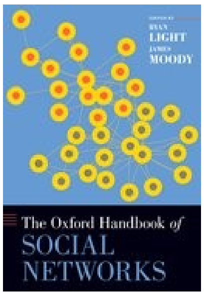

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CHAPTER

11 Dyadic, Nodal, and Group-Level Approaches to Study the Antecedents and Consequences of Networks: Which Social Network Models to Use and When?

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Abstract

Social network analysis encompasses a variety of methods to study the social relations and social interactions between individual units in a group. This chapter offers an overview of the types of research questions that can be answered with social network analysis and discusses appropriate statistical methods and network sampling approaches to answer such questions. Six basic types of models are identified, based on two criteria: (1) whether the researchers are interested in the antecedents of networks and/or their consequences and (2) the appropriate level of analysis, in particular the dyadic, nodal, or group level. Extensions and variations of these six basic models are discussed, for example models where networks take on the role of mediator or moderator, as well as models that incorporate multiple levels of analysis and models that integrate network antecedents and network consequences simultaneously.

Keywords: social network analysis, statistics, multilevel, social network models, methodology

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p. 188 SOCIAL network analysis has become an increasingly popular way of looking at the social world. In fields such as sociology, anthropology, psychology, epidemiology, political science, management, and educational research, social network analysis has helped generate novel insights into a variety of social phenomena. Examples of topics being studied with social network analysis include friendship among students in classrooms (e.g., Van de Bunt, Van Duijn, & Snijders, 1999; Moody, 2001), advice between employees in organizations (e.g., Lazega et al., 2012; Agneessens & Wittek, 2013), cosponsorship of legislative bills by politicians (e.g., Fowler, 2006), interlocking directorates among firms (e.g., Burt, 1980; Mizruchi & Stearns, 1988), and trade relations between countries (e.g., D. A. Smith & White, 1992; Kim & Shin, 2002). This network approach has not only enabled social scientists to tackle existing research questions in an innovative way but also allowed scholars to develop and answer new exciting research questions (cf. Wellman, 1983, 1997; Burt, Kilduff, & Tasselli, 2013). As a result, social network analysis has become a well-established approach to study social phenomena, bringing together a range of theories and methods (cf. Wellman, 1997; Borgatti & Halgin, 2011).[1]

Methodologically, social network analysis encompasses a variety of methods to study the social relations
p. 189 and social interactions between individual units or nodes[2] in a particular ↳ social setting or group. To ensure that the research questions posed in a specific study are answered correctly, it is crucial that the correct (causal) model is chosen, the appropriate network data are collected, the right network measures are used, and the most suitable statistical methods are applied. While specific social network studies might focus on fundamentally different areas of research, they may nevertheless use similar types of network methods and models. Focusing on research questions that aim to explain (rather than merely describe), this chapter offers an overview of (causal) models for common and less common types of questions that can be answered with social network analysis and discusses appropriate statistical methods and network sampling approaches to answer such questions.

The chapter starts with a classification of the main types of basic models based on two criteria: (1) whether the researchers are interested in the antecedents of networks and/or their consequences and (2) the appropriate level of analysis, in particular the dyadic, nodal, or group level.[3] This results in six basic types of models: dyadic-, nodal-, and group-level models that either aim to explain why specific network structures emerge (i.e., where the dependent variable is a network) or aim to understand the consequences of such network structures (i.e., where the network is an independent variable).

The second part of the chapter focuses on models that are extensions and variations of these basic models. In particular, the focus will be on models where networks take on the role of mediator or moderator, as well as models that incorporate multiple levels of analysis and models that integrate network antecedents and network consequences. The examples discussed will primarily be drawn from the fields of management and educational research.

A Framework of Basic Models for Social Network Analysis at Different Levels

The main components of any social network analysis are relational data, that is, network data that capture the *social relations* between two nodes (i.e., a dyad). These relational data can be directed or undirected; they can be valued, categorical, or binary; they can be positive, neutral, or negative (Yang, Trincado, Labianca, & Agneessens, 2019; Harrigan, Labianca, & Agneessens, 2020); and they can represent information about interactions, flows, relational roles, and interpersonal evaluations (cf. Borgatti et al., 2009). In addition to network data, supplementary information can be collected regarding group-level characteristics (e.g., information about *group-level attributes* such as size, location, or type of group), nodal-level characteristics (e.g., information about *individual-level attributes* such as demographics, norms, values, or behavior in the case of people), and *dyadic-level transmissions* of specific characteristics (e.g., information about the transfer of behavior, norms, values, or resources between individual nodes).[4]

While dyadic social relations are the basic building blocks for any social network analysis, the actual analysis can occur at a number of different levels. The three most common levels of analysis are the dyadic
p. 190 level, the nodal (or individual) level, and the group level ↳ (cf. Marsden, 1990; Contractor, Wasserman, &

Faust, 2006; Mizruchi & Marquis, 2006; Brass, 2012).[5] Analysis at a particular level requires network measures or properties and statistical methods at that particular level. Table 11.1 provides a list of examples of network properties that are commonly used at each of these three main levels.

Table 11.1 Examples of Network Properties at a Dyadic, Individual, and Group Level

Group-level network properties: Network structure
- Density of a group
- Level of centralization in a group
- Level of homophily in a group
- Level of transitivity/clustering in a group
- Core-periphery structure of a group
- Number of cliques in a group
Nodal-level network properties: Network position
- Degree centrality
- Closeness centrality
- Betweenness centrality
- Constraint index
- Number of cliques a node is part of
Dyadic-level network properties: Network connectedness
- Direct (network) connection between two nodes
- Geodesic distance between two nodes
- Level of structural equivalence between two nodes
- Number of clique memberships shared between two nodes

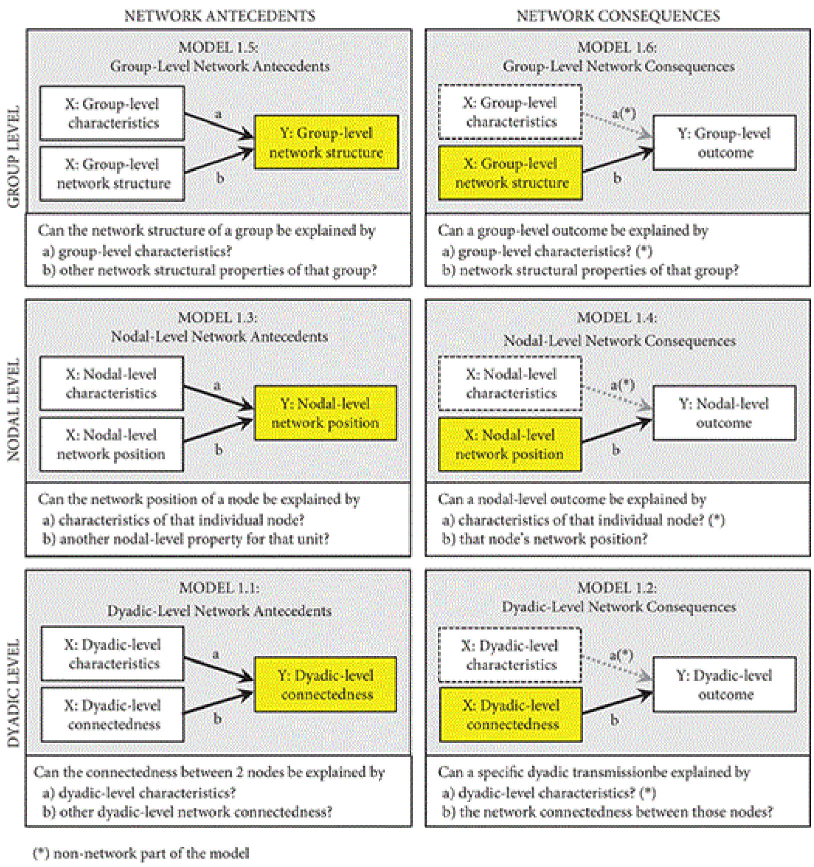
At a *dyadic level*, the emphasis is on how two nodes are related (i.e., connected) to each other. At this level the focus could be on the "direct connectedness" between these two nodes, for example, how frequently there is a direct interaction between two nodes or how much (e.g., how strongly or closely) two nodes are directly related. However, dyadic analysis can also focus on the "indirect connectedness" between two nodes, such as the geodesic distance between two nodes or their level of structural equivalence (Lorrain & White, 1971; see Table 11.1). At the *nodal (individual) level*, the focus is on the position of the individual node (unit) in the network, that is, the relation of the individual node to some or all other nodes in the group. Popular measures of position include degree, closeness, betweenness centrality (Freeman, 1979), and measures to capture structural holes (Burt, 1992). Finally, at the *group level*, the analysis focuses on the network structure of the group as a whole. This includes group-level network properties, such as the density or centralization of the group (Freeman, 1979), but also more complex structural aspects, such as the extent to which the group exhibits a core-periphery structure (Borgatti & Everett, 2000).

