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Social Network Analysis in the Science of Groups: Cross-Sectional and Longitudinal Applications for Studying Intra- and Intergroup Behavior

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Social scientists increasingly recognize the potential of social network analysis, which enriches the explanation of human behavior by explicitly taking its social structure into account. In particular for the science of groups, social network analysis has reached a point of analytic refinement that makes it a valuable tool for investigating some of the central mechanisms that underlie intra- and intergroup behavior. The present article highlights the general relevance of this scientific approach and describes the background, generation, and application of cross-sectional as well as longitudinal network statistics that are of specific interest to group researchers. In doing so, we aim to provide a general introduction for researchers new to this approach, while demonstrating the potential and limitations of social network analysis for different areas in this field.

Keywords: group research, intergroup behavior, intragroup behavior, social network analysis

Recent conceptual, empirical, and technical advancements have facilitated a growing interest in social network analysis (SNA). This scientific approach structures ties between network members through certain interdependencies and assumes that these interdependencies explain something about the network members (Borgatti, Mehra, Brass, & Labianca, 2009). Whereas ties can be based on affiliations (kinship, friendship), similarities (comembership, co-occurrence), interactions (cooperation, communication) or the flow of resources (information, material), network members include all kinds of entities such as individuals, small groups, institutions, cities, or even concepts in semantic networks.[1] A complete social network contains a quantity of members with incoming and outgoing ties (see left side of Figure 1). If our information is limited to someone's connections to other network members and does not include, in turn, their interconnections, then this would represent a so-called ego-network (see right side of Figure 1). An ego-centered network is still valuable for some research analyses, such as the investigation of an individual's general embeddedness, but it is less comprehensive and thereby lacks many analytic possibilities with regard to the investigation of structural patterns.

In accordance with the definition of SNA, network theory highlights the importance of relationships, interdependencies, or intermediating processes for explaining the behaviors of network members, above and beyond their individual characteristics (Borgatti & Halgin, 2011). That is, how things are structured in the social network is assumed to determine the flow between, the power of, and the coordination among network members, which—in combination with their individual characteristics—explains the behaviors of the network members to some extent. The most advanced network

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[1] In line with the scope of this journal, our conceptualization of network members will focus on individuals.

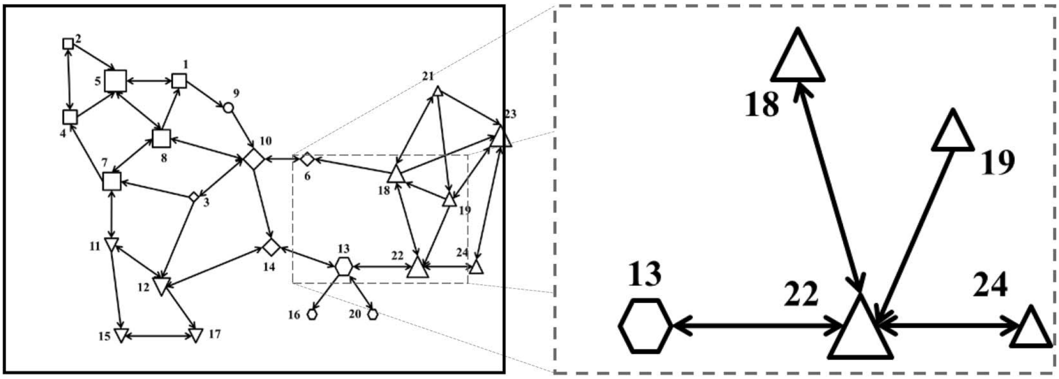


Figure 1. Left: Complete social network; Right: Ego network of network member #22. Nodes represent network members whose size is proportional to their indegree and whose shape denotes their group membership (the circle is an isolate with no group); lines represent relationships that are connected by double-headed arrows in case of mutual relationships.

theoretical approach explicates the flow between network members and is rooted in the strength of weak ties theory (Granovetter, 1973) and the structural holes theory (Burt, 1992). Both network theories emphasize the value of atypical connections, which tend to connect dissimilar others that are more likely to exchange novel information, attitudes, or resources. Independently of their specific focus, the core idea of all network theories is the same: structure matters.

SNA allows researchers to examine naturally existing social structures, which is especially useful for studying human behavior. A social structure among human beings evolves based on internal mechanisms (e.g., homophily for individual attributes; McPherson, Smith-Lovin, & Cook, 2001) as well as external mechanisms (e.g., sociostructural conditions such as proximity; Preciado, Snijders, Burk, Stattin, & Kerr, 2012). The resulting social network will, in turn, socialize attitudes, beliefs, and behavior via norms that spread among individuals across their interrelating ties (Brechwald & Prinstein, 2011). Therefore, considering this social structure and its dynamic is a beneficial perspective for understanding, predicting, and explaining human behavior.

In particular for the field of group research, SNA represents a valuable approach for studying both the social structure that channels intra- and intergroup relations, and the processes that underlie them. Its psychometric properties enable scientists (a) to consider more objective information, which relies on a comprehensive amount of relational data that is produced by different sources; (b) to specify complex patterns of relationships covering indirect, transitive, and intermediate connections; (c) to capture the social influence processes operating within the interdependencies of a network; (d) to identify latent social-psychological entities such as peer groups or cliques; and (e) to examine the structure of, and investigate effects across, different levels including the individual, the group, and the entire social network. In this article, we will explain these unique methodological features in more detail and illustrate how SNA could enrich different areas of group research including social identity, conformity, leadership, group decision making, group performance, group socialization, intergroup contact, and in-group versus out-group behavior.

