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Towards understanding longitudinal collaboration networks: a case of mammography performance research

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Abstract In this paper, we explore the longitudinal research collaboration network of 'mammography performance' over 30 years by creating and analysing a large collaboration network data using Scopus. The study of social networks using longitudinal data may provide new insights into how this collaborative research evolve over time as well as what type of actors influence the whole network in time. The methods and findings presented in this work aim to assist identifying key actors in other research collaboration networks. In doing so, we apply a rank aggregation technique to centrality measures in order to derive a single ranking of influential actors. We argue that there is a strong correlation between the level of degree and closeness centralities of an actor and its influence in the research collaboration network (at macro/country level).

Keywords Research collaboration network · Mammography performance · Social network analysis · Longitudinal data · Influential actors

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Introduction

Over the last decade there has been a significant change in the number of international partnerships examining patterns of 'research collaboration networks' (Luukkonen et al. 1993; Katz and Martin 1997; Wagner and Leydesdorff 2005; Abbasi et al. 2011b). The exchanges occur among two or more scientists within a social setting that help in the sharing of meaning and execution of tasks are known as research/scientific collaboration (Sonnenwald 2007). Social networks among scientists can produce and extend research collaborations. To recognise the areas of strengths and weaknesses amid research institutions, businesses and nations and to conduct scientific progress and supporting policies, social network analyses have been applied widely (Owen-Smith et al. 2002; Sonnenwald 2007). Similarly, to evaluate the networks' structural and relational properties for different domains, research collaboration networks are commonly employed (Melin 2000; Newman 2001; Barabási et al. 2002; Newman 2004; Jiang 2008; Abbasi et al. 2011a). Usually, in a research collaboration network, authors are 'actors' (nodes) and among them co-authorship relations are 'ties' (links). In other words, if at least one co-authored paper is present between two particular actors (scientists), a tie occurs between them.

The primary focus/question of this study is to investigate how research collaboration networks grow and develop through time from a network structural perspective. Following this, a specific research question arises as: what kinds of actors influence the network as a whole from an actors' positional perspective. To answer these questions, by the application of network analysis techniques, a throughout explanation of different topologies of research collaboration networks in 'mammography performance' has been examined over the past 30 years. The development of this collaboration network, since initial publications in the field, is explored and collaborative high performing countries are examined. The techniques and findings presented in this work are intended to be applicable for identifying the 'main actors' in other research collaboration networks. By applying a rank aggregation method to centrality measures, a single ranking of influential actors can be achieved. Our results show that a strong association occurs between the level of degree and closeness centralities of an actor (at country level) and its influence on the network.

Previous studies conducted on research collaboration networks have concentrated on just evaluating network properties where, most of the time, the networks are investigated on a binary basis (Bian et al. 2014). Nevertheless, it is quite common in a research collaboration network, that some connections and ties are 'stronger' compared to others. In this work, networks models denote this fact by assigning, as the tie weight, the number of collaborative papers among two authors. In calculating some of network measures (average value and clustering coefficients), ties are considered weighted to reveal the degree of collaboration. This does not occur for all of our calculations since we believe that certain measures are more meaningful when computed from binary networks (compared to weighted networks).

The structure of the paper is as follows. In the "Materials and methods" section, the theoretical underpinnings of our network analysis techniques and associated network measures are presented. Following this, a summary on the extracted dataset will be presented by describing how the meta-data has been transposed into co-authorship network at country level. In the "Results and discussion" section, the results of our static and static–comparative network analyses are provided along with our interpretations. In the "Conclusions" section, our major findings and results are emphasised and concluded upon.

Materials and methods

Theoretical background

Two general perspectives can be considered in analysing social networks; the Structure-oriented perspective, which examines the 'the networks topological characteristics' and the actor-oriented perspective, which investigates attributes and properties of 'social actors' behaviours' (Jiang and Jiang 2014). Both approaches are significant and may be applicable to different social networks. The first approach is very useful when networks locational characteristics are of importance and the second approach is advantageous when attributes and behaviours of social actors, especially humans, have a major role in the network evolution (Jiang and Jiang 2014).