As in standard social science research, the research questions in quantitative social network studies can be either descriptive or explanatory. *Descriptive network research* might aim to (1) identify specific properties of a group (e.g., by calculating the density or level of centralization in a group), (2) detect the network position of an individual node in a group p. 191 ↳ (e.g., identify the most central node), or (3) define the relation between two nodes (e.g., describe how far removed two nodes are from each other). In descriptive network research, attributes can feed into these network constructs. For example, nodal-level attributes are needed to identify homophily[6] and to calculate the heterogeneity (diversity) index for the ego network of an individual node (Blau, 1977).

Explanatory network research, on the other hand, concentrates on the antecedents of networks and/or on their consequences (cf. Brass, 2012; Brass et al., 2004), either aiming to uncover why specific dyadic-, nodal-, or group-level network properties (such as those described in Table 11.1) emerge or attempting to uncover the effects of such network properties. Hence, explanatory studies focus on *causal mechanisms*. When the focus is on network emergence, the relational data take the role of the dependent variable in the *(causal) model*, with attributes and/or other network relational data as independent variables. When the focus is on network consequences, relational data are in the independent part of the *model*, with (nodal or group-level) attributes as dependent (i.e., outcome) variables.

As the focus can be on either network emergence or consequences at a dyadic, nodal, or group level, six basic types of (causal) models can be identified. Figure 11.1 provides a graphical representation of the generic format of these six types. The three models on the left side are concerned with network emergence at a dyadic, nodal, and group level (Models 1.1, 1.3, and 1.5, respectively), while those models concerned with the effects of networks at each specific level are on the right side (Models 1.2, 1.4, and 1.6, respectively). This classification provides the basic framework for this chapter and is a starting point for the discussion about the more complex models later in the chapter. In the remaining part of this section, these six models are discussed in more detail.

Figure 11.1



Social network models for network antecedents (left) and network consequences (right) at the dyadic, nodal, and group levels.

Network Antecedents at a Dyadic Level (Model 1.1)

One of the most fundamental questions that social network researchers have raised is *how or when* social network relations emerge. Model 1.1 incorporates studies that aim to answer such a question by focusing on the direct or indirect connectedness between two nodes (i.e., by focusing on the dyadic level). In principle, this can encompass research questions that aim, for example, to understand the reasons that two nodes are structurally equivalent or two nodes have a specific geodesic distance (cf. Table 11.1). However, in practice, most studies that are concerned with the emergence of networks from a dyadic perspective have focused on the direct relations between those two nodes.[7]

Typical types of explanations for the presence of a direct relation between two nodes include (1) the presence of such a tie between both nodes in the past; (2) surrounding structural mechanisms such as reciprocity, transitivity, and cyclicality; (3) the presence of other network relations; (4) the physical distance between two nodes; and (5) explanations involving attributes of these nodes, such as homophily. For example, the presence of a friendship tie between two students might be explained by a number of different factors, such as both students (1) having been friends in the past, (2) having many common friends (and friends of friends becoming friends), (3) having collaborated on a group project together in the past, (4) being neighbors, and (5) sharing an interest in the same type of music.

p. 192 The first four types of explanations focus on independent variables capturing some sort of dyadic-level connectedness (corresponding to *arrow b* in Model 1.1), while the last type focuses on dyadic-level characteristics, that is, the attributes of either or both nodes (*arrow a* in Model 1.1). A more thorough overview of some of these mechanisms and related theoretical arguments can be found in Contractor et al. (2006) and Rivera, Soderstrom, and Uzzi (2010).

When network data are collected among all nodes in a group (i.e., complete network analysis), *exponential random graph models* (ERGMs; Lusher, Koskinen, & Robins, 2013) and *multivariate regression quadratic* p. 193 *assignment procedures* (MRQAPs; Krackhardt, 1987) ↳ have been the most common methods used to answer such questions, while *stochastic actor-oriented models* (SAOMs; Snijders, van de Bunt, & Steglich, 2010) and *relational event models* (Butts, 2008; Stadtfeld, Hollway, & Block, 2017) are frequently used when network data in a group are collected over time. Network data for a single group with a sufficient number of nodes can, in principle, suffice to perform such statistical tests, provided the researcher aims to only draw conclusions about the social processes taking place in that specific group. However, as will be discussed in the section on *"Multiple Groups and Multilevel Models"*, data among a set of groups are obviously needed to make more generalizable statements regarding these social processes beyond a specific context (i.e., beyond a single group).[8]

Network Consequences at a Dyadic Level (Model 1.2)

Model 1.2 concentrates on how the direct or indirect connectedness between two nodes might contribute to the *transmission* of a particular nodal attribute, such as a particular idea, practice, behavior, or resource between those nodes (e.g., Travers & Milgram, 1969; Stevenson & Gilly, 1991). This transmission process is sometimes also referred to as social contagion (Burt, 1987). Examples of transmissions include the diffusion of innovation (i.e., the transfer of an idea, practice, or object that is new to the recipient) via a communication or friendship network (Rogers, 2003; Coleman, Katz, & Menzel, 1966; Valente, 1995, 1996; Burt, 1987), as well as the spread of a specific sexually infectious disease via a sexual contact network (Klovdahl, 1985; Keeling & Eames, 2005). Salancik and Pfeffer (1978) used a *social information processing approach* to explain why employees who share information would have more similar attitudes about their job. When social contagion among nodes is due to the presence of a direct network relation among those nodes, the result will be a high level of homophily in that group.

However, some researchers (e.g., Friedkin, 1984; Burt, 1987; Borgatti & Li, 2009) have argued that the level of structural or regular equivalence (rather than the presence of a direct link) between two nodes might be more relevant for the adoption of innovation or transmission of specific behavior. Those in structurally equivalent positions may adjust their behavior to each other because they feel in competition with each other (Fujimoto & Valente, 2012), or these nodes might feel more related to each other because they take on a similar role in the network.

Methodologically, the study of the effects of networks on specific transmissions requires the explicit recording of the transmission of a specific, unique characteristic (attribute) between two nodes and the time at which this happens, as well as network information among these nodes. Data collection can involve recording specific transmissions and network data among a random sample of dyads or among all dyads in a group. When sampling dyads randomly, standard techniques can be used, for example, to examine whether the transmission of a disease among two nodes is more likely to take place when they are friends. However, if the focus is on the sequential process of a disease flowing through a friendship network, the friendship relation and the transmission of a specific attribute would need to be recorded among all nodes in a bounded group, so the analysis becomes more complex.[9]

p. 194 While many of the theoretical arguments made in this subsection in principle could be approached from a dyadic perspective (as in Model 1.2), most studies have actually focused on the aggregated effect of "implicitly" measured transmissions from multiple connections,[10] that is, a focus on the effects at the nodal level (as in Model 1.4). The reason for this is that the focus is often on the aggregated result, such as a person exhibiting specific behavior, holding specific beliefs, or having a certain amount of aggregated knowledge (i.e., the cumulative effect of contagion processes from being connected to multiple alters), rather than a focus on a single transmission from one node to another. For example, the amount that a person smokes is generally considered as the aggregated effect of social influence from all his or her friends (and their behavior or attitudes), and therefore models similar to Model 1.4 might be more appropriate in such a case.

Network Emergence at the Nodal Level (Model 1.3)

At the nodal level, both the antecedents and consequences of nodal network positions have been widely studied. Focusing specifically on humans as units of analysis, the *social support* and the *social capital* literature has been particularly influential (e.g., Wellman, 1979; Lin, Vaughn, & Ensel, 1981; Sarason et al., 1983; Burt, 1984; Campbell, Marsden, & Hulbert, 1986; Marsden, 1987, 1990; Borgatti, Jones, & Everett, 1998; Lin, Cook, & Burt, 2001).

