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The cross-cutting edge: social network analysis in medical education.

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Abstract

Context

Humans are fundamentally social beings. The social systems within which we live our lives – families, schools, workplaces, professions, friendship groups – have a significant influence on our health, success, and wellbeing. These groups can be characterised as networks, and analysed using social network analysis.

Social network analysis

Social network analysis is a mainly quantitative method for analysing how relationships between individuals form and affect those individuals, but also how individual relationships build up into wider social structures that influence outcomes at a group level. Recent increases in computational power have increased the accessibility of social network analysis methods to be applied to medical education research.

Application to medical education

Social network analysis has been used to explore team-working, social influences on attitudes and behaviours, the influence of social position on individual success, and the relationship between social cohesion and power. Social network analysis theories and methods are therefore relevant to understanding the social processes underlying academic performance, workplace learning, and policy-making and implementation in medical education contexts.

Conclusions

Social network analysis is underused in medical education, yet it is a method that could yield significant insights to improve experiences and outcomes for medical trainees, educators, and ultimately for patients.

Overview

What is already known on this subject: social network analysis is used in many fields of social science and provides important and interesting insights into individual behaviour in the context of social structures.

What this study adds: social network analysis can be successfully applied to the field of medical education and yields results with implications for medical educators.

Suggestions for further research: social network analysis can be applied to look at aspects of the hidden curriculum, such as the influence of peers on the development of professionalism and friendship groups.

Introduction

Humans are fundamentally social beings. We are motivated by a need to belong, which we achieve by forming and maintaining interpersonal attachments. These relationships have significant impacts on our health, success, and wellbeing (1). The social systems within which we live our lives – families,

schools, workplaces, professions, friendship groups, and so on - can be characterised as networks, and analysed using social network analysis (2).

Social network analysis (SNA) is a method for studying the individual relationships between individuals, or groups of individuals, while simultaneously studying the social context (3). The value of SNA as a research approach lies in its ability to examine how individuals are embedded within a social structure and also how social structures emerge from the micro-relations between individuals (4). By visualising and quantifying patterns within networks, such as the overall level of connectivity between network members and the presence or absence of cliques, network analysts can learn how the structural properties of a network can constrain or enable the social behaviour of individuals (5). SNA therefore has the major advantage of allowing researchers to measure both individual and socio-cultural influences on educational, psychological, economic, and health outcomes.

A relatively popular approach in sociology, economics, and public health (6-9), SNA remains underused in medical education, despite its huge potential for investigating fundamental questions about, for example, the social influences on individual knowledge and skill acquisition, and the development and influence of cultures within specific educational and clinical settings. In this paper we will explain the ideas underpinning social network analysis by briefly describing its origins, then give examples of work in the wider field, and then move to how social network ideas and methods have been or could be applied in medical education.

Origins of social network analysis

The origins of social network analysis are found in a 1930s girls' boarding school in upstate New York. Jacob Moreno and Helen Jennings mapped the social relations between the pupils to explore why 14 girls had run away over a two week period (10). They argued that whether or not a girl ran away was not a function of her individual psychology, but of the relationships that she had with the other girls (and whether or not those girls had run away). Whilst their proposal – that an individual's behaviour depends on, and is influenced by, the behaviour of those around them – seems obvious, Moreno's breakthrough was to create a method to measure social relations and use them to understand and systematically predict behaviour in a scientific way.

Individuals and relations

Despite the obvious importance of social relations to individual outcomes in medical and social science research, usually research data are analysed in terms of individuals rather than in terms of relations. For example, in a drug trial the analysis is at the level of the individual in that it is assumed that each participant's outcome is unrelated to - or statistically independent of - all other participants' outcomes. SNA on the other hand takes a relational rather than an individual approach. The unit of analysis in SNA is typically the link (tie) between two members (nodes) of a network – collectively called a dyad.