As this article attempts to analyse a research collaboration network at macro/county level, the recognised attributes/characteristics of the actors (courtiers) may have small effects on the network evolution in comparison with their structural and positional effects. Thus, this study has chosen a structure-oriented approach for its analyses.

Moreover, in recent years, greater attention has been paid to the study of the dynamics of networks since they provide an improved understanding of network formation and network evolution mechanisms (Hossain et al. 2012). What is referred in the literature as the dynamics of networks can be categorised in two types. The first approach is indeed a static–comparative analysis, which studies the dynamic change of actors' positions in different time periods of network evolution (Uddin et al. 2012; Abbasi and Kapucu 2012).

The second approach, however, investigates how actors drive network's evolution as a stochastic process and examines the dependencies between creation and termination of ties for a link prediction purpose (Liben-Nowell and Kleinberg 2007; Snijders et al. 2010; Wang et al. 2011). Again, for the purpose of this article, we take the first approach of static–comparative analysis because characteristics of actors' behaviours are hard to define at country level.

A diagrammatic representation of the difference between two types of social network analysis (SNA) topologies has been given in Fig. 1, where SNA methods are applied to the

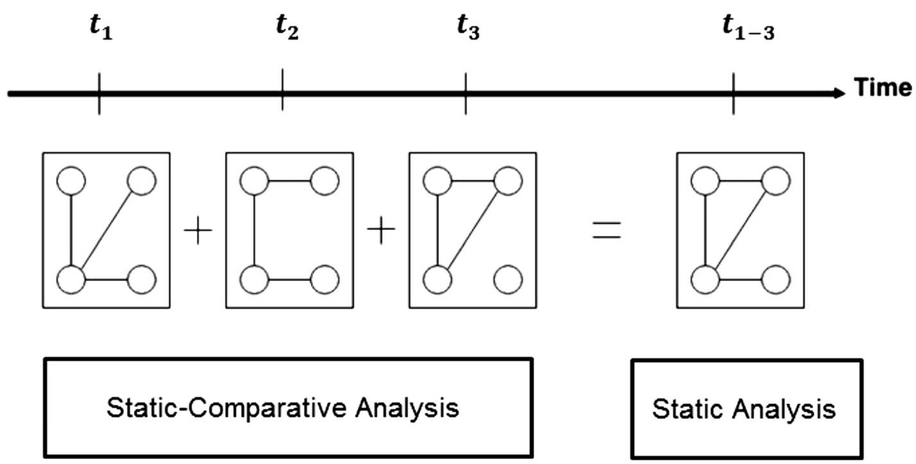

Fig. 1 Research model for analysing different topologies of networks in time and over time

aggregated network (t_{1-3}) for the purpose of static network analysis. On the other hand, SNA methods are applied to each period of study (t_1, t_2, t_3) for the static–comparative analysis.

A series of network properties are evaluated in this paper, where some are affected by only the number of actors' collaborators and few by the frequency of the collaborations in research collaboration networks. We discuss these network properties in details further in this paper.

Structural properties

For the recognition of cohesion, network structural properties provide measures (Kim and Shin 2002). At heart, these measures are a group of network attributes that illustrate the connectivity and density of a network in the eyes of the network as a whole. Trust among the members may expand by cohesive networks (Coleman 1989). By the features of cohesive networks such as recurrent and reciprocal associations among the actors who can cross-check information through indirect paths in the network, trust is developed (Cassi et al. 2012). Among the nodes in a cohesive network, consistency is promoted, since alike nodes are inclined to connect to each other and connected nodes are likely to become more alike (McPherson et al. 2001). Cohesion is often taken as a symbol of cognitive lock-in and the decay of knowledge in networks of scientific communities since the nodes of cohesive networks have access to similar information (Cassi et al. 2012).

Density Among the nodes, the widespread level of linkage in a network is provided by density (Scott 1991). The network is denser as more nodes are connected to one another. The sum of ties divided by the sum of possible ties comprises the density of a binary network, whereas, it is the total of all values divided by the number of possible ties for a valued network.

