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## Social Network Analysis as Mixed Analysis

Dominik E. Froehlich and Jasperina Brouwer

Social network analysis (SNA) has become an important theoretical and methodological framework to investigate research questions in both the social and natural sciences. This is illustrated by the surge in SNA-related publications, for example in the domain of learning and instruction research: from 37 publications in 2003 to more than 400 a decade later in the Education Resources Information Center database (Froehlich, Rehm, & Rienties, 2020a; Froehlich, Van Waes, & Schäfer, 2020). In this chapter, we will discuss the foundations of social network analysis as mixed analysis.

### 1 Definition of Social Network Analysis

In order to review an SNA manuscript, there are three important points we need to understand about the nature of the analysis to be reviewed: the perspective SNA has on social phenomena, the different types of networks one may investigate, and the “mixed nature” of SNA as a method.

#### Social Network Analysis as a Lens to See the World

Researchers use SNA if they are interested in the relationships and structural features of networks (Wellman, 1983). A *network* is defined as a set of *nodes* (or vertices, or actors)—for example, pupils in a classroom—and *edges* (or ties, or relationships)—for instance, conversations or friendship relationships between pupils. Nodes may contain *attributes* (e.g., gender, age, motivation). Edges may be weighted (e.g., weighted by the frequency of interaction) or directed (i.e., having a specified direction). In social networks the nodes are active agents, such as individuals or teams (Borgatti, Everett, & Johnson, 2013).

The term SNA itself is somewhat misleading because SNA is not only about analytical procedures but also describes an integrated set of theories (“network theory,” e.g., Borgatti & Halgin, 2011) and research methods. The SNA perspective differs from other approaches in several ways (Wasserman & Faust, 1994). First, the focus is on relational theories and concepts (Monge & Contractor, 2003). The unit of analysis is not simply the characteristic or attribute of an individual (although SNA can produce input for such analyses), but rather dyads (two nodes), triads (three nodes), or groups (Froehlich, Galey, Mejeh, & Schoonenboom, 2020; Froehlich, Rehm, & Cornelissen, Forthcoming). Actors and their behavior are seen as interdependent. The actors’ relationships and behaviors, or personal characteristics—attributes—can influence each other. Relationships with others make certain behaviors more

likely and limit others. For example, it is more likely that adolescents who smoke are likely to be friends to other smokers (Mercken, Snijders, Steglich, Vartiainen, & de Vries, 2010).

#### Types of Networks

There are two distinct types of networks that can be analyzed, each with their own set of methods and theories: namely, sociocentric and egocentric networks. In a *sociocentric network*, the relationships among all the actors within previously defined boundaries are measured and analyzed. For instance, all the pupils within a specified class may be surveyed about their friendship relationships in the class. However, in an *egocentric network* (Crossley et al., 2015), the emphasis is on one individual—the ego—and his or her relationship to others—the *alters* (and potentially about the relationship between alters). For instance, one pupil is asked about their contacts with other class members (an *ego-alter question*) and whether he or she thinks relationships exist between the other class members (an *alter-alter question*). The main difference with egocentric measures is that in the ego network the information about the relationships comes from one individual rather than from all of the class members who can nominate each other (Prell, 2012). The difference between the types of networks is represented in Figure 19.1.

So far, we have only discussed relationships among actors of one kind; for instance, interactions among pupils (another example would be e-mails sent between managers). This is called a *one-mode network* with similar types of nodes. Another variant of social network analysis called *two-mode networks* or bipartite graphs allows researchers to study ties between dissimilar types of nodes (Agneessens & Everett, 2013). A two-mode network features two sets of nodes; for example, adding teachers to a network of pupils. A special type of a two-mode network is an *affiliation network*, in which the nodes/sets are actors and events (Wasserman & Faust, 1994). An example is the study of Davis, Gardner, and Gardner (1941), who investigated a group of 18 women (first node set) who joined a series of 14 society events (second node set). Other examples are members joining different clubs in a city (Wasserman & Faust, 1994).

#### The Nature of Social Network Analysis

SNA is often considered to be a quantitative technique (Hollstein, 2014). However, this does not appropriately capture the highly qualitative origins of the method (Freeman, 2000, 2004) or the

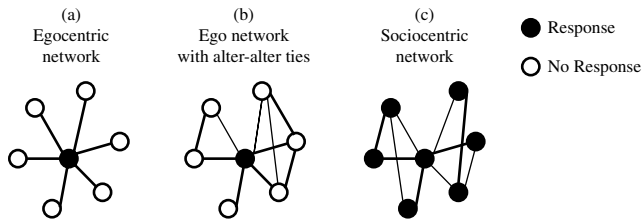


FIGURE 19.1 Egocentric and sociocentric networks.

current breadth of methods that go under the banner of SNA. Onwuegbuzie and Hitchcock (2015) highlighted the potential to integrate qualitative and quantitative strands of network research, and described the method as quantitative-dominant crossover mixed analysis. Other researchers agree with this requirement to include more qualitative information to produce more meaningful research (Bolíbar, 2015; Domínguez & Hollstein, 2014; Franke & Wald, 2006; Rienties, Johan, & Jindal-Snape, 2015). As noted by Hollstein (2011), qualitative data collection and analysis can facilitate social network analysis because qualitative data can “explicate the problem of agency, linkages between network structure and network actors, as well as questions relating to the constitution and dynamics of social networks” (p. 404). More specifically, Hollstein identified six areas in which qualitative research can enhance SNA: the exploration of networks, network practices, network orientation and assessments, how and why networks matter, understanding network dynamics, and the validation of network data and field access.

Carrington (2014) describes SNA as neither qualitative or quantitative but mathematical and structural. This is echoed in the SNA community, where quantitative approaches are commonly referred to as *formal network analysis*. This term is more focused on the perspective taken than the underlying type of data.

