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# An analysis of international coauthorship networks in the supply chain analytics research area

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**Abstract** This work characterized the research community of supply chain analytics (SCA) with respect to coauthorship, a special kind of collaboration. A characterization of coauthorship in terms of researchers' countries, institutions and individuals was elaborated, so three different one-mode networks were studied. Besides, the SCA research community is characterized in terms of Supply Chain Management (SCM) research streams. Coauthorship among researchers working on different streams is also analyzed. Metrics that depict the importance of the network nodes were studied such as degree, betweenness and closeness. This study found out an intense collaboration between USA and countries such as China, India, United Kingdom and Canada. Researchers from Canada and Ireland are better situated (central) in the network, although they have not published a considerable amount of papers. The presence of cliques and the small-world effect were also observed in these networks. In terms of research streams, more research on SCA located at the Strategic Management, Technology-focused and Logistics streams was found. The most common links between research streams are on the one side, Technology-focused with both Strategic Management and Logistics and on the other side Strategic Management with both Logistics and Organizational behavior. SCA researchers are rarely working with a

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focus on Marketing. This study contributes to the SCA literature by identifying the most central actors in this area and by characterizing the area in terms of SCM research streams. This study may contribute to the development of more focused research incentive programs and collaborations.

**Keywords** Social network analysis · Coauthorship networks · Big data analytics · Business analytics · Supply chain analytics

## Introduction

The development of a science is a social process that occurs through networks of researchers forming communities. Such researchers interact and collaborate with one another to contribute to the overall knowledge of the community (Hu and Racherla 2010). How knowledge is created and disseminated within the academic community has been the subject of academic interest for some years now. Besides, over the past few decades, collaborations among individuals, research institutions, and countries have been increasing at a remarkable pace (Ye et al. 2011) and have become international and cross-disciplinary, being hard to construct and maintain, especially when individuals or organizations are in different countries (Munoz et al. 2016). For such reasons, in the research field of complex networks and bibliometric analysis, collaboration networks represent an important area of study.

An increasing number of researchers have performed bibliometric studies in order to evaluate the evolution of specific disciplines. Bibliometric studies do so by clustering and analyzing the various facets of written research. These studies are characterized as highly objective and quantifiable (Kilubi 2016). Scientific collaboration is a well-established research topic and is studied by three methods: qualitative methods (surveys, questionnaires, interviews or observations); bibliometric methods (publication counting, citation counting or co-citation analysis) and complex network methods (for example, social network analysis, which involves shortest paths, centralities and network parameters) (Milojević 2010).

Collaboration is intrinsic to a network of researchers. A series of forms of collaboration have been identified, including electronic communication, physical proximity, acknowledgement, visiting scholars, interpersonal communication channels, co-citation and coauthorship (Hu and Racherla 2010; Ye et al. 2011), being the last two often used in papers that study research communities. If on the one hand, the analysis of citation counts is one of the most popular methods of research assessment, on the other hand, it does not capture the social aspect that supports and transmits scientific ideas neither how network communities are assembled. In turn, the analysis of coauthorship of articles enables the construction of observable and visual measures of a research field community. Citation analysis might help identify the central and important scientific papers of a research field, whereas coauthorship analysis identifies who the important scientists are (Hu and Racherla 2010). The citation network approach works on the assumption that citing and cited papers have similar research topics (Colicchia and Strozzi 2012).

Coauthorship is the information most frequently used in exploring collaboration patterns among researchers (Stefano et al. 2011). Coauthorship is one of the most relevant outcomes of collaboration given that publication of scientific results is one of the classical outcomes of research activities (Finardi and Buratti 2016). Moreover, the growing importance placed upon research publications in academia, together with significant advances in communication technologies have led to an increase in coauthorship in different areas, such as operations management, economy, tourism and human resources management (Behara et al. 2014; Cainelli et al. 2015; Fischbach et al. 2011; Henneberg et al. 2009). The analysis of coauthorship networks draws on the closely related research stream of Scientometrics, a discipline that aims at analyzing and measuring systematic knowledge creation (Fischbach et al. 2011). Coauthorship is commonly used to analyze the association between researchers at individual, institutional and national levels (Kumar 2016).

Collaborations through coauthorship, also called joint authorship, form a "coauthorship network" in which the network nodes represent authors and a connection between two authors exists if they have coauthored a study. Such network of collaborations is a type of social network. A social network is a set of individuals or groups (called nodes or actors) each of which has some kind of connections to some or all of the others. The study of these networks, their participants and the interactions among them is called social network analysis (SNA) (Abbasi et al. 2012; Wasserman and Faust 1994). SNA is a relatively new, but rapidly growing field in sociological and economic research. Although its origins can be traced back to early sociology and social psychology, it has become one of the most popular interdisciplinary analysis techniques (Ye et al. 2011). SNA offers significant assistance as we use it to map not only the various relationships that occur among actors, but also the network structure arising from these relations (Sloane and O'Reilly 2013).

Despite the significance of networks for modelling complex adaptive systems, the literature has few examples of the application of the latest developments in network theory specifically to supply chains (Hearnshaw and Wilson 2013). The use of SNA in supply chain analysis has been focused on network inter-dependences and emphasizes the impact of the network structure on firm competitiveness (Sloane and O'Reilly 2013). In this case, network nodes represent firms and links among them represent interactions among such companies. In this scenario, SNA can help managers to effectively map informal communication and workflow networks and can allow organizations to better manage knowledge, information and organizational learning (Carter et al. 2007). Besides, a representation of such networks provides for a rich understanding of large and complex communities such as academic researcher groups. Measures derived from these analyses are useful for assessing the impact of network formation, access and utilization on research productivity, coauthorship networks and relationships (Hu and Racherla 2010).

Previous studies have characterized research on Supply Chain Management (SCM) recenlty, either using SNA or other methods. Behara et al. (2014) identified and examined an European Operations Management (OM) research coauthorship network and ranked authors, institutions, and countries using network centrality measures. In addition, they showed that European OM research has focused most on the area of SCM, more particulary on manufacturing. Spain and United Kingdom were found to lead European research in this area. By analyzing the most frequently cited publications in three OM journals over a period of 27 years, Pilkington and Meredith (2009) found that, in general, the field appears to be currently focusing on more strategic and macro issues such as supply chains and research methodology, characterizing the field as a dynamic area. Also assessing the evolution of the field over the last 20 years, Giannakis (2012) analyzed papers that were published in ten leading academic journals in the field. A combination of social network and citation analysis among the selected journals was applied. The analysis reveals that the current structure of the network of journals is characterized by an evident shift of focus of OM journals towards more SCM phenomena. The have also found that the cohesion of the discipline has improved but is still fragmented due to a lack of reciprocal co-citations among the journals. Finally, Carter et al. (2007a, b) performed a SNA of the citations within the 40-year history of the Journal of Supply Chain Management. The authors found a significantly greater number of citations per article over time, particularly in the last 15 years. Specifically, work which has been published in the last 5–10 years of the 40-year time period has cited existing research from the fields of logistics and transportation, management and marketing to a significantly greater extent than in earlier periods. Colicchia and Strozzi (2012) performed a literature review, using Citation Network Analysis, focused on robustness and resilience applied to Supply Chain Design. The authors identified research areas, influential groups and journals. With a similar objective, Kilubi (2016) analyzed the structure of the discipline of Supply Chain Risk Management area in order to identify knowledge groups and subfields of research. The author identified important clusters of papers and five research areas.

Within SCM, one of the promising research fields is supply chain analytics (SCA). Analytics, in broad terms, does not refer to a particular technology, method or practice. Rather, it is a combination of multiple IT-enabled resources, which includes both IT assets and organizational resources, in order to gain information, answer questions, predict outcomes of problem solutions and support decision-making, consequently creating competitive advantage (Bose 2009; Davenport and Jeanne 2007; Davenport et al. 2010; Trkman et al. 2010). SCA, being Analytics applied to the supply chain, aims at extracting and generating meaningful information for decision makers in the enterprise from the enormous amounts of data generated and captured by supply chain systems. In a supply chain context, such data originated and collected across the supply chain is crunched, numbers are analyzed, and information is generated for decision makers (Sahay and Ranjan 2008). To Souza (2014), SCA focuses on the use of information and analytical tools to make better decisions regarding material flows in the supply chain.

