 2020). Very recent examples underpin this direction: private firms that share results on their advancements in the development of a vaccine for COVID-19, Microsoft that threw its weight fully behind the open data movement, Airbus with its Skywise – aviation's open data platform. Obviously, data sharing does not mean that every firm allows any other firm accessing its data/results, but rather entails that the

right partners within its ecosystem are identified (Adner, 2017).

Thus, through "learning by sharing" (Verganti, 2020), firms are putting into place the approach historically followed by researchers and scientists, who, indeed, are used to building data together and share them (Petersen et al., 2019). Obviously, and similarly to what happens for firms, data building and sharing in the academic environment do not imply that anyone indistinctively can access them. Rather, data building and sharing take place in environments that can be defined as scientific ecosystems, composed of a variety of competing and/or collaborating autonomous actors, aiming at developing theory. Data building and sharing within scientific ecosystems can take place between scientists working together in research projects, or between scientists and firms within research projects with well-defined objectives and governance rules.

Therefore, scientific ecosystems are interesting not only *per se*, but also because they can provide an inspirational example for business ecosystems coping with the need of implementing a "learning by sharing" approach in order to succeed in the 'new normal'. In this paper, we start analyzing scientific ecosystems, with the aim of investigating the way they work and possibly learn some lesson for business ecosystems.

2. THEORETICAL BACKGROUND

Three main conceptually distinct archetypes of ecosystems inspire researchers in management studies (Hakala et al., 2019): entrepreneurial ecosystems (Cohen, 2006; Isenberg, 2010; Neck et al., 2004), business ecosystems (Adner, 2017; Moore, 1993; Zahra and Nambisan, 2012), and innovation ecosystems (Adner, 2006; Iansiti and Levien, 2004; Ritala and Almpanopoulou, 2017). Although innovation ecosystems draw upon business ecosystems (Gomes et al., 2018), and hence some overlap between the two is possible, these three ecosystems markedly diverge in terms of plot (focal point, involved actors, relationships between them) and desired outcome (Jacobides et al., 2018).

Given that ecosystems are structures formed by interrelated entities that have significant autonomy (Jacobides et al., 2018), ecosystems can be managed, albeit not fully hierarchically controlled (Hakala et al., 2019). Therefore, an interesting topic regarding ecosystems is their governance or orchestration (Paquin and Howard-Grenville, 2013). Specifically, an orchestrator can coordinate and motivate activities by: (i) setting rules and norms (Colombo et al., 2017); (ii) establish the legitimacy of the ecosystem activities with a wide audience; (iii) attract potential actors who will create ties (Paquin and Howard-Grenville, 2013); and (iv) support them in thinking strategically about the ecosystem in which they operate (Zahra and Nambisan, 2012).

Orchestration has been investigated in the three archetypes of ecosystems. For instance, Colombo et al. (2017: 421) investigate if entrepreneurial ecosystems are "*governed top-down by a "visible hand", or navigated bottom-up by an "invisible" Darwinian process*". In innovation ecosystems the anchoring point is not a firm, but rather "*the system of innovations that allows customers to use the end product*" (Jacobides et al., 2018,: 2257). With reference to business ecosystems, the literature stresses the role of ecosystem managers – "hub" or "keystone" firms – as the providers of stability (Iansiti and Levien, 2004), knowledge mobility, innovation appropriability, and network stability (Dhanaraj and Parkhe, 2006). Zahra and Nambisan (2012) distinguish four different models of business ecosystems that differ in terms of the nature of the innovation space they inhabit and the nature of governance. Specifically, one of these four – the Jam Central Model – is an ecosystem in which research centers collaborate to develop an innovation in an emergent/radically new field emerging from the collaboration, with no dominant company regarding governance responsibility, which indeed is diffused among partners.