## 2 When the Use of Social Network Analysis is Appropriate in MMR

Social network analysis has his roots in several disciplines, including mathematics, psychology, and sociology. From there, the method has been adapted and applied in virtually all academic domains: for instance, history (Elo, 2015), politics (Ansell, Bichir, & Zhou, 2016; Apkarian, Bowler, Hanneman, & Martin, 2015), economics (Harris, Louis, & Baker, 2014), music (Vlegels & Lievens, 2015), health (Yang, Latkin, Muth, & Rudolph, 2013), and education (Rienties, Hélot, & Jindal-Snape, 2013). More information about the historical development of social network analysis can be found in Freeman (2004).

It is appropriate to use SNA whenever the research question addresses (perceived) structures or (perceived) connections or relationships between any entities, that is, social or non-social entities. For instance, friendships between students, trust between managers and employees, or the spread of a virus via personal contacts. Social network theory has led to a few frequently researched concepts and theories in the past, including

social capital, homophily/similarity attraction, and contagion. These three theories will be discussed in more detail in this section to provide a brief overview of some of the most important network theories and concepts.

### Social Capital

The concept of social capital became popular in the late 20th century and is frequently used by researchers. Social capital is the advantage one obtains from a certain position in a network (Burt, 2005). For instance, social networks permit access to variable resources, such as information, trust, practical or emotional support, community values and norms (Kadushin, 2012). Through the use of these resources an individual can reach personal goals that could not be reached without these resources (Coleman, 1988). Coleman (1988) has suggested that people also build networks of trust, reputation, obligation, norms, and values through social exchanges. For example, as a form of students’ social capital, students create informal support networks (Hommès et al., 2012). In these informal peer networks, students inform each other, help one another, collaborate, and share trustworthy information when they become friends. These peer relationships among first-year university students might facilitate both their adjustment to university life and their academic performance (Brouwer, Jansen, Flache, & Hofman, 2016; Brouwer, 2017).

Social capital and social networks share similar dimensions of social structures and content. The position in the networks and the type of ties determines the amount of social capital. Granovetter (1973) emphasized that to create new ideas, or to get a job, an individual needs connections he or she does not know very well (weak ties). These weaker ties are a bridge to other, different information. In this respect, Putnam (2001) has distinguished between bridging social capital and bonding social capital, which is linked to the social network structure. Bridging social capital refers to weak ties and less dense networks, whereas bonding social capital refers to strong ties and dense, knitted networks.

### Homophily and Propinquity

Lazarsfeld and Merton (1954) introduced the principle of *homophily*, which means that it is more likely that a close relationship will develop between people who are similar than between people who are dissimilar. Or, to put it colloquially, “birds of a feather flock together” (McPherson, Smith-Lovin, & Cook, 2001). To define homophily in a more formal way, when two people are randomly drawn from a population or from a network they belong to, there is a larger chance that they will have similar characteristics (Verbrugge, 1977). This means that people within networks are likely to be more homogeneous in their backgrounds, attitudes, and opinions. Homophily exists in all types of close relationships, such as within student groups (Brouwer, Flache, Jansen, Hofman, & Steglich, 2018; Lomi, Snijders, Steglich, & Torló, 2011) or between colleagues in a small organization (Froehlich & Messmann, 2017).

Proximity (or propinquity) makes it more likely that there will be a relationship between spatially close actors (Monge & Contractor, 2003), for instance, when the actors are sharing the

same office or sitting next to each other in the same classroom. The effects of proximity and distance were also discussed by Festinger, Schacter, and Back (1950; cited by Kadushin, 2012), who gave the example of a housing project for World War II military veterans. Festinger, Schacter, and Back found that the veterans became friends more often when they lived near each other, whereas the veterans in the corner houses frequently became isolated.

Regarding the attraction between two individuals, Lazarsfeld and Merton (1954) distinguished between status homophily and value homophily (Frieling & Froehlich, 2017). Status homophily can be ascribed to a person based on their background characteristics, such as gender or age; or status homophily can be acquired, based on, for example, the person's education or occupation. Value homophily, on the other hand, refers to similarity in attitudes, beliefs, or stereotypes. Two of the main characteristics of homophily are that people are similar when they meet (the selection effect), or they become similar when they interact (the influence effect) (McPherson et al., 2001). This can be addressed with stochastic actor-based models to investigate longitudinally collected social network data (Snijders, Van de Bunt, & Steglich, 2010).

### Contagion or Diffusion in Networks

Diffusion means that certain aspects or components are transmitted through a social system, such as ideas, opinions, and diseases (Valente, 1996). When graphically depicted, the diffusion usually follows an S-curve, which means that in the beginning only a few people adopt, for example, an idea. Then, people share this idea with others, who also adopt the idea. The proportion of people who adopt the idea increases when more people transmit the idea (diffusion), but the increase slows down when there are fewer people to adopt the idea (Kadushin, 2012).

Epidemiology diffusions should be distinguished from social diffusions. Social influence and social diffusion exist in different forms, and the term means that at the social level something has been transmitted through social contacts, for example through influence, or persuasion to buy something, or to influence opinions in a certain way. Epidemiology or biology diffusions refer to the spread of diseases or health risks. Social network analysis also appears a useful method to investigate the contagion among people (see Kadushin, 2012).

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## 3 Technical Outline of Social Network Analysis for MMR

### Defining Research Questions at Different Levels of Analysis

Social network research questions differ from commonly used research questions in that we are not interested in only personal perceptions or characteristics but in the actual social relationships. Social networks can be either the independent variable or the dependent variable. When social networks are investigated as an independent variable, social network theory can be used to explain or predict certain outcomes, such as individual

performance or organizational benefits. When social networks are investigated as a dependent variable, individual or group characteristics, behaviors, or attitudes can be used to explain social structures (Borgatti et al., 2013). Here are examples of research questions at different levels: (1) Do students who have higher grades have more friends? (actor level, social network as a dependent variable); (2) Are students who sit next to each other more likely to become friends? (dyad level, social network as a dependent variable); (3) Do well-connected networks tend to spread information faster? (network level, social network as an independent variable).

