UNDERSTANDING SCIENTIFIC COMMUNITIES: A SOCIAL NETWORK APPROACH TO COLLABORATIONS IN TALENT MANAGEMENT RESEARCH

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ABSTRACT AND KEYWORDS

Abstract

Research on Talent Management (TM) is an emerging field of study and little is known about the connections among authors in this research community. This paper aims at disclosing the dynamics in TM research by offering a detailed picture of its evolving collaboration networks. By means of Social Network Analysis (SNA), we both show and explain the extent of collaboration, taking articles' co-authorship as an indicator of collaboration. We graphically display how the network builds up throughout time, which has allowed us to examine its main structural characteristics. We analyze the contribution of individual researchers and identify key players in the research network and their characteristics. The co-authorship network is composed by loose and low-density collaborations, mainly consisting in two big components and surrounded by scattered and weak relationships. Two main research perspectives are built and consolidated through time, but they are missing the richness of exchanging ideas among different views. Our results complement recent studies on the dynamics of TM research by offering evidence on how and why collaboration among researchers shapes the current debates on the field. Some basic hypothesis about network indicators are also tested and provide further evidence for the Social Network Analysis advancement. The findings can be of value in the design of strategies that might improve both system and individual performance.

Keywords: Talent Management; Collaboration Networks; Co-authorship; Science Mapping; Social Network Analysis

1. Introduction

TM has become ‘one of fastest growing areas of academic work in the management field over recent decades’ (Collings, Scullion and Vaiman 2015). Indeed, recent literature reviews show how scholarly interest in TM has grown over the last decade, being specifically noticeable since 2013 (Thunnissen, Boselie and Fruytier 2013; Gallardo-Gallardo et al. 2015; Gallardo-Gallardo and Thunnissen 2016). To date, however, there has been no proper analysis of the dynamics of TM as a research network.

In their recent literature review Gallardo-Gallardo et al. (2015) argue that TM research is in a growth stage due to, among other things, the formation of a ‘core’ scientific TM research community that acts as a reference group to new entrants to the field. At this point, scientific communities tend to be largely made up of a small circle of scholars who interact among them and who are familiar with each other’s work (Krogh et al. 2012). In a rather more mature phase of the phenomenon, these scholars may also establish new associations (Sarafoglou and Paelinck 2008). This paper offers a detailed analysis of collaborative research that would help to clarify the evolution stage of the TM field.

Research collaboration has become an essential part of academic life (Henriksen 2016), and the study of such collaborations counts on a long tradition in the specialized literature (Fan et al. 2016). The evolution of collaboration and networks, as well as the identification of key actors in a field, has increasingly attracted the interest of the academia, also among those researchers in the areas of business management and organization (Koseoglu 2016).

Our study makes use of co-authorship (Katz and Martin 1997; Liu and Xia 2015; Costa, Quin and Bratt 2016) and Social Network Analysis (from now on SNA) to capture the structure of scientific collaboration and individual researcher position within the community. We will show collaboration networks as prototypes of evolving networks, where the emphasis is placed on how the networks are built and grow over time. Certainly, the co-authorship network expands constantly by the addition of new authors and co-authorships (Barabasi et al. 2002). Further, Perc (2010) points out that the growth of social networks is frequently governed by preferential attachment among similar authors (defined as 'homophily' in SNA), and that the resulting network structure resembles what the author labels as "small worlds".

In brief, by using SNA this paper discloses the structure and dynamics in TM research, offering a detailed picture of the collaboration networks in the field since its origins in 2001. Specifically, we provide answers to the following research questions:

(1) What is the extent of collaboration among authors that publish research in TM?
(2) What are the main characteristics of the emerging collaboration networks and how have these networks evolved through time?
(3) Which is the impact of individual researchers in such networks by considering contribution to the connectivity and productivity? and
(4) To what extent a network core can be identified and which are the authors participating in it?

2. Methods

We started by compiling a database of relevant TM publications since 2001, using a sequential three-step approach to data collection and analysis:

Step 1: Data collection

The databases Web of Science (WoS) and Scopus were used to identify relevant articles and to retrieve bibliographic data. Both databases are considered reliable sources of information and are used as reference in a large number of bibliometric studies (Ciomaga 2013). We used the search term "talent management" (in either topic, keywords or abstract fields) since previous literature reviews (Gallardo-Gallardo et al. 2015; Gallardo-Gallardo and Thunnissen 2016) have shown its appropriateness and accuracy (i.e. sensitivity and specificity) in maximizing relevant papers and minimizing noise.

We restricted our search to articles published in international peer-reviewed journals since they adequately determine the state of the art of a topic providing a guarantee of quality and relevance (Boselie, Dietz and Boon 2005; Arduini and Zanfei 2014).

Following a common practice, we excluded conference proceedings, editorial notes, interviews, books, book chapters and book reviews. We only included articles published in the English language. However, no limitation of time frame was used for the present study. Our search strategy generated 547 articles from the Scopus database, and 284 from the WoS database. The publication period ranges between January 2001 and December 2016 (i.e., when we closed our data collection procedure).

We removed duplicates and manually deleted those articles in which ‘talent management’ was used in a rather tangential manner. The last step was to ensure that the selection was consistent: we made a cross-comparison of our eventual sample against a) the list of articles that have been used in previous literature reviews on TM, and b) against those articles cited in relevant recent publications. After this process we ended up adding 12 articles to our database. A final list of 354 articles was primarily selected for our analysis.

Step 2: Data preparation

Bibliographic information on each article (i.e. author/s, year, title, journal, keywords and summary) included in the database was imported into an Excel file. As noted in previous reviews (Gallardo-Gallardo and Thunnissen 2016) the Excel program allows creating pivot tables that help to sort, count and summarize a great amount of data in a worksheet. To minimize possible errors and ensure consistency we crosschecked the retrieved descriptive information for each article. For example, since different spelling for the same author (e.g. D. Collings and D. G. Collings) is quite common, when tabulating the data we made sure of writing the author name equal each time. We decided to choose the most complete signature to identify that author, which usually coincide with the most recently used (following with the previous example, we tabulated D. G. Collings).

Since we are interested in collaboration networks and co-authorship we selected papers written by two or more authors. Our final database ready for network analysis was comprised of 274 co-authored papers (73% of all papers) and 588 authors.

Step 3: Data analysis

Data processing started with the creation of co-occurrence matrices of authors that provided a picture of the extent of collaboration among authors. The matrix is by nature symmetric. Two authors were tied together (i.e. connected) if they had at least one publication in common. The strength of the tie (i.e. the sum of joint papers among them) indicates intensity. So as to better show the evolution of the network with time we decided to build one matrix per year starting in 2003 (first co-authored published paper in TM) through 2016, as well as a final matrix accounting for the entire period of analysis.

We implemented a double approach in our analysis. First, we studied the evolution of the collaboration network in TM research, that is, a longitudinal study of the field. To this aim we analyzed annual datasets in sequence. This analysis included visualization and comparison of macro indicators of the network (density and cohesion measures), meso indicators (fragmentation) and micro indicators at node level (centrality), which will lead us to the identification of the key nodes (actors) of the network. As regards centrality, we made use of a multidimensional approach combining *Freeman Degree*, *Betweenness*and *Closeness*[2] to offer a comprehensive picture of the importance of each node, following the work of Abbassi and others on network evolution and preferential attachment (2012). The correlations among the different indicators will be tested to follow and enrich the debate pioneered by Valente et al, exploring the association between centrality measures using different datasets and studies (Valente et al. 2008). This test also allows us to contrast the results with existing evidence to more accurate interpretations.

Secondly, we performed a full period analysis of the structure of the network that allowed us to identify the core subsets of actors within the network. We then focused on a core of actors (those participating in the two main components) in order to do a more in-depth analysis of individual characteristics and attributes, particularly gender, country and main research area. The data required for this analysis was obtained from the publication itself, from the authors' information on the internet (i.e., institutional web page, personal web pages, Google scholar, and Social Network profiles including LinkedIn, Research Gate). The definition of the main research area was done, whenever

[2] We also tested the Eigenvector to offer a wider perspective, but after some analysis we decided to focus on degree, betweenness and closeness as the best indicators for the identification of key players.

possible, according to the author's own words (if they made that explicit in their affiliation web page, their CV or bios in social network profile). The aim is the identification of homophilic patterns among schools of thought, that is, to explore to what extent authors with similar ideas are related to each other in terms of co-authorship[3].

All SNA requires of a specific software package. In our case we used UCInet 6 for calculations and NetDraw for visualizations (Borgatti, Everet and Freeman 2002). A non-expert in TM literature performed the analysis of the dataset. All team members participated in the interpretation and discussion of the findings. By doing so, we tried to guarantee quality, objectivity and rigor.

[3] There was only one author for which was impossible to find trustworthy information.

3. Findings

Before stepping into the social network analysis, we offer an overview on all the selected publications during the period 2001-2016.

3.1. The evolution of co-authorship in TM research (2001-2016)

The majority of articles (73%) published in the period considered were written by two or more authors (see **Figure 1**). So, in TM research multi-authored papers dominated single-authored papers (27%) throughout the period. This is consistent with findings in other disciplines (cf. Koseoglu 2016).

-- Insert Figure 1--

The first collaborative paper was published in 2003 by three authors. By June 2016, a total of 588 different authors had participated in at least one co-authored publication. As shown in **Figure 2**, the network size presents a growing pattern, being 2016 the year with the highest number of authors collaborating in published papers.

-- Insert Figure 2--

In addition to the growth pattern of the network displayed above we studied how the actors in the network are connected, using the Social Network Analysis (SNA) approach. In SNA the basic elements in the network are nodes (actors) and ties (links). In this respect **Figure 3** shows how the network of collaborations has changed across time, both in terms of structural composition and role played by actors in the network. The network starts as a rather atomized structure, and as more authors get to contribute and collaborate, the structure gains in complexity, and some subsets become close-knit communities as a result of more collaborative papers. Each circle (or node) in **Figure 3** represents an author, and the lines or ties connecting them represent co-authorship in publications. It is important to bear in mind that in SNA the visual representations do not follow a spatial logic (such as Multi-dimensional Scaling, in the layout, the nodes are placed randomly in the graphs, following the optimization rule of avoidance (Hanneman and Riddle 2005). Consequently, the relevant information is the existence (or not) of ties, their strength and structure, rather than the location of any node in the visual display.

