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Title:

Interpreting social network metrics in healthcare organisations: a guide to validating small networks

Abstract:

Social network analysis is an increasingly popular sociological method used to describe and understand the social aspects of communication patterns in the health care sector. The networks studied in this area are special because they are small, and for these sizes, the metrics calculated during analysis are sensitive to the number of people in the network and the density of observed communication. Validation is of particular value in controlling for these factors and in assisting in the accurate interpretation of network findings, yet such approaches are rarely applied. Our aim was to bring together published case studies to demonstrate how a proposed validation technique provides a basis for standardised comparison of networks within and across studies. A validation is performed for three network studies comprising ten networks, where the results are compared within and across the studies in relation to a standard baseline. The results confirm that hierarchy, centralisation and clustering metrics are highly sensitive to changes in size or density. Amongst the three case studies, we found support for some conclusions and contrary evidence for others. This validation approach is a tool for identifying additional features and verifying the conclusions reached in observational studies of small networks. We provide a methodological basis from which to perform intra-study and inter-study comparisons, for the purpose of introducing greater rigour to the use of social network analysis in health care applications.

1. Introduction

Social network analysis is a relative newcomer to the discipline of medical sociology but it is becoming increasingly popular. Networks observed in health care organisations are often small in relation to the size of networks studied in other disciplines (as a conservative guide, a network with fewer than fifty communicating entities). This feature makes them special because at this size, the network metrics typically used to analyse them are sensitive to changes in size and density (Anderson, Butts, & Carley, 1999). As a consequence, comparisons amongst networks of different sizes and densities can (and do) lead to misinterpretation if reported without validation.

In organisational behaviour studies, networks comprise a set of *nodes* that typically represent people or organisations, and a set of *connections* between the nodes defined by observed or reported communication. A connection is defined as *directed* if the interaction is not reciprocated by both people, for which the specific definition depends on context. The size of the network, n, is given by the number of nodes. The *density* of the network is given by the number of connections as a proportion of the total number of possible connections (or the average degree, k_μ, divided by the size). Network metrics are indicators of the properties of networks and include measures of individual properties (the location of people in a network) and aggregate properties (measures of a network configuration as a whole). In what follows, only aggregate metrics are considered.

Centralisation metrics (Freeman, 1978), which operate over a whole network (as opposed to centrality (Borgatti, 2005; Borgatti & Everett, 2006), used to summarise flow across nodes or connections), generally indicate the disparity of information flow within a network. For example, maximum *betweenness centralisation* occurs when one person provides information for all others in the network and no other connections exist (Fig. 1a). Betweenness centralisation is known to be influenced by the size of the network, especially for small networks (Anderson et al., 1999; Nakao, 1990), simply because larger networks provide more opportunity for communication that features intermediaries.

Figure 1 approximately here

Hierarchy (Krackhardt, 1994) describes how well the network structure mimics the shape of a typical organisational hierarchy that contains no redundant links, and where information flows from the top level of the network down (see Fig. 1b). The metric is sensitive to changes in density (Krackhardt, 1994), since maximum hierarchy is achieved at a specific density and decreases rapidly as more connections are added.

A network's *mean clustering coefficient* is a measure of a network's tendency to form well-connected sub-groups (Watts & Strogatz, 1998), and is typically interpreted in terms of cliquishness – the tendency for sub-groups to feature more internal ties and be linked to other groups via fewer ties (see Fig. 1c). The value of the clustering coefficient for simulated random networks depends primarily on density.

Case studies using network analysis in healthcare organisations typically involve comparisons between two or more similar networks, or the assessment of individual networks with regards to their configuration, using at least one network metric (Benham-Hutchins & Effken, in press; Creswick, Westbrook, & Braithwaite, 2009; Creswick & Westbrook, 2010; Fattore, Frosini, Salvatore, & Tozzi, 2009; Harris, Luke, Burke, & Mueller, 2008; Hawe & Ghali, 2007; Jippes, Achterkamp, Brand, Kiewiet, Pols, & van Engelen, in press; Keating, Ayanian, Cleary, & Marsden, 2007; Lewis, Baeza, & Alexander, 2008; Lurie, Fogg, & Dozier, 2009; Meltzer, Chung, Khalili, Marlow, Arora, Schumock et al., in press; Merrill & Hripcsak, 2008; Pagliccia, Spiegel, Alegret, Bonet, Martinez, & Yassi, in press; Scott, Tallia, Crosson, Orzano, Stroebel, DiCicco-Bloom et al., 2005; Wensing, van Lieshout, Koetsenruiter, & Reeves, in press; West, Barron, Dowsett, & Newton, 1999). The specific application domains vary considerably but the three network metrics described above are typical and small sizes are common to all these case studies.