### Defining the Network

Before we can measure and analyze a network, we need to define what the network actually is—the so-called *boundary-decision* (Laumann, Marsden, & Prensky, 1983; S. S. Smith, 2013). Based on the definition of networks given above, this means that we need to define who the actors are (e.g., pupils within a classroom, any people in a region) and what the focal type of the relationship is (e.g., trade between countries, intimate relationships among teenagers, seeking feedback among employees). In other words, we need to define the boundary of the set of actors (nodes), which allows researchers to investigate a specific population. The boundary of members in a network is commonly contrasted with non-members and defined based on the frequency of interactions (e.g., pupils in a class) or the strength of the relationships (e.g., family or friendship; Wasserman & Faust, 1994). There are two approaches to this question (Smith, 2013): the nominalist and the realist way. The *nominalist approach* is theory-driven: Based on theoretical considerations, the researcher defines who or what is to be considered in the network. For example, when researching the development of occupational expertise we might want to focus on an employee's relationship with colleagues and not with friends and other emotional contacts outside the company or field of occupation (Froehlich, 2015; Froehlich, Beusaert, Segers, & Gerken, 2014). Conversely, the *realist approach* considers the network and its boundaries as perceived by the actors themselves. This openness on the side of the researcher may lead to unexpected findings, such as Granovetter's (1973) discovery that often the "weak ties" (in terms of emotional intensity, time spent with each other, reciprocal service, and intimacy) are more important than "strong ties," for instance, when getting a job via one's network.

Many network studies include social entities or communities of a manageable size, for example neighborhoods, clubs, or classrooms. Most often, these networks have a plain boundary of actor sets. When the network can be clearly defined, sociometric (full network) and egocentric measures are appropriate for making inferences about the population of networks. Sometimes the boundaries of the network are not as clearly defined or it is not possible to include all actors. In this case, a sample can be taken from the larger population. This can be done by snowball or chain sampling, which is a non-probabilistic sampling technique. It starts with the report of a key actor about the actors with whom they have a certain connection. This will be continued by approaching the actor's connections, and so on, up to several waves; for example, there

have been studies of the connections of gang members (Borgatti et al., 2013; Wasserman & Faust, 1994).

## Collecting Data

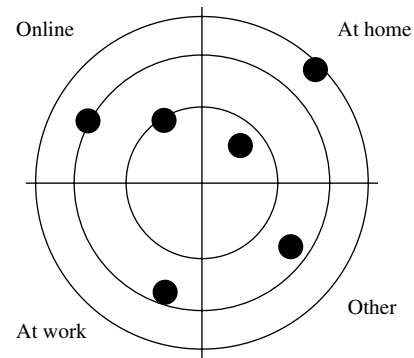
A large number of social network studies use different methods for data collection, either quantitative or qualitative or both (cf. Froehlich, 2020a). The diversity of data collection methods applied in social network research varies from text analysis to contact diaries for collecting data about ego networks. Researchers can investigate the type of ties, the strength of the ties, the frequency of interactions, and also information about the actors' personal attributes (Wasserman & Faust, 1994).

When it comes to drawing samples, and collecting data, another difference from traditional approaches exists. For socio-centric network analysis to work as intended, a census of the defined network is desirable. This emphasizes a high response-rate of ideally above 80%, or even 90% (Wasserman & Faust, 1994). It is also important to highlight the ethical considerations concerning SNA data collection. Since we are mostly interested in some feature of a relationship between people, asking respondents for evaluations of that other person's or their joint relationship is often required (even if the other party does not take part in the research!). These "third parties" may be affected by the conclusions. Therefore, a thorough ethical review of the data collection procedures and the potential implications for participants and third parties is a must.

For data collection, SNA is open to both qualitative and quantitative methods. For quantitative data collection, sociometric questionnaires are the method used most often. These questionnaires differ from psychometric questionnaires in so far as they contain two separate parts. First, the researcher needs to identify relevant alters that the ego has relationships with. Second, more detailed information about these relationships must be acquired. There are two prominent methods for finding out about relevant alters. One can provide a list of all potentially relevant persons; for example, all the pupils in a class. This approach is usually referred to as the "roster method," as a full roster of relevant alters is provided to the respondent. An alternative, and more open-ended, approach is the "free recall" method, in which the respondents are asked for names via a name-generator (Burt et al., 2012) or, more abstractly, for relevant other positions the respondent has been in contact with (position generator; see Van Der Gaag, Snijders, & Flap, 2008). After providing or collecting relevant other names or positions, the relationship to each alter is specified through a so-called name interpreter question. For instance, this could mean indicating the frequency of contact for each alter. The number of alters to be enlisted may or may not be limited by the researchers (Wasserman & Faust, 1994).

Data mining approaches (especially from online networks such as Twitter) are gaining momentum (Barbier & Liu, 2011; Srivastava, 2008). Also, other technologies may be used to track relationships, such as electronic badges (Pentland & Heibeck, 2010) or contact logs.

On the qualitative side, the method of concentric circles is a popular approach to collecting data (Kahn & Antonucci, 1980). Here, an interviewee (as the ego) is asked to place alters on a map of concentric circles that represent closeness (or some



**FIGURE 19.2** Example of using the concentric circles method for qualitative data collection.

other defined feature) of the relationship. Information from the interview can then be used to corroborate or aid the interpretation of the different positions. This process can be augmented with software (Hollstein & Pfeffer, 2010).

As a qualitative approach to data collection, face-to-face interviews are commonly used. This is a popular way to collect ego network data (Froehlich, 2020b). The procedure is similar to the sociometric questionnaire, in that name generating questions (e.g., "Who do you ask for advice when you do not understand the study material?") are followed by name interpreting questions (e.g., "Is this person older than you?").

Another qualitative data-collection approach is observation, which can be used to study small groups (Wasserman & Faust, 1994). The advantage of the observation approach is that it is not necessary to rely on the memory of the interviewee or the respondent. The researcher can simply observe who is interacting with whom. However, the type of interaction should be defined and coded as such. Another issue is that several interactions can take place at the same time. Finally, diary data or archiving data (e.g., newspapers, minutes of gatherings) can also be used for collecting network data. An example is the use of citations of scientific articles.