Although a growing number of research has been made on SCA, Bonnes (2014) argues that this is still a relatively premature research area and that there is limited amount of research available on this subject, very much of it realized in the past few years. In fact, academic research into data science, predictive analytics, and big data in SCM has been scarce (Schoenherr and Speier-Pero 2015). Recent review studies (Chen et al. 2012; Côrte-Real et al. 2014) corroborate such statements by identifying that most research on Business Intelligence and Analytics (BI&A) is aimed at characterizing the current research state with focus on technologies and systems and that most top-20 academic authors with BI&A publications are from Information Systems and Computer Science. These authors have identified no emphasis on the application of Analytics in SCM contexts. A study that unveils the research community and its research topics within SCA is, therefore, highly recommended.

A marked uprising in publications on the subject of Analytics can be observed over the last few years (Holsapple et al. 2014) and some studies have analyzed the evolution of its use in SCM research (Liu 2010; Stefanovic and Stefanovic 2009). With such evolution of the field, a characterization of its research community is necessary to identify major players in the field and their interactions. We believe SNA is a suitable approach to satisfy such goal.

It has been observed that SNA studies on SCM have focused mainly on citation analysis (Carter et al. 2007b) with very few exploring the research community from a social network perspective. In this way, the objective of this study is to characterize the research community of supply chain analytics in terms of its network of researchers and main research streams. More specifically, this work is interested in answering the following research questions (RQ):

- RQ1—Who are the most influential actors (researchers, research institutions and countries) in the SCA field in terms of number of publications and collaborations?
- RQ2—What are the macro and micro topological properties of the coauthorship networks in each of these levels?
- RQ3—Is the SCA research community coherent? Are there dominant components within the group?
- RQ4—What are the content research areas within SCA and how researchers from these areas have been interacting among them?

This paper contributes to the SCA literature in different ways. First, it identifies who the most central actors in this area are. Second, it characterizes this research area in terms of research streams of SCM literature. We are not aware of any previous work that has done so until now. Third, it highlights interactions among researchers of different SCA sub-streams. It is known that partnerships among researchers are hard to construct and maintain, especially when individuals or organizations are in different countries. This paper still contributes to the SNA literature by performing such analyses considering coauthorships between not only individuals, but also between their institutions and countries. Such analyses are not common in other SNA papers (Carter et al. 2007a; Ding 2011; Fischbach et al. 2011; Henneberg et al. 2009; Hu and Racherla 2010; Ye et al. 2011).

The remaining of this article is organized as follows. "Theoretical background" section presents the theoretical background with emphasis on supply chain analytics and social network analysis. "Research methodology" section describes how SNA was adopted in this study and which metrics were used to characterize the network of researchers in this field. "Results and discussions" section presents our results while "Conclusions, limitations and future work" section describes our conclusions, limitations and future work.

## Theoretical background

### Supply Chain Management and supply chain analytics

Mentzer et al. (2001, p. 4) define a supply chain as "a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances and/or information from a source to a customer". The authors categorize a supply chain in three levels: direct supply chain (dyadic), extended supply chain (including first tier suppliers and customers) and ultimate supply chain (end-to-end including ultimate supplier and customer). To Raisinghani and Meade (2005), a supply chain consists of all stages involved, directly or indirectly, in fulfilling a customer request. The supply chain not only includes the manufacturer and suppliers, but also transporters, warehouses, retailers and customers themselves.

Stock and Boyer (2009) argue that there are multiple definitions and nuances of the term Supply Chain Management in the literature. Mentzer et al. (2001) define SCM as "the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole". Over the past few decades, more executives have realized the strategic importance of SCM and recognized the distinctive competitive advantages that a well-managed supply chain can yield to the company (Shi and Yu 2013).

SCM has experienced several stages of development since its inception, from the traditional procurement and supply management, to the subsequent production operation management and logistics management, and to the integration management from supplier to customer, from logistics to the capital, information and even decision-making flows (Liu 2010). SCM has been seen as a tool for gaining competitive advantage through real-time collaboration with trading partners, and offers a way to rapidly plan, organize, manage, measure and deliver new products or services (Stefanovic and Stefanovic 2009).

Although varying definitions of SCM exist, most scholars have agreed that SCM includes coordination and integration, cooperation among chain members, and the movement of materials to the final customer (Stock and Boyer 2009). Integration among companies has been made possible mainly due to the wide adoption of CRM and SCM software that has allowed enterprises to fully interface/integrate their demand and supply chains. Based on this integration, enterprises are able to capture up-to-the-minute data about the demand of a particular product, as well as data of similar granularity about the corresponding data's supply (Kohavi and Rothleder 2002).

SCM presents a holistic, organizational, and inter-organizational focus and involves multiple interrelated firm and interfirm processes. Supply chain research often involves phenomena possessing complex behavioral dimensions at both the individual and organizational levels. Therefore, research into SCM requires a method that understands inter- and intra-organizational systems as a whole. Modern supply chain complexity requires a research methodology that describes how individuals interact within the whole (Randall and Mello 2012).

Through their process maturity journey, organizations have automated significant portions of their supply chain with applications that are able to analyze huge amounts of data to provide insights about the performance of suppliers and partners, material expenditures, accuracy of sales forecast and production plans and order delivery (Kohavi and Rothleder 2002). The analysis of such volumes of information in a SCM context has been called supply chain analytics.

Supply chain analytics has its root on the application of Business Intelligence (BI) and Business Analytics (BA) techniques. Although such techniques are widely used for managing the supply chain, there is not a consensus or common understanding as to what BI, BA or its supply chain related terms, Supply Chain Intelligence (SI) and supply chain analytics mean. These terms are frequently used in the same context and sometimes are even used interchangeably.

Although these terms present common characteristics, it is possible to outline some differences. Davenport (2014) differentiates these terms from a historical perspective as well as according to their main purpose. On the one hand, BI focuses on tools to support data-driven decisions, with emphasis on extracting information and reporting. On the other hand, BA encompasses the use of statistical and mathematical skills, aligned with Information Technology (IT) abilities and business vision for decision making. BI usually focuses on a set of tools and technologies, such as data warehousing, online analytical processing (OLAP), data mining dashboards, analytic and reporting tools, among others that enable information gathering, recording, recovery, manipulation and analysis. Sangari and Razmi (2015) state that BI can be viewed both technically and analytically. The technical view of BI usually centers on the process of using applications and technologies for gathering, storing, analyzing and providing access to data to help make better business decisions (Bose 2009). The key analytical component of BI is Business Analytics (Chen et al. 2012). In this context, BA is not a technology but a group of approaches, organizational procedures and tools used in combination with one another to gain information, and predict outcomes of problem solutions (Trkman et al. 2010).

Supply chain analytics, understood as BA applied to the supply chain, extracts and generates meaningful information for decision makers in the enterprise from the enormous amounts of data generated and captured by supply chain systems. In a supply chain context, such data generated and collected across the supply chain is crunched, numbers are analyzed, and information is generated for decision makers (Sahay and Ranjan 2008). To Souza (2014), SCA focuses on the use of information and analytical tools to make better decisions regarding material flows in the supply chain.

The difficulty in clearly establishing boundaries between BI and BA has led some authors to prefer the term Business Intelligence and Analytics (BI&A), combining characteristics of both concepts. Since there are multiple understandings of these terms and such differences appear in published papers; in this study, we opted to consider a broader concept of SCA, which embraces both the technical and the analytical components discussed previously. This decision reflects the way the SCA research community is assembled in this study as a social network. The procedures used to analyze such networks are described in the next section.

## Social network analysis

Individuals, organizations and countries participate in several different kinds of interaction among them. In order to facilitate the study of such interactions, networks may be used to model and graphically represent these interactions and actors that participate in them. In a graphical representation of a network, which is called a sociogram, objects (vertices) are represented by points or circles and relations are drawn as lines connecting pairs of vertices. If an adjacency matrix representation is used, columns and tables represent objects while the intersection between columns is filled in with the number '0' if there is not a relation between these objects and the number '1' if there is such a relation or even a greater number representing the intensity of such relationship. In such networks, the vertices usually represent people, organizations or countries and the lines represent interaction, information (Nooy 2003), communication, friendship, exchange of goods, or workflow (Behara et al. 2014). Networks are categorized in modes. One-mode networks are the ones in which all nodes belong to the same set of actors. Two-mode networks or affiliation networks are the ones in which two sets of social entities (and the relations connecting one set to the other) are present (Cainelli et al. 2015).