With regard to the antecedents of network positions (Model 1.3), classic studies primarily concentrated on explaining the size of a person's network (i.e., degree centrality) or the characteristics of a person's direct contacts (e.g., how dissimilar or diverse the alters of a person are with regard to a specific attribute). Demographic and other individual (nodal) characteristics of the person, such as age, gender, socioeconomic status, educational level, ethnicity, and religion, have been commonly used to explain differences in size, in the level of homophilous connections, and in the heterogeneity of a person's alters with a particular focus on different types of emotional and instrumental support (Wellman, 1979; Burt, 1984; Sarason et al., 1983; Moore, 1990; Ibarra, 1992; van Emmerik, 2006; Fischer, 1982).

A more recent stream of research that fits within this general framework has focused on the reasons that some individuals take on a *brokerage* role in a network, that is, why they tend to connect with others who are themselves not connected (Burt, 1992). In this respect the focus has been especially on the impact of *personality* (e.g., Burt, Jannotta, & Mahoney, 1998; Oh & Kilduff, 2008) and *strategic orientations* (e.g., tertius gaudens and tertius iugens; Obstfelt, 2005). For example, Kalish and Robins (2006) have studied the effects of the Big Five personality traits on the preference to be surrounded by open versus closed triadic structures, while Mehra, Kilduff, and Brass (2001) have studied the effects of self-monitoring on the level to which a person is high on betweenness centrality.[11] These studies fit perfectly with Model 1.3 (*arrow a*), whereas Model 1.3 (*arrow b*) focuses on explanations where the network position of a node in one network might impact its position in another network. For example, the centrality in the collaboration network might impact the centrality in the friendship network.[12]

Methodologically, both ego network data and complete network data have been widely used to explain why nodes end up in a specific network position. While the generalizability of the conclusions that can be drawn from sampled ego networks is a clear benefit of such a design, only information about ego's direct contacts
p. 195 tends to be available and this ↳ information tends to be based on self-reports. Hence, only ego network–based measures such as degree and ego betweenness can generally be calculated (see Perry, Pescosolido, & Borgatti, 2018).

Conversely, when network information is collected about the ties between all nodes in a group (i.e., complete network data), the indirect ties between ego and all the other nodes in a group can be calculated and therefore more complex network measures of position involving geodesic distance or walks (e.g., closeness and betweenness centrality) can be used as a dependent variable. However, because the network position is calculated for all nodes in a specific group, generalization beyond the group could be problematic (see the section on *"Multiple Groups and Multilevel Models"*).

The choice between an ego network and a complete network approach also has important implications for the choice of statistical method. With ego networks, standard statistical techniques, such as linear regression, are often applied. However, since ties are nested in nodes, a multilevel approach might be more appropriate to disentangle within-egos and between-egos variance when studying the impact of nodal attributes and prior network position on outcomes (van Duijn, van Busschbach, & Snijders, 1999).

Similarly, in case complete network data are used, it might, on certain occasions, be more appropriate to perform a dyadic analysis (as proposed by *arrow b* in Model 1.1) rather than simple nodal-level analysis, especially when interested in explaining measures of nodal position such as degree centrality. This is because many of these measures of position are actually based on some additive aggregation of the direct and indirect ties between a focal node and all other nodes (Bloch, Jackson, & Tebaldi, 2017).[13]

Network Consequences at the Nodal Level (Model 1.4)

Regarding the consequences of an individual node's network position (Model 1.4), the main measures being considered again include degree centrality, closeness centrality, betweenness centrality, and the constrain index.[14] To explain how nodal-level network properties impact outcomes, three broad types of arguments can roughly be identified (cf. Brass, 1984).

One main argument focuses on how networks provide *access* to specific resources, attitudes, and values (Brass, 1984).[15] Such an approach tends to focus on nodal-level properties that concentrate on reach (cf. Borgatti, 2005; Agneessens, Borgatti, & Everett, 2017). Measures can focus on direct reach, such as degree centrality (e.g., when focusing on emotional support; cf. Haines & Hurlbert, 1992; Thoits, 1982), or on indirect flows, such as closeness centrality (e.g., when focusing on easily transferable knowledge about where to find a job; cf. Granovetter, 1973). Measures can also focus on shortest paths only (degree and closeness) or incorporate all walks (Borgatti, 2005).

A second broad approach focuses on the *power and control* that result from being in a brokerage position between others (e.g., Brass, 1984; Burt, 1992). Such brokerage roles or structural hole positions have been captured by a number of measures, including the constraint index (Burt, 1992), that is, the amount of open triadic structures one is part of, and betweenness centrality (Freeman, 1979). For example, in one classic study Burt (2000) showed how managers who are in such a brokerage position tend to get promoted faster, while in another study Burt shows how such situations are related with higher creativity (Burt, 2004).

p. 196 Finally, a third major stream of research, already discussed when covering Model 1.2, focuses on *social contagion* of attitudes and behavior, such as the contagion of smoking behavior (Mercken et al., 2009), criminal behavior (Baerveldt, Völker, & Van Rossem, 2008), or job satisfaction (Agneessens & Wittek, 2008).

To explain how a specific network position affects nodal-level outcomes, standard statistical techniques, such as linear regression, are quite popular. For ego network data, such an approach might seem reasonable since the dependent variable is measured at the nodal level (McCallister & Fischer, 1978; Burt, 1984; Marsden, 1987, 1990; see Perry et al., 2018 for more on ego networks). However, when complete network data are used, the network position is calculated for all nodes in a group and used to predict their nodal-level outcome. Since these outcomes are not independent of each other, the regression model needs to take this complex interdependence into account. For example, when wanting to predict how the number of friends impacts one's happiness, the value for ego's happiness (Y_{ego}) might be dependent on the happiness of ego's connections (Y_{alter1}, Y_{alter2}, etc.), while at the same time the happiness for ego's connections (Y_{alter1}, Y_{alter2}, etc.) might be dependent on the value of happiness for ego (Y_{ego}). *Network autoregression models* have been proposed to incorporate such recursive effects explicitly (Doreian, Teuter, & Wang, 1984; Marsden & Friedkin, 1993; Leenders, 2002). Alternatively, longitudinal models (see later in this chapter) and a number of other influence models have been proposed (see Valente, 2005; cf. Mouw, 2006).

Network Emergence at a Group Level (Model 1.5)

At the group level, studies focusing on the antecedents of network structures (Model 1.5) have primarily concentrated on one of three types of structures: (1) cohesion as measured by density, (2) centralization and hierarchy, and (3) fragmentation and subgroups. Research on teams and in school classes has often used aggregated nodal-level characteristics, such as age, gender, educational level, and expertise, to explain the emergence of such network structures (e.g., by taking the average or standard deviation of such nodal-level attributes; see Harrison & Klein, 2007). For example, Reagans, Zuckerman, and McEvily (2004) found an effect of demographic diversity on network density, while Balkundi et al. (2007) concentrated on the effect of age diversity on the proportion of structural holes in a team. Besides aggregated nodal-level characteristics, actual group-level properties, such as the size of the group, and properties of the group leader or the teacher in a school class could also be used to explain the group-level structure (*arrow a* in Model 1.5). Finally, studies might also incorporate other networks as an independent variable to explain, for example, how a centralized collaboration network leads to a centralized friendship network, or how a high level of subgroup formation based on friendship cliques might result in a higher number of conflict ties, especially between such subgroups (*arrow b* in Model 1.5).

In practice, most studies have tried to explain basic structural properties, such as density, while far less attention has been paid to the antecedents of more complex group-level structural properties, such as core-periphery structures. Part of the reason for this is that the emergence of such group-level structures is hard to understand when the focus is solely on group-level antecedents and when no attention is given to dyadic- or nodal-level mechanisms (see the Section on "Macro-Micro-Macro Models").

From a methodological point of view, groups are the basic units of analysis in such group-level studies, and therefore intragroup network data need to be collected among a ↳ sufficiently large number of groups to be able to explain the occurrence of a specific group-level network structure. Provided a sufficiently large random sample of groups is selected and individual nodes are not members of multiple groups,[16] standard statistical techniques, such as linear regression, can be used with group-level network constructs as the dependent variable.