Clustering coefficient There is often clustering of the networks, which means they acquire local communities in which a greater than average number of people are familiar with one another. A method to verify the existence of such clustering in a network data is by computing the clustering coefficient in a network (Newman 2001). Clustering coefficient of each node is same as the density of the local neighbourhood of an actor (removing ego). The overall graph clustering coefficient is calculable as the average of the densities of the neighbourhoods of all of actors.

Network centralisation

Evaluating the position of actors in the network is another technique used to appreciate networks and their participants. By determining the centrality of an actor, its location within the network is estimated. The degree to which cohesion is structured around certain nodes is determined by centrality (Scott 1991). Centrality measures can also 'be interpreted as how influential and important' an actor is in a research collaboration network (Bian et al. 2014).

An investigation of three widely used network measures is done to recognise central nodes:

- *Degree centrality* Degree centrality is the number of other nodes connected directly to one node.

- *Closeness centrality* Farness is the 'sum of the geodesic distances' (the shortest path) of a node to all other nodes in the network. The reciprocal of farness is closeness centrality. This definition of closeness is only applicable to networks in which all nodes are connected through intermediary acquaintances. To taking account of other networks (with all or some nodes unconnected), Freeman (1979) defined closeness as the 'sum of reciprocal distances' of a particular node to all other nodes in the network. In this way, infinite distances contribute a value of zero. The degree of how rapid information can pass from a node to all other nodes is estimated by the closeness centrality value (Newman 2005).
- *Betweenness centrality* Betweenness centrality is the number of shortest paths (between all pairs of nodes) that pass through a certain node (Borgatti 1995). A node's power of the communication between other nodes in the network is estimated by betweenness centrality (Freeman 1979). Theoretically, in the research collaboration networks, a node having a high betweenness centrality value can be considered as the actor regularly plays the role of a bridge for other actors in the research community.

For the network level rather than just actor level, centrality measures are also assessable. According to Freeman (1979), the Network Centralisation (NC) can be defined as a property of the whole network (for each of degree, closeness and betweenness centralisation) as:

$$\mathrm{NC} = \sum (C_{\max} - C_{n_i}) / \left(\sum (C_{\max} - C_{n_i}) \right)_{\max},$$

where C_{n_i} is the centrality of node n_i. The centrality measures of an actor in social network analysis are mostly used to establish the relative influence/significance of it in the network. We can grade an actor's influence in the research community by using degree, closeness and betweenness centrality measures.

Reviewing the literature, degree centrality is mostly considered 'as a measure of immediate influence' which can be interpreted as the ability to affect others 'directly or in one time period' (Wasserman 1994; Borgatti 2005). Closeness centrality, on the other hand, is another 'influence measure in sociology' because it is believed that actors 'with short paths' to others influence them more (Kempe et al. 2003). Closeness is sometimes reflected as an index of the time until arrival of what is flowing in the network (Borgatti 1995). In the same way, betweenness centrality characterises 'how influential' an actor is in 'communications between' its pairs (Freeman 1977; Goh et al. 2003). This can be inferred as the 'control' of a given actor on the network flow (Borgatti 2005).

Nevertheless, in the network, the ranking orders of these three centrality measures are difficult to correlate. As a result, in order to merge multiple rankings of actors to produce a more applicable ranking of influential actors, we use a rank aggregation method. By doing so, two concepts of '*Relative Centrality*' (RC_{n_i}) of each node n_i (for each of degree, closeness and betweenness centralities) and 'Comparative Influence' (CI_{n_i}) of each node can be defined:

$$\mathrm{RC}_{n_i} = C_{n_i} / C_{\max}$$

$$\mathrm{CI}_{n_i} = \frac{(\mathrm{RC}_{n_i})_{\text{degree}} + (\mathrm{RC}_{n_i})_{\text{closeness}} + (\mathrm{RC}_{n_i})_{\text{betweenness}}}{3}$$

A single figure of merit is provided by the comparative influence ($0 \leq \mathrm{CI}_{n_i} \leq 1$) which shows the level of influence of an actor in the network. What this measure reveals is the overall importance of an actor compared with all other actors in the network. The contributors of this overall score are: the ability of an actor to affect others directly, its capacity to influence them in a short time, and its power to control their communications. Therefore, when the comparative influence of a node is higher, one can conclude that the authority of that actor in the network is higher.