Social network analysis is the analysis of a set of relations among objects (also called nodes or actors). SNA, thus, is a methodology for studying informal communication networks. This type of communication takes place when people discuss ideas at various locations like places of work and conferences, while engaged in different relationships such as mentor/advisee, colleague, and coauthor (Marion et al. 2003).

One of the most important uses of SNA is the identification of those actors that are most central within the network. Centrality is a structural attribute of the relations among actors in a network rather than an attribute of the actors themselves (Carter et al. 2007a). Centrality in a social network is a concept that illustrates the most important and prominent actors in the network. Actors with high centrality possess a strategic location within the network (Giannakis 2012). Actors who are the most prominent in the community are often located in strategic locations which may allow them to communicate directly and be close to many other actors and to serve as an intermediary node in the interactions of many other pairs of actors.

There are many ways of measuring the dimensions of prominence in a network. One possible way is to calculate degree centrality, which defines the most important node as the one with the greatest number of connections. Degree centrality represents the total number of nodes a specific node is connected to. It is the most common and simplest measurement to evaluate the extent of collaboration (Ye et al. 2011). This can be determined by counting the number of links between a specific actor and the other actors in a network, or by summing a row or a column of an adjacency matrix (Carter et al. 2007a), depending on how the network is represented.

Another possible centrality metric is node-betweenness centrality. It refers to the extent to which a particular point lies between the various other nodes in the graph: a node of a relative low degree may play an important intermediary role and so be very central to the network. Thus nodes that are "in between" may act as gatekeepers in the dissemination of knowledge among the network (Giannakis 2012). Betweenness refers to the number of paths that pass through an actor on the shortest paths connecting two other actors. The concept behind this metric is based on information flow: a node has high betweenness if it lies on many shortest paths connecting two other nodes. This is an important metric since a node with high betweenness centrality has better access to information, is better positioned to act as an intermediary in exchanges and may be able to control flows of information or exchange (Sloane and O'Reilly 2013), can control communication flows and can potentially serve as a liaison between isolated areas of the network (Carter et al. 2007a). In terms of academic exchanges and flow of knowledge, researchers who have high betweenness centrality are at the core of the collaboration network (Ye et al. 2011). As so, betweenness centrality is calculated as $C_B(k) = \sum_i^n \sum_j^n b_{ij}(k)$; being $b_{ij}(k) = g_{ij}(k)/g_{ij}$. In the formula, $g_{ij}$ refers to the total number of shortest paths between nodes $i$ and $j$, and $g_{ij}(k)$ refers to the number of shortest paths that pass through node $k$ (Ye et al. 2011).

Opposite to degree centrality that shows the "local centrality" (i.e. the centrality in the immediate environment of a node), the level of closeness indicates how "globally central" a node is. Closeness is the sum of the shortest distance between an actor and every other actor in the network (Carter et al. 2007a). This measure focuses on how close an actor is to all the other actors in the network and expresses the global centrality of a network, i.e. a node would be globally central if it lies at short geodesic distances from many other nodes of the network. Actors with high level of closeness centrality could be very productive in disseminating knowledge to other actors in the network (Giannakis 2012). Closeness centrality is calculated as $C_c(p_k) = \sum_{i=1}^n d(p_i, p_k)^{-1}$ where $d(p_i,p_k)$ is the geodesic distance (shortest paths) linking $p_i$ and $p_k$ (Abbasi et al. 2012).

## Research methodology

The development of a research design in SNA differs in several specific aspects from that in other methods, whether survey research or qualitative case study. Sloane and O'Reilly (2013) define five key stages involving the choice of: (1) sampling units; (2) relational content; (3) relational form; (4) level of data analysis; and (5) specification of the network boundary. In a similar way, Stefano et al. (2011) defines the following stages for any research in SNA: data collection, setting network boundaries, definition of the coauthorship matrix and network data analysis and interpretation of results. The research design presented in this work is based on the aforementioned studies and its stages are described as follows.

## Data collection

This study aims to characterize the research community of supply chain analytics using social network analysis. In the context of this study, a network of actors is defined as researchers, research institutions or countries that have coauthored papers on the subject.

In order to identify researchers and institutions that form this community, a search for their work was performed. The search was initially executed in the scientific databases ISI Web of Science, EBSCO and Emerald Insight, which are databases used in other similar studies (Chen et al. 2012; Fabbe-Costes and Jahre 2008). The identification of search terms was built from the scoping study and literature. Although the goal of this study is on SCA only, a set of search strings was used allowing the retrieval of all studies that use any of the related terms or their combinations. Therefore the set of search strings composed by—(“big data” or “analytics” or “intelligence”) AND “supply chain”—was used in all three databases in order to capture every possible related research in the field. Being able to assemble a research community based on papers retrieved from different scientific databases is a major difference from most studies since most of them select prominent journals in the field to do so while others have concentrated their analyses only on one prominent journal (Kumar 2015).

The search period was defined as from 2005 to 2015. The rationale for considering this interval is that Analytics as a field of study has only relatively recently been addressed and the interest in this topic is growing increasingly in the past few years (Chen et al. 2012; Holsapple et al. 2014). Thus, a 10-year analysis allows for a sufficiently exhaustive search. By summing up all the results initially retrieved, 714 articles were found. All duplicated papers were eliminated as well as conference papers, books, editorials, communications to the press and any material other than research papers published in journals. By the end of this process, a total of 324 articles were considered. Table 1 shows some information of the

**Table 1** Summary characteristics of the full data set

| Variables | Value |
|---|---|
| Total papers | 324 |
| Single-authored papers | 50 |
| Coauthored papers | 274 |
| Two-authored papers | 103 |
| Three-authored papers | 81 |
| Multi-authored papers | 90 |
| Total number of authors | 810 |
| Total number of coauthors | 766 |
| Mean papers per author | 1.117 |
| Mean collaborations per author | 1.111 |
| Total number of countries | 47 |
| Total number of research institutions | 386 |
| Universities, colleges and schools | 313 |
| Research laboratories, foundations or institutes | 36 |
| Companies and nonprofit organizations | 37 |

retrieved studies. When analyzing coauthorships networks, since the primary focus was on research collaboration, the methodology required that single authored papers be omitted from the analysis. This procedure is in accordance with (Hu and Racherla 2010). So, in this case, a set of 274 papers was used. When characterizing the research community in terms of research streams, all 324 were considered. Table 1 summarizes the main characteristics of this sample of articles.

Coauthored papers represent the largest part of the data set analyzed. Single-authored papers represent only 15.4% of the total amount of studies. Two-authored papers accounted for 37.6% of the 274 coauthored papers. Three-authored papers represent 29.6% while multi-authored (4 or more authors) papers accounted for 32.8% of the coauthored papers identified. Most authors have published a paper with some other author (94.6%), which shows that in this field coauthorship is a very frequent option of work. Besides, this research field already involves researchers from 47 different countries, showing the range SCA has achieved. A considerable amount of research is done in alliance with research laboratories, institutes, companies and other organizations other than universities (18.9%). This fact illustrates that SCA is also an interesting research theme for practitioners.

## Identification of coauthorship matrices and networks

Besides gathering information on authors, we referred to the original articles to identify the authors' nationalities and affiliations and stored such information on Excel sheets. So, three matrices representing three networks were built: one for collaborations among countries, other matrix for collaborations among research institutions and the last one for collaborations among individual researchers. Each matrix is square and its entries are equal to 0 if two countries or research institutions have never coauthored a paper; otherwise, they hold the number of coauthored papers by pairs of countries, institutions and researchers. In this way, each link between actors of the network is weighted by the number of publications among them. Thus, networks analyzed are one-mode networks. Links between two actors in a coauthorship network are non-directional, since both actors coauthored the study with each other.

Network diagrams were drawn using the Ucinet software (Borgatti et al. 2002). Ucinet provides a wide range of SNA methods, the results of which can be displayed as tables, trees and dendrograms, and which can be further visualised using the program's graphical module NetDraw (Borgatti 2002; Sloane and O'Reilly 2013). UCINET features a large number of metrics that can be used to characterize whole networks and positions of nodes within networks as well as a number of analytical techniques such as finding cohesive groups (clusters). Although it contains a number of advanced features, it does not demand technical orientation. It accepts a large number of data and file formats being the usual method of data entry to cut-and-paste the contents of an Excel file into UCINET's data editor (Borgatti et al. 2014), which was also used in this study.