Adding relational factors to individual factors significantly increases our understanding of behaviour in real life because it is so often enacted in a social context. For example, a social network analysis of the predictors of smoking behaviour of 1,716 adolescents in 11 British schools examined the influence of gender, age, socioeconomic status, and parental smoking behaviour on students' smoking behaviour over time, but also looked at the friendships (or absence of friendships) between students and the similarity between friends in terms of their smoking behaviour, gender, age,

socioeconomic status, and whether they were in the same tutor group. Results showed that selection effects (students choosing friends with the same smoking behaviour as themselves) were more important than peer influence effects (smoking students persuading non-smoking students to smoke), especially as the students got older. Friend influences were also more important than individual influences of age, gender, socioeconomic status, and parental smoking (11)

The focus on relational data means social network researchers can investigate three factors usually hidden from view in conventional social science. Firstly, the effects of indirect ties – how your friends' friends, and their friends, may influence you without your ever having met them, or even being aware of their existence (12). Secondly, how particular network structures may facilitate or hinder the spread of behaviour via social processes and norms, for example the decision by medical students to accept (or decline) seasonal influenza vaccination whilst at medical school (13). Thirdly, how a person's position within a network – whether she is popular, powerful, or peripheral - can affect how successful she is (14).

Designing social network studies

Just as there are myriad ways of collecting data on individuals, so there are many ways of collecting relational data and the methods depend on the research questions. However two major distinctions can be made: between self-report and secondary source data.

Self-report

Self-report survey data are an important method of collecting information on social contacts and processes (15). There are two main ways of collecting self-report social network data: name generation and roster. The name generation method involves asking individuals to recall the names of people they have a particular type of relationship with, for example Burt et al (15) asked paediatric gastroenterologists to name up to five people they trust and up to five people they talk about quality improvement with, and Vaughan, Sanders, Crossley et al (16) asked medical students to name up to 10 people important for their academic success. With the roster method, participants are given a list of names and asked to indicate which people they have a particular relationship with for example Woolf et al (17) asked all Year 2 medical students in one medical school to underline the names of their close friends. Name generation may provide incomplete network data because people can forget to nominate even close friends (18), but the roster method only works if the researcher knows which names to put on the list in advance, something which doesn't work in all settings. The methods used will determine the boundary of the network, for example the name generation methods used by Vaughan et al (16) and Burt et al (15) will create a network that could include many individuals who have no relation to one another. While it is possible to ask participants to describe the relationships between their connections (e.g. students state who is friends with whom in their class), this is less reliable than self-report (19). The roster method such as that used by Woolf et al (17) and Isba (2015, unpublished data) creates a network with a clearly defined boundary – see Figure 1.¹ Laumann et al (20) provides further discussion of network boundaries.

¹ The data presented in Figure 1 were collected via a paper-based roster whereby each medical student at Lancaster Medical School in academic year 2013/14 was asked to indicate the strength of their relationship with every other medical student on the list. Year 1 and Year 2 students are densely connected within their years and fairly well connected to one another. By contrast, there are no direct ties between students in Year 1 and those in Years 3, 4, and 5, meaning information flowing from the higher years to Year 1 students would