To the best of our knowledge, scientific ecosystems have not been investigated, yet. Specifically, as scientific researchers, we are adamant to claim that researchers operate in scientific ecosystems, i.e. decentralized systems of autonomous actors characterized by a specific plot and desired outcome. Specifically, the focal point concerns research, with the aim of developing theory, i.e. a body of understanding cumulatively built through descriptive and normative stages (Christensen, 2006). Scientific ecosystems are composed of a variety of actors: senior and junior academics, universities, private and public institutions providing funding, editors of journals, and also firms (as object of investigation, if the investigated research topic is management, or proposer of topics to be investigated).

Relationships of collaboration and competition take place between all these actors. For instance, on the one hand, researchers need to collaborate with other academics to achieve the critical mass needed to cope with challenging research projects and attract financial resources raffled off by (public) funding bodies. Although researchers sometimes need to prevent knowledge leakages to other researchers, achieving visibility to colleagues is generally important. The development of theory very often entails different knowledge requirements, depending on the features of the research objective to be framed and achieved. For instance, some actors are very knowledgeable about specific scientific fields and the related theories, others are very knowledgeable about methodological aspects (specific research methodologies or techniques), while yet others may act as senior experts who are endowed with a higher level perspective needed to identify the most promising research questions or the right research setup.

The phases along which theory building proceeds may entail specific patterns of coupling among the ecosystem's actors, i.e. specific linkages among the actors characterized by different levels of strength and intensity. According to Brusoni and Prencipe (2013), who build on Orton and Weick (2010), coupling can be operationalized through the interplay between responsiveness (the property of the system elements to maintain a degree of consistency with each other, even in a changing environment) and distinctiveness (the property in the system elements to retain their identities). The system is defined as "tightly coupled" or "decoupled" if responsiveness or distinctiveness prevail, respectively; the system is described as "loosely coupled" if distinctiveness and responsiveness are quite well balanced.

For instance, when researchers are confronted with ambiguous situations – as it is now, for instance, with COVID – new theories have to be developed. In such situations, researchers do not yet have the interpretative knowledge that is necessary to identify the constructs involved, i.e. the "*abstractions that help us rise above the messy detail to understand the essence of what the phenomena are and how they operate*" (Christensen, 2006: 40) and to bring them together in a coherent theoretical framework. The necessity to set up a shared framework is at odds with distinctiveness and rather requires responsiveness: many researchers need to interact, share ideas, communicate and exchange their knowledge. In this case, conferences may provide researchers with a socially cohesive environment in which they share their ideas on the pivotal constructs at play and their relationships, in order to get to a common and shared frame of reference. On these premises, the scientific ecosystem is tightly coupled.

However, as soon as researchers achieve a general theoretical framework, ambiguity leads to complexity. More precisely, within the shared general framework, which works as a sort of agreed-upon architecture, researchers dig deeper in order to better detail the framework, enriching it with a finer-grained operationalization of the constructs, adding new constructs that enrich the general framework and elaborating new categorization schemes that attempt to simplify and organize the world. While the framework grows in

complexity, researchers in the ecosystem can work independently of and concurrently with other researchers. In this scientific environment, in which researchers' distinctiveness prevails on responsiveness, conferences may serve as stages where results regarding the developments of the general framework are presented and debated.

Although scientific ecosystems share some of the characteristics of business ecosystems (value creation), specifically of the Jam Central model type (research with no dominant actor with governance responsibility), some important differences emerge. In scientific ecosystems, research is mainly conducted by (groups of) researchers and not by firms, with the aim of developing theory and not innovation. In addition, in scientific ecosystems there are not dominant actors with governance responsibility, but rather moments/events, such as conferences/seminars/workshops that, while pulling together the dispersed resources/capabilities and hence assuring knowledge mobility (Dhanaraj and Parkhe, 2006), seem to orchestrate the ecosystem in order to create value.

This approach consisting in interpreting the orchestrator as something different from an organization is not new. For instance, Longo and Giaccone (2017) speak about institutions as socially shared and embedded institutional arrangements (rules for access, ways of interaction and operational mechanisms). Institutions and institutional arrangements, while aiming at coordinating the co-creation of value, "*are not intended as organizations but as sets of rules, norms and beliefs*" (ibid.: 883) guiding and coordinating innovation activities inside the hub.