## Networks data analysis

The relationships among countries, research institutions and researchers of each network, and the role that each one plays in the network, have been analyzed by evaluating several SNA metrics. These metrics include the level of centrality degree of each actor (the level to which a particular actor is related to others), the level of betweenness (the degree to which a particular actor cooperates with many others and not just a few), and the level of closeness (how close is one actor to another through reciprocal collaborations (coauthorships) as well as how close is an actor to all the others in the network). The centrality positions of the leading actors are indicative of their importance and influence in coauthorship within SNA research networks. These measures are the same used in several SNA studies (Carter et al. 2007a; Ding 2011; Fischbach et al. 2011; Henneberg et al. 2009; Hu and Racherla 2010; Ye et al. 2011).

### Results analysis

Results are shown and analyzed in the next section. Network metrics and diagrams are analyzed in order to characterize the SCA research community.

## Results and discussions

This section describes the coauthorship networks at three sub-levels. First, general statistics on the identified articles are presented, such as top researchers and institutions and number of papers published by each of them. Next, an analysis of the network formed by country collaborations is presented. Then, an analysis of the network of research institutions is performed and finally the analysis of the researchers' network is described.

### General statistics and global level properties

This section presents data that answer RQ1 about the most influential actors in the networks studied. Data presented on "Country-network centrality metrics" and "Research institutions ranking based on centrality metrics" sections complement these findings. The first basic statistic at the individual author level is the number of papers published by each author. Table 2 shows the top publishing authors who have published at least three studies in our sample (including individual and coauthored papers).

Table 3 lists the top research institutions and Table 4 depicts the top countries regarding the number of publications. Table 3 shows research institutions with at least 4 published articles and Table 4 shows countries with at least 6 published studies.

The study of networks within SNA is based on several network properties determined at two levels—macro (global) and micro (local). The presentation and analysis of such data in this section and the following ones answer RQ2. The global level properties reveal the overall structure of the network. One measure that refers to the whole structure of the network is density. The density of a network captures the idea of cohesion. It is defined as the proportion of possible lines that are actually in a graph, thus, it ranges from a minimum of 0 to a maximum of 1. So, in the context of coauthorship networks, it represents the percentage of the total network with which an actor has coauthored a paper (Hu and Racherla 2010). The density of the country network is 7.2% while the density of the institutions network is 0.4%. This means that only 7.2 and 0.4% of the potential connections occur in each network, respectively. These numbers are consistent with the ones found in similar studies (Giannakis 2012; Henneberg et al. 2009; Munoz et al. 2016). Besides, when considering coauthorship involving researchers from all over the world, it can be expected that collaborations that actually occur between them will be a limited percentage of all links that are theoretically possible between them.

**Table 2** Top researchers

| Author | University | Country | Number of articles |
|---|---|---|---|
| Edgeman, R. L. | Aarhus University | Denmark | 6 |
| Fawcett, S. E. | Weber State University | USA | 5 |
| Waller, M. A. | University of Arkansas | USA | 5 |
| Chae, B. | Kansas State University | USA | 4 |
| Gunasekaran, A. | University of Massachusetts | USA | 4 |
| Ho, G. T. S. | The Hong Kong Polytechnic University | Hong Kong | 4 |
| Niaki, S. T. A. | Sharif University of Technology | Iran | 4 |
| Olson, D. L. | University of Nebraska | USA | 4 |
| Chen, J. C. H. | Gonzaga University | USA | 3 |
| Choy, K. L. | The Hong Kong Polytechnic University | Hong Kong | 3 |
| Jones-Farmer, L. A. | Auburn University | USA | 3 |
| Kadadevaramath,R. S. | Siddaganga Institute of Technology | India | 3 |
| Kumar, S. | University of St. Thomas | USA | 3 |
| Kuo, R. J. | National Taiwan University of Science and Technology | Taiwan | 3 |
| Lau, H. C. W. | The Hong Kong Polytechnic University | Hong Kong | 3 |
| Shankar, B. L. | Siddaganga Institute of Technology | India | 3 |
| Stefanovic, N. | University of Kragujevac | Serbia | 3 |

A component is a maximal connected sub-graph, i.e. a path exists between all authors in the sub-graph and there is no path between a node in the component and any node outside the component. In this context, all nodes are reachable (Wasserman and Faust 1994). The country network is composed of 9 components while the institutions network has 165 components, showing a high degree of fragmentation. Such values are similar to density values obtained in other studies (Fischbach et al. 2011).

A path is the sequence of nodes from one node to another in the network. The geodesic distance is the shortest path between a specific number of nodes. The diameter of the network is considered the longest geodesic distance (Kumar and Jan 2014). Diameter is an informative measure because it represents the time and effort it would take for any piece of information to pass through the network (Henneberg et al. 2009). The diameter for the country network is 5 and the average geodesic distance is 2.39. For the institutions network, the diameter was calculated as 9 and the average distance as 3.52. The relatively low average distance is indicative of the existence of the small-world phenomenon. In a small world network most nodes are not neighbors of one another, but are separated only by a small number of steps (Cainelli et al. 2015). The small world configuration describes the simultaneous presence of dense local clustering with short network distances that can facilitate knowledge flows inside a network (Stefano et al. 2011).

## Country-network centrality metrics

This section presents statistics concerned to the network that is formed by countries whose authors have coauthored a paper together. These actors are the nodes of this network while a link between two actors exist if they have published a study together. This link is

**Table 3** Top research institutions

| Research institution | Number of articles |
|---|---|
| The Hong Kong Polytechnic University | 9 |
| Aarhus University | 8 |
| Islamic Azad University | 8 |
| The University of Hong Kong | 8 |
| University of Arkansas | 6 |
| University of Tennessee | 6 |
| Auburn University | 5 |
| Indian Institute of Technology | 5 |
| University of Massachusetts | 5 |
| Weber State University | 5 |
| Kansas State University | 4 |
| Michigan State University | 4 |
| National Taipei University of Technology | 4 |
| Pennsylvania State University | 4 |
| Purdue University | 4 |
| Sharif University of Technology | 4 |
| Université de Toulouse | 4 |
| University of Nebraska | 4 |
| University of Tehran | 4 |

**Table 4** Top countries

| Country | Number of articles |
|---|---|
| USA | 109 |
| China | 41 |
| United Kingdom | 26 |
| Taiwan | 23 |
| France | 19 |
| Hong Kong | 19 |
| Iran | 18 |
| Germany | 16 |
| India | 15 |
| Canada | 14 |
| Spain | 14 |
| Australia | 10 |
| Brazil | 9 |
| Denmark | 9 |
| Turkey | 8 |
| Italy | 7 |
| Netherlands | 7 |
| Ireland | 6 |
| Portugal | 6 |

weighted by the number of coauthored publications between each pair of countries. The network is composed of 47 different countries.

The first metric to be analyzed is degree centrality. As described previously, degree centrality reflects the number of links each node in the network has. In the case of this coauthorship network, it is the number of coauthored papers a country participates in. Researchers from USA have participated in so many more coauthored studies when compared to researchers from other countries.

The degree centrality only reflects how many researchers have written a paper together with one author. A variation of this metric is Bonacich's power index, which is a metric that can describe an author's embeddedness in the coauthorship network. It identifies researchers who coauthored with others who have also coauthored with many other researchers. In this way, this metric proposes that the centrality of one node depends not only on its own but also on its neighboring nodes. If a node has many adjacent nodes with high degrees, then it has a more central position in the network when compared with more isolated nodes. So, the centrality of a node should also be determined by the degree of its neighbors (Ye et al. 2011). Bonacich centrality index is calculated as $C_i = \sum A_{ij}(\alpha + \beta Cj)$, where $\alpha$ and $\beta$ are parameters; $\alpha$ is used to normalize the formula and chosen in such a way that the sum of squares of the actors' power indices equals the total number of actors in the network; and $\beta$ is the attenuation factor, which requires a given value in the calculation depending on the research context (Fischbach et al. 2011; Ye et al. 2011).

Tables 5 and 6 show the results of the top 21 countries based on these two centrality metrics presented. It is interesting to observe that some countries are more inclined to collaborate in research with others. While researchers from USA and China have coauthored 47.7 and 46.3%, of their papers, respectively, with researchers from other countries, this percentage increased to 80.7% for the United Kingdom and 73.7% for Hong Kong.

This phenomenon shows that actors, in this case, countries, that have a relatively low degree centrality may be better positioned to the top of the Bonacich centrality ranking or the other way around. For instance, Netherlands is in 16th position in centrality degree, but ranks number 10 in terms of Bonacich power centrality. It can be inferred that although Netherlands' researchers have not coauthored many papers with foreign authors, some of their research collaborators may have a higher number of coauthored papers. This may be evidence of their future potential. An opposite situation in a similar scenario of difference between there two metrics is faced by German researchers, who are number 8 in centrality degree but fall down to the 16th position when Bonacich power centrality is used.