## Analyzing the Data

Visual analysis plays an important role in SNA (Brandes, Indlekofer, & Mader, 2012; Freeman, 2000). Indeed, an image of a network often shows its distinct features very well and offers a great basis for discussions with stakeholders. The depicted positions and networks can also be expressed in more quantitative terms—for example (Carrington, 2014; Schoch & Brandes, 2016; Wasserman & Faust, 1994) density (the proportion of actual connections to potential connections), geodesics (the shortest path between two actors), node centrality (a measure of how well connected an actor is to the rest of the network), or centralization (the overall consolidation of the network).

Traditional inferential statistics are often not applicable in SNA, since the data usually violates the assumption of independent cases. Alternative descriptive statistics that can be used are correlations and regressions using quadratic assignment procedures (QAP; Dekker, Krackhardt, & Snijders, 2003; Krackhardt, 1992). Also, for data synthesis across studies,

specialized procedures exist (e.g., Krackhardt & Kilduff, 1999). Exponential random graph modeling (ERGM; Robins, Pattison, Kalish, & Lusher, 2007) is another approach that compares the features of an observed network (e.g., reciprocity) with other potential instances of the same network. For dynamic longitudinal networks, stochastic actor-based models are most frequently used (Snijders et al., 2010).

The qualitative methods applied for data analysis are less proprietary to SNA; “standard” qualitative methods are often applicable. An example for an adapted qualitative method is qualitative structural analysis (QSA; Herz, Peters, & Truschkat, 2015), a “combination of the analytical perspective of structural analysis and analytical standards taken from qualitative social research” (p. 1).

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#### 4 Empirical Demonstration of Social Network Analysis for MMR

As an empirical demonstration, research performed using first-year students at a university in the Netherlands is described below (see Brouwer, Jansen, Flache, & Hofman, 2018). A mixed methods SNA approach was used to combine the collection and analysis of complete social networks with open-ended questions.

Interactive small group learning approaches, such as learning communities, have been increasingly implemented at universities worldwide. A learning community is a group of about twelve students who take the same courses. The rationale behind learning communities is that students can collaborate with each other, get to know each other easily, and learn from each other through shared knowledge construction (Brouwer, 2017). In fact, the learning communities facilitate building a new social peer network after the transition from high school to university. There were two major research questions:

1. How do learning communities contribute to academic help-relationships and friendship relationships?
2. How do students appreciate the learning communities in term of peer network formation?

Previous research investigated the benefits of learning communities for individual outcomes, such as academic performance (Hotchkiss, Moore, & Pitts, 2006) and student satisfaction (Zhao & Kuh, 2004), but learning communities were rarely investigated from a social network perspective.

The sample included 95 first-year social sciences students who were part of learning communities. The network boundary was defined as the complete degree program, because Brouwer et al. (2018) were interested in the students’ contacts with their fellow students in their learning community compared to their contacts outside their learning community. Complete social network data were collected online at the end of the first and at the end of the second semester (longitudinal measurements). This means that students could nominate fellow students from the complete degree program. The names of their learning community members were shown on a roster, and students could add additional names from other learning communities of the degree program.

Each student was asked two social network questions that were adapted from Van de Bunt (1999). The first item was, “I ask this fellow student (name) for help when I do not understand the study material?” The second question was, “What kind of relationship do you have with (name)?” The questions could indicate whether the students are best friends, friends, possible friends, have a neutral relationship, or an unknown relationship (you know only the other person’s name or face), or even indicate not knowing the person at all. For the given analysis, it was a technical requirement to dichotomize the answer categories and indicate best friend, friend, and possible friend as one category (friends) and the other answer categories as zero (not friends). An open question was asked about the students’ opinion of learning communities and suggestions for improvement at the end of the year and coded these as a positive or negative evaluation. The other question concerned the students’ perceived contribution of learning communities on relationship formation and the learning process.

The social network data were analyzed descriptively for the first research question regarding how learning communities contribute to network formation. The statistical network statistics showed that the students had more relationships with fellow students in their learning community compared to students outside the learning community. The density of seeking help in friendship networks, which is the ratio of the actual relationships divided by the possible relationships, was ten times higher in the learning communities than outside the learning communities. The degree centrality (the number of an actor’s ties) indicated that students asked on average two to three students for help from their learning community in the first semester, which decreased in the second semester. In the second semester, students asked relatively more students outside their learning community for help. The same held true for friendship, but the decrease in the number of friendships in the learning communities was less strong than in the help-seeking network. The graphs of the results showed that learning communities formed dense subgroups in the degree program, particularly in the first semester. Evidence for this came from the qualitative analysis (the second research question): Students indicated that they found learning communities helpful for building relationships with their peers, mentioning that they get to know each other easily in this safe environment.

This example shows the contribution of an analysis of complete social networks using a mixed methods design. Social networks were analyzed descriptively and based on graphical presentations. The open-ended question was added to investigate the students’ opinions in addition to what we learned about in the social network structure.

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#### 5 Suggested Applications of Social Network Analysis in MMR

SNA and its focus on relationships and structures has helped advance science in many fields. It also lends itself very well to more applied research projects to drive change on a local level. This is especially true for SNA’s capability to produce network

charts that can mostly be understood intuitively by the participants (see Technical Outline in this chapter).

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## 6 Strengths and Limitations of Social Network Analysis in MMR

Despite the strength of social network data and analysis, we need to also consider some limitations of the resulting data. First of all, let us consider the reliability of the data. Social network data can change rapidly, because social relationships are often volatile. However, some social network questions lead to more reliable results than others. In SNA, the mutual or reciprocal ties are more reliable when the two actors of this specific relationship perceive the relationship similarly. Reciprocated ties occur more often in close relationships, such as friendships. This means that social network measures tend to be more reliable in close networks with reciprocated ties (Marsden & Campbell, 1984). The same holds true for the questions about close ties, because in close connections reciprocated ties exist more often (Wasserman & Faust, 1994).