The basic idea of the social network perspective—that behavior is a function of both individual dispositions as well as the social structure human beings are embedded within—is, in fact, far from new. To our knowledge, the first social network study was conducted in 1880–81 (see Delitsch, 1900; for a recent reanalysis see Heidler, Gamper, Herz, & Eßer, 2014). Driven by the idea: “Tell me who you interact with, and I will tell you who you are,” (pp. 150–151, our translation from German[2]), Delitsch’s pioneering work used relational data

[2] Original quote: “Sage mir, mit wem Du umgehst, so will ich Dir sagen, wer Du bist.”

to explain the friendship formation among 53 students of a German school class with the help of different network parameters. Later, Moreno (1934) furthered the scientific applicability of SNA by demonstrating its potential to explain network members' behavior—in this case, a spike in the number of runaways at a boarding school for girls in New York. Thereafter, it took about 30 years until sociologists started to use SNA systematically, and another 20 to 30 years before this approach became established in other research fields (for a detailed historical introduction see Freeman, 2004).

Nowadays, SNA is of substantial importance in psychology, as evidenced from a literature review that we conducted recently (as of January 2014). In PsycINFO, we searched for articles with "social network analysis" or "social network analyses" as a keyword and found a continuous increase in the five-yearly number of published network papers from 10 (from 1970–74) to 2,430 (from 2010–2014). This rising application of social network research is based on statistical advances over recent years and the complexity of analysis that they permit. While Delitsch (1900) needed 20 years from data assessment to publication, complex calculations with and detailed visualizations of large network graphs takes a matter of seconds today. These improved statistical possibilities also stimulate conceptual and empirical advancements (e.g., SIENA; see section on longitudinal applications), which in turn attract more scientific attention.

SNA has now reached a level of conceptual and statistical refinement that makes it an appealing method for all research fields that aim to explain behavior in general and social behavior within and between groups in particular. In fact, researchers, in particular in organization science, started to use this approach and have advanced our understanding of groups, as summarized in seminal reviews (Borgatti & Foster, 2003; Brass, Galaskiewicz, Greve, & Tsai, 2004; Burt, Kilduff, & Tasselli, 2013). However, despite promising developments in some fields, SNA is still underused in the science of groups, which is in part attributable to the largely unknown analytic possibilities this approach offers. Hence, in the present article, we seek to explicate classic and new network-analytic techniques that would allow us to enrich different topics in group research. For this purpose, we organize this article around the introduction of a large variety of well-established network parameters and procedures—broadly classified into cross-sectional and longitudinal network applications—that are of specific interest to this field. After a general introduction of cross-sectional and longitudinal network applications, we will provide a brief explanation of different network statistics, including procedural information about how they are generated, and demonstrate their application to illustrative topics in group research. This overview of network applications is not exhaustive, but rather a selection that aims to highlight the strong potential of SNA to shed light on open research questions within the science of groups.

Cross-Sectional Applications

In general, cross-sectional forms of SNA are useful to study precisely the social structure of networks. In this regard, the main questions concern (a) who is directly or indirectly connected to whom, (b) which substructures exist, and (c) how does social influence spread among the interrelated network members within the overall social network? To address these research objectives, network analysts have to be clear about the network boundary. Having a well-defined boundary does not only specify the elements for the data assessment, but also ensures that we capture the actual population to which we want to generalize our findings. Network boundaries can occur naturally (e.g., school class, neighborhood, business company) or need to be defined by the researcher (e.g., a specific subgroup of interest). Whenever possible, researchers should consider more than one network (e.g., studying many school classes that form separate social networks) to test the robustness and increase the external validity of their revealed network effects. These comparisons within and across different social networks represent possible study designs for inter- and intragroup researchers. However, it should be noted that the network boundary does not have to be the group boundary. The identification of substructures—either by means of SNA (e.g., peer groups within a school class) or external attributes (e.g., gender, ethnic background)—also allows intergroup comparisons within one social network, which are of specific interest to small-group researchers.

Once group researchers have specified the network boundary, different forms of data allow the elicitation of social networks. These include questionnaires, observations, or archival analysis that assesses some kind of interdependency information. The most common and economical method is a brief and simple questionnaire that asks all network members to nominate other network members with respect to one or more forms of connection (e.g., friendship). Usually with the help of a roster that lists all network members, participants nominate each other either on an open-ended list (e.g., *Who are your friends?*) or by applying a limited nomination procedure (e.g., *Who are your five best friends?*). Network scientists debate about the relative advantage of these two assessment techniques (cf., Cillessen, 2009), but additional data gained from unlimited nomination procedures do not necessarily result in improved information about the network (Frederickson & Furnham, 1998), especially in small social networks such as a school class. Depending on the nature of assessed ties, network information can capture very different types of connections. Although most research focuses on friendship or other positive interdependencies like cooperation, there is an increasing interest in studying negative forms of connections such as disliking, bullying behavior, or intergroup conflict (Labianca & Brass, 2006; Labianca, Brass, & Gray, 1998; Huitsing et al., 2012). These connections can be assessed on a binary level (tie is present or absent), ordinal level (tie is negative, neutral, or positive), or interval level scaling format (tie is evaluated on an equidistant scale), but binary connections represent the most common scaling format in SNA and are the required input data for the majority of network statistics (Hanneman & Riddle, 2005).