Another measure that represents the importance of a researcher is betweenness centrality. As describes previously, this index measures if a node is on the shortest path of many pairs of nodes and consequently if it is in a critical position to act as an information hub. In a coauthorship network, a researcher presenting high betweenness centrality can be considered an actor that bridges distinct groups or themes of research and publishes papers with authors who would not be linked to one another if it weren't for this researcher. Table 7 lists the top 10 countries by betweenness centrality considering the sample of studies analyzed. Again, it can be observed the prominent role of USA in SCA research, being the most efficient path for information delivery. It is also relevant to notice how betweenness centrality values differ from degree values. For instance, Germany presents a very high betweenness score, ranking number 2 in this list while it is the 8th country in terms of both degree centrality and productivity. A similar situation is faced by Canadian and Irish researchers.

Other important measure is closeness. Researchers with high levels of closeness are able to reach other authors in the network via a shorter chain of coauthors than authors with

**Table 5** Degree centrality ranking

| Rank | Country | Centrality degree |
|---|---|---|
| 1 | USA | 52 |
| 2 | United Kingdom | 21 |
| 3 | China | 19 |
| 4 | Hong Kong | 14 |
| 5 | France | 13 |
| 6 | India | 13 |
| 7 | Canada | 13 |
| 8 | Germany | 11 |
| 9 | Taiwan | 9 |
| 10 | Spain | 7 |
| 11 | Iran | 6 |
| 12 | Portugal | 6 |
| 13 | Ireland | 5 |
| 14 | Brazil | 4 |
| 15 | Denmark | 4 |
| 16 | Netherlands | 4 |
| 17 | Singapore | 4 |
| 18 | Slovenia | 4 |
| 19 | Australia | 3 |
| 20 | Japan | 3 |
| 21 | Norway | 3 |

lower closeness values. Top 10 countries in closeness are shown in Table 8. Again, researchers from Canada and Ireland are better situated (central) in the network, although they have not presented a considerable amount of papers.

Figure 1 shows the graphical representation of the country coauthorship network. The size of the nodes is proportional to the number of collaborations (degree centrality). The width of each edge represents the intensity of the collaboration, that is, the number of coauthored papers. This figure helps visualizing which the top collaborating countries are as well as which other countries they publish papers with. It is possible to see a more intense collaboration between USA and countries such as China, India, United Kingdom and Canada. There is a remarkable number of coauthored studies between China and the United Kingdom.

In this representation, we can see 7 countries that are not connected to any other node in the network and a small component composed of two countries—Pakistan and Oman. The other 38 countries are part of a big component. This phenomenon was also observed in other similar studies and is called giant component. A giant component is the largest component of a network. The size of this component matters as it reveals how cohesive or fragmented a network is. A larger giant component may mean that knowledge and information flow faster in the network or may indicate the existence of a core field of research in the community (Kumar 2015). In this study, the giant component comprises 80.85% of the nodes in the network. This result is in accordance with previous studies that have found giant components between 82 and 92% of the network (Newman 2004).

**Table 6** Bonacich power centrality ranking

| Rank | Country | Bonacich power centrality |
|---|---|---|
| 1 | USA | 7738.202 |
| 2 | China | 5051.012 |
| 3 | United Kingdom | 4901.416 |
| 4 | India | 3659.080 |
| 5 | Hong Kong | 3617.806 |
| 6 | Canada | 3126.956 |
| 7 | France | 2394.917 |
| 8 | Taiwan | 2237.118 |
| 9 | Spain | 1637.869 |
| 10 | Netherlands | 1406.664 |
| 11 | Denmark | 1255.598 |
| 12 | Singapore | 1230.772 |
| 13 | Iran | 1209.206 |
| 14 | Brazil | 1019.533 |
| 15 | Slovenia | 1019.533 |
| 16 | Germany | 977.936 |
| 17 | Portugal | 822.302 |
| 18 | Macao | 743.508 |
| 19 | Ireland | 618.500 |
| 20 | Australia | 603.165 |
| 21 | Mexico | 589.510 |

**Table 7** Betweenness ranking

| Publication rank | Betweenness rank | Country | Betweenness centrality |
|---|---|---|---|
| 1 | 1 | USA | 378.926 |
| 8 | 2 | Germany | 100.921 |
| 5 | 3 | France | 92.862 |
| 10 | 4 | Canada | 68.467 |
| 3 | 5 | United Kingdom | 67.367 |
| 18 | 6 | Ireland | 48.202 |
| 2 | 7 | China | 41.319 |
| 7 | 8 | Iran | 41.293 |
| 21 | 9 | Japan | 36.000 |
| 11 | 10 | Spain | 23.152 |

## Research institutions ranking based on centrality metrics

This section presents an analysis of metrics of the coauthorship network formed by research institutions whose researchers have published together. Data are presented in a similar way to the previous section. Tables 9 and 10 show degree centrality and Bonacich

**Table 8** Closeness ranking

| Publication rank | Closeness rank | Country | Closeness value |
|---|---|---|---|
| 1 | 1 | USA | 0.430 |
| 2 | 2 | China; | 0.368 |
| 3 | 2 | United Kingdom | 0.368 |
| 5 | 2 | France | 0.368 |
| 6 | 2 | Hong Kong | 0.368 |
| 10 | 2 | Canada | 0.368 |
| 4 | 7 | Taiwan | 0.359 |
| 9 | 7 | India | 0.359 |
| 11 | 9 | Spain | 0.357 |
| 18 | 10 | Ireland | 0.351 |

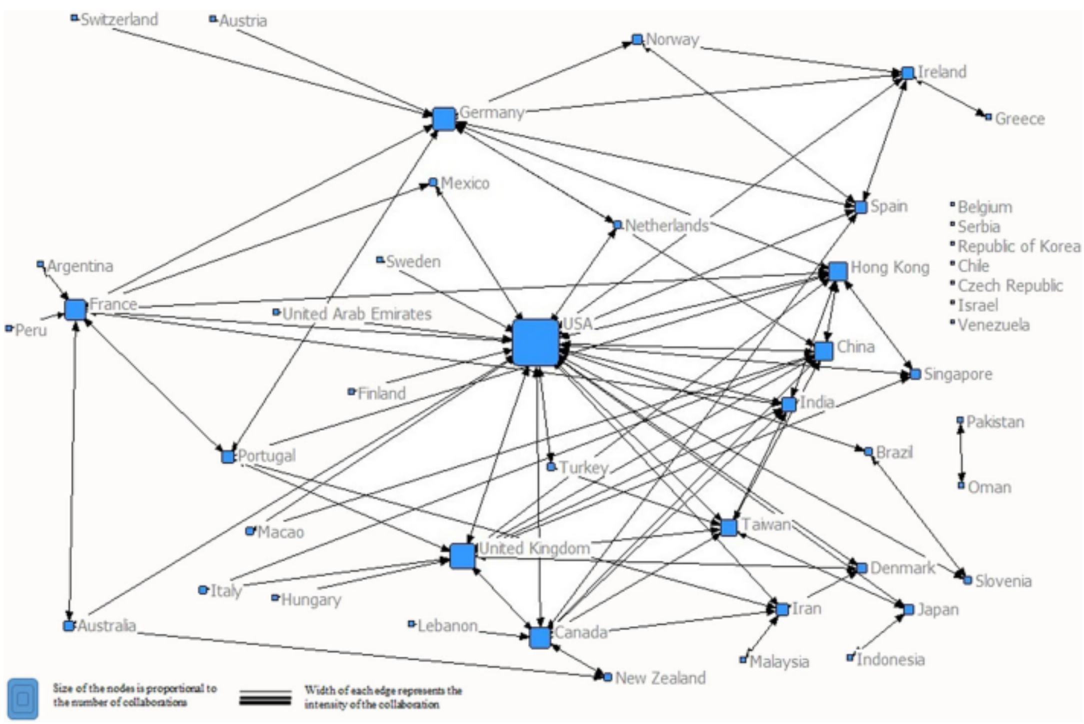


**Fig. 1** Country coauthorship network

centrality measures for top research institutions. Data on research institutions with centrality degree greater than 6 are shown.

