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Social network analysis: Presenting an underused method for nursing research

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Abstract

Aim—This paper introduces social network analysis as a versatile method with many applications in nursing research.

Background—Social networks have been studied for years in many social science fields. The methods continue to advance but remain unknown to most nursing scholars.

Design—Discussion paper.

Data Sources—English language and interpreted literature was searched from Ovid Healthstar, CINAHL, PubMed Central, Scopus and hard copy texts from 1965 –2017.

Discussion—Social network analysis first emerged in nursing literature in 1995 and appears minimally through present day. To convey the versatility and applicability of social network analysis in nursing, hypothetical scenarios are presented. The scenarios are illustrative of three approaches to social network analysis and include key elements of social network research design.

Implications for Nursing—The methods of social network analysis are underused in nursing research, primarily because they are unknown to most scholars. However, there is methodological flexibility and epistemological versatility capable of supporting quantitative and qualitative research. The analytic techniques of social network analysis can add new insight into many areas of nursing inquiry, especially those influenced by cultural norms. Furthermore, visualization techniques associated with social network analysis can be used to generate new hypotheses.

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No conflicts of interest have been declared by the authors.

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All authors have agreed on the final version and meet at least one of the following criteria [recommended by the ICMJE (http://www.icmje.org/recommendations/)]:

- substantial contributions to conception and design, acquisition of data, or analysis and interpretation of data;
- drafting the article or revising it critically for important intellectual content.

Conclusion—Social network analysis can potentially uncover findings not accessible through methods commonly used in nursing research. Social networks can be analysed based on individual-level attributes, whole networks and subgroups within networks. Computations derived from social network analysis may stand alone to answer a research question or incorporated as variables into robust statistical models.

Keywords

complex adaptive system; complexity; nursing; nursing research; research method; social network analysis

1 | INTRODUCTION

Often, phenomena of interest in nursing involve complex relationships that include social processes and social structures, acting on each other through direct, indirect and reciprocal interactions to have an impact on health. Nursing's disciplinary lens has traditionally used approaches from biology, medicine and social sciences that centre on properties of the individuals. These properties commonly serve as variables in research designs where we expect outcomes to be linear and proportional to their predictors. However, when humans interact in a unique environment, the relationships are never simple and the results are often unpredictable. Thus, in addition to being concerned with the individual patient, student, community resource or family member, the nursing scholar must also give special attention to the interconnectedness between and among individuals and the nonlinear nature of their interactions. Increasingly, the effects of social relationships and social networks on nursing outcomes are being considered. Furthermore, since social processes and relational norms vary across cultures, nursing scholars would benefit from methods that can capture such differences.

Many conceptual frameworks, including those grounded in complexity science, support a relationship-based approach to inquiry. These frameworks are well-suited to assist researchers in guiding studies that employ methods of social network research. Both empirical and interpretive methods of inquiry have been used successfully when incorporating complexity as a framework.

1.1 | Background

Researchers in fields such as computer science, physics and economics, place immense value in studying interactions among units of interest. Social networks and social network analysis have the ability to provide researchers with information that may improve our understanding of complex relationships and provide better insights into where and how to intervene to improve outcomes. When taking a relationship-based approach and applying it to certain health-related phenomena of interest, attention can be shifted from the individuals to the relationships among them. Social network analysis (SNA) is an increasingly used method in a variety of disciplines (Borgatti, Mehra, Brass, & Labianca, 2009; Otte & Rousseau, 2002; Scott et al., 2005). The rigorous methods associated with SNA account for mathematical properties, and unique attributes of the individuals. Ontologically, SNA demands an emphasis on connectivity and interdependence of individuals in a group.

Outcomes are affected not only by unique individuals but also by relationships and interdependence among them. Additionally, outcomes can be related and interdependent.

As the methods used by nurses require greater sophistication, SNA can help nurse scientists around the world explore complex phenomena. As evidenced by a recent systematic review, social network analysis does not appear in nursing literature until 1995 and remains rare well into the 21st century (Benton, Perez-Raya, Fernandez-Fernandez, & Golzalez-Jurado, 2015). Additionally, the literature is predominantly American which demonstrates a need to incorporate international awareness of the methods.