After all network data have been collected, the information is entered into statistical programs as directed or undirected graphs. Whereas directed graphs specify the relation between network members and can distinguish whether A nominates B, B nominates A, or whether A and B are reciprocally connected (see Figure 1), undirected graphs only indicate the existence or absence of a connection between two members. As a matter of course, directed graphs contain not only more, but also more valuable information that is of specific interest for many research questions.[3] From the variety of established statistical programs for the cross-sectional analysis of social networks, we personally recommend the R package sna (Butts, 2008) and the UCINET Software (Borgatti, Everett, & Freeman, 2002), which both allow the calculation of all network parameters and procedures presented below. Helpful software tools to visualize social networks are NetDraw (Borgatti, 2002) for small to medium large networks and Pajek for larger networks (Batagelj & Mrvar, 1998). More detailed conceptual and practical information about cross-sectional SNA can be found in the seminal book by Wasserman and Faust (1994) as well as in the instructive manual by Hanneman and Riddle (2005).

Usually, a social network includes different analytic levels. These can typically be categorized as micro-, meso-, and macrolevel or, in network terms, as individual, group, and network level, which structure the following presentation of cross-sectional network statistics and their application to relevant issues in group research.

Individual Level

N-step ego networks. This information specifically addresses an individual's connections in the network, with *n* specifying the number of linking steps from ego. That is, a *1-step ego network* illuminates ego's direct connections (see right side of Figure 1), whereas a *2-step ego network* illuminates ego's direct and extended connections by additionally determining the connections of ego's connections.

The detailed identification of ego's embeddedness within the social network provides researchers with helpful data for studying intergroup contact, in particular extended contact, which refers to the amount of out-group contact that someone's in-group friends have (Wright, Aron, McLaughlin-Volpe, & Ropp, 1997). The assessment of extended contact may be inaccurate when relying on self-reports, because indi-

[3] However, it may be worth symmetrizing data to undirected graphs in some cases. For example, undirected graphs increase the likelihood of an overall connectedness and thereby facilitate the estimation of some network parameters (e.g., closeness, explained below).

viduals are likely to have difficulties in reporting accurate information concerning the friends of their ingroup members. However, initial studies demonstrate that network data can enrich the assessment of extended contact, either with 2-step ego networks (Munniksma, Stark, Verkuyten, Flache, & Veenstra, 2013) or with a combination of network and self-reported contact data in 1-step ego networks (Wölfer & Hewstone, 2014). More specifically, the latter study used SNA to compute reciprocal friendship patterns between classmates of the same in-group (i.e., A likes B and B likes A). This more objective assessment of contact advances standard self-reports that merely consider an individual's unidirectional perspective. Then, within each 1-step ego network, the authors averaged the degree of out-group contact that these identified in-group friends reported in a separate questionnaire, which precisely meets the above mentioned definition of extended contact. These research efforts represent a promising starting point that facilitates the examination of extended intergroup contact as well as its relation to further topics in group research such as intergroup prejudice or discrimination.

Network centrality. Within the scope of group research, another application of SNA on the individual level concerns the analysis of network centrality or the social status of network members. Established centrality parameters are the *degree centrality* (Freeman, 1979), *Bonacich's centrality measure* (Bonacich, 1987), *closeness* (Freeman, 1979), and *betweenness* (Freeman, 1977), each of which captures a very specific aspect of social status.

The degree centrality quantifies a network member's number of connections or in directed graphs the number of incoming ties (indegree) and outgoing ties (outdegree). In Figure 1, individuals are sized by their indegree, which indicates that the network members #5, #10, #22, and #23 are the socially most central network members in this regard.[4] An extension of the degree centrality represents Bonacich's centrality measure. Although member #6 and #15 have the same indegree, with two connections each, they are not equally important within the social network of Figure 1, because the direct connections of #6 (i.e., #10 & #18) are, in turn, more strongly connected to other network members than are the direct connections of #15 (i.e., #11 & #17). Bonacich's centrality measure takes these indirect relations into account by considering the number of someone's connections and the number of connections from those to whom someone is connected. Another conceptually different centrality parameter represents closeness that indicates spatial centrality within the social network. The closeness parameter specifies the sum of geodesic distance, which is the total number of least necessary steps from a network member to all other network members. Network members with a high closeness score, like #14 in Figure 1, are—independently of the number of connections—important to the extent that they have good reachability for and to every member of the social network. Finally, sometimes network members are important to the extent that, although they are neither strongly connected, nor central, many members depend on them to make connections to others, like member #13 in Figure 1. This idea is reflected with the betweenness parameter that indicates someone's linking role within the social network or the extent to which the social network would separate without this network member. Even though these centrality parameters differ conceptually, they tend to have a moderate to strong empirical overlap (Valente, Coronges, Lakon, & Costenbader, 2008). Therefore, to avoid conceptual redundancies or statistical multicollinearity, it is advisable to concentrate on one network centrality parameter, which is best suited to operationalize the respective research question.

The detailed examination of network centrality with a broad variety of different parameters allows intragroup researchers to generate useful variables that can further our understanding of social influence processes and the consequential behavior within groups. For example, in research on decision making in groups, ties can be structured via the extent to which group members exchange information. The corresponding centrality in these networks specifies the amount of information that an individual possess, which has been found to positively predict

[4] Technically speaking, researchers do not need SNA to generate this parameter, but can simply count the number of connections by using other statistical programs. However, many network statistics build on the degree centrality, for which it is important to be familiar with this concept.

this member's influence on the group decision (Kameda, Ohtsubo, & Takezawa, 1997). Moreover, centrality in friendship networks reflects popularity, which allows researchers to identify salient network members, who—depending on their degree of prosocial behavior—exert either positive influence by reducing prejudice (Paluck, 2011) or negative influence by victimizing less powerful peers (Wölfer & Scheithauer, 2014). Furthermore, centrality in advice networks provides valuable information for studying the antecedents and consequences of leadership behavior. More specifically, individuals who are active in giving and receiving advice, are perceived as charismatic leaders, whose presence is, in turn, positively associated with the overall group performance (Balkundi, Kilduff, & Harrison, 2011). Besides pursuing these valuable lines of research, further applications are possible, in which group researchers could make use of network centrality measures in order to explore different aspects of intragroup behavior. Given that network centrality parameters provide insights into the social influence individuals exert, it is plausible that this information assists, for example, the examination of processes related to minority and majority influence. That is, individuals' degree of influence within the social network can be determined precisely and, depending on the measured social importance and structural influence possibilities of majority versus minority group members, related to the likelihood of different attitude change processes (Kelman, 1958).