Another limitation of social networks is missing data. The most common problem is that a possible respondent does not participate in the study even though he or she belongs to the target population. Such missing values can make the network seem less connected and dense than it actually is. When central persons in the network are missing, it is even more problematic (Smith & Moody, 2013; Smith, Moody, & Morgan, 2017). In sum, the data collected for sociometric network analysis must be very inclusive regarding achieving large samples and high response rates. For certain populations, this may not be feasible.

The theoretical definition of a network—a set of nodes and edges—is straightforward. However, applying this thought to (research) practice triggers a host of open questions, and most prominently the boundary specification problem (Laumann et al., 1983). Basically, the boundary question is what is in the network and what is not (which is discussed in the technical outline of SNA in this chapter).

A problem commonly identified in MMR is the (mixed) competencies required by the researchers (cf. Onwuegbuzie & Hitchcock, 2015; Froehlich, Mamas, & Schneider, 2020). This problem can be aggravated when applying mixed approaches to SNA, as the quantitative methods are—compared to “standard” statistics—even more sophisticated. This, and the fact that few researchers get formal training in the field of SNA early in their career, results in a steep learning curve that may be difficult to master along with a diffuse set of interests and learning goals. Being acquainted with the quantitative side of SNA, however, can be very important, at least for academics, as the field is very much driven by quantitative analyses (Hollstein, 2014). Qualitative approaches have existed from the beginning of SNA, and—also thanks to the massive amount of data available online (e.g., Twitter networks)—there has been an emphasis on quantitative methods to conduct SNA research.

Anonymity is important in social science research, but in full network designs it is hard to guarantee anonymity. Although cover names can be used, in full network designs

it is necessary that the actors be identified. In this case, the researcher needs to promise and maintain confidentiality.

Another problem occurs when a person who should be part of the sample is not willing to participate. Even if this actor does not participate, he or she may still be nominated by other actors. Deleting this specific actor leads also to ethical concerns, because the data are not representative of the population under study anymore and, therefore, the study becomes biased and of lower quality.

Data visualization is often applied and informative. However, a researcher needs to take care that the actors in the graphs cannot be traced to the specific individuals, for example by limiting the background information in the graph and by making node labels invisible (Borgatti et al., 2013). Merely deleting the names is not enough, as the social structures often make it easy for “insiders” to reveal identities (Palonen & Froehlich, 2020).

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## 7 Resources for Learning More About Social Network Analysis

### Associations, Conferences, Journals

The International Network for Social Network Analysis (INSNA, 2017) is the largest association for social network analysts. It organizes annual, method-focused conferences around the globe—including the international Sunbelt conference and also more local conferences, such as the European Conference on Social Networks (EUSN)—and promotes dedicated journals such as *Connections and Social Networks*. For the purpose of learning more about SNA, the SOcNET list-serv hosted by INSNA is an excellent resource.

### Important Texts

Borgatti et al. (2009) have written an important introductory article about SNA in the social sciences. The book by Wasserman and Faust (1994) is a very complete classic on SNA. Borgatti, Everett, and Johnson (2013), Crossley et al. (2015), and Scott (2000) are important textbooks for (application oriented) social network analysis. Freeman (2004) sketches the development of SNA from a historical perspective. The books by Domínguez and Hollstein (2014) and Froehlich, Rehm and Rienties (2020b) zero in on mixed methods approaches to SNA. As previously mentioned, SNA comes not only with tools for analysis, but also has a strong theoretical foundation of its own. To learn more about theories of networks, the texts of Monge and Contractor (2003) are important starting points.

### Software

A host of different software packages exist to aid in the conduct of social network analysis. One of the most popular stand-alone applications is probably UCINET and its integrated visualization software Netdraw (Borgatti, Everett, & Freeman, 2002). Also, R packages and Python libraries exist for analyses and visualization work—statnet (Karlsson, 2006) and igraph (Csardi & Nepusz, 2006) are often used. In addition

to these rather general applications, specialized software, for example for longitudinal analysis, exist (e.g., SIENA by Ripley, Boitmanis, & Snijders, 2015). Mixed approaches to SNA may not require the emphasis on analysis that all of the mentioned programs have; more visualization oriented software packages like Gephi (Bastian, Heymann, & Jacomy, 2009) or visone (Brandes & Wagner, 2004) are easy to learn alternatives.

A more complete and in-depth overview of software packages in the field of SNA is provided by (Huisman & Van Duijn, 2005).