1.2 | Data sources

This discussion paper is being presented to provide the nurse scholar with an overview of SNA and convey its utility. English language and interpreted literature was searched from Ovid Healthstar, CINAHL, PubMed Central, Scopus and hard copy texts from 1965 – 2017. To support the assertion that the methods associated with SNA are applicable to nursing research, this paper provides hypothetical and practical examples that are relevant to various areas of nursing research.

2 | DISCUSSION

2.1 | Theoretical underpinnings

The nursing profession benefits when researchers acquire scholarly information through evolving methods of inquiry (Kulbok & Ervin, 2012) and multiple ways of knowing (Carper, 1978). Bonis (2009) noted that knowledge is of two types: objective knowledge that is logically constructed and subjective knowledge that is inductively constructed as it is shaped through personal engagement with the environment. When humans interact in a unique environment, the relationships are never simple and the results are often unpredictable. Thus, in addition to being concerned with the individual patient, student, community resource or family member, the nursing scholar must also give special attention to the interconnectedness between and among individuals and the nonlinear nature of their interactions.

Conceptual frameworks that support a relationship-based approach, such as those grounded in complexity, are suited to guide researchers in studies that employ social network research. Central to complexity research is the complex adaptive system (CAS) which is characterized by a network consisting of many agents that follow simple rules, are in constant dynamic interaction with one another and can generate complex structures (Miller & Page, 2007). The CAS operates as a self-organizing system from which diverse humans interact with each other, leading to what complexity theorists would term emergence. Both empirical and interpretive methods of inquiry have been used successfully when studying CASs through complexity research. A good example of using qualitative and quantitative approaches in complexity research is described by Anderson, Issel, and McDaniel (2003) in their studies that investigate relationships among nursing home residents and the employed Registered Nurses.

2.2 | Testing hypotheses

Inquiry and analysis can be conducted at many levels of the social network. The three most common levels are: 1) the individuals in the network, 2) the whole network and 3) cohesive subgroups in the network. Social network research and the methods of social network analysis have an expanding vocabulary but for introductory simplicity, attention will be called to four key terms:

1. Network—A conceptualization of an organization, system, community, or group that focuses attention on the relationships among the constituent individuals
2. Node—A single unit or individual person engaged in some type of action in a network; usually depicted pictorially as a point. “Actor” is also used synonymously by some social network researchers.
3. Tie—Collaboration or direct sharing between two nodes or individual persons in a network; represented pictorially as a line joining two nodes. “Arc” is also used synonymously by some social network researchers.
4. Path—Indirect sharing along a sequence of adjacent nodes; represented pictorially as a string of ties and nodes

Three hypothetical examples will help to illustrate three levels: node level, whole network level and cohesive subgroup level. The three examples will include how associated hypotheses can be tested. To demonstrate analysis at the individual node level, a case of communicable disease transmission will be presented. Whole network level will be presented as a case involving varying levels of success of a fall intervention programme in a hospital. Finally, cohesive subgroup level will be illustrated by presenting a case of disagreements about a research topic.

The individuals, or nodes, in the social network can be studied by quantifiable properties such as closeness, betweenness and reciprocity, all of which are calculated based on interactions, or ties, with others in the network (Table 1). An example for clinical nursing research, scientists can study a phenomenon such as communicable disease transmission based on how these properties apply to individuals who carry, or are at risk for contracting, diseases. Mathematical calculations of betweenness may correlate with disease spread while closeness may predict immunity development. Similarly, higher reciprocity may influence mutation of the pathogen if host vectors are limited. Of note, reciprocity can also be considered a network-level measure if the researcher studies overall reciprocity in the network rather than dyadic interaction of certain nodes or individuals.