Validation of network metric results is rare in social network analysis related to healthcare organisations. One of the fifteen case studies cited above considered a comparison with random networks (Merrill, Keeling, & Carley, in press), and none included detailed comparisons with networks from existing published studies. Theory-driven research has previously demonstrated the effects of size and density on these metrics but this has not been adopted by case studies in this domain.

Our aim was to define a simple method for validating and interpreting aggregate network metrics from small networks observed in case studies. The purpose of the validation is to enhance existing analyses and to find support for existing conclusions.

2. Method

Samples

We performed a search of Medline for journal articles published between 2005 and May 2010 that included the phrase “social network analysis” or “social network methods” in the abstract or keywords (185 articles). After removing those concerned with infectious diseases, bipartite information from large cohorts of subjects, research collaboration networks, and commentaries, we selected all case studies that performed analyses related to either centralisation, hierarchy or clustering (15 case studies), which were the three commonly-used metrics. From these studies, we selected three case studies that provided enough detail, reported more than one network and reported on two or more of the network metrics in question. We then applied the validation technique and related the results to the published conclusions.

Case Study 1 – Networks of the patient handoff communication

Benham-Hutchins and Effken (2010) observed patient handoff communication for five networks comprising hospital staff and their interactions in a USA hospital, each with different sizes and densities. They calculated that the networks had low levels of betweenness centralisation and high levels of hierarchy. The authors concluded that there was no central coordination of the handoff procedure.

Case Study 2 – Networks of primary care practices

Scott et al. (2005) observed advice-seeking between clinical and non-clinical members of two primary care practices in the USA, to determine the disparity in hierarchy and degree centralisation for networks of different size and density. The authors selected two extremes of primary practice communication and concluded that there were more collaborative groups in one network compared to the other, and on this basis suggested testable hypotheses regarding policy in primary care practices, such as adherence to guidelines.

Case Study 3 – Networks of formal inter-organisational ties in primary care

Lewis et al. (2008) investigated social aspects of primary care governance via the dynamics of relationships between individuals in one partnership involving primary care, hospitals and government positions in Australia, over three years. Over the three years, the people comprising the network changed significantly, as did the density of reported communication. The authors used quantitative and qualitative observations to conclude that dedicated staff employed specifically to manage the partnerships were fundamentally important throughout the three years. While it was not stated directly, the assumption we may apply is that the networks feature consistently strong levels of betweenness centralisation, since dedicated staff are described as being fundamental in the information transfer process.

Validation approach

A simple way to describe the nature of a network using social network analysis is to compare the network metric values with results from other possible configurations. Essentially, the tests described here involve calculating a metric for the network under observation and then comparing that calculated value against the non-uniform distribution of values from many simulated random networks that have the same size or density (see Newman, Strogatz, & Watts, 2001 for the properties of random networks).

The steps involved in this comparison with simulated random networks are as follows:

1. Construct as many random networks as feasible (we use 10^5), each with the same size or density as the observed network, ensuring equal chance for all configurations.
2. Calculate the network metric in question for each of the networks in the randomly-generated control set as well as the observed network.
3. Determine the percentile of the metric score of the observed network in relation to the distribution of scores from the randomly-generated control set.
4. Interpret the metric score of the observed network against the percentile to establish its uniqueness or to make comparisons between networks of different size or density.

To interpret the network metric score by comparison with the random baseline, the analyst looks for metric scores that are unlikely to occur by random construction alone. This is done by comparing the observed score to the distribution of scores from the random networks, producing a percentile. The approach also provides an appropriate way to compare networks of different sizes, by comparing percentiles.