Dataset

In this paper, different topologies of research collaboration networks across countries are investigated. 'performance in mammography' is chosen as the area of interest (and importance) within Medical Imaging domain. In discussion with experts, reading mammograms was identified as one of the most challenging diagnoses in the profession, with high error rates comparatively. From a Medical Imaging perspective, performance can include: observer (reader) performance, technical (equipment and detectors) performance and system performance. All scientific co-authorships in certain area of 'mammography performance' are provided by this research collaboration network. Bibliographical data was extracted with the help of lexical search methods to build the dataset for this study. This includes certain search strings applied to the keywords of publications. We used the strings of both 'mammography' and 'performance' and limited the document to journal articles (ar) and conference papers (cp), however, no publication year restriction was made.

730 publications from 1984 until 2013 (inclusive) were comprised in the meta-data extracted from Scopus. Affiliation data was quite important for our research since we planned to carry out macro level analysis (country level). We manually applied data cleaning to meta-data since certain information was missed in the original dataset. Therefore, from the final dataset consist of 719 publications, the contributions of 2189 authors (3543 unique author-papers) from 48 countries were reflected. We used the CRRCN (Tavakoli Taba and Mirkarimi 2014) in the next step; an application program based upon Macro Excel and R program (R Core Team 2013) which extracts co-authorship associations among actors, and stored the relational matrices.

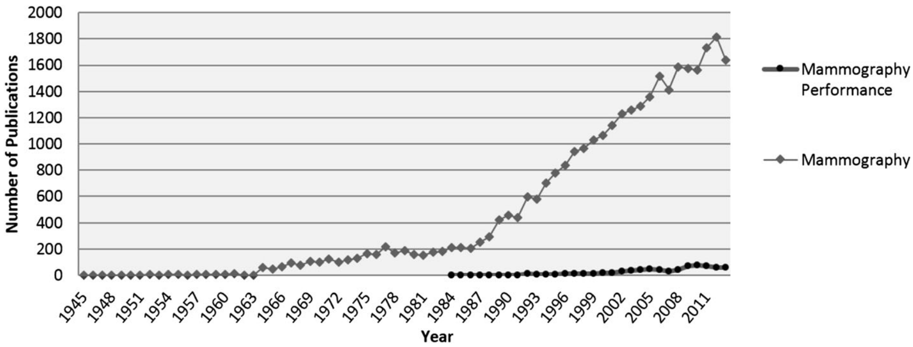

Fig. 2 Comparison of the number publications per year in mammography performance and mammography

Results and discussion

Descriptive statistics

To compare the expansion of publications in mammography performance with its super-field of 'mammography', we extracted another dataset from Scopus. This time, we took out all the journal articles and conference papers with the word 'mammography' in their keywords. Again, we did not apply any restriction on publication year. The first publication in this new dataset goes back to 1945, which is about 40 years before the first publication in mammography performance in 1984. Figure 2 compares the number of publications in the field of mammography and its sub-field of mammography performance from 1945 to 2013.

The number of publications in mammography have been always below nine papers per annum in the first 20 years (19 years to be exact). In 1964, the number of publications rapidly rises to 59 papers compared with just two papers in 1963. In the next 20 years, the number of publications in mammography increases gradually, reaching to 212 papers in 1984. This is the point that the first paper on mammography performance was published and we believe the emergence of this sub-field may be a good sign for the maturity of the super-field. This fits with the technological advances in medical imaging that allow for mammography to be considered a viable and reliable radiological examination.

Based on work by Jarrett and Clarkson (2002) and Reay Atkinson (2010), the time to reach scientific maturity is considered as a time constant which [after Chen and Yu (2001)] may be about 45 years. This would suggest that, in 1985–1990, the scientific field of mammography has moved from adolescence to maturity and adulthood (Modis 1994). Figure 2 demonstrates clearly that the rate of occurrence of publications in mammography has amplified after this period.