In addition to quantifiable properties at the node level, whole networks such as families, communities or hospitals can be analysed through mathematical measures representing cohesion. Common measures include centralization, density and connectedness (Table 2). Perhaps a nurse executive is interested in assessing why there is variation among nursing units related to patient falls after a recently implemented initiative to reduce falls. The researcher could assess the centralization of the nursing units and determine if the nurse educators contribute highly to this, which might predict knowledge dissemination and application. The researcher could also test to see if nursing units with higher density are associated with quicker reductions in fall rates, leading to the possibility that dense networks can more quickly share and apply information. In cases where the day-shift saw improvements, but the night-shift did not or vice versa, the researcher could determine if connectedness among the unit or shift is a better predictor of success for the fall-reduction initiative.

Cohesive subgroups often emerge in social networks resulting in cliques and factions which can influence health and other phenomena of nursing interest (Table 3). In SNA, the terms cliques and factions are not intended to have negative connotations. Rather, they delineate the size of cohesive subgroups observed in a social network, with the former being the smaller of the two. Suppose a certain nursing research topic is being debated at an upcoming conference. A social network analysis to explore the unity or division among the topic can be quickly conducted. This can begin by performing a literature review of the topic which can be used to create a graph or matrix of authors who have written on the topic of debate. The matrix shows ties among the researchers based on those who co-publish articles related to the topic. A select number of researchers who frequently publish together may emerge as a clique within the topic of debate. Similarly, if there are debating schools of thought about the topic, the cohesive subgroups may be so large and possibly polarized, that two distinct factions exist.

2.3 | Sampling techniques

When the phenomena and population of interest have been identified and the researcher begins to plan the study's methods, another benefit of social network research emerges. Often with traditional methods, the researcher is challenged with identifying a properly representative sample or sampling frame. Fortunately, the social network of interest is usually apparent and it can serve as the sample. But care must be taken to not look outside of the network—a process known as boundary specification. Qualitative researchers may accept limited participants with samples derived through purposeful sampling and filtering of participants (Heath, Fuller, & Johnston, 2009). However, the quantitative researcher may aim for dense sampling where all potential ties are accounted for. There are methodical approaches to limit samples for large- or small-world networks (Borgatti, Everett, & Johnson, 2013; Doreian & Woodard, 1994; Robins, 2015) but for many phenomena of nursing interest, the sample needs no truncation and the researcher should aim to capture all ties. As with all research, the sample is determined by the purpose of the study and the research question to be answered.

Dense sampling initially may seem daunting as the aim of most social network analyses is to capture all relevant pair-wise connections among individuals. However, SNA presents an unique ego/alter ego sampling approach that has the potential to accomplish two important things: 1) a single response can usually reliably represent another omitted response (i.e. alter ego); and 2) two paired responses can confirm a tie, or cross-validate (Borgatti et al., 2013; Hawe, Webster, & Shiell, 2004).

In the first case presented about a communicable disease, the setting might be a homeless shelter; the outcome of interest is influenza spread. The sample is easily identified as the residents who reside in the shelter. When quantifying interaction and potential exposure time, residents who may not be able to respond due to being out of the shelter during data collection, can likely be accounted for by the responses of others.

In the second case involving the efficacy of a hospital's fall prevention programme, the sample would be the nursing organization of the whole hospital. Calculating the whole network values of centralization, density and connectedness (Table 2) for each nursing unit would produce the independent variables representing properties of the nursing units; the dependent variables are the normalized number of falls, or measures such as the rates of decrease in falls. This also brings forward the concept of nesting or embeddedness where some social networks are actually smaller sub-networks embedded in larger networks (Benham-Hutchins & Clancy, 2010). The individual nursing units are social networks with their own properties, but the nursing organization is also a larger network made up of the nursing units. Beyond the scope of this article, but worth mentioning, this nesting effect of some social networks may present an opportunity to formulate hypotheses that are tested through complex hierarchical or multi-level modelling techniques.

In the third example presented about the debated research topic, the sample is the group of nurse scholars who study and publish on the topic. Without even engaging participants, the social network researcher may access the curriculum vitae (CV) of each scholar or do a literature review of the topic of debate. A matrix can be created that identifies the number of times nurse scholars co-publish thereby representing social ties. Various properties emerge as certain groups of nurse scholars are identified as frequently publishing together.