Group Level

Beyond the individual level, network members appear together in clusters with stronger in-group than out-group connections and consequently form the next mode: the group level. This latent social structure can be identified exclusively by means of SNA, which, comparable with a cluster analysis, determines the strongest connections within the social network. In the course of this analysis, researchers can also identify isolates that do not belong to any group. Figure 1, in which network members' shape denotes their group membership, reveals a network composition of five groups and one isolate (network member #9).

Social groups can be extracted in many different ways, but two common methods are the *social–cognitive mapping* (Cairns, Cairns, Neckerman, Gest, & Gariépy, 1988) for data produced with a group nomination technique and the *hierarchical clique clustering approach* (Everett & Borgatti, 1998) for data produced with an individual nomination technique. With the social–cognitive mapping, participants are asked to name all groups (e.g., students who frequently spend time with each other) within their social network including those of which they are a member as well as those they do not belong to. For example, Amy can nominate the group 'Sarah, Michele, and Amy' as well as the group 'Sean, Michael, and Jack.' For the subsequent group extraction, data will be arranged in a matrix that plots all network members against each other. The cells of this matrix summarize the frequency with which two individuals were named as belonging to the same group. The next step intercorrelates all columns of this matrix to specify the correspondence of this co-occurrence between two network members, while network members with a significantly intercorrelated co-occurrence are grouped together. And finally, non-overlapping groups are identified by determining the best-fitting structure of discrete clusters. More detailed procedural information on this approach can be found in Cairns and colleagues (1988) as well as in Gest, Farmer, Cairns, and Xie (2003).

The hierarchical clique clustering approach is based on the analytic unit of a clique, which is defined as the maximum number of network members who have all possible ties present among each other (Luce & Perry, 1949). That is, if A is connected to both B and C, which are in turn connected among each other, then A, B, and C would constitute a clique. The concept of cliques is very precise, but it allows for multi-group membership, so that the hierarchical clique clustering approach is used in order to produce non-overlapping groups. Comparable to the social–cognitive mapping, this approach starts with a matrix that summarizes the clustered co-occurrence of network members. With this matrix, non-overlapping groups are produced by creating a maximally large group of network members that were all co-members within a previous clique. Hence one can think of this procedure as a meta-clique approach, in which co-membership is used for group extraction in the same way as ties are used for clique extraction.

Social network statistics on the group level are appealing to both intra- and intergroup researchers. The group structure per se already contains important information, and the presented methods that extract these latent social entities equip researchers to objectively identify and subsequently analyze this structure of interest. Extracting the group structure has already been used in previous intra- and intergroup research. Poteat (2007), for example, identified peer groups to investigate homophobic attitudes and behavior on this contextual level and revealed a strong group socializing effect. That is, being a member of a homophobic peer group positively predicted individuals' future degree of homophobia, while controlling for individuals' own homophobic attitudes and behavior. Moreover, the group structure can also advance research on in-group versus out-group behavior, because it allows researchers to determine structural group patterns within social networks (e.g., peer groups in a school class) and analyze how and why individuals favor their own group over other groups (Tarrant, 2002). At the same time, information regarding the group structure promises to enrich yet unexplored areas in this regard including the development of social identity (cf., Tajfel & Turner, 1979), normative conformity (cf., Deutsch & Gerard, 1955), or information exchange and decision making in groups (cf., Stasser & Titus, 1985). For example, a better understanding of individuals' group membership helps in studying the extent to which their social identity is formed through group experiences in their social network. Moreover, given that conformity is shaped by the direct influence of close network members, it is useful to identify individual's closest members in a network. Finally, social network data equip researchers to examine the flow of information with regard to the role of group members' motivations (cf., Faulmüller, Mojzisch, Kerschreiter, & Schulz-Hardt, 2012) or to disentangle individual- and group-level factors that are responsible for the process of group decision making (cf., Faulmüller, Kerschreiter, Mojzisch, & Schulz-Hardt, 2010).

Network Level

The final level, the network, refers to the macro mode and describes the overall structure of the social network. The purpose of graph-level parameters is twofold: On the one hand, they serve as important control variables for researchers, who analyze connections across different social networks and, on the other hand, they allow researchers to examine the contextual routes along which social influence may spread. Besides established graph-level parameters, such as *density*, *reciprocity*, and *centralization*, the *E-I index* (Krackhardt & Stern, 1988) is of specific value for group researchers.

Density reflects the overall connectedness within a network by relating the number of existing ties to the number of theoretically possible ties between all network members. Reciprocity specifies the number of mutual relationships by measuring the extent of bidirectional connections. Centralization indicates the variance of centrality within a social network by determining the difference in the network members' number of connections (i.e., the degree centrality). And finally, the E-I Index captures the contextual network connectedness between two groups by subtracting the number of out-group ties from the number of in-group ties and dividing this difference by the total number of ties.