## REFERENCES

- Agneessens, F., & Everett, M. G. (2013). Introduction to the special issue on advances in two-mode social networks. *Social Networks*, 35(2), 145–147. <https://doi.org/10.1016/j.socnet.2013.03.002>
- Ansell, C., Bichir, R., & Zhou, S. (2016). Who says networks, says oligarchy? Oligarchies as “rich club” networks. *Connections*, 35(2), 20–32. <https://doi.org/10.17266/35.2.2>
- Apkarian, J., Bowler, S., Hanneman, R., & Martin, B. (2015). Donor motivations in the California State Legislature: A social network analysis of campaign contributions. *Connections*, 35(1). <https://doi.org/http://dx.doi.org/10.17266/35.1.3>
- Barbier, G., & Liu, H. (2011). Data mining in social media. In Charu C. Aggarwal (Ed.), *Social Network Data Analytics* (pp. 327–352). Boston, MA: Springer. [https://doi.org/10.1007/978-1-4419-8462-3\\_12](https://doi.org/10.1007/978-1-4419-8462-3_12)
- Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: An open source software for exploring and manipulating networks. *International AAAI Conference on Weblogs and Social Media*.
- Bolfbar, M. (2015). Macro, meso, micro: Broadening the “social” of social network analysis with a mixed methods approach. *Quality & Quantity*, 3, 2217–2236. <https://doi.org/10.1007/s11135-015-0259-0>
- Borgatti, S. P., Everett, M. G., & Freeman, L. C. (2002). *UCInet for Windows: Software for social network analysis*. Harvard, MA: Analytic Technologies.
- Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing social networks*. London, England: Sage.
- Borgatti, S. P., & Halgin, D. S. (2011). On network theory. *Organization Science*, 22, 1168–1181. <https://doi.org/10.1287/orsc.1110.0641>
- Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *Science*, 323(5916), 892–895. <https://doi.org/10.1126/science.1165821>
- Brandes, U., Indlekofer, N., & Mader, M. (2012). Visualization methods for longitudinal social networks and stochastic actor-oriented modeling. *Social Networks*, 34(3), 291–308. <https://doi.org/10.1016/j.socnet.2011.06.002>
- Brandes, U., & Wagner, D. (2004). visone—Analysis and visualization of social networks. In M. Jünger & P. Mutzel (Eds.), *Graph drawing software* (pp. 321–340). Heidelberg, Germany: Springer.
- Brouwer, J. (2017). *Connecting, interacting and supporting. Social capital, peer network and cognitive perspectives on small group teaching*. (Doctoral thesis). University of Groningen, Groningen.
- Brouwer, J., Flache, A., Jansen, E., Hofman, A., & Steglich, C. (2018). Emergent achievement segregation in freshmen learning community networks. *Higher Education*, 76(3), 483–500. doi: [10.1007/s10734-017-0221-2](https://doi.org/10.1007/s10734-017-0221-2)
- Brouwer, J., Jansen, E., Flache, A., & Hofman, A. (2016). The impact of social capital on study success among first-year university students. *Learning and Individual Differences*, 52, 109–118. doi: [10.1016/j.lindif.2016.09.016](https://doi.org/10.1016/j.lindif.2016.09.016)
- Brouwer, J., Jansen, E., Flache, A., & Hofman, A. (2018). Leergemeenschappen en de vorming van hulp- en vriendschapsrelaties van eerstejaarsstudenten in het hoger onderwijs [Learning Communities and the formation of help relationships and friendships of first-year students in higher education]. *Tijdschrift voor Hoger Onderwijs*, 35(4), 52–66.
- Bunt, G. G. V. D., Duijn, M. A. J. V., & Snijders, T. A. B. (1999). Friendship networks through time: An actor-oriented dynamic statistical network model. *Computational & Mathematical Organization Theory*, 5(2), 167–192. <https://doi.org/10.1023/A:1009683123448>
- Burt, R. S. (2005). *Brokerage and Closure: An Introduction to Social Capital*. Oxford, England: Oxford University Press.
- Burt, R. S., Meltzer, D. O., Seid, M., Borgert, A., Chung, J. W., Colletti, R. B., ... Margolis, P. (2012). What’s in a name generator? Choosing the right name generators for social network surveys in healthcare quality and safety research. *BMJ Quality & Safety*, 21(12), 992–1000. <https://doi.org/10.1136/bmjqs-2011-000521>
- Carrington, P. J. (2014). Social network research. In S. Domínguez & B. Hollstein (Eds.), *Mixed methods social networks research: Design and applications* (pp. 35–64). New York, NY: Cambridge University Press.
- Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, 94, S95–S120. <https://doi.org/10.1086/228943>
- Crossley, N., Bellotti, E., Edwards, G., Everett, M. G., Koskinen, J., & Tranmer, M. (2015). *Social network analysis for egonets: Social network analysis for actor-centred networks*. Thousand Oaks, CA: Sage.
- Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal Complex Systems*, 1695.
- Davis, A., Gardner, B. B., & Gardner, M. R. (1941). *Deep South: A social anthropological study of caste and class*. Chicago, IL: University of Chicago Press.
- Dekker, D., Krackhardt, D., & Snijders, T. A. B. (2003). *Multicollinearity robust QAP for multiple-regression*. Nijmegen, The Netherlands.
- Domínguez, S., & Hollstein, B. (2014). *Mixed methods social networks research: Design and applications*. (S. Domínguez & B. Hollstein, Eds.). New York, NY: Cambridge University Press.
- Elo, K. (2015). The content structure of intelligence reports. *Connections*, 35(1). <https://doi.org/10.17266/35.1.2>
- Franke, K., & Wald, A. (2006). Möglichkeiten der Triangulation quantitativer und qualitativer Methoden in der Netzwerkanalyse [Opportunities for triangulating quantitative and qualitative methods in social network analysis]. In B. Hollstein & F. Straus (Eds.), *Qualitative Netzwerkanalyse: Konzepte, methoden, anwendungen [Qualitative network analysis: Concepts, methods, applications]* (pp. 153–175). Wiesbaden, Germany: VS Verlag für Sozialwissenschaften.
- Freeman, L. C. (2000). Visualizing social networks. *Journal of Social Structure*, 1.
- Freeman, L. C. (2004). *The development of social network analysis*. Vancouver, Canada: Empirical Press. Retrieved from <http://aris.ss.uci.edu/lin/book.pdf>