2.4 | Data collection

Data collection for SNA is not significantly different from most other social research. As noted in the third case on the debated research topic, archival data such as CVs and bibliographies can be used to conduct an SNA of nurse scholars. Electronic transmissions such as emails among colleagues or clinical messages with an electronic medical record (EMR) can be used to construct a social network of relationships among healthcare professionals. The qualitative researcher can easily gather data from participant interviews, direct observations and ethnographic approaches (Munhall & Oiler Boyd, 1999) which can be advantageous with small networks.

The use of questionnaires is perhaps the most common way of gathering data from social networks. Care should be given to structure the question(s) so that the responses are reflective of the phenomena of interest (Borgatti et al., 2013). In reasonably sized networks and those with engaged participants, a roster can be provided to everyone with an accompanying question or set of questions. The questions should elicit insight into only the topic of interest. In the first example presented, residents of the homeless shelter can estimate the hours spent in interaction with all other residents in the month preceding the outbreak of influenza. This could be done by Likert-type rating where a zero would represent no-interaction and 1–5 could approximate a scale of hours, days or weeks spent in close contact. Another questionnaire approach would be an open-ended estimation whereby the respondents estimate their interaction time with other residents. In the second example about assessing a hospital's fall prevention programme, the Registered Nurses may rate their colleagues, using a roster, based on the number or quality of informative discussions about fall prevention or patient safety. Higher ratings would indicate more meaningful discussions while lower ratings would indicate few to no meaningful discussions. The questionnaire approaches, just like compiling publication records, provide quantitative data from which matrices and graphs can be constructed and from which social networks can be analysed.

2.5 | Data analysis

There is a robust and growing, collection of computational techniques for analysing social networks. The mathematical foundations and meanings of the basic concepts previously covered are presented in each table (Tables 1–3). Fortunate for the nurse researcher, there are software packages that are reasonably priced and in some cases available free-of-charge. Most of these packages also easily interact with common computer office programs. UCINET (Borgatti, Everett, & Freeman, 2002) is one such program that has a free downloadable option accompanied by a user-friendly guide and visualization software.

The SNA can be reliably used to analyse the properties of nodes, networks or subgroups. Depending on the research question, the SNA can also be used as a data-gathering tool for additional statistical analyses. In cases of the latter where the SNA is a tool, calculated values are entered into other analytic packages such as SPSS to derive statistical comparisons, complex regression models and other statistical output. The network properties presented herein represent a small fraction of those in use today. Researchers are encouraged to seek other sources as the scope of this article is intended to present an introductory overview and encourage further exploration.

2.6 | Data and results visualization

Visualizing networks is exciting and what attracts many researchers and consumers to SNA. As previously noted, SNA involves matrices of varying dimensions and attributes. When data are properly managed, these matrices can be represented in ways that not only simplify dissemination of the research findings but also generate new questions and give rise to new, or support existing, theory.

To illustrate the benefits of visualization, the first author conducted an SNA. The sample was the social network of doctor of philosophy (PhD) students at a nursing school. The study was determined to not require institutional review board (IRB) approval. Figures 1 and 2 represent the social network of PhD students. The phenomenon of interest was peer support. A survey was distributed, along with a roster of all 23 doctoral students, asking each student to estimate how many hours per week he or she engaged in academic or scholarly interaction with the other students (0 = none, 1 = only while in class, … 20 = twenty or more hours per week). The boundary of the study was easily identified as all enrolled doctoral students at the nursing school. Figure 1 shows the adjacency matrix where self-reported approximated hours are numerically listed. It is easy to note that the ego/alter ego responses are not perfectly aligned but are correlated. As previously noted, this is helpful if there is non-response of participants. Of note, in similar survey techniques, researchers may aim to only capture binary responses where, instead of interval-level data, the responses are simply yes or no (often represented in a matrix as 1 or 0).

