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Social Network Analysis

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Social network analysis (SNA) offers an innovative lens for conducting community-based research. It focuses on identifying patterns of relationships among sets of actors in a particular system (e.g., friendships among children in a classroom or collaboration among organizations in a coalition). In this chapter, we will describe how to collect network data and how to apply network measures to examine phenomena at multiple levels of analysis, including the (a) setting (i.e., characteristics of the whole network), (b) individual (i.e., an actor's position within the network), and (c) dyad (i.e., network characteristics of pairs of actors). Additionally, we use a case example to illustrate how SNA can be used to understand how the structure of teacher advice networks might facilitate or hinder the spread of classroom intervention practices.

INTRODUCTION TO SOCIAL NETWORK ANALYSIS

One of the pivotal differences between conventional data analysis and SNA is that the former focuses on individual actors and their attributes, while the latter extends beyond individual actors to quantify the structure of relationships between all actors in a setting (Hanneman & Riddle, 2005; Neal & Christens, 2014). Therefore, at its core, each social network includes a set of actors (e.g., individuals or organizations) and a type of relationship (e.g., friendship or collaboration).

Notably, SNA moves beyond an individual perspective and instead adopts a structural lens that is well suited for community-based research (Neal, 2008; Neal & Christens, 2014). In particular, researchers have stressed the importance of capturing whole networks to guide social action (Christakis & Fowler, 2009; Neal & Christens, 2014; Neal & Neal, 2013; see Chapter 22, this volume). To measure whole networks, researchers conduct SNA using a finite group of actors referred to as a system (e.g., students in a classroom or organizations in a coalition). Using whole network data, SNA can provide measures of the entire system (i.e., setting-level measures), individual actors' positions in this system (i.e., individual-level measures), or pairs of actors in the system (i.e., dyad-level measures). These measures can provide a rich array of information regarding interconnectedness in a community, distributions of power and centrality, and individual actors' perceptions of their surrounding community. Moreover, whole network analysis has been used to examine many phenomena of interest to community-based researchers, including coalitions, empowerment, dissemination, and implementation (Neal & Christens, 2014).

Network Data Collection and Management

SNA has been applied to diverse and unique communities, such as substance use recovery houses, coalitions, and schools (e.g., Jason, Light, Stevens, & Beers, 2014; Long, Harré, & Atkinson, 2014; Nowell, 2009). To conduct this type of research, it is necessary to identify a system and to determine a boundary that constrains which actors are included in the system (Wasserman & Faust, 1994). In many cases, these boundaries are natural and are often set by the actors under study (e.g., classrooms, clubs, organizations, or coalitions). Here, it may even be possible to find a roster of individuals who participate in the system. However, in other cases such as sexual networks or drug injection networks, system boundaries may be more fluid and, therefore, more challenging to determine. In these cases, researchers often employ snowball sampling methods or more rigorous respondent driving sampling methods to delineate the network (Hanneman & Riddle, 2005).

The accurate measurement of social networks requires much information. Therefore, methods for collecting network data diverge from the probabilistic sampling typically employed in more traditional forms of data collection. Because network methods focus on the relationships among actors, actors are not independent from one another. SNA analysts tend to study whole populations by means of census, which requires collecting data from every actor in a particular setting. Using a census in SNA is vital for holistically and accurately capturing every present relation within a network. For instance, if an actor's data are missing, the presence and absence of that actor's relations with every other actor in the network are absent. Notably, in SNA, data about nonrelationships are just as crucial for understanding the network structure as data about relationships. Thus, self-report measures require notably high response rates (i.e., greater than 80%–90%) (Neal, 2008).