However, since scientific ecosystems have not been studied in the literature, questions regarding their orchestration emerge. While aiming at answering them, we will analyze events, in this case conferences, as opportunities for a decentralized orchestration of scientific ecosystems, interpreted as a set of evolving actions, not a static structural activity (Paquin and Howard-Grenville, 2013). More precisely, we investigate the questions: *To what extent and how does event-based orchestration favor 1) collaboration between the key actors of the ecosystem, and 2) international collaboration?*

3. RESEARCH DESIGN

We investigated the Continuous Innovation Network (CINet) as a scientific ecosystem. In order to answer the research questions, we utilized Social Network Analysis (SNA) (Burt and Minor, 1983; Wasserman and Faust, 1994). SNA is a discipline aiming at investigating social structures through the exploitation of graph theory and networks (Otte and Rousseau, 2002). It finds application in different fields, including sociology, anthropology, economics, marketing and computer science. SNA characterizes networks in terms of nodes (e.g. individual people or organizations) and edges (relationships or interactions) connecting them (Wasserman and Faust, 1994).

In this study, instead of using citations and co-citation methods, the analysis was based on the co-authorship networks (Santonen and Ritala, 2014; Vidgen et al., 2007), which allows evaluating the actual relationships between researchers and investigating how the scientific community is orchestrated. Co-authorship networks are made up of nodes, i.e., the authors, who are connected by one or more links representing co-authored papers (Santonen and Ritala, 2014; Abrahams et al., 2019; Vidgen et al., 2007).

Based on the co-authorships of publications, the structure of the research collaboration network within CINet and its evolution over time were investigated, by considering key authors and countries.

3.1 DATA COLLECTION

We collected data from four CINet conferences between 2014 and 2017. The data source

used was the CINet conference database, from which we extracted two datasets, including all papers accepted for the four conferences and all participants to the events over the years. Altogether, 385 research papers and about 580 authors are involved. Data included basic information about these research papers submitted to CINet these years (i.e., title, co-authors and keywords) and their authors (i.e., name, country, affiliation, and institutional position).

To carry out the co-authorship analysis, we firstly checked the two datasets to ensure that each author and each paper was identified correctly. In case of missing information, we conducted an additional web-based search, exploring the authors' personal pages. Then, for each paper, we explicitly specified the co-authorship relationships between the authors. The resulting dataset was visualized and analyzed using Gephi (Bastian et al., 2009).

3.2 SNA METRICS

To characterize the CINet co-authorship network and evaluate the importance of all actors within it, we resorted to the common and widely used SNA measures: size, density, average path length and centrality (Freeman 1978; Wasserman and Faust, 1994). Understanding the characteristics of the CINet community allows inferring how well connected and close authors are to each other, how effectively information passes across the network, and whether some members have a central role within the network. A brief description of each metric is provided next:

- *Size*: The size of the network was measured in terms of *number of nodes*, which expresses the number of authors within the network, and the *number of edges*, which represents the number of co-authored papers among the network nodes. If the number of nodes remains the same over the years but the number of edges increases, connectivity between the nodes also growths.

- *Density*: The density of the network was calculated as the actual number of edges divided by the number of possible combinations of edges. This metric indicates the degree of network connectivity, i.e. how the nodes in the network are interconnected. A dense network means that many authors communicate and collaborate with many other members of the community.

- *Average Path Length (APL)*: This dimension was measured as the mean of the shortest distances between each pair of nodes (Watts and Strogatz, 1998; Lee and Kim, 2018). A low value of APL indicates a highly efficient diffusion of information within the network. If there are many nodes in a bridge position within the network, APL is short. If, in contrast, there are many local hubs within the network, APL is large.