To be able to compare the growth rate of publications in mammography with the subfield of mammography performance, we need to make the data dimensionless. In order to do this, we used Z-Score statistical measure. Z-Score analysis is quite beneficial to determine score's relationship to the mean in a group of scores. Figure 3 shows the dimensionless growth rate of publications in both the super-field and its sub-field. From this figure, it can be understood that although the number of publications in mammography and mammography performance are very different, the growth rate is quite similar, except that the growth in sub-field have many fluctuations comparing with the super-field which is now matured. This is because mammography is now accepted as a part of medical imaging; it is the technology (image receptor, digital display) and 'performance of units and readers' that is now fluid.

Within the perspective of Performance in Mammography, our dataset has the ability to illustrate the expansion and development of Medical Imaging research publications. The incidence of publications per year between 1984 and 2013 can be seen in Fig. 4 in which a considerable escalation in the number of publications has taken place over time. In 1984, the first paper was published, in 1985 the second paper was published and there was no paper until 1990 which was considered a restart for publications. Between 1991 and 1997, a reasonable increase with minor fluctuations is demonstrated in the graph. A significant development at this stage can be seen when the number of publications increased from 9 in 1997 to 43 in 2006. Apart from certain negligible perturbations (e.g. 2006–2007 and 2012–2013), the general trend of growth has continued. The first perturbation may be a consequence of digital mammography development in 2005–2008.

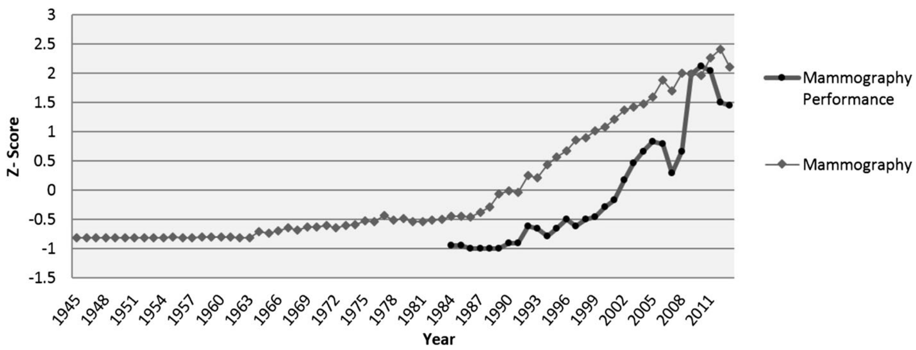

Fig. 3 Growth rate of publications per year in mammography performance and mammography

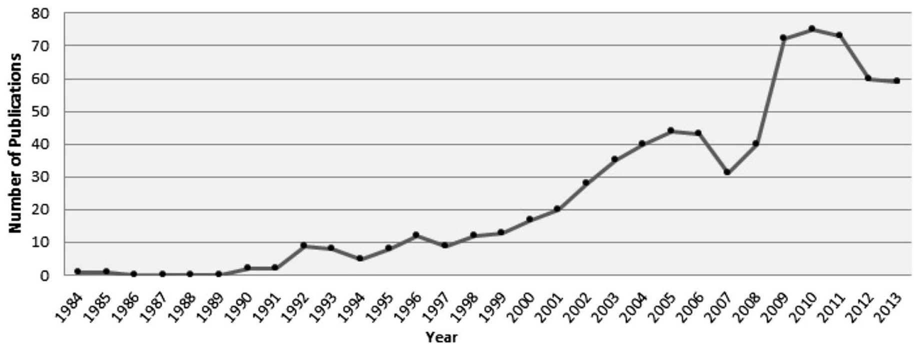

Fig. 4 Number of publications per year in mammography performance

In order to have a better understanding of the development of longitudinal research collaboration networks, we divided the whole time-frame of the dataset (30 years) into three equal periods of 10 year; t_1: 1984–1993, t_2: 1994–2003 and t_3: 2004–2013. By this division, evaluation of the network can be facilitated in its real time of evolution rather than only in its static topography. Certain attributes of the dataset at different periods of time (t_1, t_2, t_3) are shown in obtainable at different periods.