-- Insert Figure 3--

First of all, there are no co-authored papers until 2003. In the period 2003-2007 the network is incipient, governed by atomization of dyads and, at its most, tryads of co-authors. In 2008 two journals' special issues on TM were published and, for the first time, the structure shows subsets of actors of four members. One special issue was related to the hospitality industry (focused on retention, recruitment engagement and development issues in this sector) and was published by the *International Journal of Contemporary Hospitality Management*. The second one, was published by *Public Personnel Management,* with two highly cited papers: the introduction to the special issue in which Reilly (2008) discussed the 'right course' for TM, and a conceptual paper from Garrow and Hirsh (2008) in which the authors posed, for the first time, TM issues of focus and fit. It is worth noting that the authors participating in such special issues did not continue with their research in TM. In brief, the special issues seem to have played a significant role in the growth and complexity of the network, connecting authors that were previously apart.

The interactional trend in the network was maintained in 2009, with a slightly minor number of authors involved but two subsets of 4 authors collaborating. A third special issue was due in 2010, and another milestone was set: the number of co-authors more than doubled, and collaborations among subsets of 4 and 5 actors are rather more present. This special issue was published by the *Journal of World Business* and focused on Global Talent Management. Contrarily to what happened following previous special issues, the vast majority of authors participating in this third special issue continued doing and publishing research on TM up until present day. In fact, two of the guest editors in 2010 are today among the most influential authors in the field. In 2011 there is a slight recession (48 nodes in 2011 vs 70 in 2010). The year 2012 seems to be the turning point for TM in terms of numbers, with over 80 authors in the network and from there on the network will steadily grow. From 2013 onwards the structure can be considered as a relatively dense network compared to what have been reported for other fields, for example, strategic management (Koseoglu, 2016). The annual EIASM Workshops on TM starting 2012 seem to have contributed to that being the case. Indeed this workshop has served as a platform for interaction and exchange of knowledge among researchers in the field. Since 2014 each annual workshop preceded the publication of a journal special issue (usually, published one year later).

In order to better capture the properties of the network, several indicators are included in this section. A common indicator in SNA to capture a general picture of a given network is *density,* which measures cohesion based on the ratio of existing ties over all the possible ties within a network, and shows connection level among authors (Acedo et al. 2006). Density is a macro level property of the network and it is generally expressed as a percentage. It is very sensitive to the size of the network (presumably, the fewer number of actors participating in the relational structure, the highest the probabilities that each node is connected to all others). In the case of the TM collaboration network the density values are higher in the 2003-2007 period since the size of the network is relatively smaller that in later years (see **Figure 4**, where density is depicted by a black line and number of nodes indicated by bars).

-- Insert Figure 4 --

At the node or actor level (micro level), the analysis starts identifying which actors are salient or central in terms of participation and connectivity. The most widely used measure of centrality is the *Freeman Degree*, which is basically the arithmetic summa of the arches coming and going from each node. In our network, the *InDegree* (arches to a given node) and *OutDegree* (arches from one node to other nodes) are equal, as co-authorship is by nature symmetric. The average degree for the nodes and the degree distribution for each year have been used to summarize the changes in the structure of the network (see **Figure 5).**

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The average degree in our TM network is generally around 2, which means that each node has a mean of two co-authors. The average degree increases from 2007 to 2012. The value of the maximum degree is rather more variable, with the highest peak in 2013 (a single actor had 8 connections). In brief, throughout the period we have witnessed how the TM network has reduced its *density* largely as a consequence of an increased number of authors publishing on the topic, while steadily increasing the average number of collaborations among authors (*degree*).

It is interesting to note the trends in terms of centrality among those who have been guest editors of special issues. Leaving aside those who were in the first special issue in 2008 and soon after abandoned the field, all the other 6 authors are in the top 20 regarding centrality. While having been a guest editor is closely associated with being central in the network, the number of issues edited is not a predictor of centrality. See for example number three in **Figure 6**: is the third author in terms of centrality ranking (with 21 co-authored pieces) and being editor 6 times. Compared with the most central actor, that in position number 1 has a degree equal to 30 and has edited 4 special issues. In contrast, the next author, that in position number 2 has edited only one volume but is almost as central as the first (degree is 27).

-- Insert Figure 6 --

3.2. The collaboration network in TM: properties

Beyond the evolution of the network shown above, our goal in this section is to explore deeper into the properties of such a community as well as the positional features of every author. Eventually, we will be able to identify the most influential actors in terms of collaboration, assess the strength of the network and provide better insight into the structure and dynamics of the network core level.

The complete TM research network contains 588 nodes and 1432 ties (see **Figure 7**), which in terms of density means a cohesion level of 0.5%. This low values responds to the size of the network: the more actors participating in the structure, the more difficult that the network presents high-density values (close to 100%).

-- Insert Figure 7 --

The first aspect captured by the graph is the unevenness in the distribution of relations. The shape and size of the different components or collaboration units (co-authorship alliances) is very heterogeneous, ranging from isolated dyads of authors with a single collaboration, to more complex structures built around central actors or stable co-authorship links (such as those substructures located at the upper right area of the sociograph).

Most of the nodes have few connections. Two out of three authors (nodes) have degree 1 or 2, which means that throughout the period these authors have contributed probably with one publication in collaboration with one or two colleagues at maximum. On the other hand, there is a 10% of authors that have a degree of 5 or above (which 5 co-authored papers). Particularly, the two most central authors mentioned before score degree 30 and 27, while the third most active author scores 21. This gap indicates the unevenness of degree distribution in the network. **Figure 7** also highlights the most active authors in a light purple color (those that score 5 or higher), and the two contributors scoring 27 and 30 in orange.

Since the *Freeman Centrality* measure is highly dependent on the size of the neighborhood, we have also used *betweenness* as an additional indicator of centrality that captures author importance and influence. Betweenness is based on the idea of intermediation, that is, the presence of a necessary actor between two others that are not directly connected[4]. In terms of co-authorship, those betweenners are important as they are key in community building and increasing the connectivity within the network. A 21% of the authors involved are acting as intermediaries in the network. This is a result of a high level of local sub-structures, that is, collaborations around given isolated publications, and some authors acting as bridges, largely those that have contributed to two papers with colleagues that are not related to each other in terms of co-authorship. In this respect, weak ties are interesting opportunities in terms of bridging, connecting different perspectives that otherwise would remain apart. There is still another indicator of centrality which measures how close or far is every actor of the rest of the network: *closeness*. Is generally used to measure the efforts that a given actor has to do to reach others in the network. In the case of the TM co-authorship network the results are limited and the interpretation is tough, as is a disconnected network, so the map shows 588 actors that are grouped in 166 separated subsets of different sizes.

To test to what extent being central, being an intermediary and being close are correlated, the association between them is run using a simple correlation (see **Figure 8**). It can be interpreted as in two out of three cases there is a correspondence between high degree values and alike betweenness (slope is 0.655). On the contrary, the proximity is loosely correlated, meaning that the being active doesn't necessary mean to be close to every other actor in the network. The low correlation levels are under 0.350 for both betweenness and degree.

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[4] We also tested *Eigenvector* centrality, which measures popularity, weighting the importance of each author/node according to how 'popular' or 'well connected' their connections are. While eigenvalues allow for the identification of "popular" actors, they is not adding useful information regarding the identification of key players, because they also highlight those that despite not being central are connected to the referential ones.

-- Insert Figure 8 --

In discussion with Valente et al (2008), the results for the TM show that centrality and betweenness are moderately correlated and the coefficient is slightly lower than expected but still is aligned with their results. However, for the case of closeness the TM network presents significantly low levels of correlation, mostly due to its disconnected composition. In this sense, once the analyses of cohesion and centrality have been performed and the micro (nodal) and macro (structural) levels explored, we draw attention to the meso level. This meso layer is associated with "Fragmentation" in SNA, and aims at detecting to what extent there are critical or weak parts in the network structure. Network fragmentation in TM is high as anticipated by a density score of 0,5%. We have identified up to 166 differentiable components in the network. As announced, the size, the structure and the composition of the clusters vary widely (as mentioned before, most of them being dyads and tryads). We found the network to be characterized by a number of key core components and an abundance of authors that hold up the network bridging and linking different parts of the structure that would otherwise be disconnected. Those authors (nodes) can be identified as *cutpoints*, just because they have other nodes depending on them. We found 40 nodes acting as cutpoints, which corresponds to the 7% of the network. Without their participation the network structure would be rather more atomized, and thus the number of components would increase.

So as to identify the core components in the network structure we have considered three different aspects: a) the size of the components (number of authors participating in them), b) the relative presence of components of that size, and c) how many authors are participating at that level of component size and which percentage they represent. **Figure 9** shows the distribution of actors by component size. The analyses of the components provides an idea of the existence of "schools" or stable subcommunities within the field. Two big components can be differentiated in terms of size: **A** (N=68) and **B** (N=24). **Figure 9** also shows the presence of other minor components (N<10).

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3. The core of the collaboration network in TM research

As illustrated by **Figure 10**, the core of the collaboration network is composed by 87 authors around two independent structures or components: component **A** (with brown coloration), and **B** (with light-grey coloration). Paradoxically, the two components are not connected together, and their respective connectivity and structure patterns are slightly different, indicating two communities have been growing in parallel. It is worth noting that to a great extent the actors within these two components enjoy salient positions in previous indicators of degree and particularly in intermediation (*betweenness*). To a great extent this is closely connected to the fact that we have used co-authorship as the measurable dimension of scientific collaboration.

-- Insert Figure 10 --

The stories behind each component differ and it can be visually seen in their growth across time. **Figure 11** shows the evolution of Core A (the biggest component) year by year and the first co-authorship appears in 2005 and there is a blank between 2006 and 2008. In 2009 appears another co-authored peace and from 2010 onwards, the community starts to build a net which will become a single community since 2013.

-- Insert Figure 11 --

Component B started later, in 2012 as two separate substructures which became three in 2013 and is not completely united until 2016. On the bottom-right can be detected a close-knit subcommunity which evolves around the author which will become the most important within this set (see **Figure 12**).

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Not all the actors within these two components are equally important, but the most central actors within the whole TM network belong to one of these two components. Taking **A** and **B** components together we find 20% of the nodes (15 actors in total) who should be considered as rather occasional contributors. They appear in the "core" structure because they are minor players well connected to those that occupy central positions in the core.