The first aspect to be noticed is that the degree centrality of one research institution might be greater than its number of publications when articles are coauthored with more than one research institution. This is the case for The University of Hong Kong, which has coauthored 8 papers but has reported 11 collaborations. This university, for instance,

**Table 9** Degree centrality ranking—research institutions

| Rank | Research institution | Degree centrality |
|---|---|---|
| 1 | The University of Hong Kong | 11 |
| 2 | University of Massachusetts | 10 |
| 3 | Nottingham University | 9 |
| 4 | Pennsylvania State University | 9 |
| 5 | Islamic Azad University | 8 |
| 6 | The Hong Kong Polytechnic University | 8 |
| 7 | University of Tennessee | 8 |
| 8 | Miami University | 7 |
| 9 | Ohio State University | 7 |
| 10 | University of Arkansas | 7 |
| 11 | Auburn University | 6 |
| 12 | City University of Hong Kong | 6 |
| 13 | Gonzaga University | 6 |
| 14 | Nanyang Technological University | 6 |
| 15 | Sharif University of Technology | 6 |
| 16 | Shenzhen University | 6 |
| 17 | Siddaganga Institute of Technology | 6 |
| 18 | University of Nebraska | 6 |
| 19 | University of Texas | 6 |

participated in a paper that was written by authors from three different research institutions. So this single paper accounted for three collaborations.

Again, a difference in performance when comparing degree centrality and Bonacich centrality can be observed. Universities of Arkansas and Weber State, for instance, can be considered to have published studies in collaboration with other institutions that have higher centrality degrees since they are better ranked according to Bonacich's index. In fact, several of well-ranked institutions in Bonacich's index are not even listed in the top 19 for centrality degree. As said previously, this indicates that many of these institutions's collaborators are critical researchers with considerable influence.

Table 11 presents betweenness centrality values for top 15 research institutions. As pointed out previously, nodes with high betweenness centrality values act as information hubs in the network. In this scenario, it can be observed the central role The Hong Kong Polytechnic University and the University of Massachusetts play connecting other institutions. It can also be observed that some well-ranked institutions in betweenness are not necessarily well-ranked in terms of number of publications too.

Table 12 presents closeness values for research institutions. Institutions that present high values for closeness are considered globally central in the network. There is little difference in closeness for top research institutions since there are 4 institutions presenting the value of 0.102 for closeness as depicted in Table 12 and other 22 institutions with closeness value of 0.101. Although some research institutions may be relatively closer to some of the others in the network, this has not led to a global proximity to most of the research institutions.

Since a diagram containing all 386 research institutions that published papers on SCA would be of difficult visualization and comprehension, we decided to depict only the top 30 research institutions in terms of coauthorship. The top 30 institutions have 5 or more

**Table 10** Bonacich power centrality ranking—research institutions

| Rank | University | Bonacich power centrality |
|---|---|---|
| 1 | University of Arkansas | 1365.540 |
| 2 | Weber State University | 1295.993 |
| 3 | Miami University | 915.812 |
| 4 | The University of Hong Kong | 895.263 |
| 5 | Ohio State University | 847.095 |
| 6 | California State University | 781.813 |
| 7 | Monash University | 781.813 |
| 8 | Oregon Health and Science University | 781.813 |
| 9 | Wake Forest University | 781.813 |
| 10 | The Hong Kong Polytechnic University | 707.404 |
| 11 | Nottingham University | 604.799 |
| 12 | University of Massachusetts | 573.490 |
| 13 | University of Texas | 542.781 |
| 14 | Shenzhen University | 482.979 |
| 15 | Nanyang Technological University | 475.175 |
| 16 | City University of Hong Kong | 466.684 |
| 17 | Indian Institute of Technology | 374.050 |
| 18 | Rockwell Automation Research Center | 361.328 |
| 19 | UCLA | 349.464 |

**Table 11** Betweenness ranking—research institutions

| Publication rank | Betweenness rank | Research institutions | Betweenness |
|---|---|---|---|
| 1 | 1 | The Hong Kong Polytechnic University | 920.533 |
| 7 | 2 | University of Massachusetts | 868.000 |
| 2 | 3 | The University of Hong Kong | 670.733 |
| 20 | 4 | University of Texas | 460.000 |
| 42 | 5 | Nottingham University | 359.267 |
| 20 | 6 | Miami University | 343.000 |
| 20 | 7 | IIT Kharagpur | 212.000 |
| 5 | 8 | University of Tennessee | 129.500 |
| 20 | 9 | Nanyang Technological University | 117.800 |
| 20 | 10 | Ohio State University | 108.000 |
| 42 | 11 | Arizona State University | 108.000 |
| 20 | 12 | City University of Hong Kong | 101.333 |
| 42 | 13 | Shenzhen University | 85.700 |
| 11 | 14 | Pennsylvania State University | 65.000 |
| 42 | 15 | Colorado State University | 60.000 |

**Table 12** Closeness ranking—research institutions

| Closeness rank | Research institutions | Closeness value |
|---|---|---|
| 1 | Nanyang Technological University | 0.102 |
| 1 | The Hong Kong Polytechnic University | 0.102 |
| 1 | The University of Hong Kong | 0.102 |
| 1 | University of Massachusetts | 0.102 |

collaborations in the dataset used in this study and its analysis help answering RQ3 on dominant components in the network. Again, nodes are sized according to their degree centrality and links' width among them represent the intensity of collaboration between institutions. Strong collaboration patterns are observed among Weber State University and University of Arkansas; Gonzaga University and Siddaganga Institute of Technology and Sharif University of Technology and Islamic Azad University. It can also be observed that collaboration among institutions is influenced by their geographical location. This results is in line with Finardi and Buratti (2016) who have found that the strongest collaborations in BRICS countries are driven by geographical proximity. They have also found collaborations that could be estimulated by cultural or historical proximity. This can be classified as assortative mixing or homophily, which is the tendency of nodes to connect to similar others, which could be influenced by several different factors such as popularity, gender, nationality and others (Kumar 2015). The bottom part of the diagram shows a tightly coupled group comprised mainly of American universities. In the center of the figure, a group composed mainly of institutions from China, India and Hong Kong is exhibited. There are not many connections among these groups, except from one link between the Hong Kong Polytechnic University and the University of Massachusetts. If it weren't for this link, the network would be even more fragmented.

Cliques show structures in the network which are characterized by linkages existing between all members of a group (Henneberg et al. 2009). In a clique, all actors are connected with all other actors. Figure 2 shows the existence of two cliques. One 3-clique represented in the right upper corner, formed by Pennsylvania State University, University of Tennessee and Auburn University. There is also a 6-clique, shown in the bottom part, formed by Miami University, Ohio State University, Wake Forest University, California State University, Monash University and Oregon Health and Science University.

## Researchers network centrality metrics

Following the previous analyses, the lower level of collaboration is represented by the coauthorship among individual researchers. The researchers' network is characterized by the following measures—an average degree of 2.874 and density equal to 0.004. It also has an average distance of 1.552 and a diameter of 5. It is composed of 210 different components.

Researchers centrality data are presented in a similar way to the previous sections. Table 13 shows degree centrality and Bonacich centrality measures for top researchers. Again, the difference observed between these two measures shows that researchers with higher number of collaborations do not necessarily collaborate with highly connected researchers.