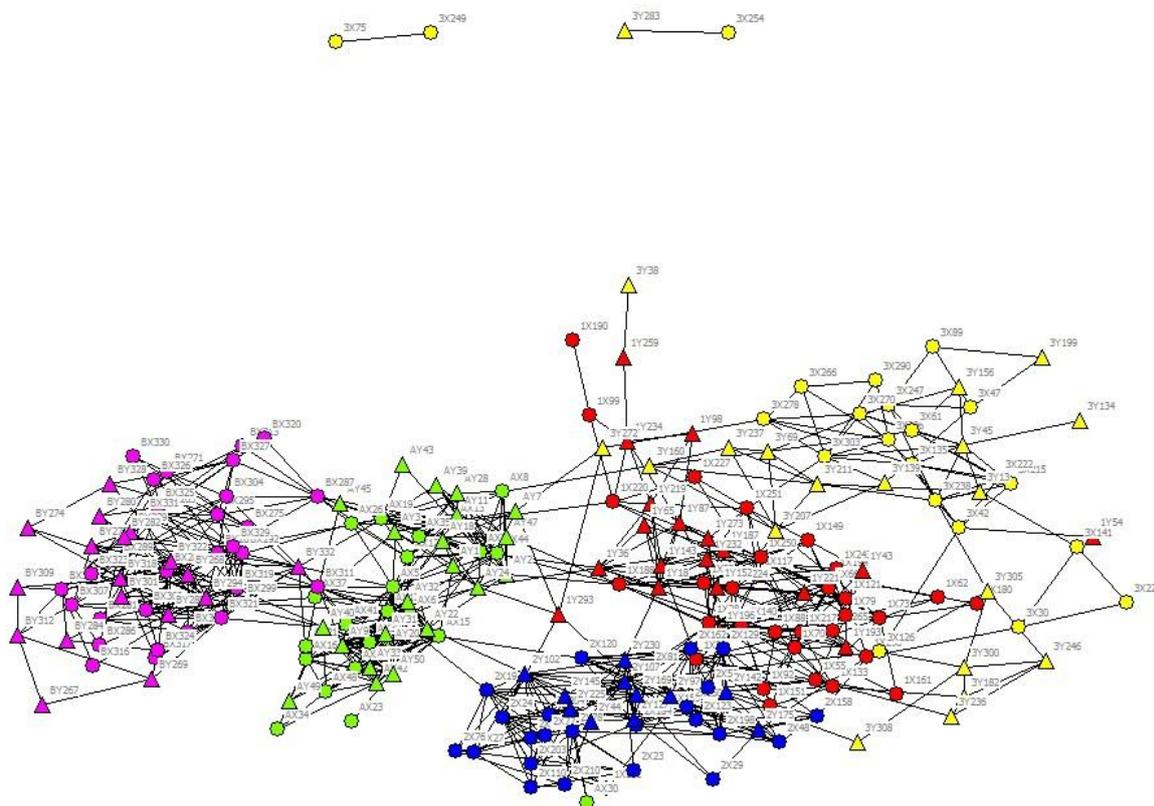


Figure 1: Friendships between Lancaster medical students during the academic year 2013-14 with isolates removed (n = 206). A tie between two individuals is present if they indicated that they knew the other person and saw or spoke to them three or more times a week, or had a close personal relationship with them. The different colours represent students in each of the five years of the course – pink = Year 1; green = Year 2; red = Year 3; blue = Year 4; and yellow = Year 5. Female students are represented by circles and male students by triangles. Unpublished data, Rachel Isba 2015.

Secondary sources

Social network data can be collected from books or other texts (21), journal article citations (22) as well as via “digital trace” data (23) such as mobile phone records (24) and online social networks like Facebook (25). Digital trace methods can get around some of the problems that can arise with self-report data such as low response rates and social desirability although the validity of such data has been relatively unexamined(23). Disadvantages include difficulties obtaining data, ethical issues (25), and data not being designed to answer research questions. The potentially huge amounts of data available can also pose difficulties for medical education researchers who may not have the training

need to flow through Year 2 students. Year 5 students are the least connected group within year, and this may reflect the fact that they are more likely to be spread out the mostly widely on clinical placements. At the top of Figure 1 there are two pairs of students who are not connected to the main part of the network structure and are therefore less likely to be influenced by, or influence, the majority of students. In contrast, the centrally-placed student represented by a red triangle in the middle of the diagram could be considered a broker between students in Years 2, 3, 4, and 5

to manage and analyse “big data”, especially when it has the additional complications that network data pose.

Ethical issues around data collection

SNA research may raise ethical issues that are not often encountered elsewhere in experimental or survey research. Since the method focuses on relations among actors, each actor is often asked to nominate specific, identifiable others to whom they are connected. The investigator may also sometimes ask the respondent to characterise the attributes of the others (to whom they are connected). Unless everyone identified in a network study is directly contactable and gives their consent to inclusion, potentially identifiable data about some subjects may be included without their direct consent. In the majority of cases, careful research oversight combined with sensitive data collection and analysis, will assure the risks are minimised. However, in work that focuses, for example, on risky behaviour or attitudes, great care must be taken to protect the privacy of research subjects.

Statistical analysis of network data

Relational data, although powerful, are potentially problematic to analyse as they are statistically non-independent and thus violate assumptions of conventional statistical tests. One of the ways in which this problem is overcome is by using permutation testing, in which the results obtained are compared against results obtained from 10,000 or so random or quasi-random permutations of the data. Until fairly recently, permutation testing was too computationally intensive for researchers to perform on their ordinary desktop or laptop computers. However, advances in processing power now mean that most researchers can easily handle data from networks of a few hundred nodes, and the ability of researchers to analyse network data with millions of nodes from online social networking sites such as Facebook and Twitter is becoming easier, almost daily (26). These technical advances have aided the development of user-friendly social network analysis programmes (many of which are available for free or for a nominal fee such as Pajek (27) and UCINET (28)), and have also helped move the field on theoretically, all of which has started to bring social network analysis into the mainstream (2). That being said, the fact that social network analysis is still a relatively new and cross-disciplinary approach means that data collection and analysis methods are still relatively specialised and there is comparatively little in the way of research methods training in understanding conceptually and statistically complex data. Some researchers have argued that this, in turn, leads to fundamental errors (29).