We have chosen a random construction method to create the simulated experimental control. The statistical properties of random networks are well-understood (Newman et al., 2001). Alternatives such as small world (Watts & Strogatz, 1998), scale-free (Barabási & Albert, 1999) and Kronecker networks (Leskovec, Lang, Dasgupta, & Mahoney, 2008) impose extra constraints on the process of construction, and are typically used in the analysis of much larger networks (for examples, see Barrat, Barthélemy, & Vespignani, 2004; Barthélemy, Barrat, Pastor-Satorras, & Vespignani, 2004; Latora & Marchiori, 2001; Leskovec & Horvitz, 2008). These extra constraints are intended to mimic the mechanisms associated with social phenomena, such as the ‘rich get richer’ phenomenon exhibited by some complex systems. A large library of observed networks may also provide an appropriate baseline if the method of observation is rigorous and uniformly practised. The random construction allows us to test to see if factors from the culture, policy or infrastructure of an organisation lead to stronger or weaker hierarchy, clustering or centralisation – factors that are apparent whenever we observe a network whose network metric values deviate away from configurations produced in the absence of these mechanisms.

Using the published information from the three case studies, we validated the results by comparing the metrics from the ten observed networks against a baseline of random small networks. Differences in percentile values (either significantly distant from the simulated random network medians or distant from the other observed networks) suggest the presence of real-world constraints. Thus the purpose of the validation is to locate individual networks from many studies on a spectrum that represents the distribution of all possible configurations, and then to use their location (as percentiles) to look for the presence of specific social phenomena that constrain the network in ways that manifest as hierarchy, clustering and centralisation.

3. Results

We present the results of the validation tests for the ten networks from the three case studies. The first sets of results (Table 1) are the percentiles associated with the centralisation measures, hierarchy and mean correlation coefficients. The percentiles may be used to establish how common the network configurations are in relation to the baseline of random networks at a given size or density. The second series of results, presented in Figs. 2 and 3, demonstrate the sensitivity of each of the metrics under changes to size or density, and give the locations of the observed networks.

To interpret the table below, a network analyst can use the percentiles as an indication of how unlikely the observed networks are in relation to simulated random networks. For example, a percentile of 50% indicates that the network has the same metric score as the median random network, indicating that it is equivalent to a network formed in a manner that is devoid of cultural or technical constraints. A percentile of 95% indicates that only 5% of the simulated random networks exhibited a higher score, which provides support for the hypothesis that the network is highly centralised, hierarchical or clustered, in comparison to a network formed with no extra constraints.

Table 1 approximately here

Figure 2 indicates that betweenness centralisation is sensitive to changes in size for small networks. The authors of the handoff study (Case Study 1) state that the five networks studied had low betweenness centralisation (because they are low in comparison to the zero-to-one scale of theoretical values) and conclude that patient handoff networks do not feature a centralised structure. However, when we locate the networks in Fig. 2, we are unable to validate this conclusion because all five networks feature stronger betweenness centralisation than the median for the simulated random networks, and three are above the 75th percentile. In addition, all networks from Case Study 1 are lower (by percentile) than the networks in Case Study 3. Our validation shows that all the observed networks tend towards a state of relatively centralised communication patterns in which information is relayed by only a few people in the networks. The locations of the networks from Case Study 3 confirm the stated conclusions about the importance of a small subset of individuals as intermediaries.

Figure 2 approximately here

Figure 3 shows that the hierarchy metric value decreases rapidly as the level of communication in a network increases. This rapid decrease happens just after the number of connections surpasses the minimum number required to connect every person in the network. The observed hierarchy scores, once located as percentiles, exhibit strong variability. Networks A2 and A4 from Case Study 1 are close to the 50th percentile of the simulated random networks, indicating that we are unable to distinguish the hierarchy of these networks from networks in which communication is purely random. For networks A1, A3 and A5 of Case Study 1 and network B1 of Case Study 2, the hierarchy values are closer to the 95th percentile, indicating high hierarchy values relative to the simulated random networks. Without performing this validation, we would not be able to make the distinction between A1, A2 and the other observed networks. Networks in Case Study 3 include a large number of connections above the number required to form an organisational hierarchy, so it is difficult to use the hierarchy metric to support any type of conclusion.

Figure 3 approximately here

4. Discussion

Our results show that simple validation techniques are able to strengthen the robustness of analyses of small networks, augment the findings and assist in the interpretation and conclusions made. By accounting for the variability associated with the changing sizes and densities of the networks studied, we were able to validate some conclusions in published case studies and reveal issues relating to the interpretation of another case study.