- Frieling, M., & Froehlich, D. E. (2017). Homophilie, diversity und feedback: Eine soziale netzwerkanalyse [Homophily, diversity, and feedback: A social network analysis]. In *Internationales Personalmanagement: Rollen—Kompetenzen—Perspektiven. Implikationen für die Praxis [International human resource management: Roles—competencies—perspectives]*. Wiesbaden, Germany: SpringerGabler.
- Froehlich, D. E. (2015). *Old and Out? Age, employability, and the role of learning* (Doctoral thesis). Maastricht, Netherlands: Maastricht University.
- Froehlich, D. E. (2020a). Mapping Mixed Methods Approaches to Social Network Analysis in Learning and Education. In D. E. Froehlich, M. Rehm, & B. C. Rienties (Eds.), *Mixed methods social network analysis: Theories and methodologies in learning and education*. London: Routledge.
- Froehlich, D. E. (2020b). Exploring social relationships in “a mixed way”: Mixed Structural Analysis. In D. E. Froehlich, M. Rehm, & B. C. Rienties (Eds.), *Mixed methods social network analysis: Theories and methodologies in learning and education*. London: Routledge.
- Froehlich, D. E., Beusaert, S. A. J., Segers, M. S. R., & Gerken, M. (2014). Learning to stay employable. *Career Development International*, 19(5), 508–525. <https://doi.org/10.1108/CDI-11-2013-0139>
- Froehlich, D. E., Galey, S., Mejeh, M., & Schoonenboom, J. (2020). Integrating units of analysis: Applying mixed methods social network analysis. In D. E. Froehlich, M. Rehm, & B. C. Rienties (Eds.), *Mixed methods social network analysis: Theories and methodologies in learning and education*. London: Routledge.
- Froehlich, D. E., Mamas, C., & Schneider, H. W. (2020). Automation and the journey to mixed methods social network analysis. In D. E. Froehlich, M. Rehm, & B. C. Rienties (Eds.), *Mixed methods social network analysis: Theories and methodologies in learning and education*. London: Routledge.
- Froehlich, D. E., & Messmann, G. (2017). The social side of innovative work behavior: Determinants of social interaction during organizational innovation processes. *Business Creativity and the Creative Economy*, 3(1). <https://doi.org/10.18536/bcce.2017.10.3.1.03>
- Froehlich, D. E., Rehm, M., & Cornelissen, F. (Forthcoming). *Investigating Informal Learning via Social Media using Mixed Methods Social Network Analysis: A Case Study. MedienPädagogik: Zeitschrift Für Theorie Und Praxis Der Medienbildung*.
- Froehlich, D. E., Rehm, M., & Rienties, B. C. (2020a). Mixed Methods Social Network Analysis. In D. E. Fröhlich, M. Rehm, & B. C. Rienties (Eds.), *Mixed methods social network analysis: Theories and methodologies in learning and education*. London: Routledge.
- Froehlich, D. E., Rehm, M., & Rienties, B. C. (2020b). *Mixed methods social network analysis: Theories and methodologies in learning and education*. London: Routledge.
- Froehlich, D. E., Van Waes, S., & Schäfer, H. (2020). Linking Quantitative and Qualitative Network Approaches: A Review of Mixed Methods Social Network Analysis in Education Research. *Review of Research in Education*, 44(1), 244–268. <https://doi.org/10.3102/0091732X20903311>
- Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, 78(6), 1360–1380. <https://doi.org/10.1086/225469>
- Harris, J. K., Louis, S., & Baker, E. A. (2014). Employment networks in a high-unemployment rural area. *Connections*, 34(1&2). <https://doi.org/10.17266/34.1.1>
- Herz, A., Peters, L., & Truschkat, I. (2014). How to do qualitative structural analysis: The qualitative interpretation of network maps and narrative interviews. *Forum Qualitative Sozialforschung/Forum: Qualitative Social Research*, 16(1). <https://doi.org/10.17169/fqs-16.1.2092>
- Hollstein, B. (2011). Qualitative approaches to social reality: The search for meaning. In J. Scott & P. J. Carrington (Eds.), *The Sage handbook of social network analysis* (pp. 404–416). London: Sage Publications.
- Hollstein, B. (2014). Mixed methods social networks research: An introduction. In S. Domínguez & B. Hollstein (Eds.), *Mixed methods social networks research: Design and applications* (pp. 3–34). New York, NY: Cambridge University Press.
- Hollstein, B., & Pfeffer, J. (2010). Netzwerkkarten als Instrument zur Erhebung egozentrierter Netzwerke [Network maps as instrument to collect data of egocentric networks]. In *Unsichere Zeiten* (pp. 1–13). Wiesbaden, Germany: VS Verlag für Sozialwissenschaften.
- Hommel, J., Rienties, B. C., Grave, W. de, Bos, G., Schuwirth, L., & Scherpbier, A. (2012). Visualising the invisible: A network approach to reveal the informal social side of student learning. *Advances in Health Sciences Education*, 17(5), 743–757. <https://doi.org/10.1007/s10459-012-9349-0>
- Hotchkiss, J. L., Moore, R. E., & Pitts, M. M. (2006). Freshman learning communities, college performance, and retention. *Education Economics*, 14(2), 197–210. <https://doi.org/10.1080/09645290600622947>
- Huisman, M., & Van Duijn, M. A. J. (2005). Software for social network analysis. *Models and Methods in Social Network Analysis*, 270, e316.
- INSNA. (2017). International network for social network analysis. Retrieved October 24, 2017, from [www.insna.org/](http://www.insna.org/)
- Kadushin, C. (2012). *Understanding social networks: Theories, concepts, and findings*. Oxford, England: Oxford University Press.
- Kahn, R. L., & Antonucci, T. C. (1980). Convoys over the life course: attachment, roles, and social support. In P. B. Baltes & O. Brim (Eds.), *Life span development and behavior* (Vol. 3) (pp. 253–286). New York, NY: Academic Press.
- Karlsson, A. (2006). statnet: Software tools for the representation, visualization, analysis and simulation of network data. *Journal of Statistical Software*, 17, 1–11. <https://doi.org/10.18637/jss.v069.i12>
- Krackhardt, D. (1992). A caveat on the use of the quadratic assignment procedure. *Journal of Quantitative Anthropology*, 3(4), 279–296.
- Krackhardt, D., & Kilduff, M. (1999). Whether close or far: Social distance effects on perceived balance in friendship networks. *Journal of Personality and Social Psychology*, 76(5), 770–782. <https://doi.org/10.1037//0022-3514.76.5.770>
- Laumann, E. O., Marsden, P. V., & Prensky, D. (1983). The boundary specification problem in network analysis. In R. S. Burt & E. Minor (Eds.), *Applied network analysis: A methodological introduction* (pp. 18–87). Beverly Hills, CA: Sage.
- Lazarsfeld, P. F., & Merton, R. K. (1954). Friendship as a social process: A substantive and methodological analysis. In M. Berger (Ed.), *Freedom and control in modern society* (pp. 18–66). New York, NY: Van Nostrand.