Applications of social network analysis

Social network analysis is an interdisciplinary field. For mathematicians and statisticians it presents interesting challenges for modelling what are often extremely complex systems. For sociologists and economists it provides a new way of understanding how large social systems work. For organisation and management scientists it gives insight into how teams work within organisations. For psychologists, medics, and educationalists, it can shed light on how individual outcomes are influenced by social processes. All of these are relevant to medical education. Some of the most common types of question addressed in social network studies and the underlying network processes being investigated are described below, followed by ideas about how these types of questions have, or might be, applied to medical education.

Team working

Creating and supporting effective teams is clearly of great importance in many areas and has been heavily researched. In SNA, questions are typically about how patterns of relationships within and between team members can affect information and resource exchange or influence performance. Effective teams tend to have a lot of within-team interactions and have non-hierarchical structures in which everyone interacts with everyone else (30, 31). However, measures of effectiveness differ hugely between studies; for example, a review of teamwork in healthcare provision included outcomes as varied as burnout at the level of the individual professional and financial profit at the level of the hospital (32). Medical education research could use social network analysis methods to explore team-working in an undergraduate setting, for example looking at how social relationships within teaching groups develop and how they are influenced by the practices of the medical school or medical teachers, as well as by the characteristics of the individual medical students. They could go on to explore how these social structures relate to educational outcomes for all team members and/or for particular individuals – for example those with low prior educational attainment.

Individual success and network position

A large strand of social network analysis has addressed questions of how an individual's position within social networks can affect their success, key theories being Mark Granovetter's theory of weak ties (33), Ron Burt's structural hole theory (14, 34), and Robert Putnam's social capital theory (35). Social ties require investment of time and resources, which limits the number of strong ties a person can have. Strong ties tend to be within close-knit communities and provide what Putnam termed *bonding capital* in the form of emotional and practical support. Ties with people in other networks outside those close-knit communities tend to be weaker. However, Granovetter theorised that weak ties are in fact the ones that provide resources and lead to success (33, 36), providing what Putnam calls *bridging capital*. Similarly, Burt refers to the individuals who connect otherwise unconnected groups as *brokers* who fill *structural holes* in networks and are therefore particularly powerful and creative (14).

Understanding the causes and effects of network position in medical education is relevant in a context in which trainees often move around departments, hospitals, regions, and even countries over the course of their training, where there is significant competition for jobs, and frequent formative and summative assessment. Despite this, there is a relative paucity of research on network position in healthcare (Long, Cunningham & Braithwaite, 2014). Medical education researchers could examine how the depth and breadth of medical students' or medical trainees' professional networks relate to successful outcomes in training, for example obtaining a job or passing an examination.

Spread of behaviour and peer influence

The spread of communicable diseases such as influenza and HIV through networks is much studied in public health. Similarly, SNA has been used to map and predict the spread of information and behaviours through groups of people, the most famous probably being Coleman, Katz and Menzel's (37) diffusion of innovation study, which found that doctors who were well-respected by their colleagues were faster to prescribe a new drug. More recently Christakis and Fowler have used the Framingham Heart Study data to show that psychological and physical phenomena such as happiness and obesity can spread through social networks (12, 38, 39). They found that happy and unhappy people tend to cluster together, and people influence each other's happiness up to three

degrees of separation (friends of friends of friends)(39). It is easy to see how methods of exploring the spread of information through social networks could be applied to social models of learning medicine. Throughout a student's time at medical school their social networks are continually developing and potentially influencing their acquisition of skills and knowledge. The greatest influence on students' development of behaviours would appear to be from their near peers (40) although the influence of wider networks that contain more senior students should not be underestimated. Woolf et al (17) showed that medical students who were friends at the start of their second year performed more similarly in their end of year examinations, even taking into account how they performed in first year examinations, suggesting a peer influence or contagion effect.