- *Centrality*: Centrality measures the importance of each node within the network (Abbasi et al., 2011). To compute centrality, we adopted three common metrics: *degree centrality (DC)*, *betweenness centrality (BC)*, and *eigenvector centrality (EC)*. In more detail, DC measures the number of other nodes connected directly to the node of interest. It specifies the popularity of a node within the network. A high DC indicates that the node has a central position and it is quite active within the network. BC measures how often a node is found on the shortest path between any pair of nodes in the network. A node with the highest value of BC is the most effective node for transferring information, which also influences other nodes, assuming the role of broker or leader (Lee and Kim, 2018; Freeman 1978). Finally, EC measures the influence of a node in a network, based on the centrality measures of neighboring nodes. A node, which is connected to many other nodes that are themselves well-connected, has a high EC score.

4. RESULTS

4.1 NETWORK ANALYSIS

Figure 1 shows the CINet co-authorship networks from 2014 to 2017. The thickness of the edges gives an indication of the number of co-authored papers between pair of authors. The size of the nodes defines the position of the authors within the network in terms of betweenness.
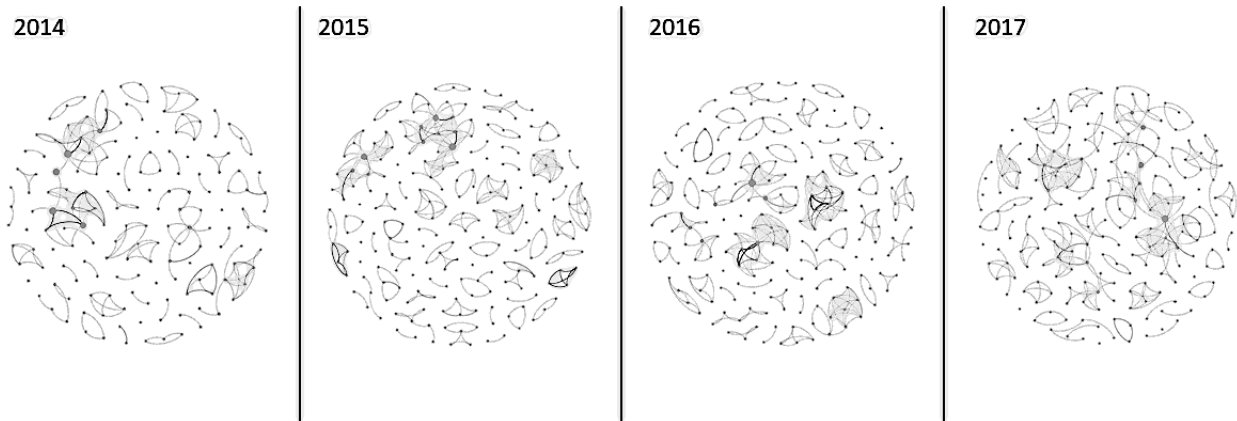

Figure 1: CINet co-authorship networks from 2014 to 2017

It is observed that the network diagram for each year indicates that the research community is largely fragmented with few researchers acting as bridge between two or more different sets of co-authors. Also, several single nodes are present, representing the authors who have submitted single-author papers. In addition, the scene is dominated by a few individuals with a central role and high popularity (see the largest nodes in Figure 1).

Table 1 summarizes the changes in network metrics over time, from 2014 to 2017. The number of nodes and the number of edges (i.e., the number of authors and the number of papers, respectively) show a growing trend until 2016, with a slight deflection in 2017. In addition, the increase in the number of edges (for example, +6.6% in 2015) is higher than the increase in the number of nodes (for example, +0.5% in 2015) over the years. This indicates an increased connectivity between nodes.

Table 1: Network metrics changes from 2014 to 2017

Year	Nodes	Edges	Density	APL
2014	162	228	0.014	2.6
2015	218	334	0.012	1.7
2016	217	356	0.013	1.7
2017	205	308	0.013	2.1

The graph density of the CINet network is pretty low and remains steady over the years. This means that the connectivity of the entire network is low. Since the CINet community encompasses a different number of research areas within, or related to, (continuous) innovation, that result suggests that the authors are dispersed along these areas, reducing the possibility of collaborations. A visual inspection of the paper titles supports this suggestion.

Finally, the APL shows a u-shaped trend. This translates to an increase followed by a decrease of the efficiency of the diffusion of information within the network over time.