In addition to specifying the set of actors to be included in a social network study, it is also necessary to specify the nature of the relationships that will be explored. Two features of relationships are particularly important to consider: directionality and value. First, it is important to determine whether the relationships should be specified as directed or undirected. Relationships should be specified as *directed* if it is important to understand who is sending and who is receiving a particular relationship. For example, in the case of advice relationships, one actor (the sender) provides advice to another (the receiver). Similarly, in the case of trust, one actor (the sender) may indicate that she trusts another (the receiver), but this relationship may not be reciprocated. However, relationships should be specified as *undirected* if they are assumed to be symmetric in nature. For example, hanging-out relationships often meet this assumption (i.e., if A hangs out with B, B logically must also hang out with A). Second, it is important to determine whether the relationships should be specified as binary or valued. Relationships should be specified as binary when it is sufficient to simply measure the presence or absence of a relationship at the nominal level. However, if researchers are interested in the strength or intensity of relationships, it may be necessary to use a valued measurement at the ordinal or ratio level.

Most commonly, researchers use sociometric surveys or interviews to collect social network data (Marsden, 1990, 2011). These sociometric surveys or interviews typically consist of name-generator questions (e.g., "In the last month, who have you gone to for advice?" "In the last 2 weeks, to which other organizations in the coalition has your organization made referrals?"). Each actor provides information about the presence of his or her own relationship (or his or her organization's relationship) with other actors in the system either through free recall or by selecting names from a roster. For example, Neal, Neal, Atkins, Henry, and Frazier (2011) used sociometric interviews to measure advice networks among teachers in three elementary schools. Teachers were asked name-generator questions about whom they socialized with and whom they went to for advice in three different areas (behavior management, family involvement, and instructional methods). In response to each question, teachers freely recalled as many or as few other teachers in their school as they wished. This is important because constraining actors' responses to a fixed number (e.g., "Name three people that you go to for advice") has been known to create serious measurement error. In particular, fixing the number of responses produces biased measurements of the network structure because it does not account for all possible relationships in the system (Holland & Leinhardt, 1973).

Although less common, structured observational methods can also be used to collect network data. For example, Schaefer, Light, Fabes, Hanish, and Martin (2010) conducted observations of social play among children in 11 preschool classrooms over the course of a school year. More specifically, they spent several hours in each of these classrooms on multiple days each week and conducted 10-second scan observations of random children to record their activities. These methods can provide rich longitudinal data on actors' behavioral interactions but are time and resource intensive to collect.

Finally, many researchers construct network data from archival sources, including meeting attendance records, Internet interactions, bill co-sponsorships, and scholarly publications (Marsden, 1990). For example, Wimmer and Lewis (2010) used Facebook friendship statuses to examine peer relations among college students. More specifically, they recorded the friendship lists from

TABLE 21.1: UNDIRECTED (SYMMETRIC) ADJACENCY MATRIX

	Actor 1	Actor 2	Actor 3	Actor 4
Actor 1	—	1	0	1
Actor 2	1	—	1	1
Actor 3	0	1	—	0
Actor 4	1	1	0	—

Note: All ties in this matrix are reciprocated.

participants' Facebook profiles. These preexisting data can provide detailed information about actors' relationships that are less prone to social desirability.

Once network data are collected, they are typically arranged in an adjacency matrix. Although quantitative data are usually organized in a rectangular case-by-variable matrix, an adjacency matrix is a square actor-by-actor matrix (Hanneman & Riddle, 2005). That is, the adjacency matrix contains the same number of rows and columns. Rows represent actor *i* (senders if relationships are directed), and columns represent actor *j* (receivers if relationships are directed). The two matrices in Tables 21.1 and 21.2 provide social network data about four actors (Actors 1–4), and thus each has four rows and four columns. Each cell in the adjacency matrix represents the relationship between actors *i* and *j*. If relationships are specified as binary, cells will be 0 if a relationship is absent and 1 if a relationship is present. In contrast, if relationships are specified as valued, cells will reflect the strength or intensity of each relationship. The example matrices in Tables 21.1 and 21.2 are both binary. In Table 21.1, the cell that corresponds to Actor 1 (row) and Actor 2 (column) has a value of "1," indicating that Actor 1 has a relationship with Actor 2. The diagonal of the matrix represents self-ties and is usually left blank. If relationships are specified as undirected, values above and below the diagonal will mirror one another (see Table 21.1). However, if relationships are specified as directed, values above and below the diagonal may be different. In Table 21.2, the cell that corresponds to Actor 1 (row) and Actor 2 (column) has a value of "1," indicating that Actor 1 sends a relationship to Actor 2. In contrast, the cell that corresponds to Actor 2 (row) and Actor 1 (column) has a value of "0," indicating that Actor 2 does not reciprocate by sending a relationship to Actor 1.