The component labeled as **A** (in brown color) has 68 members (60% men and 40% women), largely coming from the US (26.5%), the UK (14.7%) and Ireland (16.2%). Around 11% of the co-authors in this component are not academic researchers per se, coming from consultancy and/or the private sector. The main research area in the component is International Human Resource Management (which has been present every year), followed by Human Resource Management (authors working on this field are present almost every year but to a lesser extent than those dedicated to HRM). In scatter numbers we find other research areas, including: Corporate social responsibility, Cross-cultural management, Information technology, Innovation, IT management, Knowledge management, Leadership, Marketing, Methods, Organizational change, Organizational diversity management, Organizational Psychology, Strategic Human Resource management, Strategic management. It is worth mentioning that five of the actors in this component have been Guest Editors of journal Special Issues, and three of these actors have acted as chairpersons of the annual EIASM Workshop on TM since 2012.

The component labeled as **B** (in light grey color) counts with 24 members. In this case the proportion of men and women is reversed (58% women and 42% male). Their countries of origin are basically The Netherlands (45.8 %), Belgium (41.7%) and Spain (12.5%). There is a strong research tradition on Organizational Psychology (50% of them) and Human Resource Management (16.7 %). While these two strains have been present since the early days of this core (in 2012), it is not until recently that both conversations become quite connected through authors. Other research areas that are present include: Academic careers, Economic evaluation of health systems, Family business, Human resources and work relations, Methods, Organization and dynamics of science, Strategic human resource management, and Strategic management. Among all participants only one has been Guest Editor of a journal Special Issue (2013).

The two components differ, not only in size, but also in density and degree distribution. Component **A** is rather more fragmented and hierarchically organized than component **B**. This can be concluded looking at their density score: while A has a density of 6.25%, B's density is 14.5%. Component **B**'s authors are rather more connected, that is, we find greater co-authorship and authors' ratio of collaboration is higher. The degree distribution in **Figure 13** also depicts different structural dynamics between components. For component **A** three major groups can be differentiated: a first group with the vast majority of co-authors presenting a degree ranging from 1 to 5; a second group less populated (ranging degree 5-9); and a third group with the most relevant actors (degree of 10 and above). In contrast, in component **B** two separate groups are clearly defined: one including degrees from 1 to 7, and a second group with degrees from 11 to 17.

As mentioned above, the degree is a measure of centrality based on the sum of ties for a given actor, so grouping actors by their score in terms of degree is to group them according their level of activity within the community.

-- Insert Figure 13 --

Regarding the indicators of betweenness, 30% of actors within this component are acting as intermediaries or connectors, the top 3 are precisely A1, A2 and A3. Besides, all actors have similar levels of closeness to all other authors within this community, which means that efforts to reach any other author within the network is not differential among them. The level of association of this indicators is significantly higher with respect to the full network: betweenness and degree have a correlation coefficient of 0.882, while closeness has a different pattern and scores around 0.540 for the other two (still moderate but almost two times the coefficient for the whole network, which was around 0.330).

Focusing more on the attributes of this actors (their characteristics), **Figure 14** shows a more detailed analysis of Component **A** by gender, degree and country of residence of co-authors.

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Green shades mark those authors from Anglo-Saxon countries, which are predominant in the network (dark green for Ireland, light green for the US and turquoise for the UK). The center of the network is predominantly Irish. The closer to the center, the more homogenous relationships within countries. The shape and characteristics of a "small world" can be observed here: cohesive clusters internally speaking, and less cohesive externally, that is few links with the network (Kronegger et al. 2012). There are two exceptions to this: the Finnish component (in red, right edge), and the German triangle (in dark purple, close to $\mathbf{A_1}$) in which the authors are only connected among them and with node $\mathbf{A_1}$. Further, the center of the network is largely represented by men, with the exception of node $\mathbf{A_2}$ that represents the most important woman position in this community.

One of the main premises in SNA is that connections tend to be made among pairs of nodes that share similar characteristics (homophily). For the **A** component we found that 54% of the existing ties are connections between authors of the same gender, while only 7% are linking people from the same country (this is also sensitive to the wide range of nationalities existing). In terms of research areas (**Figure 15**), 45% of existing ties are made within the same research area. The network is mainly centered around experts working on International Human Research Management (bottle green) and Human Research Management (black). It is also worth noting the participation of non-academics (in white).

-- Insert Figure 15 --

The second biggest component is labeled as component **B**, and it is half the size of component **A**. As mentioned above, it has higher cohesion and less country diversity. However, it is richer in terms of variety of research areas. **Figure 16** shows the relational structure of the network. It is clear that $\mathbf{B_1}$ is the most central actor (node). The second ($\mathbf{B_2}$) and third ($\mathbf{B_3}$) most important actors in the network are much less central than $\mathbf{B_1}$. The collaboration pattern reveals that co-authorships are built and maintained, to a great extent, around $\mathbf{B_1}$. Those collaborators close to the central node may act as intermediaries indirectly connecting the central nodes with those other more peripheral.

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In terms of intermediation (*Betweenness*), only a third of the authors are betweenners and the most frequent intermediaries are precisely those named in **Figure 16**. It is interesting to note that $\mathbf{B_3}$ is rather more central to the network than $\mathbf{B_2}$, as she is bridging two co-authorship substructures. In other words, $\mathbf{B_3}$ plays a crucial role in connecting different groups as a broker (Yin et al. 2006) or as a gatekeeper who controls information flows in the network (Abbasi et al. 2011). Surprisingly, only a third of them have a closeness score to the rest of authors of the network, as relations are a bit scattered. In this case, the correlations among indicators are partially similar the results for the whole network. Being central and being intermediary are correlated at a level of 0.770, while being close is higher than for the whole network. (0.544)

To go into further detail, **Figure 17** shows the analysis of attributes of nodes in component **B**. The homophilic pattern by country is clear, with a predominantly Belgian nucleus around $\mathbf{B_1}$ (in light blue, upper left), a Belgian-Spanish collaboration (in light blue and orange), which is directly connected to the center and intermediating two Dutch sub-communities bridged by $\mathbf{B_3}$. Among all existing ties in component **B**, 72% are made within the same country.

-- Insert Figure 17 --

In terms of research areas in component **B**, three different patterns emerge (see **Figure 18**). First, most actors tied to the main core ($\mathbf{B_1}$) belong to the same research area: Organizational psychology (in purple). Second, the nodes acting as intermediaries come from the field of Human Research Management ($\mathbf{B_2}$ and $\mathbf{B_3}$, in orange). Third, the rest of contributors come from other research interests or expertise (e.g., specific research methods and technique), which are less central to the network and represented by other colors below:

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4. Final remarks

The goal of this study was to shed light on the collaboration patterns among authors in the field of Talent Management, through co-authored papers. Co-authorship is quite important as more than 70% of academic production in TM is co-authored. Overall, the results in this study demonstrate the rapid evolution of the network despite it cannot be considered a full community as it is highly fragmented and the groups of reference are many and usually not connected to each other. The density levels are low and the members within co-authorship groups are generally under 10. We have been able to identify two clear communities (cores A and B) which are close-knit and are fully connected. Both have been evolving (since 2009, component A; since 2013 component B) around key authors and their specific approaches to Talent Management.

These two communities also follow homophilic patterns, and it has been tested using gender, countries and main research area. Component A (with 68 nodes) is mainly composed by males coming from Anglo-Saxon countries, and writing on Human Resource Management with an International perspective (i.e., their research field or background is International Human Resource Management). It started in 2012 and it had three different subsets until 2016. The most central authors are embedded within this component and it is coincident with those that have been Guest Editors of special Issues or have acted as chairpersons of the annual EIASM Workshop on TM. Component B (with 24 nodes) is mainly composed by female (around 60%) and is highly centralized in the most salient woman in the whole structure. The precedence of authors is limited to The Netherlands, Belgium and Spain and their main research background is based on Organizational Psychology. They also adopt a Human Resource Management perspective but completely isolated from the big component A, despite the topic converges. The second component started in 2012 and it had three different subsets until 2016. The stronger community evolves clearly around the leader woman since 2013.

The key author analysis by using different measures of centrality reveals interesting facts around degree, betweenness and closeness. Regarding the first, degree is connectivity and in this type of networks also reflects the efforts of each author to generate cohesive ties. We have proven that is highly correlated with betweenness and that is because in a big and low dense network, those with high degree are the most connected and their chances to be connecting structures apart are high. This is true and consistent for previous studies we have used for reference in the paper but also for the full network and component A. In the case of component B the level of correlation between both indicators is sensitively lower, as it is a highly centralized network and those actors with high degree are connected around the central woman and not necessarily connecting separate parts of the network. In this sense, the weak ties within component B are basic for the creation and maintenance of the component. We have also correlated the previous indicators with Closeness and two different patterns have been found. While for the whole network closeness, considering the whole network was not related to degree or betweenness because of the general fragmentation. However, closeness was moderately correlated for both components (which are smaller, denser and fully connected).

Thus, this paper is the first study to provide evidence on both the structure and evolution of collaborations among authors in the TM research field. We used co-authorship as the proxy to collaboration and we performed analysis from macro, meso and micro perspectives. We believe the study findings are useful in many ways we convey below.

First, we support the fact that TM research has evolved from its earliest stage of development to a rather more mature phase. Single-authored articles are declining significantly in recent years. Moreover, we have witnessed the creation of research teams, which can be seen as evidence of its growing stage (Gallardo et al. 2015). When looking at evidence on production growth, rate of collaboration and the structure of the network we can argue there are some signs indicating the field is evolving to a much more mature phase of development.

Second, we have shown the EIASM workshops and the journal special issues have revealed as key strategic policies for network creation and development to date. Our longitudinal analysis allows pinpointing factors that may explain growth and peaks in the collaboration trends. As Nerur et al. (2008) highlight, a longitudinal analysis informs us about the possible changes occurring in the social construction of the field. Since 2008, year of publication of the first two journal special issues on the topic, the collaboration trend has increased considerably, being peak years 2013 and 2015. The number of actors participating in the network has followed this trend. From a practical point of view in the years to come we could argue for a strategic policy that favors network development by means of encouraging leaders supporting the organization of specialized conferences and the publication of journal special issues. Further, future success would largely depend on how we best identify the knowledge areas around which conferences, workshops and special journals issues would be organized.