- Lomi, A., Snijders, T. A. B., Steglich, C. E. G., & Torló, V. J. (2011). Why are some more peer than others? Evidence from a longitudinal study of social networks and individual academic performance. *Social Science Research*, 40(6), 1506–1520. <https://doi.org/10.1016/j.ssresearch.2011.06.010>
- Marsden, P. V., & Campbell, K. E. (1984). Measuring tie strength. *Social Forces*, 63(2), 482–501. <https://doi.org/10.2307/2579058>
- McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, 27, 415–444. <https://doi.org/10.1146/annurev.soc.27.1.415>
- Mercken, L., Snijders, T., Steglich, C., Vartiainen, E., & de Vries, H. (2010). Dynamics of adolescent friendship networks and smoking behavior. *Social Networks*, 32(1), 72–81. <https://doi.org/10.1016/j.socnet.2009.02.005>
- Monge, P. R., & Contractor, N. S. (2003). *Theories of communication networks*. New York, NY: Oxford University Press.
- Onwuegbuzie, A. J., & Hitchcock, J. H. (2015). Advanced mixed analysis approaches. In S. Hesse-Biber & R. B. Johnson (Eds.), *The Oxford handbook of multimethod and mixed methods research inquiry* (pp. 275–295). New York, NY: Oxford University Press.
- Palonen, T., & Froehlich, D. E., Van Waes, S., & Schäfer, H. (2020). Linking Quantitative and Qualitative Network Approaches: A Review of Mixed Methods Social Network Analysis in Education Research. *Review of Research in Education*, 44(1), 244–268. <https://doi.org/10.3102/0091732X20903311>, D. E. (2020). Mixed-Methods Social Network Analysis to Assist HR Practices and Consultancy. In D. E. Froehlich, D. E., Van Waes, S., & Schäfer, H. (2020). Linking Quantitative and Qualitative Network Approaches: A Review of Mixed Methods Social Network Analysis in Education Research. *Review of Research in Education*, 44(1), 244–268. <https://doi.org/10.3102/0091732X20903311>, M. Rehm, & B. C. Rienties (Eds.), *Mixed methods social network analysis: Theories and methodologies in learning and education*. London: Routledge.
- Pentland, A., & Heibeck, T. (2010). *Honest signals: How they shape our world*. Boston, MA: MIT Press.
- Prell, C. (2012). *Social network analysis: History, theory and methodology*. SAGE.
- Putnam, R. D. (2001). *Bowling alone: The collapse and revival of American community*. New York, NY: Simon and Schuster.
- Rienties, B. C., Hélot, Y., & Jindal-Snape, D. (2013). Understanding social learning relations of international students in a large classroom using social network analysis. *Higher Education*, 66(4), 489–504. <https://doi.org/10.1007/s10734-013-9617-9>
- Rienties, B. C., Johan, N., & Jindal-Snape, D. (2015). Bridge building potential in cross-cultural learning: A mixed method study. *Asia Pacific Education Review*, 16(1), 37–48. <https://doi.org/10.1007/s12564-014-9352-7>
- Ripley, R., Boitmanis, K., & Snijders, T. A. B. (2015). *Siena—Simulation investigation for empirical network analysis*. Oxford: University of Oxford.
- Robins, G., Pattison, P., Kalish, Y., & Lusher, D. (2007). An introduction to exponential random graph (p\*) models for social networks. *Social Networks*, 29(2), 173–191. <https://doi.org/10.1016/j.socnet.2006.08.002>
- Schoch, D., & Brandes, U. (2016). Re-conceptualizing centrality in social networks. *European Journal of Applied Mathematics*, 27(06), 971–985. <https://doi.org/10.1017/S0956792516000401>
- Scott, J. (2000). *Social network analysis: A handbook*. Thousand Oaks, CA: Sage Publications.
- Smith, J. A., & Moody, J. (2013). Structural effects of network sampling coverage I: Nodes missing at random. *Social Networks*, 35(4), 652–668. <https://doi.org/10.1016/j.socnet.2013.09.003>
- Smith, J. A., Moody, J., & Morgan, J. H. (2017). Network sampling coverage II: The effect of non-random missing data on network measurement. *Social Networks*, 48, 78–99. <https://doi.org/10.1016/j.socnet.2016.04.005>
- Smith, S. S. (2013). Social network boundaries and tricky to access populations: A qualitative approach. *International Journal of Social Research Methodology*, 17(6), 613–623. <https://doi.org/10.1080/13645579.2013.820076>
- Snijders, T. A. B., van de Bunt, G. G., & Steglich, C. E. G. (2010). Introduction to stochastic actor-based models for network dynamics. *Social Networks*, 32(1), 44–60. <https://doi.org/10.1016/j.socnet.2009.02.004>
- Srivastava, J. (2008). Data mining for social network analysis. In *2008 IEEE International Conference on Intelligence and Security Informatics* (pp. xxxiii–xxxiv). <https://doi.org/10.1109/ISI.2008.4565015>
- Valente, T. W. (1996). Social network thresholds in the diffusion of innovations. *Social Network*, 18(95), 69–89. [https://doi.org/10.1016/0378-8733\(95\)00256-1](https://doi.org/10.1016/0378-8733(95)00256-1)
- Van Der Gaag, M., Snijders, T. A. B., & Flap, H. D. (2008). Position generator measures and their relationship to other social capital measures. In N. Lin & B. Erickson (Eds.), *Social capital: An international research program* (pp. 27–48). Oxford, England: Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780199234387.001.0001>
- Verbrugge, L. M. (1977). The structure of adult friendship choices. *Social Forces*, 56(2), 576–597. <https://doi.org/10.1093/sf/56.2.576>
- Vlegels, J., & Lievens, J. (2015). Music genres as historical artifacts: The case of classical music. *Connections*, 35(1). <https://doi.org/10.17266/35.1.4>
- Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. New York, NY: Cambridge University Press.
- Wellman, B. (1983). Network analysis: Some basic principles. *Sociological Theory*, 1(1), 155–200.
- Yang, C., Latkin, C., Muth, S. Q., & Rudolph, A. (2013). Injection drug users' involvement in drug economy: Dynamics of sociometric and egocentric social networks. *Connections*, 33(1), 24–34. <https://doi.org/10.1097/MPG.0b013e3181a15ae8.Screening>
- Zhao, C.-M., & Kuh, G. D. (2004). Adding value: Learning communities and student engagement. *Research in Higher Education*, 45(2), 115–138. <https://doi.org/10.1023/B:RIHE.0000015692.88534.de>



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