TABLE 21.2: DIRECTED ADJACENCY MATRIX

	Actor 1	Actor 2	Actor 3	Actor 4
Actor 1	—	1	0	1
Actor 2	0	—	1	1
Actor 3	0	1	—	0
Actor 4	0	1	0	—

Note: Actor 1 has nonreciprocated relationships.

Social Network Measures

Community-based researchers can apply SNA to understand the context of a particular setting or community using measures at multiple levels of analysis, including the (a) setting (i.e., characteristics of the whole network), (b) individual (i.e., an actor's position within the network), and (c) dyad (i.e., network characteristics of pairs of actors). Once whole network data are collected, any of these types of measures can be utilized, allowing community-based researchers to mix and match measures across these different levels of analysis depending on their research questions. Table 21.3 provides an overview of the setting-, individual-, and dyad-level social network measures discussed in this chapter.

Setting-Level Measures

Setting-level measures provide information about the structural characteristics of a whole system (i.e., the resource sharing ties among all organizations participating in a coalition). These measures can help researchers track and identify prominent relational patterns within the system. Although many different setting-level measures exist (e.g., density, reciprocity, transitivity) in SNA, here we concentrate on just one example: multiplexity measured using Jaccard similarity coefficients.

Multiplexity is a setting-level measure that focuses on types of relationships. Any set of actors can have multiple types of relationships with one another (e.g., friendship or advice), each forming a separate network. Researchers can examine these different networks to determine the extent to which these actors share different types of relationships (i.e., multiplexity). Specifically, researchers can use Jaccard similarity coefficients to examine the overlap between two networks representing

TABLE 21.3: SOCIAL NETWORK MEASURES

Network Measure	Example Measure	Case Example
Setting: Setting-level measures provide information about the structural characteristics of a whole system.	Jaccard similarity coefficients: Examine the overlap between two networks representing different types of relationships. They are calculated by dividing the number of present relationships that are reported in both networks by the total number of present relationships that are reported in either network. Scores range from 0 (no overlap in relationships across the two networks) to 1 (100% overlap in relationships across the two networks).	Jaccard similarity coefficients ranged from .19 to .42, indicating that the overlap between different types of networks was only moderate. Findings suggest the need to examine whether lead teachers are ideally located to provide support for all components of the intervention (e.g., Are they well situated in all advice networks?).
Individual: Individual-level measures focus on each specific actor's location within the network.	Degree centrality: Refers to the number of relations that an actor has in a network. It can be expressed as a raw number or can be normed to reflect the percentage of ties that an actor has out of all possible ties in the network.	Teacher 4's out-degree centrality shows that she or he gave advice about involving families to 42.11% of the other teachers, whereas Teacher 8 gave advice about involving families to only 5.26% of the other teachers. Findings suggest that Teacher 4 may be more ideally situated to support the dissemination of PAS strategies for involving families than Teacher 8.
Dyad: Dyad-level measurements explore network characteristics of pairs of actors in the network.	Geodesic distance: Calculates the shortest path between two actors within a network. A geodesic distance of 1 means that two actors in the network have an existing relationship, whereas a geodesic distance of 2 means that two actors can reach each other by going through one intermediary actor.	Teacher 4 was connected to 18 of 19 other teachers with a geodesic distance of three or less. In contrast, Teacher 8 was connected to only 1 of 19 other teachers. Findings suggest that Teacher 4 is more optimally situated to spread PAS strategies about involving families than Teacher 8.

different types of relationships. (Jaccard similarity coefficients are appropriate for examining multiplexity when relationships are specified as binary. If relationships are valued, Pearson correlation coefficients can be used.) Jaccard similarity coefficients are calculated by dividing the number of present relationships that are reported in both networks by the total number of present relationships that are reported in either network. Scores range from 0 (no overlap in relationships across the two networks) to 1 (100% overlap in relationships across the two networks).