Network Consequences at a Group Level (Model 1.6)

Similar to the studies on group-level network antecedents, the prevalent structural properties found in studies investigating the consequences of network structure on group-level outcomes (Model 1.6) are cohesion (density), centralization, and fragmentation.

Using a social capital perspective, the concept of group cohesion (e.g., Mullen & Copper, 1994) has been widely studied, linking a high network *density* with a range of positive outcomes. As an example, Sparrowe et al. (2001) found that a high density for advice in groups had a positive effect on their performance. In one intriguing classic network study Bavelas (1950) and Leavitt (1951) showed how a more *centralized* communication structure had a positive effect on efficiency, but a negative impact on the team members' average satisfaction with the task (cf. Shaw, 1954; Shore, Bernstein, & Lazer, 2015). Besides density and centralization, studies have considered subgroup formations and the amount of brokerage in a group as an explanation for group outcomes (Balkundi et al., 2007).[17]

To study such models, standard statistical techniques, similar to those discussed previously for Model 1.5, can be used provided enough groups have been randomly sampled and there is no overlap in membership across groups. While the antecedents and especially the consequences of networks have been widely studied from a group-level perspective, it is worth noting that the network characteristics that scholars have focused on in such cases have been predominantly restricted to constructs such as density, centralization, and, to a lesser extent, fragmentation. However, because of the aggregated nature of many group-level properties (such as density being an aggregate of dyadic network relations and diversity being an aggregate of nodal characteristics), group-level analysis may not always be the correct level to analyze the antecedents and consequences of network structure. Given the danger of "fallacies of the wrong level" (Rousseau, 1985) and in particular of ecological fallacy, in some cases these macro- (group-level) processes can be better understood from a dyadic or nodal perspective. For example, a centralized friendship network might emerge from a centralized collaboration network because the central node in the collaboration network also becomes central in the friendship network, which requires a nodal-level or even dyadic-level analysis. This concern is discussed in more detail in the section on "Macro-Micro-Macro Models").

Variations and Extensions of the Six Basic Models

While a considerable amount of social network research might fit one of the six basic types of models, a
p. 198 growing number of studies have incorporated network data in a more advanced ↳ and complex way, by building on and extending the six basic models discussed before. In this section some of these more complex types of models are discussed.

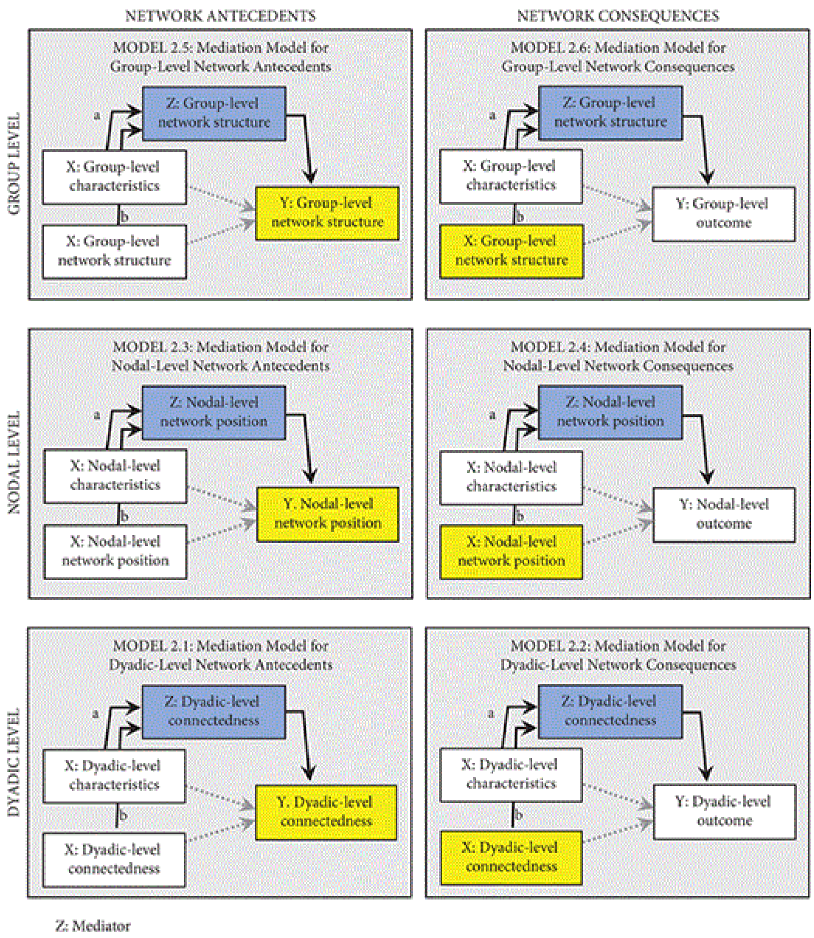
Network Mediation Models

One important way in which the aforementioned models have been extended is by incorporating social networks as a mediator. Such *network mediation models* can provide insights into the social processes and interactions that take place in a group, that is, *how* specific initial states might lead to particular outcomes.

Researchers interested in group composition and diversity (in terms of demographic characteristics, personality, values, and expertise) have become particularly interested in the mediating role of social relations (e.g., K. G. Smith et al., 1994; Pfeffer, 1997; Reagans et al., 2004). By focusing on the communication, trust, (dis)liking, and conflict ties that emerge between group members, the social network approach helps the researcher uncover exactly *how* the composition of the group affects outcomes, such as well-being, performance, or the generation of innovative ideas. In team research this line of inquiry is commonly referred to as the *intervening model* (K. G. Smith et al., 1994; Pfeffer, 1997) or the *input-process-output model* (see Marks, Mathieu, & Zaccaro, 2001; cf. Palardy, 2008, for a similar argument concerning educational research).

For example, teams with low age diversity might exhibit a greater proportion of structural holes, and such structural holes might in turn have important performance implications (Balkundi et al., 2007). Similarly, transformational leadership in a group might affect team performance through the advice-seeking behavior that emerges among team members (Zhang & Peterson, 2011). Such studies are examples of *group-level network mediation* models (Model 2.6, *arrow a* in Figure 11.2). Other examples of studies that fit with Model 2.6 might focus on how prior network structures (*arrow b*), such as the level of centralization of the workflow network, might impact the centralization or density of the (focal) friendship network, which in turn might inhibit or enhance group performance.

Figure 11.2



Network mediation models at the dyadic, nodal, and group levels.

At the *nodal level* (Model 2.4), studies such as those by Fang et al. (2015) have explored how personality traits of employees impact job performance and career success through the centrality and brokerage role they achieve in the expressive and instrumental networks of these organizations (*arrow a*). Similarly, the position of employees in the formal workflow network might affect their centrality in the (focal) friendship network, and this in turn might impact their happiness with their job (*arrow b*). Core to both these examples is the idea that the impact of individual-level attributes or prior network positions on individual outcomes is mediated through the position these nodes acquire in a focal network.

An example of network mediation at a *dyadic level* (Model 2.2) could focus on the similarity in values between two nodes (*arrow a*) or, alternatively, the level to which both nodes are required to work together (*arrow b*), and how this might generate specific network relations (such as friendship), which then result in the transmission of specific outcomes (e.g., the spread of specific gossip).