4.2 ANALYSIS OF KEY AUTHORS

After the analysis of the characteristics of the CINet network as whole, we investigated the individual nodes of the network, i.e., the authors, in terms of their centrality within the network.

Table 2: Key authors of CINet community over the years

Year	Betweenness		Weighted Degree		Eigenvector	
2014	1. Mariano Corso	160	1. Mariano Corso	13	1. Mariano Corso	1
	2. Lara Agostini	149	2. Luca Gastaldi	12	2. Luca Gastaldi	0.96
	3. Astrid Pietrosi	143	3. Antonella Martini	11	3.Antonella Martini	0.81
	4. Anna Nosella	108	4. Valentina Lazzarotti	11	4. Elisabetta Raguseo	0.72
	5. Antonella Martini	64	5. Luisa Pellegrini	11	5. Paolo Neirotti	0.72
2015	1. Antonella Martini	89	1. Antonella Martini	15	1. Antonella Martini	1
	2. Mats Magnusson	71	2. Mats Magnusson	13	2. Emilio Paolucci	0.88
	3. Emilio Paolucci	70	3. Emilio Paolucci	13	3. Francesco P. Appio	0.85
	4. Luca Gastaldi	27	4. Luca Gastaldi	11	4. Luca Gastaldi	0.84
	5. Mariano Corso	27	5. Mariano Corso	11	5. Mariano Corso	0.84
2016	1. Mats Magnusson	104	1. Emanuele Lettieri	22	1. Emanuele Lettieri	1
	2. Antonella Martini	53	2. Valentina Lazzarotti	21	2. Valentina Lazzarotti	0.85
	3. Emanuele Lettieri	45	3. Raffaella Manzini	21	3. Raffaella Manzini	0.85
	4. Sofia Ritzén	30	4. Luisa Pellegrini	21	4. Luisa Pellegrini	0.85
	5. Wolfgang Gerstlberger	26	5. Federica Segato	16	5. Davide Aloini	0.68
2017	1. Luca Gastaldi	229	1. Luca Gastaldi	16	1. Valentina Lazzarotti	1
	2. Paolo Neirotti	159	2. Valentina Lazzarotti	12	2. Luca Gastaldi	0.97
	3. Emilio Paolucci	110	3. Luisa Pellegrini	12	3. Luisa Pellegrini	0.94
	4. Antonella Martini	71	4. Antonella Martini	9	4. Lars Bengtsson	0.90
	5. Daniele Battaglia	50	5. Lars Bengtsson	9	5. Raffaella Manzini	0.89

Specifically, Table 2 lists the five individuals scoring highest in terms of betweenness, weighted degree and eigenvector, for each year. The researchers listed in Table 2 are senior researchers.

Looking at the role of each author, the evolution of the co-authorship network shows the emergence of new different key authors each year. In addition, from 2014 to 2017, most of the authors who occupied central positions in the network come from Italy, followed by Sweden. The authors' nationality is intended in the sense of their first affiliation nationality.

However, for each single year, nearly the same authors occupy the highest positions with respect to all the three aforementioned metrics. Specifically, when all metrics of a particular node are high (for example, Corso in 2014 or Martini in 2015), this means that such a node is likely to be the global hub within the CINet community because it has multiple connections to other nodes, particularly to well-connected nodes (both from the same and from different countries), and it controls the information transfer towards other nodes.

Conversely, authors with high betweenness but low weighted degree (for example Magnusson in 2016) have a central role within the network despite a lower number of connections and act as bridges linking different subgroups.

Finally, authors with a high weighted degree or eigenvector but low betweenness (for example Manzini in 2016 or Lazzarotti in 2017) represent local hubs within the CINet network because they have co-authored different papers with many different

collaborators, but information flows bypass them.