Multiplexity has important implications for understanding communication structures that influence the diffusion of information in communities (Rogers, 1962). For example, Neal et al. (2011) compared teacher advice networks involving families with advice networks focused on classroom instruction and found Jaccard coefficients ranging from .28 to .36. In other words, only one third of advice-giving relationships in one network were present in the other network, indicating that teachers tended to get advice from different teachers depending upon the type of information they were seeking.

Individual-Level Measurements

Individual-level measures typically focus on each specific actor's location in the network. For social network analysts, centrality measures are common.

Centrality measures examine the extent to which an actor is embedded in a relational network (e.g., How many ties does an actor have with other actors?). In some cases, high centrality can be an asset. For example, occupying a central position in an advice-giving network can provide access to different sources of information. However, in other cases, high centrality is a detriment. For example, occupying a central position in a contact network may make an actor more susceptible to contracting the cold that is going around that season. Furthermore, actors' placement in the network can provide them with opportunities to exert control over other actors or, conversely, constraints placed upon by them by other actors. Although there are many ways to assess an actor's centrality in a network (Freeman, 1978/1979), here we will discuss the most common measure: degree centrality.

Degree centrality refers to the number of relations that an actor has in a network (Freeman, 1978/1979). Degree centrality can be expressed as a raw number or can be normed to reflect the percentage of ties that an actor has out of all possible ties in the network. In directed networks, degree centrality is reflected using two values, *in-degree* and *out-degree*. *In-degree* represents the number or percentage of ties that a particular actor receives in the network, while *out-degree* represents the number or percentage of ties that a particular actor sends in the network.

In friendship or advice networks, actors with higher degree centrality may have more information and resources at their disposal. Furthermore, in these networks, actors with many relations are less dependent on each particular tie for resources. For example, Neal (2009) found that children's use of relational aggression was associated with degree centrality in their classroom peer networks. The study indicates that, although relational aggression peaked for students with moderate levels of degree centrality, students with the highest levels of degree centrality were less likely to engage in relational aggressive behaviors.

Dyad-Level Measurements

Dyad-level measurements explore network characteristics of pairs of actors in the network. Typically, dyad-level measures are used by community-based researchers to examine the co-occurrence of attitudes, behaviors, and/or attributes (e.g., sense of empowerment, political activities, obesity) among pairs of related actors (Burk, Steglich, & Snijders, 2007). For instance, Burk et al. (2007) found that adolescents whose friends engaged in delinquent behaviors were more likely to engage in delinquent behaviors themselves. Dyad measures are also commonly applied to understand the mechanisms by which relationships influence the diffusion and adoption of innovations (e.g., health care practices, social media technology) (Rogers, 1962). Here, we focus on one mechanism of diffusion: cohesion (typically measured using geodesic distance).

Cohesion examines the diffusion of behaviors or innovations among actors with ties to one another, emphasizing that information, behaviors, and/or resources tend to spread among close directly or indirectly connected groups of individuals. Cohesion is often measured using geodesic distance, or the shortest path between two actors within a network. If two actors (A and B) have a geodesic distance of 1, it means that Actors A and B have an existing or direct relationship in the network. In contrast, if Actors A and B have a geodesic distance of 2, it means that Actors A and B can reach each other by going through one intermediary actor (e.g., Actor C). Coleman, Katz, and Menzel's (1966) classic study used geodesic distances to examine the doctors' adoption of a new pharmaceutical drug. They found that doctors who were less distant in the network to doctors utilizing the pharmaceutical drug were more likely to follow suit and prescribe the drug. In comparison, doctors who solely received information about the drug from advertisements or empirical research were less likely to prescribe it. Burt (1999) has since theorized that the mechanism of cohesion may be particularly important for diffusing information about new innovations.