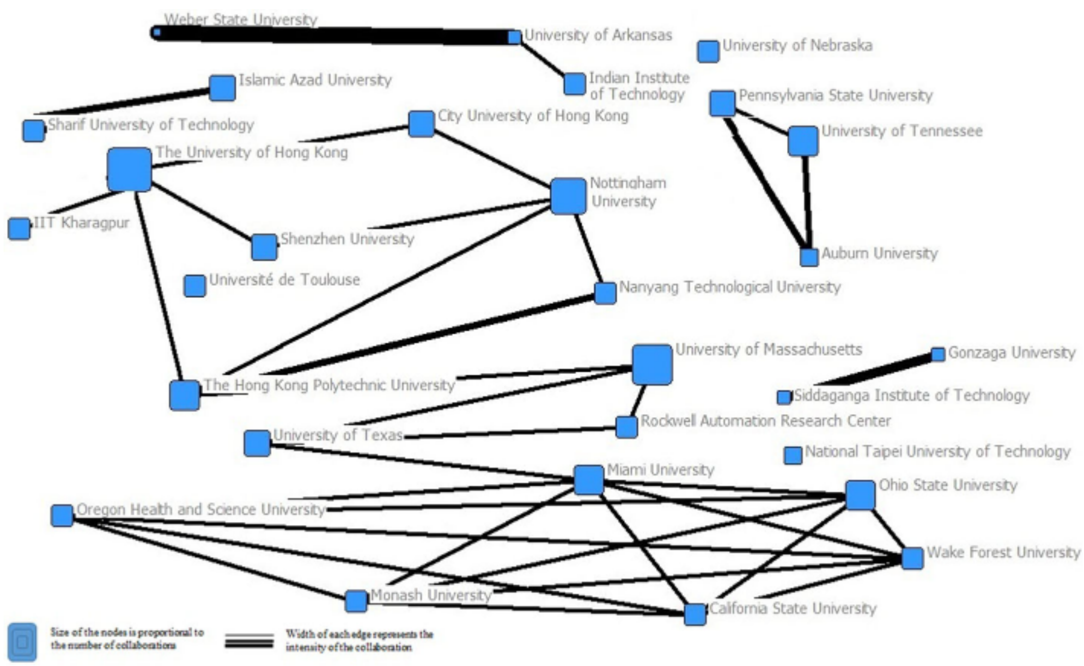


**Fig. 2** Top 30 degree centrality research institutions network

**Table 13** Degree centrality ranking and bonacich power centrality ranking—researchers

| Degree rank | Researcher | Degree centrality | Bonacich power centrality rank |
|---|---|---|---|
| 1 | Choy, K. L. | 12 | 13 |
| 2 | Ho, G. T. S. | 12 | 14 |
| 3 | Arya, Vijay | 11 | 1 |
| 4 | Chakraborty, Dipanjan | 11 | 1 |
| 5 | Charbiwala, Zainul | 11 | 1 |
| 6 | Ganu, Tanuja | 11 | 1 |
| 7 | Ghai, Sunil | 11 | 1 |
| 8 | Hazra, Jagabondhu | 11 | 1 |
| 9 | Kalyanaraman, Shivkumar | 11 | 1 |
| 10 | Kodeswaran, Palani | 11 | 1 |
| 11 | Mitra, Rajendu | 11 | 1 |
| 12 | Narayanaswamy, Balakrishnan | 11 | 1 |
| 13 | Seetharam, Deva P. | 11 | 1 |
| 14 | Sengupta, Neha | 11 | 1 |
| 15 | Niaki, Seyed Taghi Akhavan | 10 | 31 |
| 16 | Tiwari, Manoj Kumar | 10 | 29 |

Table 14 presents betweenness centrality values for top 13 researchers. As pointed out previously, nodes with high betweenness centrality values act as information hubs in the network. Some researchers play the roles of hubs to other scholars. It can also be observed that some well-ranked researchers in terms of betweenness centrality are not necessarily also well-ranked in terms of number of publications.

## Research streams

Researchers usually publish their work in specific research streams, according to their interests. One way to categorize a research community is by identifying groups of interest as well as how authors of a research stream interact and work with authors from other research streams. In order to identify research streams in the SCA area, we have based our classification of research streams in SCM described in the work of (Croom et al. 2000). These authors have developed and presented a framework for the categorization of literature linked to SCM. Their study was based on the analysis of a large number of publications on SCM. Six streams were originally identified: Strategic Management, Logistics, Marketing, Relationships/partnerships, Best practices and Organizational Behavior. For each stream, research components were identified. We have extended their classification in order to include one research stream as well as research components in the SCM area as shown in Table 15. By analyzing the keywords and abstracts of the papers obtained in our study, a seventh stream was identified and named Technology-focused. Its components were also identified. A few more components were added in order to highlight in which stream relevant current research components were allocated. The extensions to the original classification of these streams are presented in italics in the Table 15.

The title, abstract and keywords of the articles were used to categorize them into these research streams. Authors were further also classified into research streams according to the streams of the articles they have published. Following Hu and Racherla (2010), if one author published more than one article, the categorization considered the stream in which the author has published more papers. Besides, in case of an equal number of papers in different streams, we have considered the author to be in the stream corresponding to the

**Table 14** Betweenness ranking—researchers

| Publication rank | Betweenness rank | Researcher | Betweenness |
|---|---|---|---|
| 17 | 1 | Chan, Felix T. S. | 180.000 |
| 15 | 2 | Tiwari, Manoj Kumar | 150.000 |
| 1 | 3 | Choy, K. L. | 128.667 |
| 1 | 4 | Ho, G. T. S. | 89.667 |
| 19 | 5 | Wu, Zhang | 75.000 |
| 15 | 6 | Niaki, Seyed Taghi Akhavan | 36.000 |
| 30 | 7 | Jain, Vipul | 34.000 |
| 30 | 8 | Kumar, Sameer | 26.000 |
| 18 | 9 | Gunasekaran, Angappa | 23.000 |
| 19 | 10 | Lee, C. K. M. | 19.000 |
| 106 | 11 | Benyoucef, Lyes | 19.000 |
| 30 | 12 | Tan, Kim Hua | 10.000 |
| 106 | 13 | Sinha, Ashesh K. | 10.000 |

**Table 15** Research streams—SCM literature (based on Croom et al. 2000)

| Research stream | Components |
| --- | --- |
| Strategic management | Strategic Networks; Control in the supply chain; Time-based strategy; Strategic sourcing; Vertical disintegration; Make or buy decisions; Core competencies focus; Supply Network Design; Strategic Alliances; Strategic Supplier Segmentation; World Class Manufacturing; Strategic Supplier Selection; Global Strategy; Capability Development; Strategic Purchasing; *Sustainable Supply Chain; Agility; Flexibility; Resilience* |
| Logistics | Integration of materials and information flows; JIT, MRP, Waste removal, VMI; Physical Distribution; Cross Docking; Logistics Postponement; Capacity Planning; Forecast Information Management; Distribution Channel Management; Planning and control of materials flow |
| Marketing | Relationship Marketing; Internet Supply Chains; Customer Service Management; Efficient Consumer Response; Efficient Replenishment; After Sales Service |
| Relationships/partnerships | Relationships Development; Supplier Development; Strategic Supplier Selection; Vertical Disintegration; Partnership Sourcing; Supplier involvement; Supply/Distribution Base Integration; Supplier Assessment (ISO); Guest Engineering Concept; Design for Manufacture; Mergers Acquisitions, Joint Ventures; Strategic Alliances; Contract view, Trust, Commitment; Partnership Performances; Relationship Marketing |
| Best practices | JIT, MRP, MRP II, Continuous Improvement, Tiered Supplier Partnerships, Supplier Associations, Leveraging Learning Network, Quick Response, Time Compression; Process Mapping, Waste Removal; Physically Efficient Vs. Market oriented supply chains; *Maturity Models; SCOR Model* |
| Organizational behavior | Communication, Human Resources Management; Employees' Relationships; Organizational Structure; Power in relationships; Organizational culture; Organizational Learning; Technology Transfer; Knowledge Transfer; *Knowledge Management* |
| *Technology-focused* | *Artificial Intelligence, Genetic Algorithms, Neural Networks, Agents, Algorithms, Internet of Things, Cloud Computing, Technology-based Solutions, Big Data, Architecture of applications, Technologies for developing e-supply chain* |

most recent paper. For this analysis, we have included the single-authored papers that were excluded from the data used to generate the coauthorship networks presented previously.

After categorizing each author into a research stream, we have assembled a coauthorship network based on such author categorization. In this network, nodes are the research streams and a link between them exists if an author from a stream has published a paper together with an author categorized in another stream. For instance, if a Strategic Management author has coauthored a paper with a Logistics researcher, then a link between these two research streams is established. The links between two different research streams are weighted, that is, they represent the number of collaborations among these streams which occurred in fact.

Table 16 exhibits the number of research articles and authors categorized in each research stream. It is possible to see that in the set of articles analyzed, more research on the Strategic Management, Technology-focused and Logistics was found. The components of Artificial Intelligence and Genetic Algorithms are the most frequent in the Technology-focused stream. In the Strategic Management field, the most common component is Supply

**Table 16** Research streams—articles and authors

| Research stream | Number of articles | % of articles | Number of authors | % of authors |
|---|---|---|---|---|
| Strategic management | 114 | 35.19 | 269 | 33.71 |
| Technology-focused | 86 | 26.54 | 227 | 28.45 |
| Logistics | 51 | 15.74 | 132 | 16.54 |
| Organizational behavior | 33 | 10.19 | 68 | 8.52 |
| Relationships/partnerships | 22 | 6.79 | 60 | 7.52 |
| Best practices | 13 | 4.01 | 36 | 4.51 |
| Marketing | 5 | 1.54 | 6 | 0.75 |

Chain Design. Logistics components are more equally distributed among Physical Distribution, Capacity Planning and Forecast Information Management. Very few papers were classified as belonging to the Best practices and Marketing streams. Consequently, fewer researchers in these streams were identified.