These parameters enable researchers to study important areas of group research. For example, the conceptualization of groups as information-processing systems that derive decisions based on the extent to which their members share cognitions or preferences (Mojzisch, Kerschreiter, Faulmüller, Vogelgesang, & Schulz-Hardt, 2014; Tindale & Kameda, 2000) implies that graph-level parameters in information networks serve as useful measures. In particular, density and reciprocity allow researchers to capture this overall sharedness and the way it structures the spread of social influence. Moreover, centralization has the potential to inform research about hierarchies within and between groups and the consequential intra- and intergroup behavior. The distinction between equally powered networks and hierarchical networks provides valuable contextual information that helps to predict network members' social behavior. For example, social dominance orientation and the related likelihood of intergroup prejudice changes across social contexts as a function of the existing inequalities between groups (Pratto, Sidanius, & Levin, 2006). Finally, the E-I index can enrich intergroup contact research by relating in-group and out-group ties (e.g., ethnic majority vs. ethnic minority group), which precisely specifies the degree of intergroup connectedness within a social network and allows researchers to examine the overall degree of integration or segregation.

Longitudinal Applications

Most social networks are highly flexible systems and the static snapshot at a given moment may change over time. Empirical information concerning the longitudinal evolution of social networks adds to our knowledge of their dynamic structure and the groups they constitute or contain. In this respect, the *stochastic actor-based model* (Snijders, 2001) represents a powerful statistical approach for longitudinal SNA.

This model includes several assumptions, which are central to the understanding of this approach and the interpretation of its estimates. We aim to frame their description as briefly and non-mathematically as possible (for more details see Snijders, 2001; Snijders, van de Bunt, & Steglich, 2010). First, the network change in the stochastic actor-based model is based on a Markov process. This assumption implies that the future network state can be predicted solely as a function of the current network state. Second, changes in the network are made by the network members. This is considered to be a purposeful process, in which individuals strive to maximize their satisfaction with the local network neighborhood. As a result, the actor-based network change is explainable by the attributes and network positions of individuals. Third, the network change takes place continuously between two measurement points. Hence the gradual change can be decomposed into smallest possible units of analysis. These so-called ministeps represent a network member's opportunity to establish, dissolve, or maintain a (non-)relationship. Finally, ministeps never happen simultaneously, but constitute a sequence of chronological elements that allow one network member at a time no more than one opportunity for a tie change. For example, two unconnected network members A and B are not assumed to suddenly become reciprocal friends, but to develop a mutual friendship connection in temporarily successive steps starting with a unidirectional link ($A \rightarrow B$) followed by the reciprocal link ($A \leftrightarrow B$). Building on these assumptions, the stochastic actor-based model explains the network dynamics with the help of the evaluation function, which estimates the tendency of individuals to create or maintain network ties in their local network neighborhood.[5]

As in cross-sectional applications of SNA, researchers need a well-defined network boundary for examining social networks over time and, whenever possible, should aim to consider many different networks to increase the generalizability of their research. With the stochastic actor-based model, it is possible to jointly analyze the dynamic of many different social networks in two ways: Either researchers define structural zeros to indicate the impossibility of ties between members of different social networks or, in a statistically more sophisticated way, they apply multilevel SNA (Snijders & Baerveldt, 2003). The latter approach allows the sequential examination of the micro-level (within-network analyses) and macro-level (between-network analysis). Whereas the micro-level separately determines the estimates across different social networks, the macro-level uses this information for the purpose of separating the error variance from the true variance of the population.

For longitudinal SNA, researchers need at least two waves that assess the social network of individuals within the same network boundary,[6] although, as usual in longitudinal research, the statistical possibilities and analytic power increase with the number of measurement points. The predominant method that is used to elicit longitudinal networks represents the nomination technique of participants by means of questionnaires. This is most likely related to the fact that the stochastic actor-based model requires network members to actively make decisions

[5] The evaluation function is the main element for modeling network change and the focus of this section on longitudinal applications. However, if researchers are further interested in unraveling the tendency to create and maintain ties, the creation or endowment functions can also be modeled. Whereas the creation function examines the preference for establishing new ties, the endowment function examines the aversion for breakoff ties or the preference for maintaining ties, respectively.

[6] In the case of network members entering or leaving the investigated social network between two measurement points, longitudinal SNA allows researchers to model this network composition change statistically (for more details see Huisman & Snijders, 2003).

about the network change, which excludes all entities that are incapable of cognitive processes (e.g., cities or concepts) and all assessment methods used in those cases (e.g., observations or archival analysis). However, among cognitively capable network members, longitudinal network researchers can study all kinds of interdependencies including friendship ties (Snijders et al., 2010), cooperative ties (Lomi, Snijders, Steglich, & Torló, 2011), or conflictual ties (Huitsing et al., 2012), while using a scaling format of binary level.

Social network dynamics can be analyzed in directed and undirected graphs, even though the former allows the researcher to model more effects. This modeling process is implemented in the Simulation Investigation for Empirical Network Analysis (SIENA), which is either embedded within StOCNET (Snijders, Steglich, Schweinberger, & Huisman, 2007) or within the R environment (Ripley, Snijders, Boda, Vörös, & Preciado, 2013). Both of these referenced SIENA manuals include helpful and understandable instructions that clarify the issues of data preparation, software handling, statistical modeling, and interpretation of effects. An advantage of SIENA is the statistically sound integration of individual characteristics, which allows researchers to investigate the longitudinal interplay between social networks and the attributes, attitudes, or behavior of their members. As described in the next two subsections, individual characteristics can be modeled as predictors (network dynamics) or as additional outcome variable (network-behavior dynamics).