Benefits and Drawbacks

The benefits of SNA for community-based research are numerous. Despite intentions to understand broader contextual forces, community-based researchers have struggled to locate methods that allow them to assess the structure of the settings and communities. As Luke (2005) noted, this has led to a disconnect where community-based researchers theorize about context but fall back on methods and analyses that measure individuals. Because SNA explicitly focuses on measuring the structure of relationships within a setting or community, it is inherently a contextual method and offers a potential avenue for remedying this disconnect. Moreover, the relational focus of SNA also permits community-based researchers to explicitly measure interdependence between actors in a setting, a key feature of ecological theories (Neal & Neal, 2013; Trickett, Kelly, & Vincent, 1985). Finally, once collected, whole network data are extremely flexible and allow researchers to move back and forth easily between multiple levels of analysis. Indeed, as illustrated in the previous section, community-based researchers can use the same whole network data to answer questions about the entire setting, actors' positions within this setting, or actors' relationships with one another.

Despite these major benefits, SNA also has some drawbacks. As noted earlier, community-based researchers who wish to analyze whole networks must have near-complete data on the relationships between actors in a setting. SNA is extremely sensitive to missing data, and even a small amount of missingness (e.g., greater than 20%) can lead to misleading and distorted results (Neal, 2008). Thus, community-based researchers who wish to collect whole network data must prioritize efforts to boost response rates or use alternate approaches to data collection that allow for more complete network data. For example, Neal (2008) has advocated using cognitive social structures (CSS) to collect whole network data in community-based settings where high response rates are typically not feasible (e.g., public school classrooms). CSS asks each respondent to identify the presence or absence of a relationship between each pair of actors in the setting. Thus, each respondent provides his or her perception of the entire network structure. These perceptions can then be aggregated across respondents to enumerate a whole network from only a subset of respondents in the setting. Although CSS is effective for collecting whole network data in settings where response rates are low, this method of data collection has a high response burden for participants and may not be feasible in settings with many actors.

There are ethical considerations that may also hinder community-based researchers' use of SNA. Because SNA requires researchers to know who is related to whom, it is not possible to collect data anonymously. Additionally, because actors are reporting on their relationships with other actors in the setting, secondary participation is common in SNA studies. Secondary participation occurs when an actor does not participate as a respondent in the study, but data are still collected from others about this actor. It is important for community-based researchers using SNA to take special steps to protect the confidentiality of both respondents and secondary participants and to provide explicit consent forms that clearly detail the unique nature of network data (see Borgatti & Molina, 2005).

CASE STUDY

In the earlier sections, we highlighted SNA's unique promise and flexibility for understanding the structure of relationships in community-based settings. However, to make these points more concrete, we now turn to an illustration of how SNA can be applied to inform the dissemination and implementation of community-based interventions, using the Promoting Academic Success Project (PAS) as a case example. PAS is a school-based intervention focused on improving the academic achievement of African American and Latino boys in elementary school. PAS is a multipronged intervention that includes mentoring, family involvement activities, and after-school programming. However, a critical component of the PAS program is a professional development series that targets classroom teachers, especially prekindergarten to third-grade teachers. Specifically, principals in each participating PAS elementary school selected one to two lead teachers who encouraged their colleagues' attendance at the PAS professional development series. These lead teachers also provided support for and promoted the use of teaching strategies designed to improve minority boys' academic, behavioral, and social outcomes (Burke et al., 2015). SNA proved to be a useful method for understanding (a) the implications of teachers' existing advice networks for the spread of PAS strategies and (b) the implications of lead teachers' positions within these advice networks for their ability to influence their colleagues (see Table 21.3).