It is also important to consider the influence that medical schools themselves have on the social networks of their medical students; for example the ways in which schools allocate students to teaching groups facilitates friendships (17). It may also be that how students are allocated to halls of residence, or how teachers encourage students to work collaboratively or competitively may influence relationships and outcomes. As a pervasive, highly influential, yet unintended part of the medical school experience, the social network within a medical school (and the multiple different networks that exist within or overlap with it), is probably best conceptualised as part of the hidden curriculum and it is only starting to be explored using social network methods (41).

The ways in which information or resources spread through networks is influenced partly by network structures, as mentioned in the team-working section above, but also by the behaviours of individuals who occupy particular positions of power and influence within networks and can therefore direct flow (42). For example, previous research has found that primary care doctors look for advice to colleagues with expertise but also those who are physically easier to reach (e.g. work in the same clinic), with implications for the spread of evidence-based medicine (43) see Tasselli (44) for a review of the social networks of healthcare professionals. An understanding of this can help researchers design network interventions to halt the spread of undesirable behaviours and promote the spread of desirable behaviours. To date there are relatively few social network-based interventions in healthcare (45) and we could find none in medical education. In education more generally, however, Paluck and Shepherd (46) identified high school students who were either well known to the whole student body (had weak influence over a large group) or clique-leaders (had strong influence on a small group) to take part in an anti-bullying intervention. Following the intervention students who were socially close to the intervention students had better attitudes and behaviours towards bullying compared to those who were socially close to control pupils, and the well-known students differed from clique-leaders in the effects they had on their peers' behaviour.

Influences on professional or unprofessional behaviour in medical students or doctors could usefully be explored using similar methods. It may be that attitudes and behaviours related to professionalism diffuse or are transmitted through social networks, with students acquiring professional behaviours from their peers through the influences of the hidden curriculum as part of a social contagion effect. If, for example, students with poor professionalism occupy certain positions with the medical student social network, and/or if there is evidence that students with similar levels of professionalism cluster together, then it might be possible to design an intervention that is based in part on these findings. A novel approach to remediating students at medical school

might lead to improved professionalism in professional practice and ultimately have a positive impact on patient care.

Social cohesion and power

A common feature of social networks is that people who are similar especially in age, sex, ethnicity, and educational level, are more likely to be closely linked and therefore tend to cluster together in networks. This is known as homophily and it can result from several possible mechanisms, including people preferring to associate with those who are similar to them (e.g. university graduates preferring friends who are also university graduates), peer influence (e.g. university graduates encouraging their non-graduate friends to go to university), or confounding (e.g. a key time for making friends is university and proximity facilitates friendship, resulting in university graduates tending to be friends with other university graduates). One strand of social network analysis is concerned with understanding and changing the power structures within societies that are based on homophilous tendencies, and which therefore constrain opportunities for people who are different from those in power such as ethnic minorities, women, or people from lower socio-economic groups (47).

In medical education, Woolf et al. (17) found that second year medical students were much more likely to be friends with students of the same or similar ethnic group to themselves, and – as mentioned above - that friendships seemed to influence examination performance. Vaughan et al. (16) showed that Muslim students were less likely to nominate a member of staff in their academic success networks, and this was associated with poorer academic performance. Creating interventions to address these inequalities requires an understanding of the causal mechanisms underpinning homophily and its role in the maintenance of power structures. Longitudinal studies and studies in which people are randomly allocated to social situations such as tutorial groups are key.

Social network analysis has also been used to study the development of social and political movements such as the civil rights and universal suffrage movements of the 20th century, often in conjunction with qualitative data for example, from letters between key actors in the movements (48, 49). Similar methods could be used to examine how medical education policies are shaped by relationships between key players in the field.

Conclusions

Social network analysis (SNA) is a research method gaining popularity in mainstream social science and the field of medical education thanks to advances in computing that make it easier than ever to analyse network data. A small but growing body of evidence in medical education research suggests that SNA may help elucidate some of the previously unknown influences upon medical students, including the spread of attitudes and behaviours through cohorts of students or trainees, and differences in attainment between social groups within cohorts. This in turn will lead to interventions to optimise positive effects and minimise that may have a negative impact on students and patients. Social network analysis is therefore an important tool in the development and delivery of undergraduate and postgraduate medical education.