Network Dynamics

In its basic form, SIENA focuses on *network dynamics*, which examine the extent to which individual characteristics affect the network formation. This network dynamic is determined with a linear combination of different effects specified with the evaluation function (explained above). One can think of this statistic as a multinomial logistic regression, which estimates the probability that a specific network member will form or maintain a relation to another specific member. Consequently, the respective effects are interpreted as log-odds ratios and, after an exponentiation, as odds ratios. For example, a reciprocity effect with an estimate of 1.5 represents the initial log-odds ratio, which—applied to the exponential function with base e, also known as Euler's number (e^x)—indicates that network members are $e^{1.5} =$ 4.5 times more likely to form or maintain a reciprocated tie compared to an unreciprocated tie. The upper half of Table 1 describes and illustrates the most important SIENA effects for modeling network dynamics.[7]

Network dynamic effects are of two kinds covering structural network effects and covariate effects. Whereas structural network effects capture endogenous network mechanisms, covariate effects estimate the network dynamics based on exogenous factors that describe the network members (e.g., group membership). Structural network effects can be further subdivided into overall network effects (density and reciprocity), network closure effects (transitive triplet and balance), triadic effects (three-cycle and betweenness), and degree-related effects (in-degree popularity and out-degree popularity), whereas covariate effects distinguish attribute effects (covariate alter and covariate ego) from similarity effects (covariate similarity). Beyond these main effects, SIENA enables modeling several interaction terms that either combine different information (Covariate ego × Covariate alter interaction) or test moderating effects (In-degree popularity × Covariate ego interaction). From this variety of available effects, the model specification should be based on the theoretical background and the research question of interest. However, effects that need to be included in every SIENA modeling procedure are density and reciprocity as well as at least one network closure effect (cf., Ripley et al., 2013).

Along these lines, SIENA offers several possible applications for studying the network dynamics within and between groups, which—in comparison with other well-established research methods in this field—specifically consider the structural dynamics of individuals' environments. A possible intragroup research example is the evaluation of group-based interventions that aim to, at least implicitly, modify the social network structure. For example, based on the relevance of social network pro-

[7] For an exhaustive list of available effects see the respective SIENA manuals (cf., Ripley et al., 2013; Snijders et al., 2007).

Table 1
Selection of SIENA Effects for Modeling Network Dynamics and Behavioral Dynamics

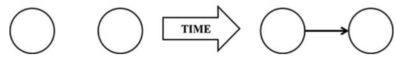
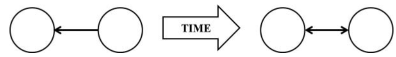
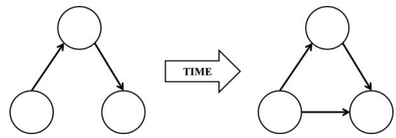
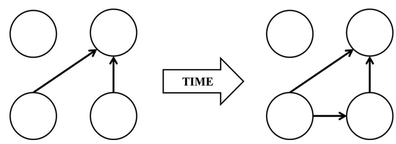
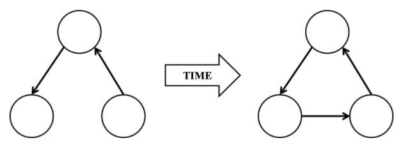
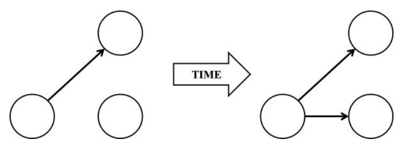
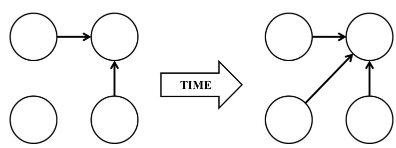
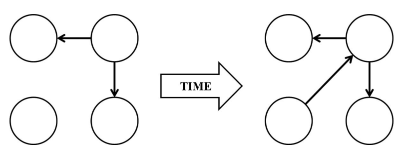
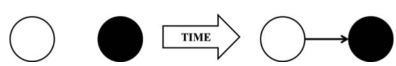
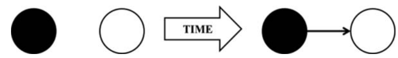
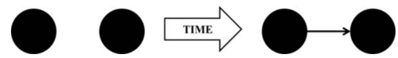
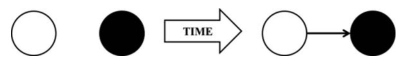
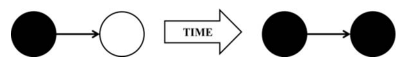
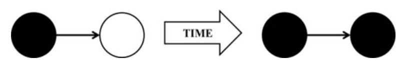
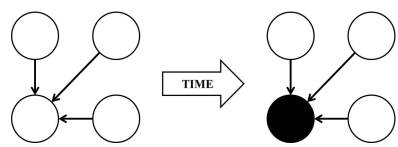
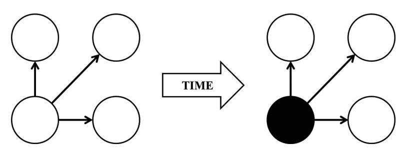
Effect	Description	Illustration
Network dynamics		
Outdegree (Density)	Preference for ties to a random network member (measure of the basic intercept)	
Reciprocity	Preference for ties that respond to an existing unidirectional connection (measure of mutuality)	
Transitive triplets	Preference for ties to network members that are the friends of my friends (measure of network closure)	
Balance	Preference for ties to network members with a similar ego network of existent and non-existent ties (measure of structural equilibrium)	
Three-cycles	Preference for ties that form unidirectional cycles (measure of non-hierarchy or generalized exchange)	
Betweenness	Preference for ties to network members, which are unconnected to each other (measure of a members linking role)	
In-degree popularity	Preference for ties to network members with many incoming ties (measure of status attraction)	
Out-degree popularity	Preference for ties to network members with many outgoing ties (measure of activity attraction)	
Covariate alter	Preference for ties to network members high on the respective covariate (measure of covariate popularity)	