Network Data Collection and Management in PAS

A team of researchers at Michigan State University (led by this chapter's second author) collaborated with five elementary schools implementing PAS to collect network data on teachers' advice and social relationships. Here, we present findings from one of these schools (Southlawn Elementary) as a case example. However, it is important to note that findings looked similar across the five schools. (Southlawn Elementary is a pseudonym. The real name of the school is protected to ensure the confidentiality of all participants.)

When collecting network data at each PAS school, our research team used staff rosters and bounded the network to include all regular and special education teachers. We collected social network data using brief 10- to 15-minute structured interviews with each of these teachers. During the interviews, a member of our team asked teachers to identify an unlimited number of teachers in their school from whom they received advice about certain issues related to minority boys' education, including (a) family involvement, (b) behavior management, (c) instructional methods, and (d) promoting positive relationships. Teachers were also asked to identify other teachers in their school with whom they socialized. Response rates using this method were very high. At Southlawn Elementary, we were able to interview 96% of the regular and special education teachers ($N = 19$). We used answers to these questions to create five separate self-reported network adjacency matrices (four advice and one social) for each school. Each of the five-adjacency matrices was directed and binary.

TABLE 21.4: JACCARD COEFFICIENTS FOR TEACHER ADVICE-GIVING NETWORKS

Networks	1	2	3	4	5
1. Instruction	—				
2. Involving families	.33	—			
3. Positive relationships	.42	.33	—		
4. Behaviors	.39	.32	.39	—	
5. Social	.35	.19	.33	.26	—

Results of the Analysis

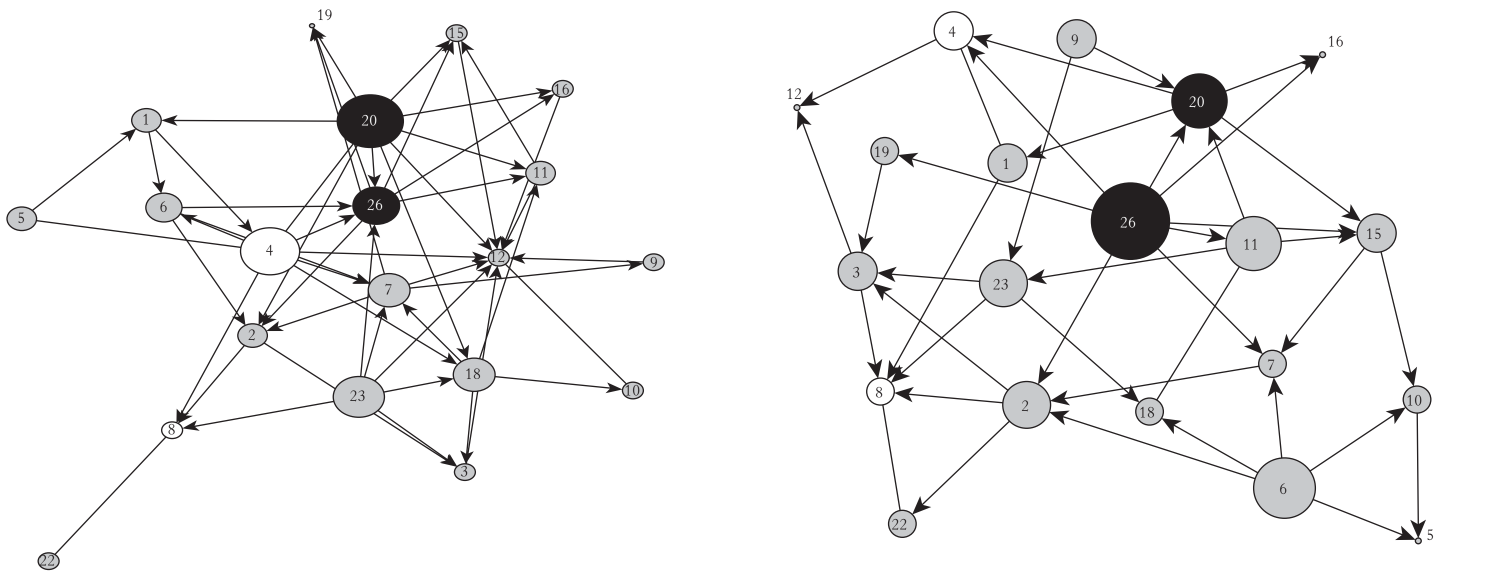
What Are the Implications of Teachers' Existing Advice Networks for the Spread of PAS Strategies?