Finally, we understand there is a great potential for greater cohesion in the TM research network. Despite being a young discipline, TM has a collaboration network relatively dense when compared to other disciplines as discussed earlier. Further, a core network based on two differentiated components (**A** of 68 actors, and **B** of 24 authors) has been identified. Actors in the network should be looking into strategies that could link these two components so as to build a more cohesive structure of collaboration. Cross-disciplinary research, that is across research areas that characterized both components could be a worthy policy to pursue. In addition, intra-country collaboration has shown to be frequent in the network for which betting on proximity in the formation of research teams seems to be a sound strategy. We have largely focused on structure and network characteristics on the TM research community. This is a fundamental first step towards a deeper understanding of the micro dynamics, that is, how research teams are really formed, how they influence scientific progress, how are research areas prioritized and how do these areas develop.

Nevertheless, more work is necessary to establish in a more concise and exact way in which way the field has theoretically and conceptually evolved, what are the hot topics at the moment and the fading themes.

4. Limitations and future research avenues

This study is subject to some limitations we would like to disclose. First, the dataset used for this study cannot be considered exhaustive, since we agreed to only include peer-reviewed articles written in English. Although, we disregarded other interesting outlets (e.g., books, conference proceedings, working papers) that could be significant to show the evolution of collaboration networks in growing fields, we do not consider this to void the results. Second, using co-authorship as a proxy to collaboration has been criticized for assuming that co-authors are always collaborators, and for neglecting informal collaborations, i.e., sharing ideas, discussions or pre-reviews of the paper

(Henriksen, 2016; Zupic & Cater, 2015). However, co-authorship proves to be the best possible proxy to collaboration (Corley & Sabharwal, 2010), and it embodies several advantages too, such as being invariable, practical and inexpensive (see Perianes-Rodríguez *et al.*, 2010). Another limitation stems from the nature of Social Network Analysis methodologies: is more an exploratory than a conclusive approach as causal relations cannot be established. Besides, the indicators are absolute and highly sensitive to the size and nature of the network under study. For this reason we have compared important indicators for the whole network with previous research and with cores A and B as subsets of the same network.

With reference to the opportunities for future search that we can identify from our co-authorship analysis mostly lie specifically in three aspects:

1) *Investigating the intellectual roots of the TM field.* By performing a co-citation analysis we would able to enhance our understanding of the theoretical origins, intellectual structure and outlook of TM research, as well as the disclosure of 'invisible colleges' (see Batistic and Kase, 2015, Cerne *et al.*, 2016, Vogel, 2012). Further, citation and co-citation analysis would allow for a better appraisal of how patterns of knowledge flow among academic papers and cast light on the salience of homophily for knowledge transfer between papers (Ciotti *et al.*, 2016). According to Nerur *et al.* (2015) there is some concern that the inevitable specialization of researchers can hinder "the flow of ideas across specialties, the cross-pollination of ideas across narrow knowledge domains, and the necessary integration of the social sciences that can lead to a more holistic understanding of social problems and their resolution" (p. 1066). Indeed, Gallardo-Gallardo *et al.* (2015) claim that advancing the understanding of TM requires exploring the potential value of alternative theoretical frameworks. Moreover, by analyzing citation and co-citation networks we would be able to estimate how authors' embeddedness in co-authorship communities affects the impact of their research in terms of impact (see Collet *et al.*, 2014, Fischbach *et al.*, 2011). Finally, the analysis of co-occurrence of author supplied keyword and title keyword would help to appraise emerging and fading themes (see Leydesdorff, 2006).

2) *Focusing on the mesoscopic level of analysis, that is "connectivity patterns between modules of closely interconnected authors in co-authorship networks in order to*

explore the field-specificity of community structures and communication patterns" (Velden *et al.*, 2010). A mixed-method approach (ethnographic and network analysis) can help to enrich the explanation of the underlying processes and their meaning of the actors involved in collaboration networks (Velden and Lagoze, 2013; Velden *et al.* 2010; Fry and Talja, 2007). This would avoid an overemphasis on the structural dimension of social networks at the expense of the relational contents (see Kase *et al.,* 2013).

3) *Disentangling how international collaboration is shaped in TM, and how national research communities are internally and internationally interlinked* (see Glänzel and de Lange, 2002). Future research may imply looking into the reasons that explains such international and national collaboration, including interpersonal relationships (i.e., informal relationships), or rather more formal arrangements (e.g., inter-departmental agreements, inter-university joint-initiatives).

Acknowledgements: We are grateful to the Editor Wolfgang Glänzel and two anonymous reviewers for their helpful observations and suggestions on previous versions of this manuscript.

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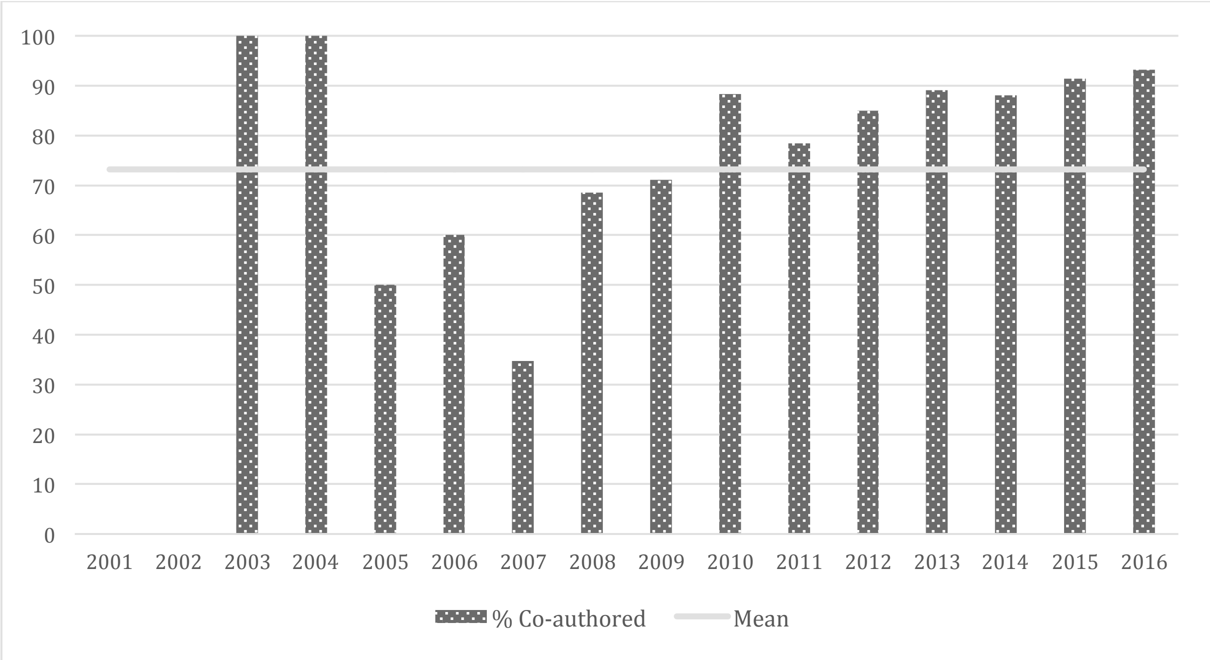
Fig. 1 Proportion of co-authored papers (% distribution per year out of total amount of papers)



Notes: (i) The horizontal line shown the average number of co-authored papers in the period.

Fig. 2 Network size: number of authors collaborating per year (absolute numbers)

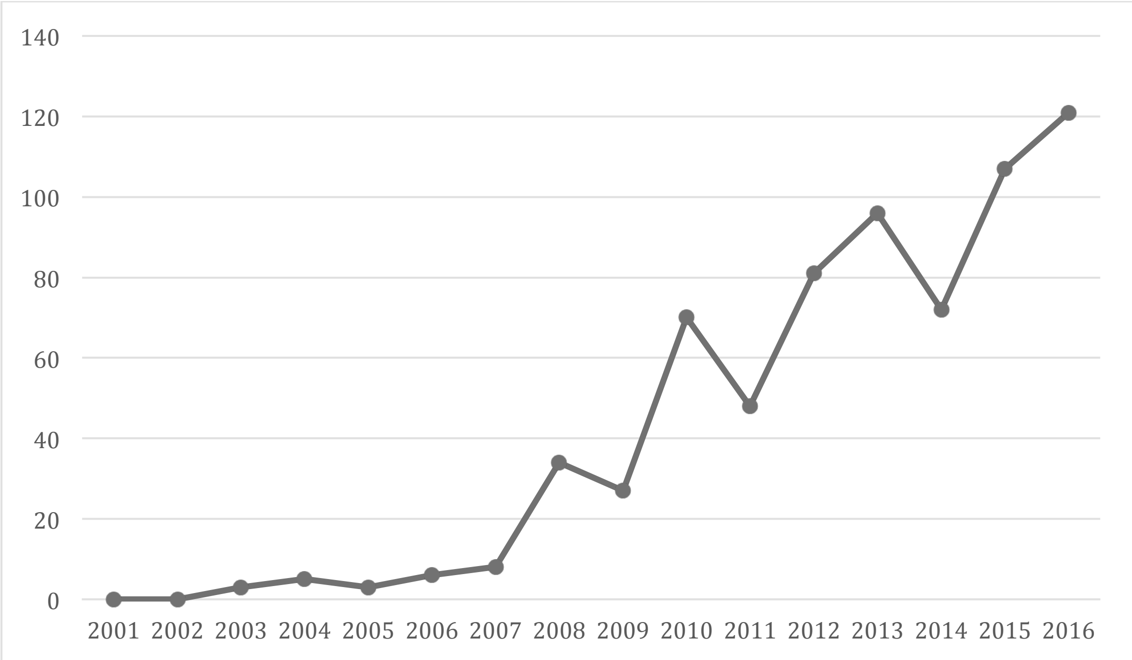


Fig. 3 Evolution of the collaboration network (by year)