Table 1 (*continued*)

Effect	Description	Illustration
Covariate ego	Preference for ties from network members high on the respective covariate (measure of covariate activity)	
Covariate similarity	Preference for ties to network members with similar values on the respective covariate (measure of homophily)	
Behavior dynamics		
Linear/quadratic shape	Preference to high values/extremes on the behavioral dependent variable (measures of distributional feature)	
Average similarity	Preference for behavioral similarity to connected network members (measure of assimilation)	
Average alter	Preference for high values on the behavioral dependent variable, if connected network members have correspondingly high values (measure of contagion)	
In-degree	Preference of network members with many incoming ties for high values on behavioral dependent variable (measure of status effect)	
Out-degree	Preference of network members with many outgoing ties for high values on behavioral dependent variable (measure of activity effect)	

Note. Black nodes indicate high scores on the covariate or behavioral dependent variable, respectively.

cesses involved in bullying and its prevention, Wölfer and Scheithauer (2014) evaluated the longitudinal network dynamic of a school-based anti-bullying program and revealed the hypothesized effect of bullies' reduced popularity (i.e., network centrality within their class). That is, in contrast to the waiting-control group, bullies in the intervention group experienced a decrease in their popularity and associated social influence due to the program-related change of students' attitudes, norms, and behavior. A possible intergroup research example concerns the examination of network members' group status, which can be defined, for example, by ethnic background, religious belief, or peer-group membership. This analytic application allows testing (a) the influence of a group membership on an individual's network position over time (i.e., whether certain groups become banished to the fringe of the network) and (b) the preference to create or maintain ties to members from the same group (i.e., homophily vs. intergroup contact). These and related group phenomena can be studied longitudinally based on individual characteristics of the network members, which can be modeled with the help of covariate effects and covariate similarity effects (see Table 1).

Network-Behavior Dynamics

The original focus of network dynamics (Snijders, 2001) became quickly enriched by the consideration of *network-behavior dynamics* (Steglich, Snijders, & Pearson, 2010; Veenstra, Dijkstra, Steglich, & Van Zalk, 2013). Behavioral dynamics additionally examine the extent to which the network formation affects individual characteristics. The reason for studying the longitudinal network dynamics together with the changing attributes of their members is grounded in the fact that the network-behavior dynamic is a mutually dependent and coevolving development. This extended stochastic actor-based model allows disentangling selection effects (network dynamics) from socialization effects (behavioral dynamics) and consequently reaches a point of analytic refinement that comes close to the explanation of causal mechanisms.

Analogous to network dynamics, behavioral dynamics happen in the smallest possible units (i.e., ministeps) and only one at a time. Their estimation similarly relies on an evaluation function, which determines the tendency of network members to increase or maintain their score on a behavioral scale. Again, this evaluation function specifies a linear combination of different effects, which can be interpreted similarly to the effects in a multinomial logistic regression. The lower half of Table 1 presents the most important behavioral dynamic effects. These effects can be classified into behavioral tendencies (linear and quadratic shape) and influence effects that are based either on the local network neighborhood (average similarity and average alter) or the overall network position (in-degree and out-degree). In addition, it is possible to include covariate effects for explaining the behavioral dependent variable based on attributes of the network members. In this regard, main effects specify the impact of a covariate on behavioral dynamics, whereas interaction effects allow the examination of moderating effects in influence processes. In any case, it is recommended to include the linear shape effect and, if the behavioral dependent variable is continuous, also the quadratic shape effect (cf., Ripley et al., 2013).

Studying network-behavior dynamics additionally allows researchers to consider the complex interplay of structure and behavior. Compared with other research methods, this analytic feature makes network-behavior dynamics specifically suitable for gaining a better understanding of the longitudinal mechanisms of group socialization. For example, Rulison, Gest, and Loken (2013) revealed a socialization effect among adolescents with regard to their aggressive behavior, indicating that individuals' aggressive behavior is shaped by the aggressive behavior of the peers they are connected to. Moreover, Molano, Jones, Brown, and Aber (2013) found that social cognitions seem to moderate this socialization effect of related peers to the extent that children with high levels of hostile attributional bias are more susceptible to aggressive behavior by their peers. Besides these initial investigations, this network approach has the potential to enrich further issues of group research by examining, for example, the effects of members' network position on the behavioral dependent variable. That is to say, the effects of leadership roles can be studied by examining the development of central members, who occupy such a leadership position within their network, with regard to their psychosocial constitution or well-being. Moreover, researchers can also study individuals' intergroup attitudes depending on the intergroup contact possibilities of their network position. These research applications are analyzable by modeling the influence effects that emanate from one's local network neighborhood (see Table 1).

Discussion

In the present article, we introduced the social network approach to group researchers and highlighted its applicability to their specific scientific interests and objectives. In doing so, we did not focus on a single procedure, but rather presented a broad range of possible applications covering cross-sectional and longitudinal social network methods. These statistics include both recent advancements that are relatively novel (e.g., network-behavior dynamics) as well as already established procedures that are still innovative for the field of group research (e.g., n-step ego networks). We contend that SNA offers the potential to enrich traditional methods of group research, but it is also—as it is true for every method—characterized by some limitations of which researchers need to be aware.