Figure 2 represents the same data but depicted differently. The same 23 doctoral nursing students are depicted along with ties to their colleagues. In this depiction, the ties are represented binarily (the tie represents contact), but most software permits the researcher to customize the ties according to strength, direction, reciprocity, etc. Stronger ties can be depicted as thicker lines and arrows can be substituted for lines. Most software also permits the researcher to vary the size, shape or colour of the nodes depending on attributes of interest.

Now consider Figure 2 and other potential hypotheses. In addition to noting students who have ties to other students, what if each node is assigned attributes such as gender, years in the doctoral programme, travel distance to school, place of employment and/or topics of research interest. Emerging hypotheses may be generated from the visualization. For example: Do newly admitted students have lower centrality in social networks among doctoral nursing students? In this example, the hypothesis would not be supported because actual calculations demonstrated that the students who had moved on to doctoral candidacy were much less connected to the network and had very low centrality measures and fewer reciprocal relationships. These students are depicted on the periphery of the network and, as visualized, they have fewer ties (Figure 2) and weaker ties (Figure 1). In this example, regression models could also be developed to explore if academic progression is a predictor of student peer support. Similarly, if the survey was distributed to both PhD and Doctor of Nursing Practice (DNP) students in the school, the researcher could visualize the data to reasonably estimate if peer support factions or cliques emerge based on a programme of study. Subsequent calculations could be performed to test the hypothesis.

When conceptualizing the whole network properties of this social network of PhD nursing students, if the same survey was distributed to multiple nursing schools across the country, a researcher could ask the question: Is there more cohesiveness among PhD nursing students in classroom-based programmes vs. online programs? A linear regression model, where the amount of online study is used as an independent variable and density measures are used as dependent variables, may produce some enlightening results.

2.7 | Limitations and ethical considerations

Care must be taken when interpreting the results of SNA. Generalizability should be inferred cautiously since every social network is unique. Additionally, limitations common to survey research remain; self-report data are only as accurate as the participants can recall or will report. It is possible that questions may be interpreted as peer rating which raises the concern for social desirability and reactivity among the participants (Shi, 2008). Perhaps the biggest threat to SNA is low response. Often, the ego/alter ego phenomenon can account for non-response, but if there are two paired non-responses, the network is compromised and may require a modified sampling approach. Albeit rare, the nurse researcher should also be prepared to deal with conflicting responses where the ego/alter ego are not congruent.

Finally, most IRBs are unfamiliar with social network analysis, so it is incumbent on the nurse researcher to uphold all ethical principles. Confidentiality should be maintained, but complete anonymity is often not possible. As such, informed consent should include this discussion. Each datum that drives the SNA is a person irrespective of being identified or not. Similarly, the aggregated data of the network represent a group of people, often vulnerable communities, so not only should the individual responses be protected but sometimes the sensitive details of the interpreted whole network should also be protected.

2.8 | Implications for nursing

Nursing is a social science but, along with other healthcare fields, has been slow to adopt the methods available with social network analysis. SNA is methodologically aligned with theoretical frameworks that support social processes, notably the emerging field of complexity. Nurse researchers attempting to understand today's health phenomena should expect a heterogeneous world made up of self-determining, autonomous individuals who co-create environments that produce health outcomes. These outcomes are often the result of the quantity and quality of culturally influenced relationships among persons and communities.

3 | CONCLUSION

The methods that accompany SNA are quite versatile and can support qualitative and quantitative researchers and a variety of nursing phenomena. Beyond traditional *p* values, effect sizes, standard errors, etc., interpretation of SNA calculations often relies on theoretical underpinnings, visualization and relative comparisons. The quantitative properties of the social network can either stand alone to answer a research question, or the values can be entered into more common software packages to create robust statistical models. For simplicity, the examples discussed herein introduced cross-sectional designs exploring bivariate relationships. However, SNA can be further extended to explore multiple phenomena or add rigour to ongoing studies. Repeated data collections over time introduce a longitudinal design that may strengthen a study or support earlier findings. Alternatively, the qualitative nurse researcher can employ an ethnographic approach or call on the experiences of the participants to explore and describe their social network.