Contributors

All authors contributed to the concept and planning of the entire paper. All authors extensively edited each portion of the paper and contributed to writing the overview and conclusion sections.

References

1. Baumeister RF, Leary MR. The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Psychological Bulletin*. 1995;117(3):497-529.
2. Borgatti SPE, MG; Johnson, JC. *Analyzing Social Networks*. Sage Publications UK. London UK: Sage Publications; 2013.
3. Scott J. Social Network Analysis. *Sociology*. 1988;22(1):109-27.
4. Jackson MO. *Social and economic networks*. Princeton: Princeton University Press; 2008.
5. Borgatti SP, Mehra A, Brass DJ, Labianca G. Network Analysis in the Social Sciences. *Science*. 2009;323(5916):892-5.
6. Eggens L, Werf MPC, Bosker RJ. The influence of personal networks and social support on study attainment of students in university education. *Higher Education*. 2007;55(5):553-73.
7. Liebowitz J. Linking social network analysis with the analytic hierarchy process for knowledge mapping in organizations. *Journal of Knowledge Management*. 2005;9(1):76-86.
8. Lindelauf R, Borm P, Hamers H. The influence of secrecy on the communication structure of covert networks. *Social Networks*. 2009;31(2):126-37.
9. Luke DA, Harris JK. *Network Analysis in Public Health: History, Methods, and Applications*. *Annual Review of Public Health*. 2007;28(1):69-93.
10. Moreno JL. *Who shall survive? A new approach to the problem of human interrelations*: Nervous and Mental Disease Publishing Co; 1934. Available from: <http://www.asgpp.org/docs/wss/wss.html>.
11. Mercken L, Steglich C, Sinclair P, Holliday J, Moore L. A longitudinal social network analysis of peer influence, peer selection, and smoking behavior among adolescents in British schools. *Health Psychology*. 2012;31(4):450-9.
12. Christakis NA, Fowler JH. Social contagion theory: examining dynamic social networks and human behavior. *Statistics in Medicine*. 2013;32(4):556-77.
13. Edge R, Heath J, Rowlingson B, Keegan TJ, Isba R. Seasonal Influenza Vaccination amongst Medical Students: A Social Network Analysis Based on a Cross-Sectional Study. *PLoS ONE*. 2015;10(10):e0140085.
14. Ronald S. Burt. Structural Holes and Good Ideas. *American Journal of Sociology*. 2004;110(2):349-99.
15. Burt RS, Meltzer DO, Seid M, Borgert A, Chung JW, Colletti RB, et al. What's in a name generator? Choosing the right name generators for social network surveys in healthcare quality and safety research. *BMJ Quality & Safety*. 2012;21(12):992-1000.
16. Vaughan S, Sanders T, Crossley N, O'Neill P, Wass V. Bridging the gap: the roles of social capital and ethnicity in medical student achievement. *Medical Education*. 2015;49(1):114-23.
17. Woolf K, Potts HWW, Patel S, McManus IC. The hidden medical school: A longitudinal study of how social networks form, and how they relate to academic performance. *Medical Teacher*. 2012;in press.
18. Brewer DD. Forgetting in the recall-based elicitation of personal and social networks. *Social Networks*. 2000;22(1):29-43.
19. Neal JW, Neal ZP, Cappella E. Seeing and being seen: Predictors of accurate perceptions about classmates' relationships. *Social Networks*. 2016;44:1-8.
20. Laumann EOMPVPD. The boundary specification problem in network analysis. In: Burt RSMMJ, editor. *Applied Network Analysis: A Methodological Introduction*. Beverley Hills: Sage; 1983.