Whichever the level of analysis, what is noticeable is that these *network mediation models* tend to assign a rather passive and even deterministic role to networks (i.e., being a product of specific attributes or prior ties), which subsequently produces a specific outcome.[18]

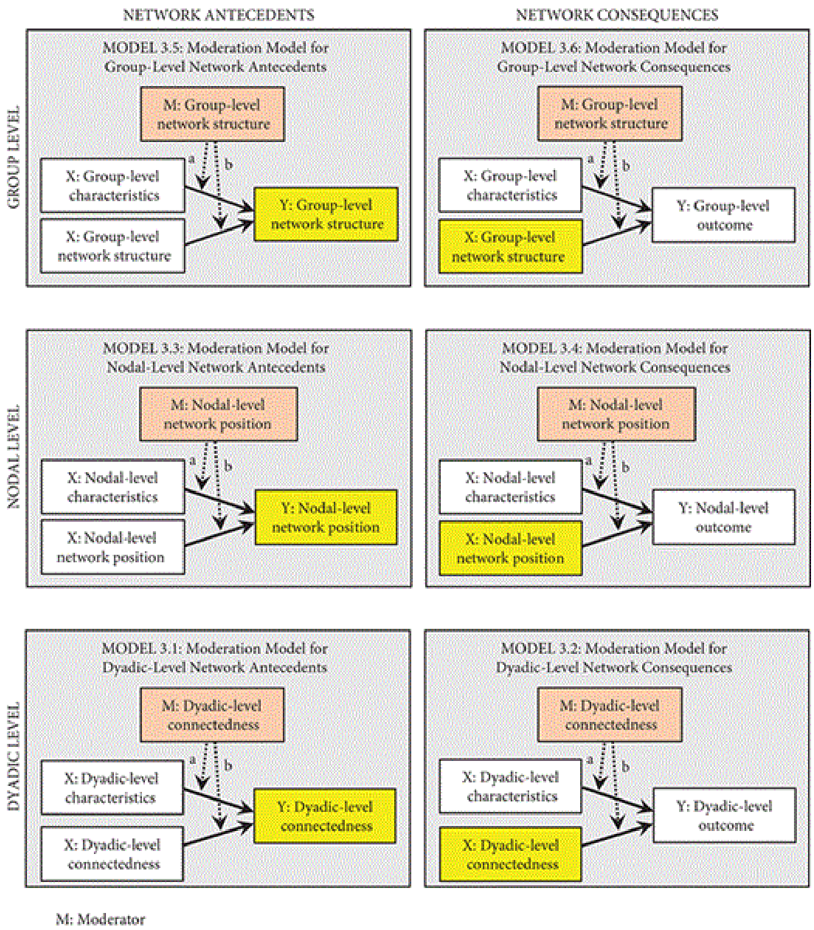
p. 199

Network Moderation Models

While *network mediation models* might tend to minimize the autonomous role of social interactions, some researchers have taken a somewhat different approach by considering the moderating role of a focal network. Instead of considering network relations as simple consequences of a specific initial state that subsequently generates specific outcomes, in *network moderation models* nodes and their social relations play a far more active role in ↳ shaping and changing the way the initial state has an impact on specific

p. 200 outcomes, that is, by moderating this relationship (see Figure 11.3).

Figure 11.3



Network moderation models at the dyadic, nodal, and group levels.

At *a group level* (Model 3.6), the moderation in such a model can involve a simple interaction between, for example, the gender diversity in a group and some network structure (*arrow b*) or an interaction between two network structural properties (*arrow a*). For example, Tröster, Mehra, and Van Knippenberg (2014) show that in culturally diverse groups, more than in culturally homogeneous groups, a higher average workflow between group members (i.e., a high network density) predicts greater team success (*arrow b*).

p. 201 Considering density and centralization, Grund (2012) observed that in English soccer teams high ↳ intensity of interaction and low centralization were associated with better team performance (*arrow a*). However, this interaction can also take a more complex form, for example, capturing the number of ties crossing faultlines (Ren, Gray, & Harrison, 2015) or the level to which the most central actor in a centralized network possesses specific attributes (e.g., leadership qualities).

At an *individual level* (Model 3.4), the position in a network can interact with either other networks (*arrow a*) or individual characteristics (*arrow b*). For example, following the buffering hypothesis, being surrounded by a large number of friends (i.e., social support) might buffer the negative effect of stressful events on well-being (Cohen & Wills, 1985). Focusing on the position of employees in both the formal and the informal network (and the overlap between both), Soltis et al. (2013) found that employees who are approached for advice by many colleagues who they are also required to work with increased their turnover intension, while being able to seek advice from colleagues who they are not required to work with in the organization decreased an employee's turnover intensions. Finally, at a *dyadic level* (Model 3.2), a friendship relation might be more likely to lead to the transfer of specific information between two students when these students hold similar background characteristics.

Network moderation models could also aim to explain the emergence of networks at a dyadic, individual, or group level, while using other network properties or network relations as moderators (Models 3.1, 3.3, or 3.5, respectively). For example, at a *dyadic level*, Grosser, Lopez-Kidwell, and Labianca (2010) found that a gossip tie is more likely to emerge between employees who are required to work together while also being friends (arrow b in Model 3.1).

What unites these moderation models is the idea that networks may play a critical role in *when* and *how* a prior state has an impact on specific outcomes by accentuating, buffering, or even reversing the relationship between two variables. Hence, compared to the mediation models focusing on the *why* question, this approach allows for a more independent role of networks.

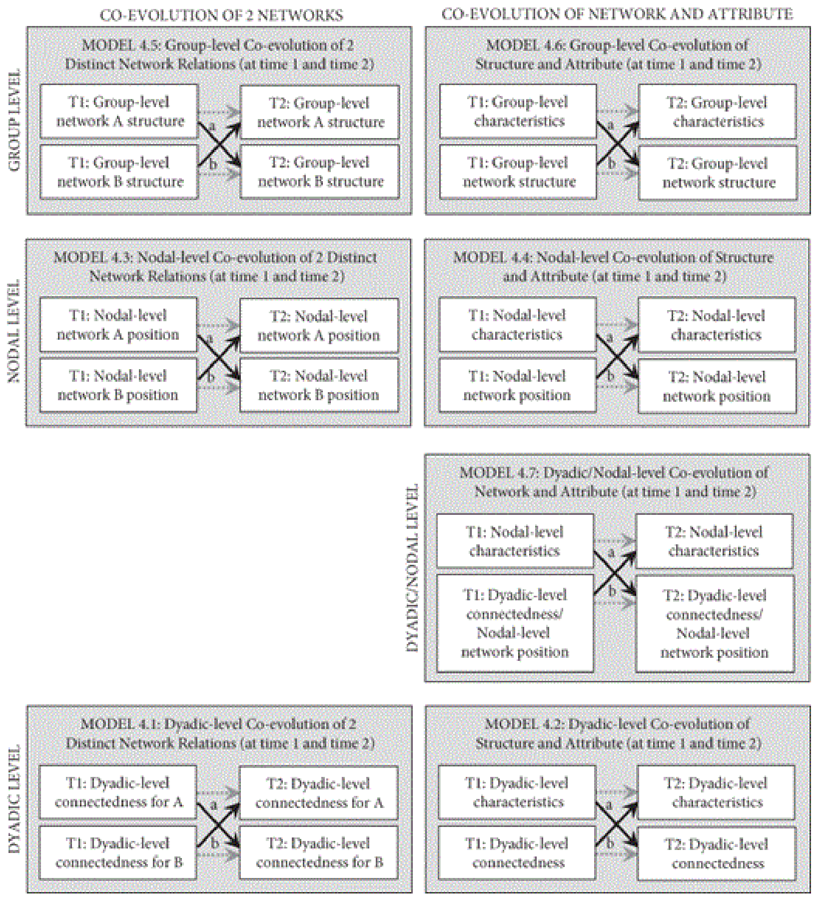
Network Coevolution Model

The models discussed so far assume that a clear causal direction can be identified between the focal network and the other networks or attribute variables; that is, either the focal network is an independent variable (i.e., a focus on network consequences) or it is a dependent variable (i.e., a focus on network antecedents). However, in many research settings the causal direction might be open for discussion and instead longitudinal models might be needed to try to uncover the true direction of the causality.

To illustrate this, consider smoking behavior among students in a school. Smokers might be more likely to nominate other smokers as friends, while nonsmokers might be inclined to nominate nonsmokers. However, the existence of a high level of homophily can be the result of (1) a tendency of friendship relations emerging between students who are similar with regard to their smoking behavior (i.e., homophily as a result of social selection) or (2) a tendency for students to be influenced in their smoking behavior by their friends (i.e., homophily as a result of social contagion) (e.g., Merken et al., 2010; see also McPherson, Smith-Lovin, & Cook [2001] and Shalizi & Thomas [2011] for a broader discussion regarding homophily). In such a case network emergence and network consequence need to be modeled simultaneously (Snijders, 2011) and data about smoking and friendship ties need to be collected at multiple time points.

 From a network perspective, two important types of models can be identified: (1) models focusing on the coevolution of a network and an attribute (Figure 11.4, right) and (2) models focusing on the coevolution of two networks (Figure 11.4, left).