Since most of the authors (more than 90%) published just one paper in this set, they are automatically classified into the same research stream as this one paper and a self-relationship is established, since all these papers' authors belong to the same research stream. So, a high number of collaborations in the same stream was found, as shown in Table 17a, b. However, authors from different research streams also work together. Results show that more links were found among researchers from the Technology-focused stream with the ones of Strategic Management and Logistics. A considerable amount of relationships were also found between the Strategic Management stream and the ones of Logistics and Organizational Behavior.

The research stream network was also analyzed using the same previous measures. It has the following characteristics. Its average degree is equal to 3.429, average distance equal to 1.524 and a diameter of 3. It has just one component and density equal to 0.571, meaning that 57.1% of the possible connections between streams exist.

Table 18 exhibits centrality measures for this network. Research streams are presented in degree order. The Strategic Management and Technology focused streams are connected to all other research streams, including themselves, except the Marketing stream. In this network, the Bonacich Index ranks the streams in the same order as the degree centrality index. The Relationships/partnerships stream presents the highest value for betweenness probably because it is the only stream connected to the Marketing stream, besides being linked to several other streams. In this way, it functions as a hub to the Marketing stream. This relation can be observed in Fig. 3.

Figure 3 shows the coauthorship network in terms of research streams. Node sizes are set by the degree measure and the link strength is set by the weight of the relationship between each pair of nodes. A 4-clique composed of the streams Technology focused, Strategic Management, Logistics and Organizational behavior can be seen. All these streams are connected to the other three of the group.

**Table 17** Research streams: coauthorship among (a) the same research stream and (b) different research streams

| (a) Among authors of the same research stream | Number of collaborations | (b) Among authors of different research streams | Number of collaborations |
|---|---|---|---|
| Strategic management | 622 | Logistics/technology focused | 35 |
| Technology-focused | 596 | Strategic management/ technology focused | 34 |
| Logistics | 375 | Strategic management/logistics | 24 |
| Relationships/partnerships | 184 | Strategic management/ organizational behavior | 22 |
| Organizational behavior | 158 | Strategic Management/ relationships/partnerships | 12 |
| Best practices | 92 | Strategic management/best practices | 8 |
| Marketing | 4 | Technology focused/best practices | 8 |
| | | Logistics/organizational behavior | 6 |
| | | Technology focused/ relationships/partnerships | 6 |
| | | Organizational behavior/logistics | 6 |
| | | Relationships/partnerships/ Marketing | 2 |
| | | Organizational behavior/ relationships/partnerships/ | 2 |

**Table 18** Research stream network analysis

| Research stream | Degree | Bonacich power | Betweenness |
|---|---|---|---|
| Strategic management | 6.000 | 1185.710 | 2.667 |
| Technology focused | 6.000 | 1185.710 | 2.667 |
| Organizational behavior | 5.000 | 1062.964 | 0.667 |
| Relationships/partnerships | 5.000 | 934.938 | 5.000 |
| Logistics | 4.000 | 873.292 | 0.000 |
| Best practices | 3.000 | 603.301 | 0.000 |
| Marketing | 2.000 | 238.877 | 0.000 |

## Conclusions, limitations and future work

This work characterized the research community of supply chain analytics with respect to coauthorship, a special kind of collaboration. A characterization of coauthorship in terms of researchers' countries, research institutions and researchers was elaborated, so three different one-mode networks were studied. Centrality metrics that depict the importance of researchers and institutions in the networks were obtained such as degree, betweenness and

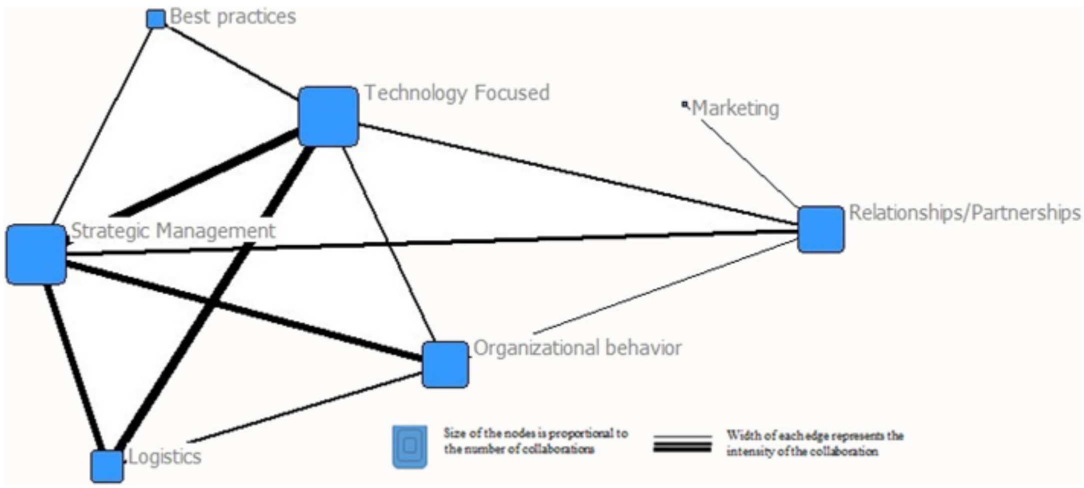


**Fig. 3** Research stream coauthorship network

closeness. This study found out that there is a more intense collaboration between USA and countries such as China, India, United Kingdom and Canada and there is a remarkable number of coauthored studies between China and the United Kingdom. Besides, there are countries and institutions that function as information hubs connecting different groups in the network. Researchers from Canada and Ireland are better situated (central) in the network, although they have not presented a considerable amount of papers. The presence of cliques and the small-world effect were also observed. In terms of institutions, it was observed that The Hong Kong Polytechnic University and the University of Massachusetts have important roles connecting other institutions.

As far as research streams are concerned, more research on SCA located at the Strategic Management, Technology-focused and Logistics streams was found. Results show that more links were found among researchers from the Technology-focused stream with the ones of Strategic Management and Logistics. A considerable amount of relationships were also found between the Strategic Management stream and the ones of Logistics and Organizational Behavior. Moreover, the Strategic Management and Technology focused streams are connected to all other research streams, except the Marketing stream.

This work presents important contributions to the Supply Chain Management field. As far as we are concerned, very few papers deal with a comparison among different disciplines. In disciplines characterized by a less intensive use of quantitative methods, researchers tend to work more independently (Stefano et al. 2011). This is not the case in the SCA research community, since in the sample of articles analyzed, only 15,43% were single-authored papers. Although there is a considerable amount of collaborations through coauthorships, it seems to be highly influenced by geographic positions. Collaborations among American universities only as well as among Chinese and Indian institutions were observed with fewer coauthorships among institutions geographically dispersed. Besides, this study explores a demand to see coauthorship networks from an interdisciplinary perspective (Kumar 2015).

This study has some limitations. Although we have performed the initial search with the objective of identifying each and every study published on SCA, considering all variations and possible definitions of this theme, only journal papers were analyzed. This may exclude some researchers who have published extensively in other media. So, including more types of research publications, such as conference proceedings articles, books and editorials is one way of analyzing an even greater research community. However, this does not change the fact that the set of analyzed papers comprises representative quality research in the field. This study also uses an extensive set of data that required a tremendous amount of time and effort to input. While every effort was made to carefully enter and standardize the data, it should be noted that any possible error or omission is entirely inadvertent.

This study opens several possibilities of future work. It focused specifically on characterizing this research community in terms of coauthorship. However, there are other forms of collaboration that were kept out of our scope, such as research projects and acknowledgements. Moreover, this study focused on a current portrait of this research community. Studying its evolution and also being able to predict future collaborations is an interesting research avenue.

Different characteristics and events may influence collaboration among researchers. Working at the same university, meeting in a conference, receiving some grant to study abroad or even being a PhD student are reasons for starting a relationship that might end up yielding a coauthorship in a paper. Studying the reasons why researchers collaborate is important since government agencies and programs could focus investments on actions and design better programs that might improve collaborations, and consequently, publications the most. Moreover, it is also important to analyze the effects that coauthorship have on research quality and author productivity.

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