A limitation of this work is that we have not discussed the appropriateness of the metrics chosen for these studies in any detail. However, we note that the choice of metrics should not be defined by the choice of software packages but rather they should accurately reflect the nature of the problem and the context for which the networks are constructed. Alternative and more recently-formulated approaches that should be considered for small networks include community structure analysis (Fortunato & Barthélemy, 2007; Girvan & Newman, 2002).

Other opportunities for further research in this area include testing the reliability of small networks in relation to the network metrics on which conclusions are based. The validations presented here indicate that small changes in configuration at specific sizes and densities (for example, sizes less than 30 and densities around 0.2) may correspond to large differences in resulting network metrics, which is an ominous sign for reliability, which measures how missing or erroneous data can affect results (see Frantz, Cataldo, & Carley, 2009). Note also that any metric that is sensitive to changes in density will also be sensitive to missing data, since missing data necessarily implies the density is under-estimated.

In the patient handoff study (Case Study 1) (Benham-Hutchins & Effken, in press), the five networks exhibited high betweenness centralisation and hierarchy in comparison to the simulated random networks, which is partly contrary to the conclusions reached by the authors of the study. In the primary care practice study (Case Study 2), the networks discussed were chosen by Scott et al. (2005) because they represented extreme behaviours. This is reflected in the results of the validation, in which many calculated metric values were uniquely high or low in relation to the 10^5 simulated random networks. This implies that the networks were highly unlikely to have occurred by chance interactions alone and might also reflect the atypical methods used to observe and construct the networks. In the government-primary partnership study (Case Study 3) (Lewis et al., 2008), the three networks exhibited higher betweenness centralisation percentiles than the networks from Case Study 1. In addition, hierarchy values for the networks of Case Study 3 are difficult to interpret because they lie on the part of the spectrum (high density) where simulated random networks mostly produce zero-valued hierarchy.

The lack of validation in published healthcare social network analyses is a potential pit fall that may lead to misinterpretation as a result of confounding factors. This has the potential to become a serious impediment to the perceived quality of research using social network analysis in health care, and for the subsequent development of policy.

We have presented a simple method for establishing a baseline from which a network analyst can validate the network metric values of individual small networks and then compare across networks with different sizes and densities. Armed with the knowledge of confounders and a method for validation, researchers and readers are better equipped to accurately interpret communication patterns and can more effectively compare their results within and between case studies. We propose that future case studies involving social network analysis in healthcare organisations would benefit from the application of this method, in turn providing more trustworthy support for the reengineering of social structures, work processes and other organisational policy development.

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Figure and table captions

Figure 1: Three networks of size ten with configurations (a) a star, representing maximum centralisation; (b) a tree, representing maximum hierarchy; and (c) two connected clusters, representing a high mean clustering coefficient.

Table 1: Statistics for the nine networks observed in Case Studies 1, 2 and 3 (labelled A1-A5, B1-B2 and C1-C3 respectively) summarising the published information about each network. In addition, percentiles are an indication of where the observed values fit in relation to the simulated random networks. Medians relate to the simulated random networks of a given size or density (as indicated).

Figure 2: Distributions of betweenness centralisation calculated from 10^5 simulated random networks are indicated by percentiles as a function of size. The betweenness centralisation values for eight networks from Case Study 1 (A1-A5) and Case Study 3 (C1-C3) are as labelled. The size 10 tree and connected clusters are also located on the plot.

Figure 3: Distributions of hierarchy calculated from 10^5 simulated random networks are indicated by percentiles as a function of density. Hierarchy values from Case Study 1 (A1-A5) and Case Study 2 (B1-B2) are as labelled. The size 10 star, tree and connected clusters are also located on the plot.

Figures

Figure 1.