Figure 11.4



Coevolution models at the dyadic, nodal, and group levels.

At a *group level*, the question could be whether a high level of communication in a group (i.e., high density) generates more innovative ideas in this group or whether, on the other hand, a significant number of new ideas in the group lead to a higher communication density in the group (Model 4.6). Focusing on the coevolution of two networks (networks A and B), the question could be whether the network structure for A impacts the network structure for B, or vice versa (cf. Model 4.5). Provided a sufficient number of groups are available, standard longitudinal models could be used to model the coevolution where the group is the unit of analysis (e.g., Duncan, Duncan, & Strycker, 2006; Preacher et al., 2008).

p. 203 At a *dyadic* or *nodal level*, two distinct types of models could be identified that combine networks and attributes (Models 4.2 and 4.4). However, in practice, stochastic actor-oriented models (SAOMs; Snijders et al., 2010; Steglich, Snijders, & Pearson, 2010; Ripley et al., 2019) have become the most popular approach to test such coevolution models between network and behavior (i.e., Model 4.7). These models tend to use a combination of (1) a nodal-level focus to model whether changes in behavior and attitudes are the result of network position (Model 1.4) and (2) a dyadic-level type of focus to model whether behavior and attitudes drive tie formation (Model 1.1).[19] Studies in education research, for example, have looked at the coevolution of friendship networks and alcohol use (Mundt, Mercken, & Zakletskaia, 2012), delinquent behavior (Baerveldt et al., 2008), and many other factors (see Veenstra et al., 2013, for an overview). Organizational scholars have considered the coevolution of perceived psychological safety and advice/friendship relations among team members (Schulte, Cohen, & Klein, 2012) or how attempts to control others' behavior is impacted by competence and affect-based status (de Klepper et al., 2017).

For the coevolution of two networks, a dyadic-level type of focus between two or more networks (Model 4.2) using SAOMs is most widely used. Examples of models focusing on multiple networks include the coevolution of friendship and gossip in organizations (Ellwardt, Steglich, & Wittek, 2012) and the coevolution between the bullying network and the defending network among pupils in elementary school (Huitsing et al., 2014).

As insights into the causal mechanisms are crucial in social sciences, *network coevolution models* have become a useful vehicle for uncovering the underlying causality.

Multiple Groups and Multilevel Models for Dyadic and Nodal-Level Analysis

One important question that has so far not been systematically addressed in this chapter is whether to collect intragroup network data from a single group or from a set of groups when performing dyadic- or nodal-level network analysis. Obviously, group-level models always require intragroup network data from a sufficiently large number of groups to perform any statistical analysis. However, for dyadic- or nodal-level models, network data from a *single group* with a sufficient number of nodes, such as a single school class or a single organization, will be perfectly suitable if one wants to solely draw conclusions about that specific group (e.g., whether in that specific school class, the students central in the friendship network have higher grades than the less central students). However, data from *multiple groups* are needed in any of the following conditions: (1) to make generalizable statements beyond a specific group about dyadic-level or nodal-level processes, (2) to test whether group-level variables might actually explain dyadic-level or nodal-level outcomes, and/or (3) to test whether group-level variables moderate dyadic-level or nodal-level processes (cf. Snijders, 2016). Each of these arguments is discussed in more detail next.[20]

Generalizability

First, scholars often aim to make generalizable statements about network emergence and/or its consequences beyond a specific context (Entwisle et al., 2007; Snijders, 2016). To ensure that the conclusions made are not an idiosyncratic result of a single group-specific context, p. 204 ↳ one needs to examine a random sample of groups or even the full population of groups to make some statement about them.

One approach to find general patterns across a set of groups is to merge all data into one dataset and perform one analysis (e.g., an ERGM, SIENA, or autoregressive analysis) taking into account that only relations within groups exist (Wang, Robins, & Pattison, 2009; Ripley et al., 2019). This approach of merging data from multiple groups into one analysis is particularly useful when the size of each group is very small, and therefore these groups do not have enough power to be analyzed separately. However, the consequence is that only an overall pattern emerges and no information is available regarding any potential variation in results between groups (i.e., homogeneity in social processes across groups is assumed).

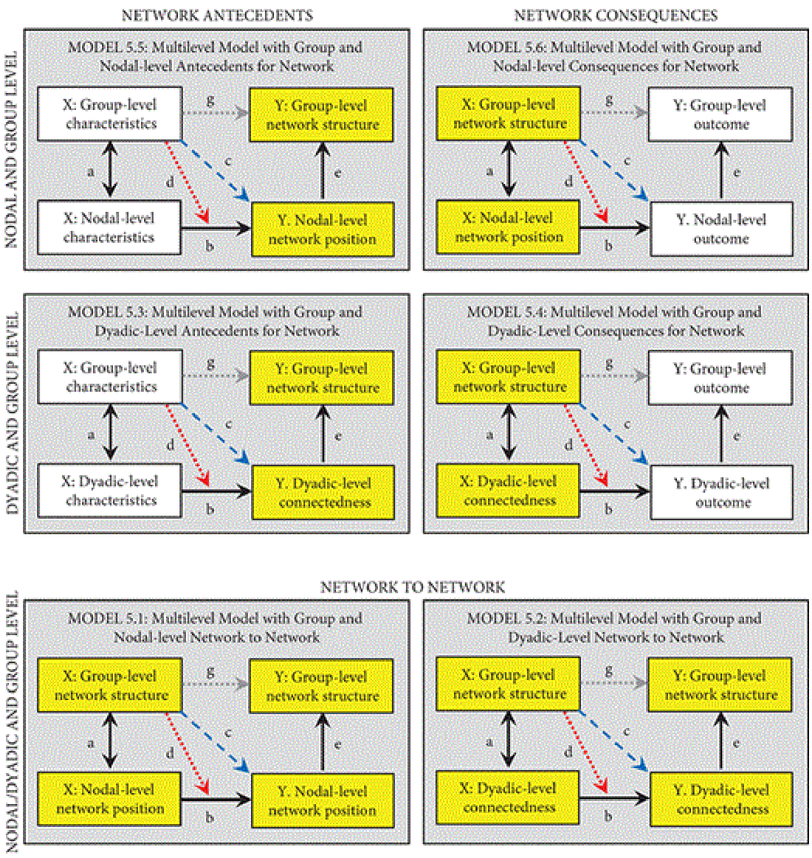
Alternatively, when the size of each group is large enough to perform a separate analysis, each group could be analyzed in turn (e.g., using ERGM) and a classic meta-analysis can be used to test for an overall effect, as well as to test for potential variation in effects across groups (e.g., Snijders & Baerveldt, 2003). This approach has been widely used in educational research aimed at finding overall patterns across schools or school classes (e.g., Lubbers, 2003; Knecht et al., 2011; Schaefer et al., 2011; Mercken et al., 2012; Huitsing et al., 2014). Again, the focus of this approach is on finding overall effects across groups, and while the approach does allow to test for differences in results across groups, these models generally do not incorporate any group-level effects, nor do they try to explain these potential differences (see An [2015] for extensions of this approach).

Group-Level Effects

However, the dyadic- or nodal-level outcomes found across a set of groups might in fact be due to group-level network or attribute characteristics. For example, when studying students across a set of school classes, students' friendship network centrality might seem to be related to their grades, whereas in reality the true differences in grades might be between school classes, with all students in more dense school classes having higher grades. In other words, there might be a group-level contextual variable (i.e., a group-level network structure, rather than the nodal-level network position) that impacts the nodal-level outcomes (Agneessens & Koskinen, 2016). In such a case, a proper multilevel approach is required with group-level variables as additional explanatory variables and a large number of groups (Snijders, 2016; Tasselli, Kilduff, & Menges, 2015).

The main types of multilevel network models can be found in Figure 11.5. In these models, *arrow b* represents the effect at the dyadic or nodal level, while *arrow c* represents the effect of the group level on the dyadic-level or nodal-level outcome. Finally, *arrow a* represents the potential link between the dyadic-level or nodal-level independent variable and the group-level independent construct, since the group-level construct might be an aggregation of dyadic-level and nodal-level constructs (such as density being the aggregate of degree or the ethnic diversity of a group being the aggregate of the ethnicity of its members).

Figure 11.5



Multilevel network models at the dyadic, nodal, and group levels.