Nurse researchers who embrace the methods of social network analysis increase their opportunities to explore phenomena and can potentially uncover findings not readily accessible through traditional methods. Furthermore, social network analysis captures social processes which often vary across cultures. Insight into these variations across social networks will allow nurses to more effectively care for patients, design healthcare facilities and educate tomorrow's caregivers.

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Why is this research or review needed?

- To present a powerful and versatile method that is unknown to most nurse researchers
- To engage nurse researchers in a growing body of scholars that use social network analysis
- To present a practical approach to linking theory and practice

What are the key findings?

- Social network analysis can support both qualitative and quantitative designs
- Social network analysis can be used to explore many phenomena of nursing interest
- Social network analysis can be used to explore individuals, groups and subgroups

How should the findings be used to influence policy/practice/research/education?

- Using visualization techniques associated with social network analysis will allow the nurse researcher to easily convey results which should translate research into practice.
- Knowing more about the nature of groups will help practitioners, educators and policy makers intervene more effectively.
- Employing the methods discussed herein will permit the nurse researcher to better analyse social structures in health care and academia.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1		0	15	0	10	1	1	5	0	0	0	20	10	10	10	1	0	5	20	10	0	0	10
2	0		5	0	0	0	5	1	0	5	0	0	0	0	1	5	0	0	15	1	5	1	0
3	15	1		0	15	5	15	1	0	1	0	10	0	10	10	15	0	5	5	5	1	1	1
4	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	1	0	5	0		1	5	1	0	0	0	5	0	5	5	5	0	1	1	1	1	1	0
6	1	1	5	0	1		1	1	0	0	0	1	0	1	1	1	0	1	1	5	1	1	0
7	1	1	10	0	15	5		1	0	5	0	15	0	15	15	20	0	1	1	5	15	15	10
8	10	1	1	0	5	1	1		5	0	0	10	0	5	5	1	0	15	15	1	1	5	0
9	0	0	0	0	0	0	0	10		0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	1	10	5	0	1	5	5	1	0		0	1	0	1	1	5	0	1	1	5	5	10	0
11	0	0	0	0	0	0	0	0	0	0		0	1	0	0	0	0	0	0	0	0	0	0
12	10	1	1	0	1	1	1	1	0	0	0		0	5	10	1	0	1	1	1	1	1	0
13	0	0	0	0	0	0	0	0	0	0	1	0		0	0	0	0	0	0	0	0	0	0
14	1	1	1	0	1	1	5	1	0	1	0	15	0		25	15	0	1	1	1	1	1	1
15	5	1	1	0	10	1	15	1	1	0	0	15	0	25		15	0	1	1	1	1	1	1
16	5	10	20	0	20	10	20	1	0	10	0	20	0	20	20		0	1	1	10	10	10	1
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	1
18	5	0	0	0	1	1	1	5	0	0	0	5	0	1	1	1	0		5	1	0	1	1
19	20	10	1	0	1	1	1	10	5	0	1	5	1	5	5	5	0	10		1	0	1	0
20	1	3	3	0	1	3	3	1	0	3	0	1	0	1	1	3	0	1	1		3	3	0
21	1	10	5	0	1	5	5	1	0	10	1	1	0	1	1	5	0	1	1	1		10	0
22	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	0	1	1	1	1		0
23	1	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	0	