The corresponding amount of each attribute for the whole time-frame of the study can be shown in column t_{1-3}. In this column, the first two attributes (number of papers and number of unique author-papers), can be calculated by summing up their related amounts of all periods. Nevertheless, it does not happen for two other attributes (number of authors and number of countries) since the identical agents might be obtainable at different periods (Table 1).

Static–comparative analysis

At a macro/country level, by using the UCINET (Borgatti et al. 2002), the topology of the network of research collaborations was evaluated over time. The publications which tend to have at least one author from another country (according to the academic affiliations of the authors) are considered as an international collaboration. The development of this

Table 1 The dataset and its attributes over time

	t_1 (1984–1993)	t_2 (1994–2003)	t_3(2004–2013)	t_{1-3} (1984–2013)
Number of papers	23	159	537	719
Number of unique author-papers	91	709	2743	3543
Number of authors	87	549	1807	2189
Number of countries	10	22	46	47

research collaboration network in three graphs has been shown in Fig. 5—one graph for each period of time. In t_1, there was an international collaboration in none of the total ten countries, which had at least one publication. In t_2, the network develops when 7 out of 22 countries exhibit international collaboration (in two components). Moreover, the evolution of this research collaboration network displays that 33 out of 46 countries were associated in one 'main component' in t_3. In all the graphs of Fig. 5, the strength of each tie can be

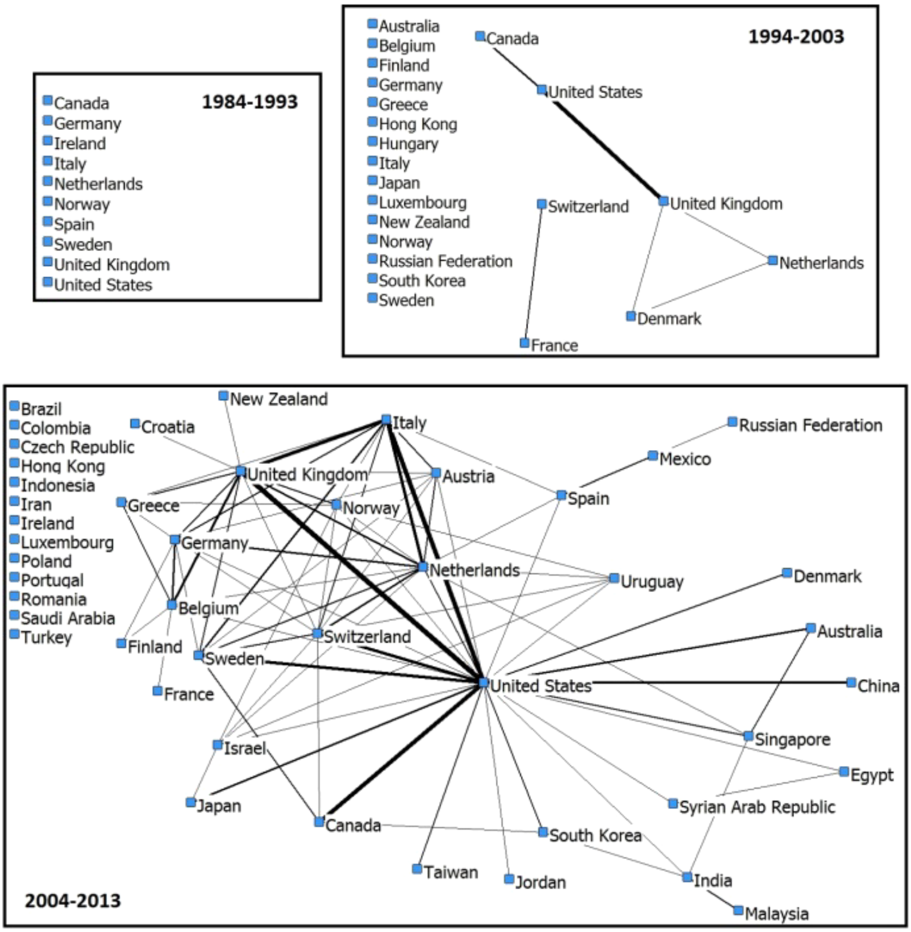

Fig. 5 The evolvement of the research collaboration network over time

seen by the width of related line—the frequency of research collaborations between two countries.