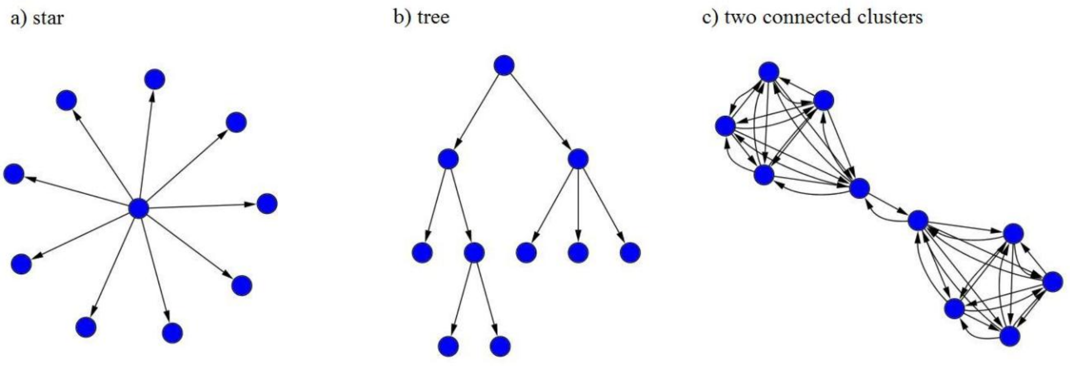


Figure 2.

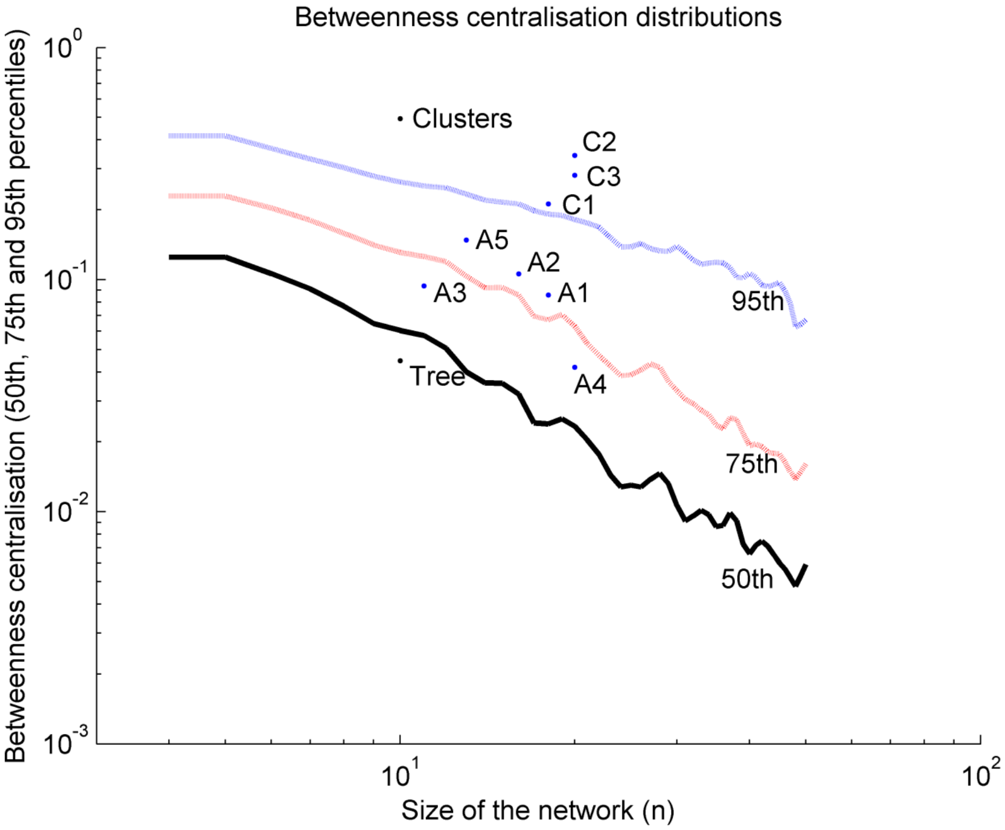
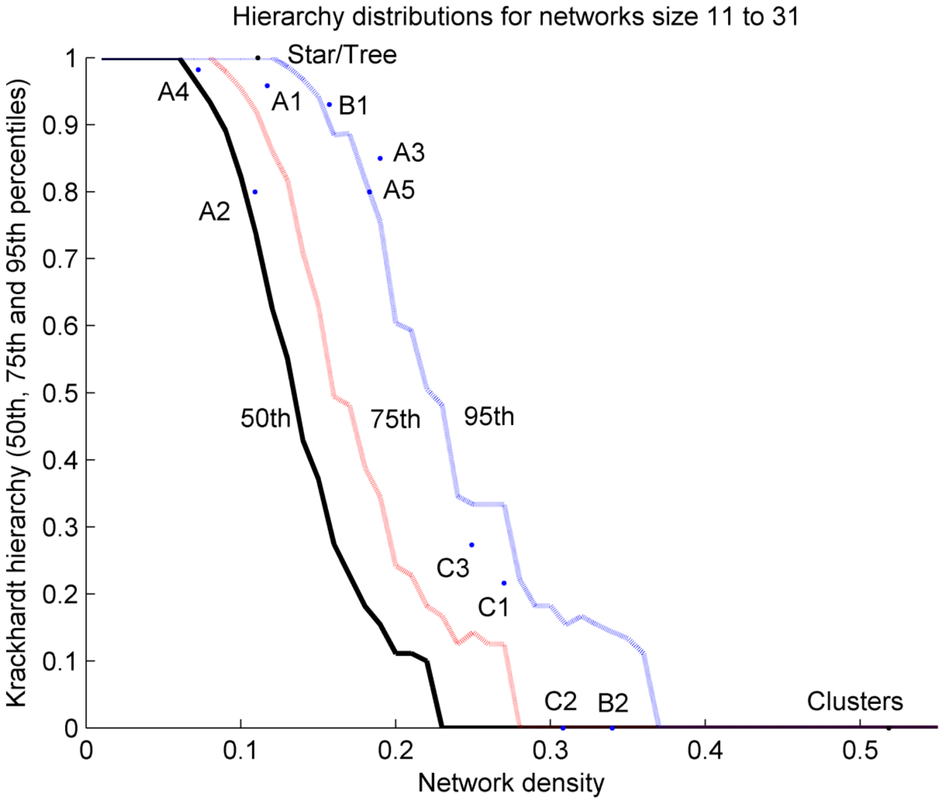