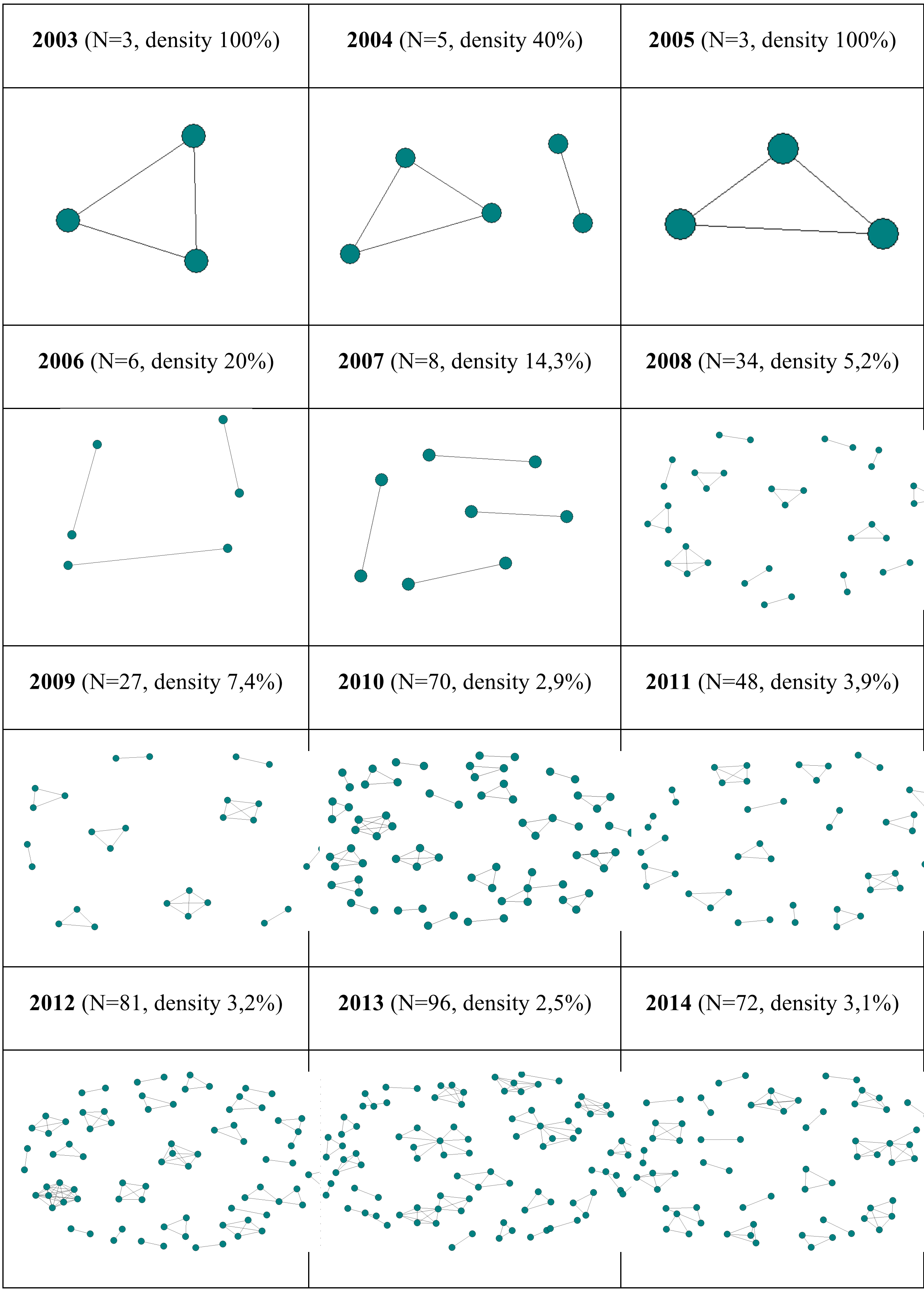
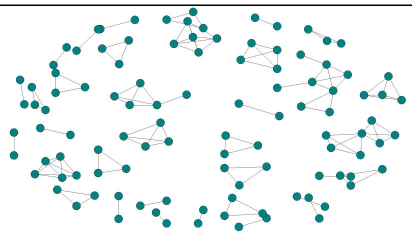
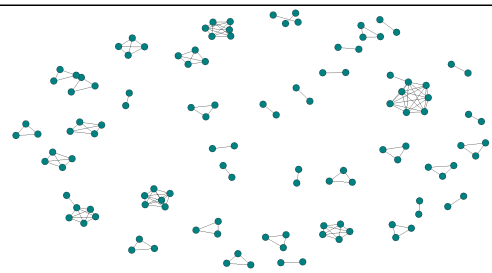


Fig. 3 Evolution of the collaboration network (by year) (cont.)

2015 (N=107, density 2,1%)	**2016** (N=121, density 4,3%)
	

Note: N= number of authors; Density = proportion of the existing ties among all the possible ties (range 0-1, in %)[5]

[5] In our case, since our matrices are symmetric, the formula is N*(N-1)/2. This would be calculated relative to the number of unique pairs (Hanneman and Riddle 2005).

Fig. 4 Evolution of density in TM collaboration network

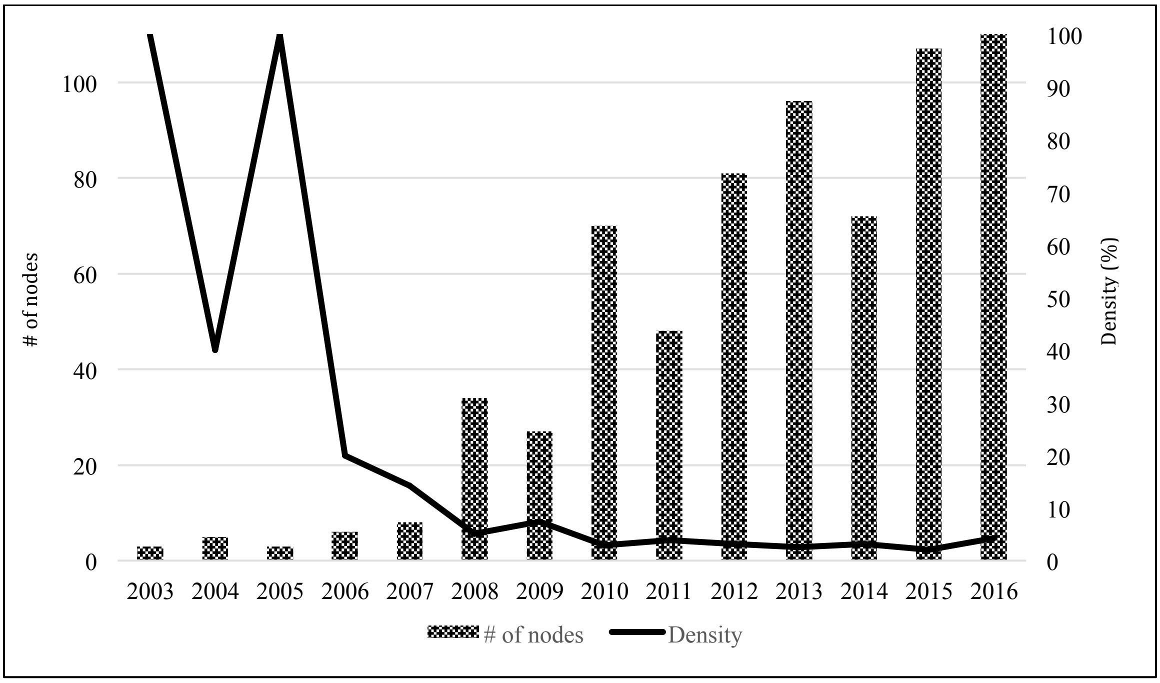


Fig. 5 Evolution of maximum and average degree by year (absolute numbers)

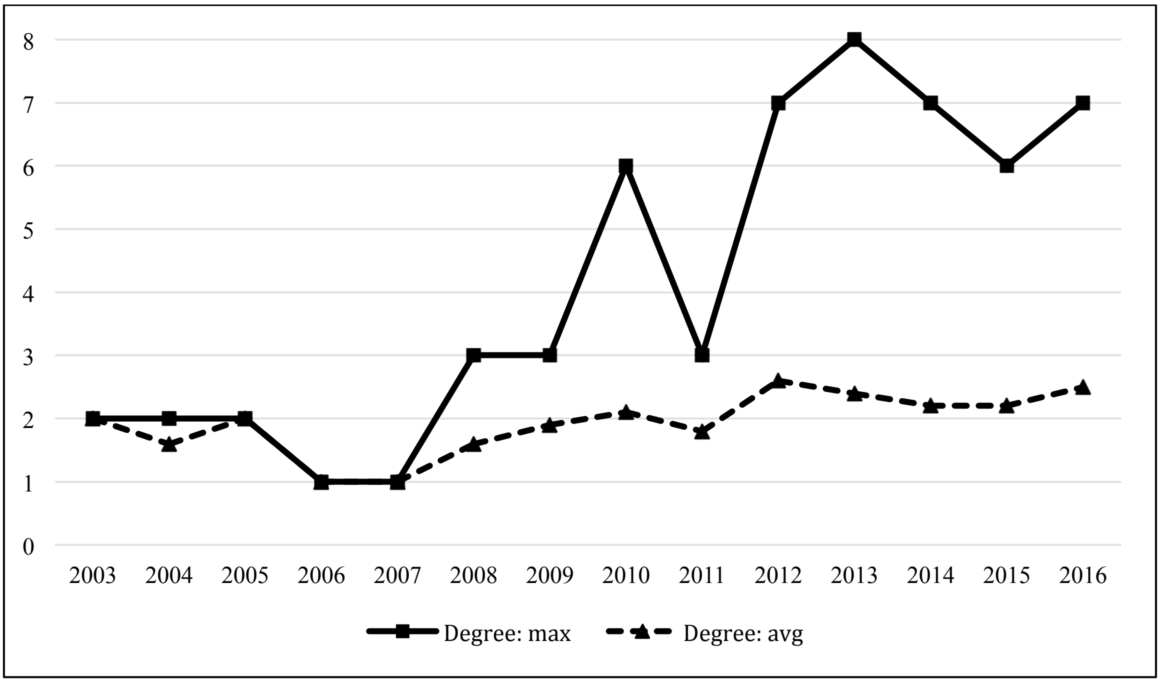
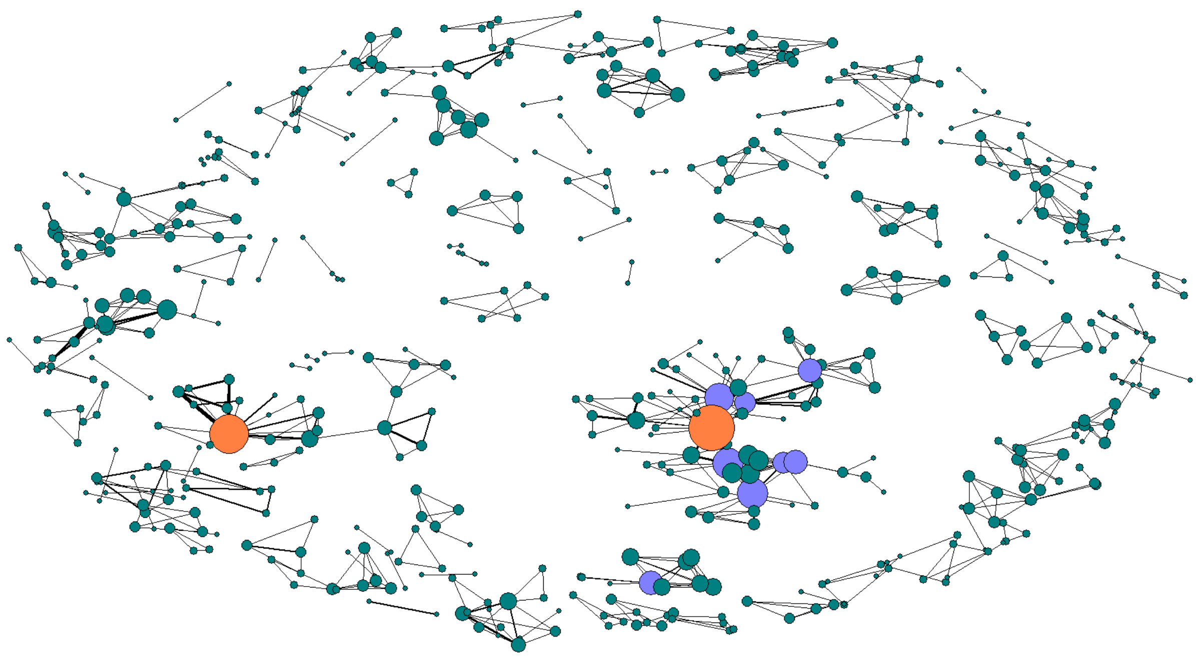