4.3 ANALYSIS OF INTERNATIONAL COLLABORATIONS

Figure 2 reports the results of the evolution of the CINet in terms of international collaborations over the years. As expected, most of the collaborations take place between authors from the same country (in terms of affiliation nationality). However, the percentage of international collaborations shows an increasing trend in the last years (up to +37% in 2016).
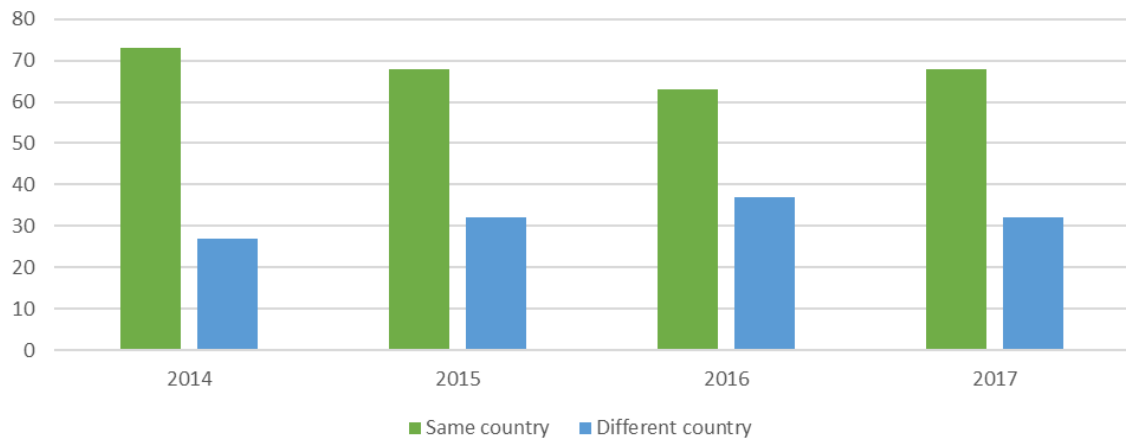

Figure 2. Evolutions of CINet collaborations

More in detail, Figure 3 depicts the co-authorship network diagrams from 2014 to 2017 from a country viewpoint. Specifically, the color of the edges indicates the type of relation: blue for international papers, i.e. co-authored by authors affiliated to different country institutions, and black for papers with authors affiliated to institutions (possibly different) from the same country. The color of the nodes represents the institutional country of the author.
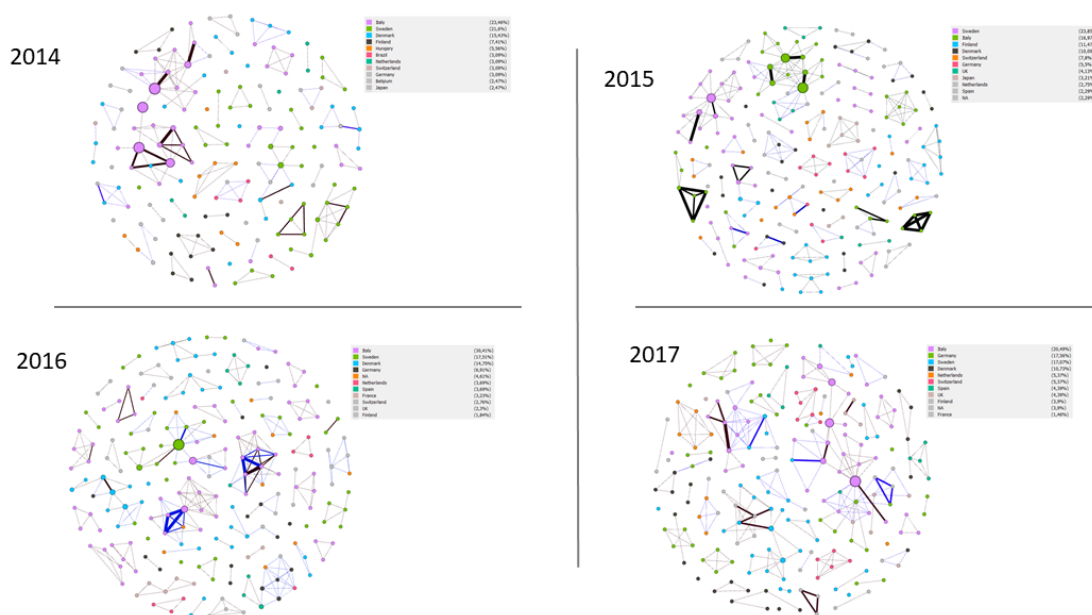

Figure 3. CINet co-authorship networks at country level from 2014 to 2017

As shown in the figure, the countries that cooperate the most are Italy, Sweden and Denmark (purple, green and azure dots, respectively). Anyway, collaborations between countries have been characterized by other different protagonists over the years, such as Finland, Germany and UK.