The results of analysis can be shown in Table 2. Except for Average Value and Clustering Coefficients, all measures are calculated based upon binary (un-weighted) networks. For t_1, the most of network measures are equal to zero (because there is lack of international collaborations). As time passes, the network is getting denser with 8 % of all possible links being present among countries in t_3 compared to t_2 with 2.60 %. The quantity of pairs of nodes that can reach each other (have a tie with any length among them) is known as connectedness. Comparing the connectedness values over time, the network was found to be very low-connected (4.80 %) in t_2, whereas in t_3 it was partly connected where 51 % of the countries are accessible by each other.

Evaluating the average values of the weighted graphs (mean of the weighted degrees) show that, on average, each country has less than one international collaboration in each period (0.21 in t_2 and 0.79 links in t_3), which is very low. Comparing the overall weighted clustering coefficients and average values for each period, it is seen that clustering coefficients values are four times and eight times larger for t_2 and t_3 respectively. As a result, it can be concluded that some collaborative countries are enclosed by local neighbourhoods which are reasonably denser compared to their entire networks and over the time these local neighbourhoods are getting denser.

On the basis of the centrality measures, it can be seen that from t_1 to t_3, the research collaboration networks are getting more centralised longitudinally. None of the measures are significant in the first two periods, thus the network is not centralised in t_1 and t_2 at all. Degree Centralisation values show that at the most evolved state of the network, which is t_3, this collaboration network is centralised as 46.46 % of a star network with the same size (the most centralised or most unequal possible network). In other words, the degree of inequality among all countries is around one half for this network. In t_3, the international network is decentralised considering the betweenness centralisation but the network is centralised around some countries close to each other (having high closeness centrality). Here, closeness is calculated as sum of reciprocal distances from one country to others (as all actors are not connected to each other). The high closeness centralisation indicates high flow of information in the network.

Static topology analysis

In this section, the most influential and collaborative countries are recognised using static topology (aggregated network).

Table 2 Network properties of research collaborations in different time periods

	t_1 (1984–1993)	t_2 (1994–2003)	t_3 (2004–2013)
Density	0.00 %	2.60 %	8.00 %
Connectedness	0.00 %	4.80 %	51.00 %
Average value (weighted)	0.00	0.21	0.79
Clustering coefficients (weighted)	0.00	0.83	6.12
Degree network centralisation	0.00 %	12.86 %	46.46 %
Closeness network centralisation	0.00 %	28.2 0 %	73.02 %
Betweenness network centralisation	0.00 %	1.84 %	31.04 %

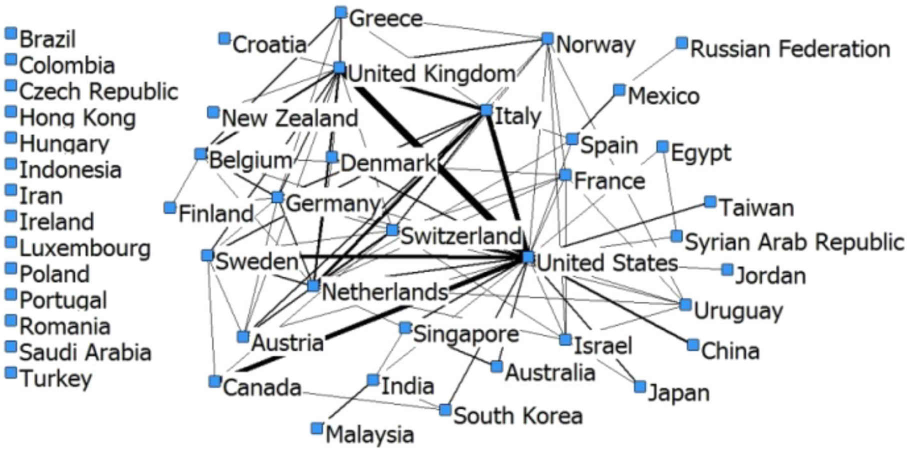

Fig. 6 Aggregated network of research collaborations

Table 3 The most influential countries, their centrality measures and associated comparative influence (CI)