The social network data collected at Southlawn elementary school demonstrate how setting-level measures provide valuable insight into the topography of teachers' existing advice networks. Specifically, multiplexity (measured using Jaccard similarity coefficients) has implications for how strategies learned as part of the PAS program might diffuse among teachers at Southlawn. Looking at overlap between the five different types of networks measured at Southlawn, Jaccard similarity coefficients ranged from .19 to .42 (see Table 21.4). These coefficients indicate that the overlap between different types of networks at Southlawn was only moderate. For example, the Jaccard similarity coefficient between advice networks for involving families and behavior management was .32, indicating that only about a third of the relationships present in the advice network for involving families were also present in the advice networks for behavior management. These scores highlight that teachers at Southlawn tended to get advice from different teachers depending on the type of information that they were seeking. Thus, at Southlawn, the diffusion of PAS strategies will likely depend on the content that they impart.

These results have some general implications for selecting lead teachers to support dissemination and implementation of the PAS intervention. Specifically, because teachers tend to go to different individuals for different types of advice, it is crucial to examine whether lead teachers are ideally located to provide support for all components of the intervention (e.g., Are they well situated in all advice networks?). For example, certain teachers may hold influential positions for communicating about family involvement but may be more limited in their ability to communicate about behavior management. Alternatively, it might be helpful to consider selecting multiple lead teachers to assist with the PAS intervention, with each lead teacher exhibiting influential positions for disseminating information about different key components of the intervention.

Are the Lead Teachers Optimally Situated in the Network to Be Able to Spread PAS Strategies?

Although setting-level network measures provide general implications for the spread of PAS strategies at Southlawn, individual- and dyad-level network measures can help assess whether the two specific lead teachers selected by Southlawn's principal are optimally situated in the network to be able to spread PAS strategies. At Southlawn, Teachers 4 and 8 were designated by the principal as lead teachers for the PAS intervention.



Involving Families

Behavior Management

ID	Title	Involving Families		Behavior Management	
		Normed Out-Degree	Number of teachers ≤ 3 steps	Normed Out-Degree	Number of teachers ≤ 3 steps
4	Lead Teacher	42.11%	18	10.53%	4
8	Lead Teacher	5.26%	1	5.26%	1
20	Alternative Teacher	52.63%	18	21.05%	11
26	Alternative Teacher	26.32%	10	42.11%	17

FIGURE 21.1: Key: Actor-level measures of lead teachers (color-coded white) and alternative teachers (color-coded black).

Here we compare involving family and behavior management advice networks to assess the extent to which lead teachers at Southlawn were well situated to spread different types of information relevant to the PAS intervention. Figure 21.1 depicts two sociograms illustrating teachers' advice-giving networks for involving families (on the left) and behavior management (on the right). Each circle represents an actor (i.e., a teacher) and is color-coded. The principal's selected lead teachers are represented in white, potential alternative teachers discussed in this chapter are represented in black, and all other teachers are represented in gray. The size of the circles represents each teacher's out-degree centrality scores with larger circles reflecting larger scores. Each arrow in the sociogram represents the act of giving advice. For example, in the behavior management sociogram, arrows point from Teacher 3 and Teacher 4 to Teacher 12, illustrating that these teachers give behavior management advice to Teacher 12. Actor size (the node diameter) is based on out-degree centrality scores.