Fig. 6 Centrality measures for Guest Editors

Position in centrality	Degree	# of special issues
1	30	4
2	27	1
3	21	6
6	13	4
7	12	1
16	9	1

Fig. 7 Visualization of the complete collaboration network in TM research (period 2003-2016)

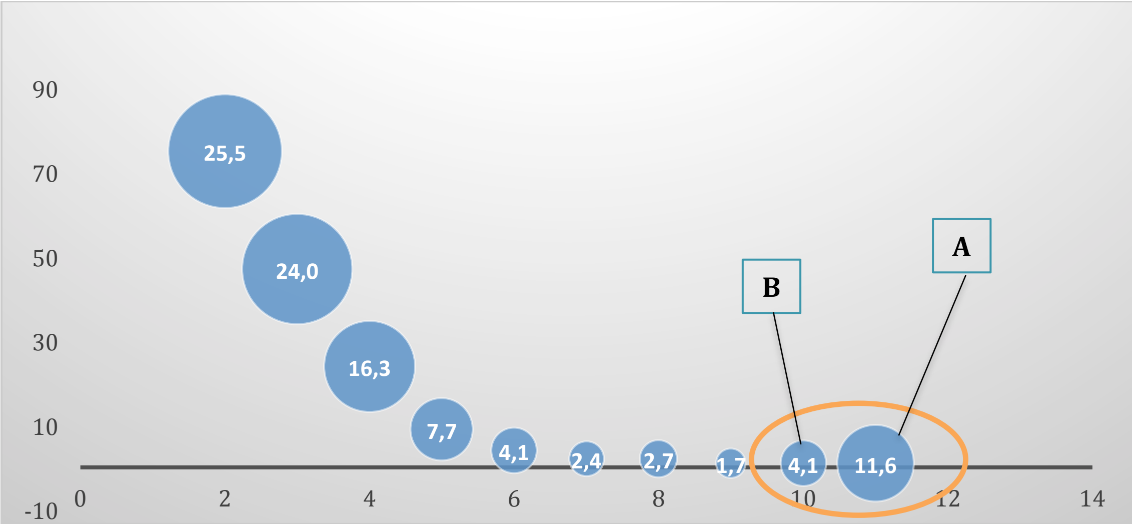


Note: To offer a richer representation, the size of the nodes has been set according to their degree (bigger nodes have higher centrality), and the strength of the ties indicates the intensity of the relationship (the more papers a pair of actors have in common, the bolder the line among them)

Fig. 8 Association matrix among three different centrality indicators

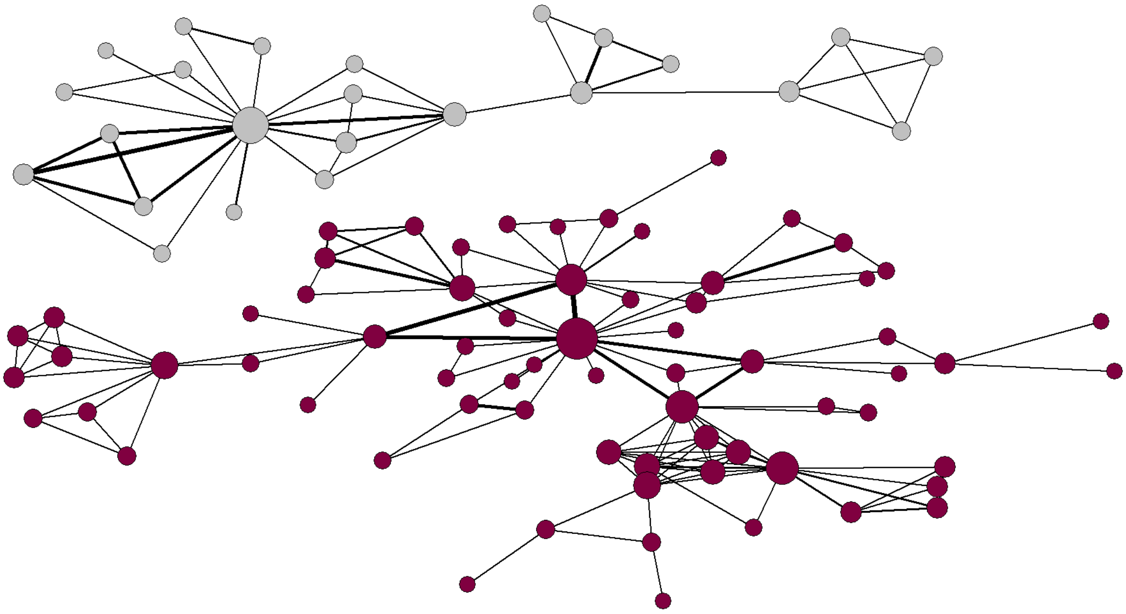
	Degree	**Betweenness**	**Closeness**
Degree	1		
Betweenness	0.655	1	
Closeness	0.343	0.316	1

Fig. 9 Distribution of actors by component size



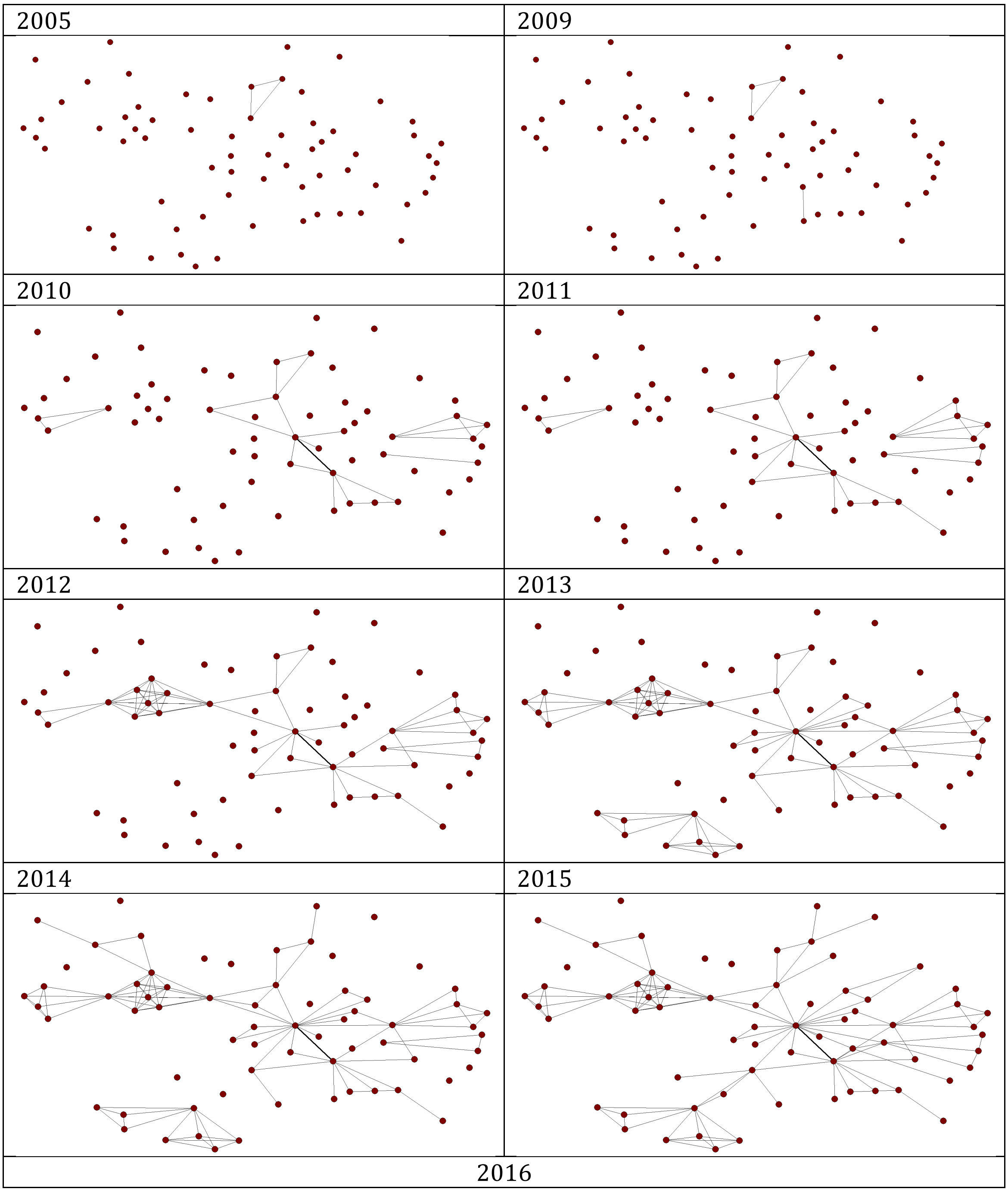
Note: The X axis shows the size of the components, while the Y axis shows the number of components existing for each size. The size of the bubbles (and the number in it) indicates the percentage of actors for each case.