5. DISCUSSION AND CONTRIBUTION

This paper broaches a key, unexplored issue in scientific ecosystem orchestration. First, scientific research is a distributed and collective process involving a variety of actors such as senior and junior academics, universities, private and public institutions providing funding, editors of journals, and also firms as proposer of topics to be investigated and/or object of investigation (especially in management disciplines). These actors are involved in cumulatively building theory through descriptive and normative stages (Christensen, 2006). Along each stage, scientific research usually shows distributed and collective features because it entails knowledge requirements which unlikely are mastered only by one single researcher. Hence, in this article we put forward the construct of scientific ecosystem, which seems to be able to capture the complexity of theory building.

Within this understanding of scientific research, conferences can be seen as opportunities for a decentralized orchestration of scientific ecosystems, interpreted as a set of evolving actions, not a static structural activity (Paquin and Howard-Grenville, 2013).

In analyzing the CINet conferences in a four-year time span (2014-17), in this paper we aimed at understanding how expansion occurred in CINet, viewed as a scientific ecosystem, and how collaborations evolved, in that this can enable more effective orchestration of the network structure, in order to maximize value creation and extraction from the actors, including increased integration of knowledge and increased research productivity.

Very preliminary results show that a conference in itself is an event that spurs the creation of a number of groups of researchers working together. These groups, which change their morphology over the years, see a variety of authors collaborating with each other. The authors who play a central role within the network (i.e. who are the most influential authors) change over the years. Moreover, the preliminary findings reveal that the CINet collaboration network is mainly based on the authors' home country. It appears that, in each of the four investigated years, groups of researchers work together within their respective scientific ecosubsystems on the basis of agreed-upon research frameworks that function as shared architectures (responsiveness). Given that collaborations are mainly at the national level, the countries seem to work mostly independently from each other. This means that the enrichment of the general framework in terms of more fine-grained operationalization, new constructs and new categorizations schemes happen "locally".

In such ecosubsystems, senior researchers, as shown in Table 2, seem to retain their identities (distinctiveness); hence, because both responsiveness and distinctiveness are balanced, the subsystems appear to be loosely coupled (Brusoni and Prencipe, 2013).

5.1 CONTRIBUTION

We recognize that this paper develops a largely descriptive contribution in that it describes what happened in an example of a scientific ecosystem, over a relatively short period of time, using constructs borrowed from adjacent areas. Thus, this paper just presents a first step towards theory development on scientific ecosystems, but an important one in that it shows that (an example of) such systems can be fruitfully described and analyzed using ecosystem theory. A lot of further work is needed to develop robust understanding of, i.e. theory on scientific ecosystems. Some important directions

for further research come from the limitations of this study.

5.2   *LIMITATIONS AND FURTHER RESEARCH*

Our analysis focuses only on a single type of actors, i.e. researchers, so disregarding other possible actors such as universities, private and public institutions, editors of journals, and firms who may play important roles in the ecosystem. This is an important venue for further research. Furthermore, a timeframe of only four years can only produce preliminary results. It will be important to extend the analyses to include the 1996 to 2013 and 2018 to 2020 conferences. Then, CINet is just one of many scientific communities. An analysis of other communities focused on innovation research as well as networks in other disciplines such as operations management, strategic management and organizational theory, would strengthen the results of this study and allow more robust scientific ecosystem theory. Finally, the analyses presented here are largely a-contextual. Not only time but also a range of other factors such as changes in funding patterns and expectations, the inherent fashionability of management research and the effects of global events such as the financial crisis and, now, the COVID pandemic, should be considered to further explain the patterns identified in this study.

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