Figure 3.



Hierarchy distributions for networks size 11 to 31
Krackhardt hierarchy (50th, 75th and 95th percentiles)
Network density
Star/Tree
A4
A1
B1
A3
A5
A2
50th
75th
95th
C3
C1
C2
B2
Clusters
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

Tables

Table 1:

Case studies observed network	A1	A2	A3	A4	A5	B1	B2	C1	C2	C3
Size (n)[a,b,c]	18	16	11	20	13	26	31	18	20	20
Density (k_{μ}/n) [a,b]	0.117	0.109	0.190	0.0725	0.183	0.1570	0.3398	0.270	0.308	0.249
Bet. Centralisation median (%,at n)	2.22	3.28	5.92	1.97	4.16	-	-	8.56	5.82	8.07
Bet. Centralisation, study (%)[a]	8.6	10.6	9.4	4.2	14.8	-	-	21.2	34.3	28.2
Bet. Centralisation percentile	**80.2**	**76.7**	**65.3**	**69.1**	**82.5**	-	-	**99.4**	**100**	**100**
Degree centralisation median (%, at n)	-	-	-	-	-	16.7	19.1	22.4	22.2	21.0
In-degree centralisation, study (%)[b]	-	-	-	-	-	6.88	64.8	44.1	55.3	61.4
In-degree centralisation percentile	-	-	-	-	-	**0.00**	**100**	**99.5**	**100**	**100**
Out-degree centralisation, study (%)[b]	-	-	-	-	-	73.4	57.9	30.9	55.3	32.2
Out-degree centralisation percentile	-	-	-	-	-	**100**	**100**	**87.9**	**100**	**94.4**
Hierarchy median (at k_{μ} /n and n)	0.627	0.733	0.154	0.933	0.1538	0.0769	0.00	0.00	0.00	0.00
Hierarchy from study[a,b]	0.958	0.800	0.850	0.982	0.800	0.93	0.00	0.216	0.00	0.273
Hierarchy percentile	**88.4**	**57.5**	**97.2**	**67.8**	**96.0**	**100**	**0.00**	**99.9**	**0.00**	**99.9**
Clust. coefficient median (at k_{μ} /n and n)	-	-	-	-	-	0.150	0.347	0.274	0.317	0.252
Clust. coefficient, study[b]	-	-	-	-	-	0.223	0.590	0.444	0.532	0.619
Clust. coefficient percentile	-	-	-	-	-	**98.2**	**100**	**100**	**100**	**100**

a, *b* and *c* indicate that values are taken directly as published in Case Study 1, 2 and 3 respectively.

In-degree centralisation – communication directed towards a person; Out-degree centralisation – communication directed away from a person