FIGURE 1.
Social network adjacency matrix of PhD students in a pilot study

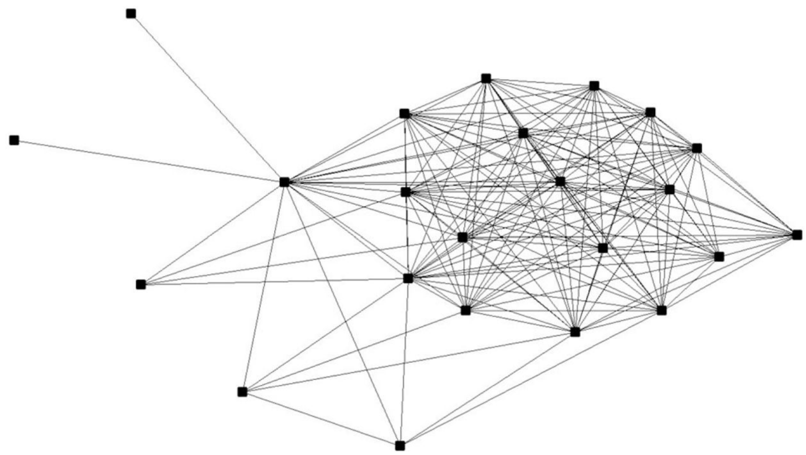

FIGURE 2.
Social network visualization of PhD students in a pilot study

TABLE 1

Social network properties—nodes

Network property	Theoretical definition	Operational definition	Rhetorical significance	Mathematical foundation
Closeness	The position of the nodes within the network; Quantifies more relationships with fewer ties	The sum of the geodesic distances from an actor to all others	Represents independence and efficiency	$\Sigma_j d_{ij}$ = Closeness of node j where d_{ij} is geodesic distance between node i and j
Betweenness	How often a node is involved in paths of other nodes	The proportion of all the shortest paths that pass through the focal actor	Shows the potential an individual has to serve as a “gatekeeper” of information	$\Sigma_{j<k}(g_{jik}/g_{jk})$ = Betweenness of node i where g_{jik} is the number of geodesic paths between j & k that include i; g_{jk} is the number of geodesic paths between j & k
Reciprocity	Bidirectional congruency of a tie between nodes	Agreement or perceived sameness of relationship	Strong (±) relationships tend to be more reciprocated and meaningful	$(\Sigma T^{\leftrightarrow})/(\Sigma T)$ = Reciprocity of the chosen node(s) where $T^{\leftrightarrow}$ represents total number of bidirectional ties and T is total number of all ties

(Hawe et al., 2004; Otte & Rousseau, 2002; Robins, 2015; Zohar & Tenne-Gazit, 2008)

TABLE 2

Social network properties—whole network

Network property	Theoretical definition	Operational definition	Rhetorical significance	Mathematical foundation
Centralization	The extent to which the network relies on a single node	Equal to the number of ties that an actor has with other actors and can be visualized as the star nature of the network	Helps to identify “key players” or highly influential individuals	$\{\Sigma\ [(C_i - C_m), (C_j - C_m), (C_k - C_m)\ldots)]\} / (C_{max})$ = centralization of the network where C_i is the centrality of node $i \ldots$, C_m is the most central node and C_{max} is the maximum possible centrality
Density	Level of connectedness or cohesion of the network.	The number of relational ties divided by the total possible number of relational ties.	Identifies social activity of the network or “popularity” of an individual	$n(n-1)/2$ = density of the network where n = number of nodes
Connectedness	Extent to which nodes are in the same central component of the network	Proportion of actor pairs that can reach each other by a path of any length	Indicates the fragility or stability of a network and identifies subgroups	$(\Sigma_{i \neq j} r_{ij}) / n(n-1)$ = connectedness of the network where r_{ij} = reach of nodes i & j

(Borgatti et al., 2013; Hawe et al., 2004; Otte & Rousseau, 2002; Zohar & Tenne-Gazit, 2008)

TABLE 3

Social network properties—subgroups

Network property	Theoretical definition	Operational definition	Rhetorical significance	Mathematical foundation
Clique-formation	Small subgroups made of nodes who are directly connected to one another but loosely connected to the network core	Presence of observed subgroups identified through a hierarchical clustering model	Gives insight into the potential for deviant/ alternate behaviours	Subgroup identification involves techniques such as hierarchical clustering, matrix threshold manipulation and systematic algorithms—often coupled with visualization of the network.
Faction-formation	Distinct groups formed from network permutations arising from mutually exclusive attributes	Presence of groups based on observed, opposing attributes	Predicts dissention, degradation within a network	

(Borgatti et al., 2013; Hawe et al., 2004; Otte & Rousseau, 2002; Zohar & Tenne-Gazit, 2008)