21. Stevenson R, Crossley N. Change in Covert Social Movement Networks: The 'Inner Circle' of the Provisional Irish Republican Army. *Social Movement Studies*. 2014;13(1):70-91.
22. Goffman C. And What Is Your Erdos Number? *The American Mathematical Monthly*. 1969;76(7):791-.
23. Howison J, Wiggins A, Crowston K. Validity Issues in the Use of Social Network Analysis with Digital Trace Data. *Journal of the Association for Information Systems*. 2011;12(12):767-97.
24. Eagle N, Pentland A, Lazer D. Inferring friendship network structure by using mobile phone data. *Proceedings of the National Academy of Sciences of the United States of America*. 2009;106(36):15274-8.
25. Stopczynski A, Sekara V, Sapiezynski P, Cuttone A, Madsen MM, Larsen JE, et al. Measuring Large-Scale Social Networks with High Resolution. *PLoS ONE*. 2014;9(4):e95978.
26. Coviello L, Sohn Y, Kramer ADI, Marlow C, Franceschetti M, Christakis NA, et al. Detecting Emotional Contagion in Massive Social Networks. *PLoS ONE*. 2014;9(3):e90315.
27. de Nooy W, Mrvar, A., and Batagelj, V. *Exploratory Social Network Analysis with Pajek: Revised and Expanded Second Edition*. . New York: Cambridge University Press.; 2011.
28. Borgatti SP, Everett, M.G. and Freeman, L.C. . *Ucinet for Windows: Software for Social Network Analysis*. . Harvard, MA: Analytic Technologies.; 2002.
29. Lyons R. The Spread of Evidence-Poor Medicine via Flawed Social-Network Analysis. *Statistics, Politics, and Policy*2011.
30. Balkundi P, Harrison DA. Ties, Leaders, And Time In Teams: Strong Inference About Network Structure's Effects On Team Viability And Performance. *Academy of Management Journal*. 2006;49(1):49-68.
31. Grund TU. Network structure and team performance: The case of English Premier League soccer teams. *Social Networks*. 2012(0).
32. Cunningham FC, Ranmuthugala G, Plumb J, Georgiou A, Westbrook JI, Braithwaite J. Health professional networks as a vector for improving healthcare quality and safety: a systematic review. *BMJ Quality & Safety*. 2012;21(3):239-49.
33. Granovetter MS. The Strength of Weak Ties. *American Journal of Sociology*. 1973;78(6):1360-80.
34. Burt R. *Structural holes: The social structure of competition*. . Cambridge: Harvard; 1992.
35. Putnam RD. *Bowling Alone*. New York: Simon & Schuster.; 2000.
36. Granovetter MS. The Strength of Weak Ties: A Network Theory Revisited. *Sociological Theory*. 1983;1:32.
37. Coleman J, Katz E, Menzel H. The Diffusion of an Innovation Among Physicians. *Sociometry*. 1957;20(4):253-70.
38. Christakis NA, Fowler JH. The Spread of Obesity in a Large Social Network over 32 Years. *New England Journal of Medicine*. 2007;357(4):370-9.
39. Fowler JH, Christakis NA. Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. *BMJ*. 2008;337.
40. J. M. What are the student interactions within the social network of a medical school? : Lancaster University; 2012.
41. Hafferty FW, Castellani B, Hafferty PK, Pawlina W. Anatomy and Histology as Socially Networked Learning Environments: Some Preliminary Findings. *Academic Medicine*. 2013;88(9):1315-23.
42. Friedkin NE, Johnsen EC. Social positions in influence networks. *Social Networks*. 1997;19(3):209-22.
43. Keating NL, Ayanian JZ, Cleary PD, Marsden PV. Factors Affecting Influential Discussions Among Physicians: A Social Network Analysis of a Primary Care Practice. *Journal of General Internal Medicine*. 2007;22(6):794-8.
44. Tasselli S. Social Networks of Professionals in Health Care Organizations: A Review. *Medical Care Research and Review*. 2014;71(6):619-60.

45. Chambers D, Wilson P, Thompson C, Harden M. Social Network Analysis in Healthcare Settings: A Systematic Scoping Review. PLoS ONE. 2012;7(8):e41911.
46. Paluck EL, Shepherd H. The salience of social referents: A field experiment on collective norms and harassment behavior in a school social network. Journal of Personality and Social Psychology. 2012;103(6):899-915.
47. Ibarra H. Race, Opportunity, And Diversity Of Social Circles In Managerial Networks. Academy of Management Journal. 1995;38(3):673-703.
48. Saunders C. Using Social Network Analysis to Explore Social Movements: A Relational Approach. Social Movement Studies. 2007;6(3):227-43.
49. Edwards G. Mixed methods approaches to social network analysis. ESRC National Centre for Research Methods 2010.