Fig. 10 Core components of collaboration in TM research



Note: The width of the tie represents the intensity of the link (collaborations between two actors), and the node size is set according to Freeman degree (total number of links per author)

Fig. 11 Evolution of Core A, year by year



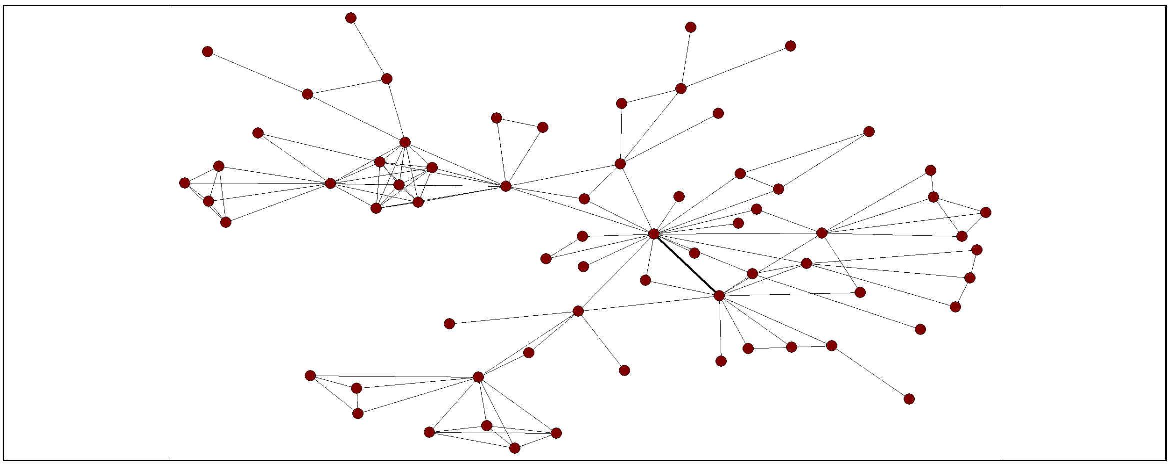


Fig. 12 Evolution of Core B, year by year

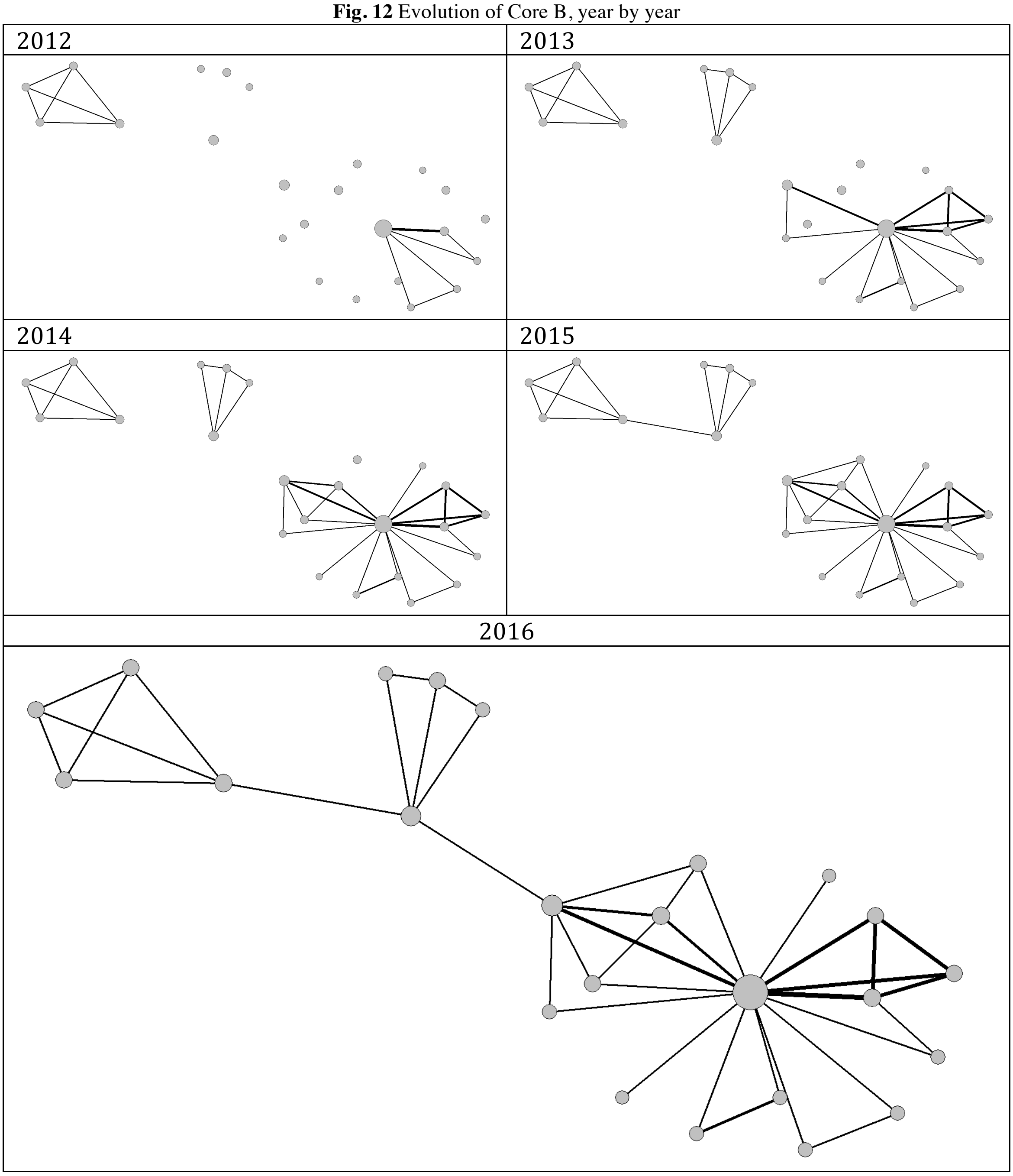


Fig. 13 Relative degree distribution for components **A** and **B**

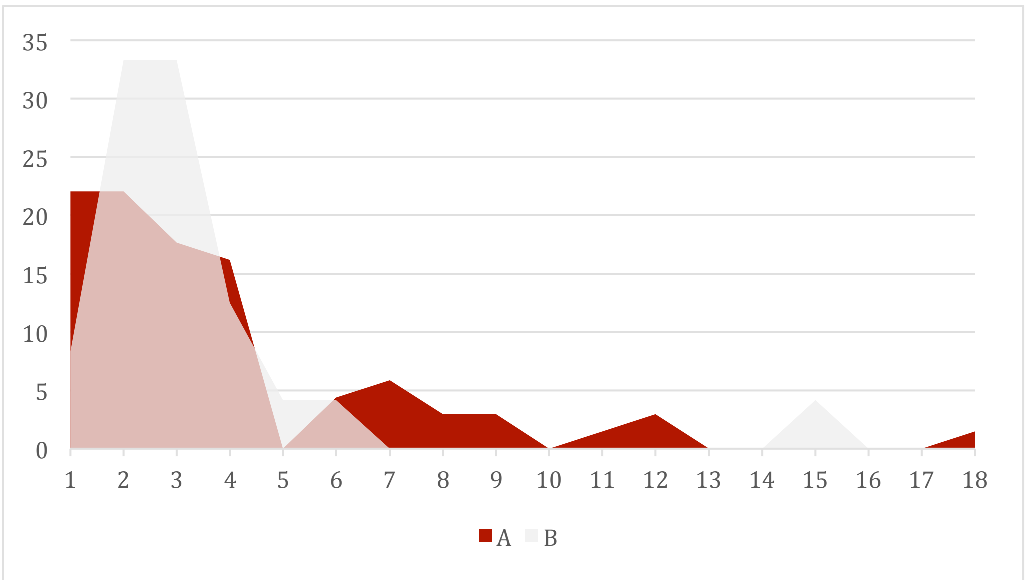
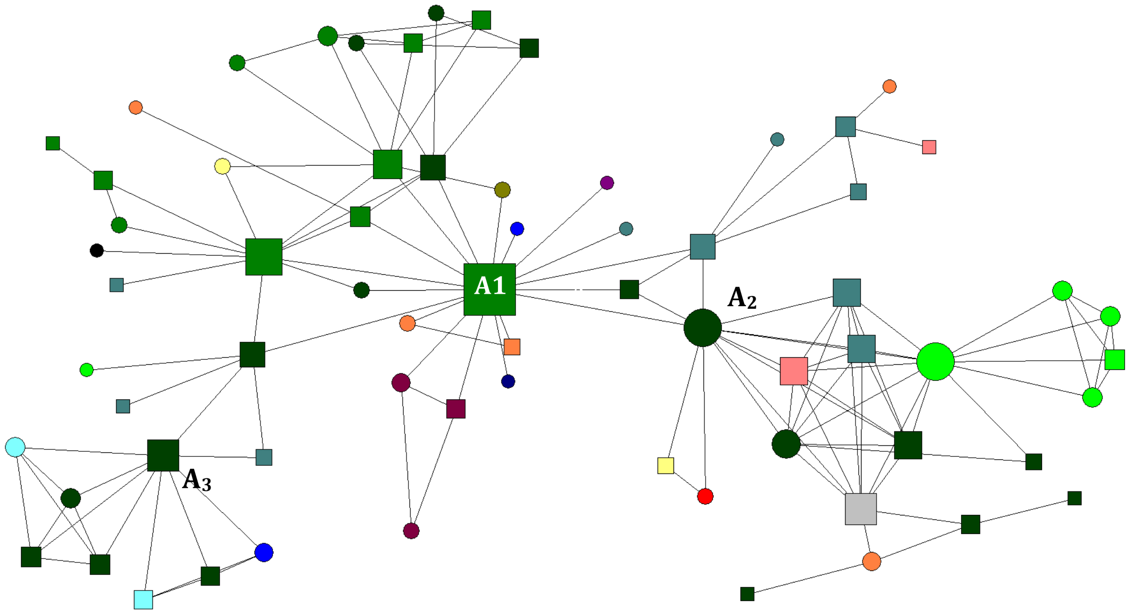
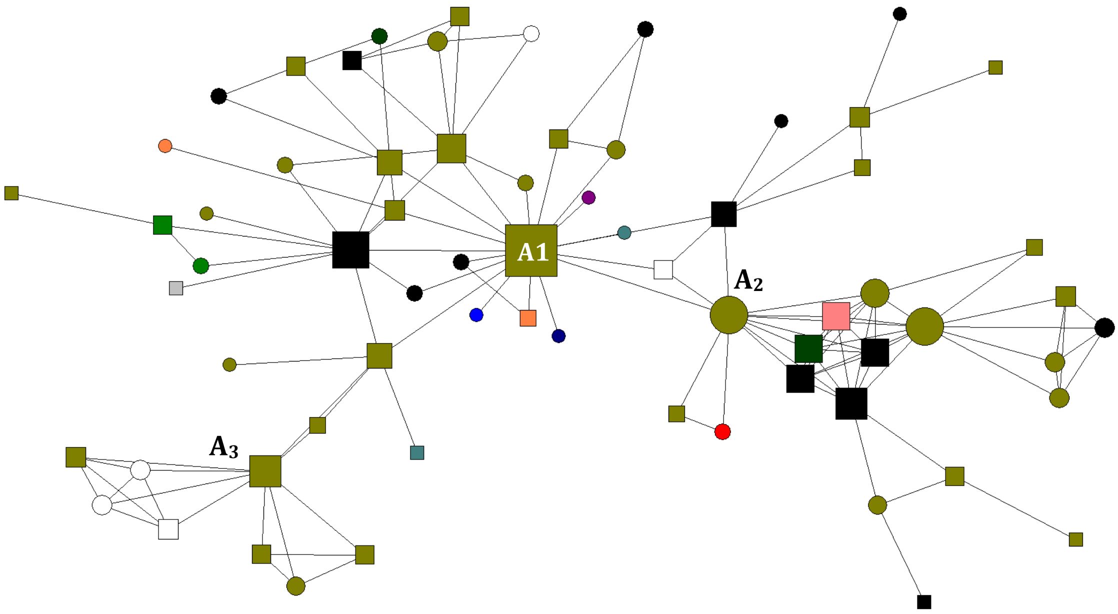