The Potential of Social Network Analysis

Although SNA has already started to make important contributions to group research across different areas (e.g., Balkundi et al., 2011; Molano et al., 2013; Munniksma et al., 2013; Poteat, 2007; Snijders & Baerveldt, 2003; Tindale & Kameda, 2000), it is still a relatively rare approach in this field. This is surprising given its conceptual suitability for studying intra- and intergroup relations, its unique psychometric properties, and its broad applicability to different research questions within the science of groups. As demonstrated throughout the present article, SNA has the potential to provide additional understanding in group research above traditional analyses by explicitly considering the social structure that forms intra- and intergroup relations. Based on comprehensive and more objective information, this social network structure allows researchers to identify complex patterns of relationships, latent social structures, and relevant social influence processes across different social levels. Hence SNA enables group researchers to adequately consider contextual and environmental factors, which—in addition to techniques already applied in this field—can advance scientific knowledge concerning behavior within and between groups. This applies especially to research questions that have not yet received much analytic consideration from a social network perspective; these include, but are not limited to, the development of social identity, use of and susceptibility to social influence, the formation and dissolution of overall intergroup relations, as well as the longitudinal effect of group membership on behavior and vice versa.

Another appealing aspect of SNA concerns its potential to build bridges to other disciplines (see, e.g., the integrative work of Westaby, Pfaff, & Redding, 2014). The main idea of studying the interdependencies and dynamics of a social structure allows researchers to address many classic problems; not only in psychology, but also in sociology, politics, education, economics, linguistics, and engineering. Moreover, even though network researchers in the social sciences pursue somewhat different goals than network researchers in the natural sciences (cf., Borgatti et al., 2009), the general applicability of SNA even includes the fields of biology, zoology, and physics. This fact creates substantive opportunities for scientific interactions or collaborations across different disciplines to further advance the science of groups.

Furthermore, the field of SNA is not only characterized by instructive handbooks, but also by inexpensive software programs. These are obtainable either for a reasonable price or even for free, which allows researchers to become acquainted with the network approach, independently of their available resources. Along these lines, we anticipate further statistical advancements. Many of the currently available techniques resulted from successful efforts that fine-tuned a method to a specific research question. Given the pioneering role of SNA in most fields, different research interests will most likely yield additional improvements that, in turn, inspire conceptual and theoretical advancements.

Limitations

SNA represents a powerful analytic approach, but analyses have to go beyond mere descriptions of the social structure. That is, analyzing network formation (e.g., friendship patterns) becomes much more informative once researchers integrate external information, especially attributes that describe the network members (e.g., their ethnic background), in a conceptually reasonable and statistically sound way. In fact, this point is not necessarily a limitation, but rather an important aspect that needs to be considered when using SNA. Fortunately, as shown throughout this article, SNA offers many ways to consider external information and its successful analytic consideration should be a major challenge.

A second limitation regards the sampling problem. In contrast to conventional sampling procedures, individuals in social networks are not sampled independently, but result from and are exposed to the interdependencies within a certain network boundary. Strictly speaking, each social network, independently of its size, represents only one unit of analysis. Therefore, whenever possible, researchers should aim to study many different social networks simultaneously in order to generalize the observed effects of the network members within a specific boundary.

A third limitation regards the sensitivity of social networks to missing data. Not only does the researcher lose the data of non-participating network members, but their absence—especially in the case of central network members—can dramatically affect the structure of the entire social network (Kossinets, 2006). Notwithstanding analytic possibilities for handling missing data in cross-sectional (Koskinen, Robins, & Pattison, 2010) and longitudinal network research (Huisman & Steglich, 2008), this specific limitation has to be taken into account when planning, conducting, and interpreting social network studies.

Moreover, cross-sectional social network statistics are, in their basic form, based on algorithms and mathematical operations, which do not allow researchers to derive essential information for statistical inference (e.g., standard errors or confidence intervals). Like the outcome variable in experiments, these parameters are of descriptive nature and need to be combined with subsequent inferential statistics in order to test scientific hypotheses. Given the multimodal structure of networks (individuals nested in groups nested in networks), an ideal form of integrating cross-sectional social network data involves the use of multilevel analysis (for a general introduction to multilevel analysis in group science see Hofmann, 1997; for an empirical example see Wölfer, Cortina, & Baumert, 2012).

Although statistical inference is possible when studying longitudinal network dynamics, using a program like SIENA is also not free of limitations, which arise from its underlying assumptions. The Markov assumption—the future state of a network can be solely determined by its previous state—excludes certain types of information as explanatory elements for the network formation such as how long there has been a connection between two network members. However, it is possible to overcome this limitation by including covariate effects, which model relevant data that are not derivable from its previous state.

Moreover, the assumption that network members control their network ties and are consequently sufficiently informed about the network is challenged by research that suggests structural knowledge deficits of network members (cf., Janicik & Larrick, 2005). That is, individuals gather information about the relationships among others around them, which unavoidably becomes less complete with increasing size and complexity of their social network. Although Snijders and colleagues (2010) correctly relativize this limitation by highlighting that this assumption requires network members to be primarily informed about their 2-step ego network, it still needs to be considered when researchers plan to study or interpret network(-behavior) dynamics.

A final limitation of SIENA is that it is restricted to operate on binary networks only, whereas the dynamics of valued network data, which consider more than the existence or absence of a tie, cannot be modeled. Even though this constraint reduces the number of possible research applications, research suggests that the analysis of valued and nonvalued network data leads to comparable results (Bauman, Faris, Ennett, Hussong, & Foshee, 2007).

Conclusion

SNA does not provide the answer to every empirical problem, but it does offer a theoretically profound and methodological powerful approach that can enrich many fields of research, in particular the science of groups. By explicitly taking its social structure into account, SNA represents a valuable approach for examining some of the central mechanisms that underlie the behavior within and between groups. We look forward to future studies in this field that shed light on open research questions or deepen our understanding of group phenomena from this additional scientific perspective.

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