Centrality scores suggest that Teacher 4 may be more ideally situated than Teacher 8 to support the dissemination of PAS family involvement strategies. Specifically, Teacher 4 gave advice about involving families to 42.11%, while Teacher 8 gave advice about involving families to only 5.26% of the other teachers at Southlawn. Both Teachers 20 and 26 gave advice about involving families to more teachers at Southlawn (52.63% and 26.32%, respectively) and may have also been more effective at disseminating PAS family involvement strategies than Teacher 8. When examining the advice network for behavior management, the out-degree centrality scores of Teachers 20 and 26 (21.05% and 42.11%, respectively) reveal that they give advice about behavior management to more teachers at Southlawn than did Teachers 4 (10.53%) and 8 (5.26%). These findings suggest that Teachers 20 and 26 could serve as alternative lead teachers who may be more effective than the principal-selected lead teachers in disseminating PAS behavior management strategies.

Dyadic-level measures can also provide information about the extent to which the Southlawn principal's selected lead teachers are well positioned to spread PAS intervention strategies throughout the school. Teachers who have short geodesic distances to other teachers at Southlawn (i.e., a geodesic distance <3) are better positioned to spread information about PAS strategies rapidly and efficiently through the mechanism of cohesion. In the advice network for involving families, Teacher 4 is more highly connected to others teachers than is Teacher 8. Specifically, Teacher 4 was connected to 18 of 19 other teachers at Southlawn with a geodesic distance of three or less. In contrast, Teacher 8 was connected to only 1 of 19 other teachers at Southlawn with a geodesic distance of three or less. Thus, this dyad measure suggests again that Teacher 4 is more optimally situated to spread PAS strategies about involving families than is Teacher 8. However, in the advice network for behavior management, neither of Southlawn's lead teachers is particularly well positioned to spread PAS strategies. Specifically, Teacher 4 was connected to 4 of 19 teachers with a geodesic distance of 3 or less, while Teacher 8 was connected to 1 of 19 teachers with a geodesic distance of 3 or less. Other teachers at Southlawn (Teachers 20 and 26) would be much better positioned to spread PAS strategies about behavior management. These findings suggest that alternate teachers, other than the principal-selected lead teachers, may be influential in spreading PAS strategies through cohesion.

CONCLUSION

Community-based research emphasizes the relational and contextual nature of human behavior and social problems (Neal & Christens, 2014). SNA complements this perspective by providing a concrete method by which to assess the pattern of relationships between a set of actors (Luke, 2005). Perhaps one of the greatest advantages of SNA is the "bird's-eye view" that it provides of complex pattern of relationships between actors in a system. This bird's-eye view generally eludes individual community members and leaders and thus cannot easily be captured through more traditional survey or interview methods (Burke et al., 2015; Provan, Veazie, Staten, & Teufel-Stone, 2005). As a case in point, SNA analyses of the PAS project revealed that the lead teachers selected by the principal occupied positions that facilitated the diffusion of some types of PAS strategies but not others.

Despite the promise of SNA, researchers must be intentional and conscientious regarding the challenges that this method poses. First, SNA is vulnerable to missing data, which can greatly obscure the accuracy of a study's findings. Second, SNA presents unique ethical considerations given the lack of anonymity and use of secondary participants in the data collection procedures. More specifically, community-based researchers have the challenge of presenting findings back to their community partners in a manner in which individual actors or organizations are nonidentifiable (see Klovdahl, 2005). To preserve confidentiality in our case study, we did not present analyses of lead teachers' position back to the schools participating in the PAS project. Instead, in our presentations to the schools, we highlighted setting-level measures that facilitated or hindered communication about PAS strategies and provided recommendations for strengthening communication networks among teachers.

Regardless of the challenges, SNA has exciting potential to examine complex social problems at multiple levels of analysis. We hope that this chapter inspires community-based researchers to use SNA to characterize community-based settings and to identify key points of intervention in community-level change efforts.

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