Fig. 14 Visualization of Component **A** network by gender, degree and country



Note: Circles represent women, whereas squares represent men. Degree is shown by the size of the node, and its different color refers to the country.

Fig. 15 Visualization of Component **A** network by gender (shape), degree (node size) research area (color)



Note: Circles represent women, whereas squares represent men. Degree is shown by the size of the node, and its different color refers to the research area (IHRM = bottle green; HRM = black; non-academics = white).

Fig. 16 Visualization of Component **B** network (Centrality)

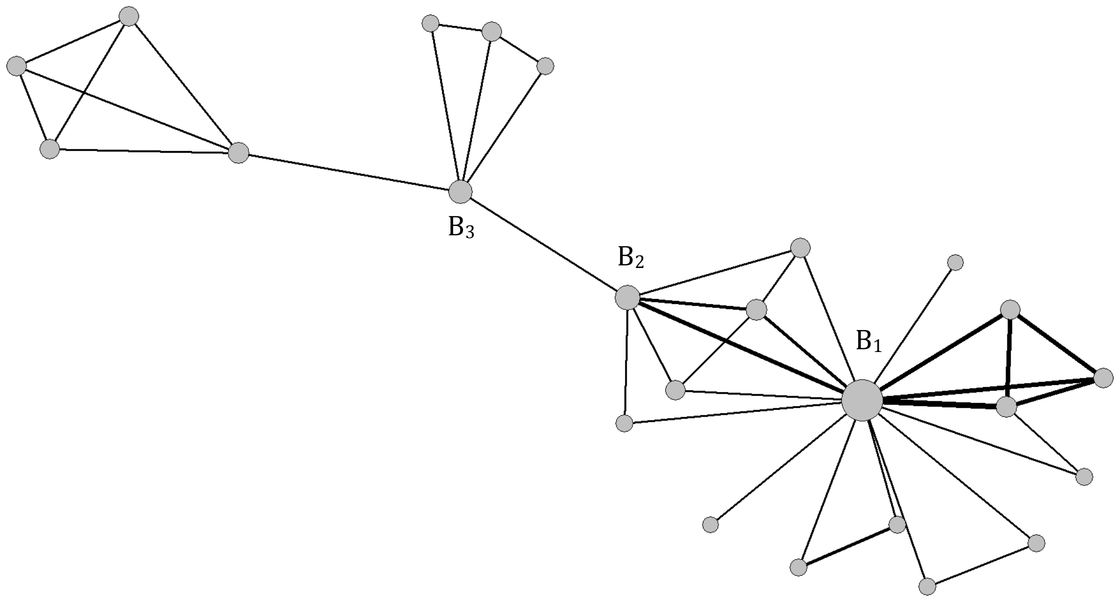
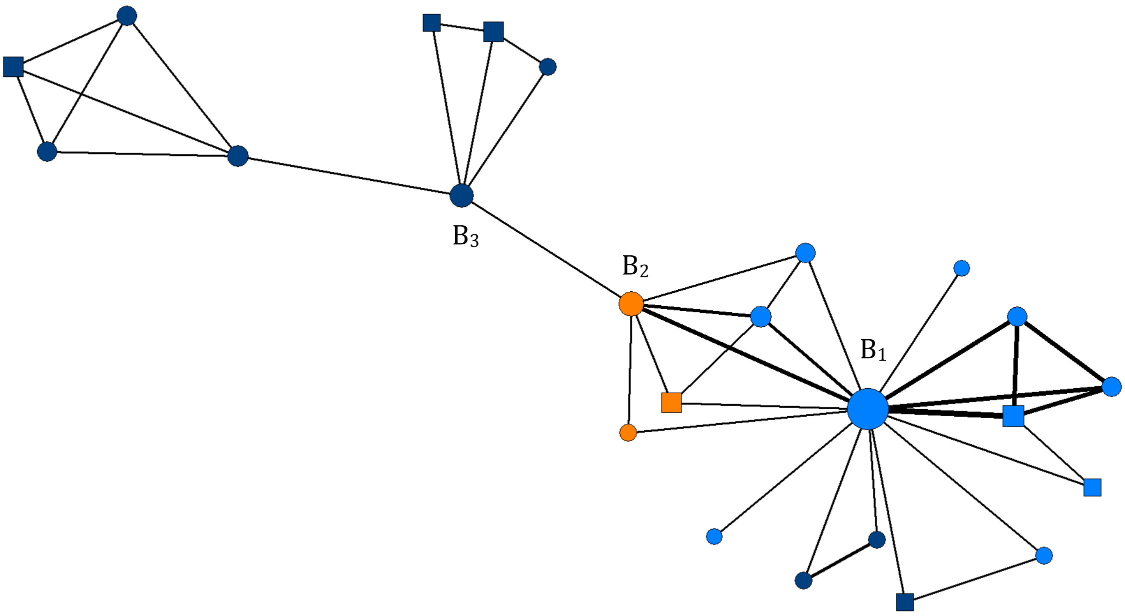
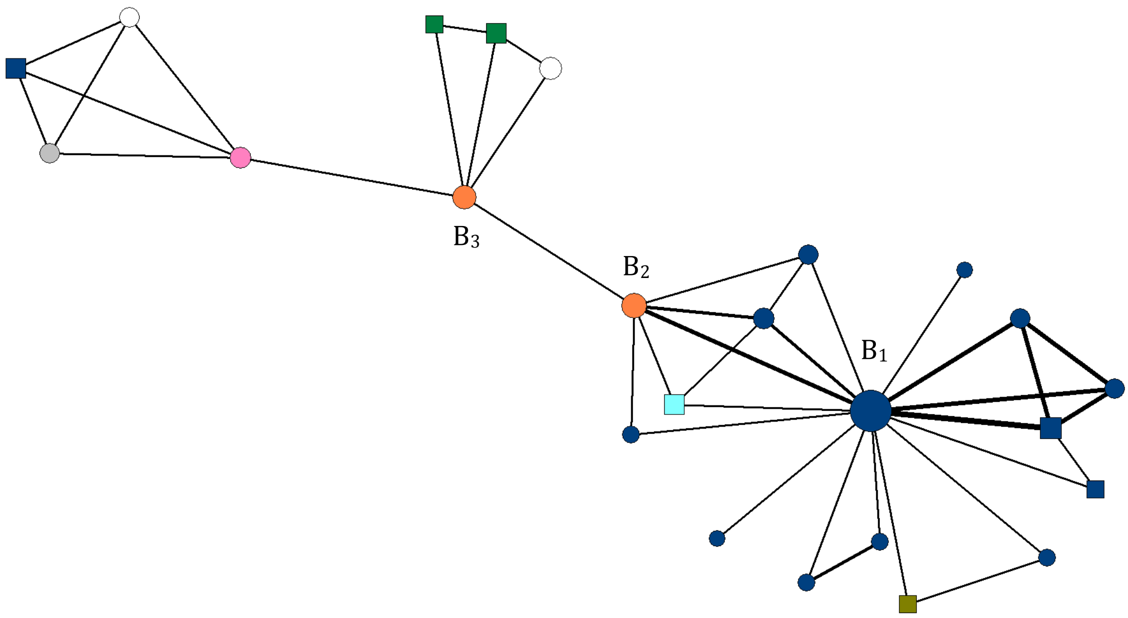


Fig. 17 Visualization of Component **B** network by gender, degree and country



Note: Circles represent women, whereas squares represent men. Degree is shown by the size of the node, and colors represent different countries.

Fig. 18 Visualization of Component B network by gender (shape), degree (node size) research area (color)



Note: Circles represent women, whereas squares represent men. Degree is shown by the size of the node, and its different color refers to the research area (Organizational Psychology = purple; HRM = orange) .