For example, combining dyadic-level and group-level factors to predict dyadic-level network ties, Tolsma et al. (2013) found that bullying between pupils is not more prevalent among ethnically mixed pairs of students than it is among nonmixed pairs. However, they did find that bullying ties are more likely to emerge when the classroom is more ethnically diverse. This example fits within Model 5.3, with *arrow b*

p. 205 representing the effect of similarity ↳ in ethnicity and *arrow c* representing the effect of diversity on network emergence. Note that *arrow a* represents the correspondence between the independent variables at two levels: similarity in ethnicity between two pupils (dyadic level) and ethnic diversity (group level). Similarly, Model 5.2 could consider how a dyadic friendship tie might be the result of either the strength of the workflow between both employees (*arrow b*) or the workflow density in the group (*arrow c*), with *arrow a* reflecting the fact that density is the aggregation of the dyadic strength between all students of a school class.

To include group-level factors in dyadic-level models, a more integrated multilevel approach has been proposed (Models 5.2 and 5.3) (Ripley et al., 2019; Snijders, 2016), while multilevel autoregressive models have been developed that can combine group-level (e.g., centralization) and nodal-level structures (e.g., degree) to predict nodal outcomes, such as job satisfaction (Model 5.6) (Agneessens & Koskinen, 2016). These are some examples of the six types of multilevel models.

p. 206 Cross-Level Interaction

Dyadic-level or nodal-level processes might also turn out to be dissimilar for different groups, in which case the question could be asked if these effects might be dependent on the group-level context. This requires a multilevel model that incorporates a *cross-level interaction effect*, represented by *arrow d* in the multilevel models in Figure 11.5. In such cases, the size and potentially even the direction of the dyadic-level or nodal-level effect(s) in such models (*arrow b*) are assumed to be contingent on the group-level context.

For example, studying the implementation success of a new system by employees in an organization, Sasidharan et al. (2012) found that the new system was more likely to be implemented among employees in decentralized groups. However, the study also found that in centralized groups the central employees were most likely to apply the new system (Model 5.6; *arrow d*). Similarly, combining a *dyadic* and a *group level*, Mehra, Kilduff, and Brass (1998) have studied the effect of the size of the minority on ethic homophily (Model 5.3, *arrow d*).

Hence, such multilevel approaches allow one to not only make statements that are valid across groups (*generalizability*) but also consider how—by incorporating *group-level effects*—these contextual factors might affect nodal-level and dyadic-level outcomes, and how these contextual factors might change the direction of nodal-level and dyadic-level effects (*cross-level interaction effects*).

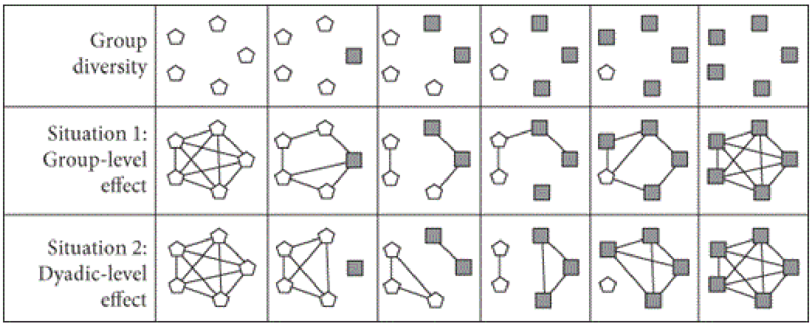
Macro-Micro-Macro Models

A final major extension concerns the group-level processes, i.e., Models 1.5 and 1.6, and the possible risk of ecological fallacy (Rousseau, 1985; Hitt et al., 2007). Problems of ecological fallacy in network research might occur when an assumed group-level process (i.e., a macro-process) should be analyzed at a dyadic or nodal level (i.e., using a micro-process) (cf. Coleman, 1986; Alexander, 1987). This problem is most apparent in studies where the group-level network properties and the group-level attribute constructs are, in fact, aggregates of dyadic-level or nodal-level data (cf. Tasselli et al., 2015; Brass & Borgatti, 2019).

To illustrate this, consider a situation where groups with low gender diversity were found to exhibit a higher density for friendship than high-diversity groups (Model 1.5). Since the group-level diversity is an aggregate construct of a nodal attribute (cf. Harrison & Klein, 2007) and the network density is an aggregate of dyadic friendship ties, two plausible reasons can be put forward to explain the macro-results (Figure 11.6). The emerging network density in low-diversity groups might indeed come about because groups with high diversity on gender tend to generate fewer friendship ties (i.e., a *group-level effect* in line with the basic Model 1.5). On the other hand, the differences in density between different groups might also be the result of dyadic-level or nodal-level processes, such as a higher tendency for friendship ties to emerge between

people of the same gender (i.e., the result of a *dyadic-level homophily effect* in line with Model 1.1). In the case of a group-level effect, there would be a higher tendency for tie formation among both homophilous and heterophilous dyads in low-diversity groups, and a lower tendency for ties to form among homophilous and heterophilous dyads in high-diversity groups as illustrated in Situation 1 in Figure 11.6. However, in the case
p. 207 of a dyadic-level homophily effect, ties would be ↳ primarily formed among nodes with the same attribute and less among heterophilous dyads. Since groups who are less diverse have more opportunities to form homophilous dyads, more ties will once again be formed in low-diversity groups than in high-diversity groups, but in this case the real reason is a preference to form homophilous ties, as Situation 2 in Figure 11.6 illustrates. While in both cases low levels of diversity would generate a higher density at the group level, what differentiates both cases is that the ties emerge in different places in the respective groups.

Figure 11.6



Different effects of group diversity on network density: group-level diversity versus dyadic-level homophily effect.

A pure group-level model (Model 1.5) would not be able to distinguish between both processes as it uses aggregate constructs and therefore would be unable to uncover a potential dyadic or nodal micro-level process. Instead, a *macro-micro-macro* step needs to be added to these models. The earlier discussed multilevel models can be further extended to provide the general framework for such a *macro-micro-macro approach*, where an extra step is added to capture the "aggregation" of micro-processes to macro-outcomes (*arrow e*), while *arrow g* represents the macro-to-macro effect (Models 1.5 and 1.6). This approach is in line with the macro-micro-macro model proposed by James Coleman (Coleman, 1986, 1990; cf. Hedström & Swedberg, 1998; Raub, Buskens, & Van Assen, 2011; Brass & Borgatti, 2019).

Considering Model 5.3 and the example in Figure 11.6, the group composition is disaggregated to the dyadic level, where the two nodes in the dyad might or might not have the same value on gender (*macro-micro or group-dyadic link, arrow a*). Second, at a dyadic level, the homophily effect is considered a potential driver for network formation (the *micro or dyadic-level effect represented by arrow b*). And, finally, as a result of the independent dyadic homophily processes, a group network structure emerges (*micro-macro or dyadic-group effect, arrow e*).

If the *dyadic-level homophily effect* is driving the network formation (Situation 2 in Figure 11.6), then the micro-level effect (*arrow b*) would be found to be important and the group-level effect (*arrow g*) could be explained away completely. However, if there is a true *group-level effect* (Situation 1), then the micro-effect (*arrow b*) would not be important, while the group-level effect (*arrow g*) would be. This example illustrates the need to consider dyadic-level and/or nodal-level processes when aiming to understand changes at the group level (cf. Wellman & Frank, 2001; Raub et al., 2011; Brass & Borgatti, 2019).

A comparable argument can be made (see Models 5.4 and 5.6) when focusing on group outcomes as a result
p. 208 of the group's network structure (cf. Model 1.6). For example, when the ↳ group outcome is the result of aggregation (such as the average satisfaction in a group or total number of creative ideas generated by

individuals in a group), this might be better studied by incorporating a dyadic or nodal perspective. First, specific individual nodes are embedded in a specific way in the network structure; that is, they have a specific position (macro-micro link, *arrow a*). This network position might lead to individual outcomes (micro-effect, *arrow b*), such as a specific level of satisfaction or level of creative ideas, which then translate (aggregate) into group outcomes such as average satisfaction or total number of creative ideas (micro-macro link, *arrow c*).