	Degree centrality	Closeness centrality	Betweenness centrality	Comparative influence (CI) (%)
United States	78.1	80.0	60.3	100
Netherlands	46.9	62.7	7.9	51
United Kingdom	40.6	58.2	14.2	49
Switzerland	37.5	57.1	2.4	41
Italy	31.3	57.1	3.2	39
Germany	31.3	55.2	4.4	39
Norway	28.1	53.3	1.7	35
Sweden	25.0	53.3	0.6	33
Belgium	21.9	52.5	3.4	33
Spain	12.5	50.0	12.1	33

Identifying influential countries

From 1984 to 2013 (t_{1-3}), Fig. 6 depicts the aggregated network of research collaborations. When a large numbers of counties (33 out of 47) are linked to one another by paths of intermediate acquaintances, a main component is formed. No international collaboration is present among the remaining 14 counties and no shape of the network is formed either. In this section, all calculations belong to the main component; so, closeness is computed based upon traditional definition as reciprocal of sum of geodesic distances from one country to all others. For these investigations, we transformed all valued data to binary.

The top ten influential and collaborative countries of the network are identified in Table 3. The counties are listed in descending order of their comparative influence. Three normalised centrality measures of degree, closeness and betweenness are computed first for each country. Then, to examine countries' influence in the network, we use our rank aggregation formulation which is described in the section "Materials and methods".

In this field, United States is considered the most influential country since it has the most degree, closeness and betweenness centralities and, as a result, the comparative influence of 100 % appears. Netherlands is in the second position as it has 51 % comparative influence, next in line is United Kingdom and Switzerland having 49, and 41 % comparative influence respectively. From Table 3, the same ranking order as comparative influence can be seen in degree centrality and closeness centrality; however, this is not the case for betweenness centrality. As a result, it can be concluded that in research collaboration networks, countries having larger number of collaborations and larger reciprocal distances to all other counties (closer) are more influential than countries having just a bridge role (high betweenness centrality).

Conclusions

In this paper, we presented a detailed account of descriptive, static and static–comparative of research collaboration networks in 'mammography performance' over 30 years. Firstly, we examined the expansion and development of publications of mammography performance from 1984 until 2013. We also compared the publications in the field of mammography and its sub-field of mammography performance from 1945 to 2013. Our analysis shows that the emergence of the subfield occurred at the end of adolescence (beginning of maturity) stage of the super-field in 1985–1990. Moreover, to evaluate the association of the growth rate of publications in the sub-field case-study and its super-field, we used dimensionless data (using Z-Score analysis) and found that the growth rate is almost the same for two.

At the next stage, we brought into focus research collaboration network of extracted meta-data at country level to investigate evolution of this network over time and illustrate the countries that are rapidly developing in this scientific field. For static–comparative analyses, we divided the whole time-frame of the dataset into three equal periods of 10 year; t_1: 1984–1993, t_2: 1994–2003 and t_3: 2004–2013.

In a research collaboration network, it is very common that certain connections are 'stronger' than others. To reflect this fact, in calculating some of network measures (average value and clustering coefficients), ties between actors are weighted through assigning the number of collaborations between two countries as the tie weight. This is not the case for all of our calculations because some measures are more meaningful when computed from binary networks, as discussed.

For t_1, there is a lack of any international collaborations among the counties with publications in mammography performance. However, the network became denser and more connected over time according to our analyses. In addition, the network demonstrates high weighted links in its clusters, and lesser weights and connections among these clusters. These local clusters are also becoming denser over time. The research collaboration network is becoming significantly more centralised when longitudinally according to degree, betweenness and closeness centrality measures.

For static topography, we examined the aggregated network to find out which counties influence the network as a whole. We applied a rank aggregation technique to degree, closeness and betweenness centrality measures in order to gain a single figure of merit for the influence of each actor, 'comparative influence' as we named. The methods and findings presented in this work aim to assist identifying key actors in other research collaboration networks.

In our dataset, there is a strong correlation between the level of degree and closeness centralities of an actor and its comparative influence in the network. The United States, the Netherlands and the United Kingdom were, respectively, identified as the most influential counties in research publications within the area of mammography performance.

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