In practice, the situation may be more complex, as (1) both dyadic/nodal-level and group-level processes might work to some extent, (2) macro-structures might impact the micro-processes (*arrow d* in Figure 11.5), (3) the independent and/or dependent variables might not be simple aggregations (but rather *configurational*, Klein & Kozlowski, 2000), and (4) multiple micro-processes (e.g., reciprocity, transitivity, homophily) might work together to create a macro-structure.

Simulation approaches such as agent-based models are promising for contributing to the understanding of such macro-outcomes (e.g., Buskens & Van de Rijt, 2008; Macy & Flache, 2009; Hamill & Gilbert, 2009; Corten & Buskens, 2010; Mäs et al., 2013; Snijders & Steglich, 2015; Stadtfeld, Takács & Vörös, 2020).

Conclusion

Social network analysis offers a powerful technique to model social relations between nodes in a group. However, to correctly answer the research questions of a study, it is important to choose (1) the appropriate (causal) model, (2) the appropriate network data collection, (3) the right network measures, and (4) the most suitable statistical method. This chapter provides an overview of the main models. In a first part, the basic explanatory models were discussed, focusing either on *antecedents* of networks or on the *consequences* of networks at a *dyadic*, *nodal*, and *group level*. The resulting six models (Figure 11.1) can be seen as the basic archetypical models. From these six basic models, different variants and extensions can be developed. The most common extensions, discussed in this chapter, are (1) approaches where a focus on network emergence is combined with a focus on network consequences (the *network mediation model* and the *coevolution model*), (2) approaches where networks take on the role of moderator (the *network moderation model*), and (3) approaches that combine distinct levels of analysis (the *multilevel model* and *macro-micro-macro models*). Based on this overview, a number of noteworthy gaps and future directions for research can be identified.

First, of the six basic types of models, the "transmission model" (Model 1.2) has arguably been one of the least studied within the field. Often network relations have been assumed to be proxies for such transitions (e.g., friendship or communication ties are expected to imply the flow of specific information and other resources) without there necessarily being sufficient empirical evidence. While tracking transitions of specific ideas, practices, behaviors, or resources between specific individual nodes has traditionally been challenging, the increasing use of online (communication) data and the growing availability of technology (e.g., to record behavior and speech or to code conversations) could make such research more conceivable.

p. 209 Second, in these classic models attributes and networks are traditionally seen as separate entities. The *network moderation* approach offers a strategy to combine network and attributes in a simple or more complex way. Further research can benefit from considering the effects of a combination of both. However, rather than, for example, simply combining network density and attribute diversity, future research, especially at the group level, might benefit from more complex, configurational approaches to combine both networks and attributes.

Another way in which networks and attributes can be combined is by modeling their coevolution over time. SAOMs have been a particularly fruitful approach that has generated considerable insights in the last two decades. The recent development of relational event-type models (Butts, 2008; Stadtfeld et al., 2017), allowing the emphasis on both states (e.g., friendship) and events (e.g., an email), provides another important direction for future research. However, one challenge to their general implementation is the need for high-quality longitudinal network data as well as attribute data.

A fourth major issue relates to the generalizability and contextual factors. Recent years have seen a considerable increase in data collection across multiple groups, especially in schools and teams. Such data allow for more generalizable statements across contexts but also open up opportunities to incorporate macro-contextual effects into the approach. From a methods perspective, proper multilevel network models are required, which allow incorporating macro-contexts into dyadic- and nodal-level analysis (Snijders, 2016; Lazega & Snijders, 2016; Lomi, Robins, & Tranmer, 2016).

A fifth issue relates to the micro-macro debate as outlined in the last section of this chapter. Social network analysis is well placed to provide more detailed insights into the processes linking micro-level processes with macro-level changes. In many cases, to understand macro changes (i.e., group-level effects), a focus on micro-processes (i.e., dyadic-level or nodal-level effects) might be required, as well as an understanding of the effects of micro-processes on macro-outcomes (Coleman, 1986). More research is needed on how micro-processes (under specific macro-conditions) could generate specific macro-outcomes. Agent-based models and other simulation methods (e.g., Buskens & Van de Rijt, 2008; Snijders & Steglich, 2015; Stadtfeld et al., 2020) may be useful in linking the micro-network processes with such macro-structural outcomes.

Acknowledgments

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Notes

1. See, for example, Wasserman and Faust (1994); Scott (2017); Carrington, Scott, and Wasserman (2005); or Robins (2015) for some excellent general theoretical and methodological overviews on social network analysis.

2. These units can be people, animals, companies, nongovernmental organizations, countries, etc. The more technical term *node* will be used in the rest of this chapter.

p. 210 3. ↳ A group is defined as a clearly delineated set of nodes within a formally and a priori (pre)defined boundary (Marsden, 1990). The term *group* is preferred over the more commonly used term *network*.

4. In this chapter the transfer of a specific nodal attribute is considered a dyadic-level outcome but does not, *in and of itself*, constitute a network relation. However, the (persistent) transfer of specific characteristics between two nodes might (theoretically) be assumed to happen because of the presence of a (latent) tie between those nodes, and therefore (under such an assumption) these transfers might be used as a proxy for the presence of a hidden network relation between those nodes (see the section discussing Model 1.2).

5. From a network perspective, the dyadic level can be seen as being nested in the individual (node) level, while the individual level is nested in the group level. For example, the degree of a node is the aggregate of the dyadic network relations between that node and all other nodes, while the density for a group is the aggregate of the degree of all nodes in the group. Similarly, individual attribute data can be used at a group level, for example, by calculating the average or variation for a specific individual attribute (e.g., Harrison & Klein, 2007).

6. Homophily can be defined as the tendency for units to be more likely to connect to others who are similar in terms of specific attributes, compared to others who are dissimilar.

7. Instead, structural equivalence and geodesic distance between two nodes are most of the time simply seen as a consequence of the emergence of a series of direct connections between a set of nodes.

8. A different approach has been to randomly sample dyads in a group and then perform a *dyadic analysis* (Kenny, Kashy, & Cook, 2006). However, while a random sample of dyads offers the possibility to make statements regarding the social mechanisms in the larger group from which the dyads are sampled, this standard design is not well fitted to consider the broader structural environment (e.g., whether friendship emerges as a result of having common friends).

9. While there is some similarity with relational events models, the later models tend to focus on more abstract versions of events (e.g., whether a call happened at a specific time) rather than a specific attribute flowing through the network (e.g., specific information being transmitted).

10. This means that what is measured is a network relation (which is assumed to imply a transmission) rather than measuring a specific transmission explicitly (cf. footnote 5) combined with a nodal-level outcome.

11. Some studies have also focused on the effect of personality on other measures of position, such as degree centrality (e.g., Klein et al., 2004). See Fang et al. (2015) for a more in-depth discussion.

12. Note that such a design does not answer the question of whether ego's collaboration ties and friendship ties are with the same alters or with different alters. This would require a dyadic analysis (arrow *b* in Model 1.1).

13. For example, degree centrality is the sum of the number of direct contacts between a focal actor and others in the group. Hence, nodes with a specific nodal-level attribute generating a higher in-degree can easily be translated into a dyadic-level analysis focusing on a tendency for other nodes to choose nodes with such an attribute.

14. However, see Borgatti, Jones, and Everett (1998) for a more extensive list of potential individual- and group-level social capital measures.

15. See Podolny (2001) for an interesting different approach.

16. If some nodes are members of multiple groups (e.g., project teams) or links within and between groups are of interest, other approaches, such as the use of a two-mode network analysis, might be more appropriate (cf. Agneessens & Everett, 2013).

p. 211 17. ↳ Some research has pointed at nonlinear effects of a specific group-level property. For example, performance might be highest when there is a relatively high level of trust among team members, but too high a level of trust might be counterproductive as it generates groupthink (Chung & Jackson, 2013).

18. In this respect it is worth noting that Fang et al. (2015) also found that the network position had an important independent effect on work outcomes after controlling for personality.

19. The reason for this is that attitudes and behavioral variables are measured at a nodal level and networks at a dyadic level. Note that since these are actor-oriented models, they rely on changes in attributes and network ties being made by an actor and hence might not be seen as purely dyadic approaches (cf. Snijders & Koskinen, 2013, p. 138).

20. The data can be either complete (intragroup) network data or a sample of ego network data or dyadic network data from a set of groups.

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