CHAPTER 12

Social Network Analysis Methods in Educational Policy Research

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Social network analysis (SNA) helps researchers to examine or uncover the underlying connections among people, behaviors, events, objects, and institutions within and across social systems that might not be obvious otherwise. SNA is a research methodology rooted in *network analysis* and *graph theory*. Some credit Moreno, as early as the 1930s, for focusing on these underlying network connections with his study of runaway girls, as he noticed that social links between girls influenced their behavior (Borgatti and Ofem 2010). Since then, SNA has played a pivotal role in paradigm shifts within and across diverse fields, including social science and epidemiology (Grunspan et al. 2014). Studies have relied on SNA methods to examine happiness and job satisfaction; health behaviors including obesity and drug use; and group behaviors such as community health access or the spread of innovative ideas throughout

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communities from business enterprises to farming. Researchers have embraced SNA in defining the structure of political, economic, and social environments (Wasserman and Faust 1994).[1] Connections explored using SNA range from similarities in affiliations (e.g., membership in the same club), to cognitive or emotional relations (e.g., liking someone), to work-related connections (e.g., giving advice), and flows of resources throughout systems (e.g., information) (Borgatti and Ofem 2010).

In this chapter, we focus on quantitative SNA because of its prominence within the field.[2] Traditional quantitative education research has focused on how the characteristics of an individual or an organization affect outcomes. Social network theory, on the other hand, is based upon an understanding that individuals in a social system are interdependent, and that these interdependencies shape opportunities and outcomes in ways that require distinct analytic techniques (Borgatti and Ofem 2010). SNA in education research allows researchers to measure and visually map characteristics and elements of social systems to explain or gain insight into a focal relationship of interest.

We begin the chapter by describing SNA with some basic displays of the underlying connections and data sets. Next, we discuss some common theoretical perspectives that frame SNA studies and have already or could inform policy-related work. We review the relevant literature on SNA in education research more broadly and then focus on the innovative application of SNA in educational policy research to strengthen our understanding of policy processes, decision making, and outcomes. Here, we focus on two particular areas—advocacy and implementation—to provide more detailed examples

[1] Note: Social network analysis studies may examine underlying connections through social media, but these are not synonymous.

[2] Though not the focus here, qualitative methods can be used for SNA and often supplement quantitative SNA methods. Qualitative analysis of intergroup relations can explain the social interpretation of one's position within a network and the meaning that emerges from the social construction of the network (Hollstein 2014). For example, see Cross, Dickmann, Newman-Gonchar, and Fagan's (2009) study of interagency collaboration that involved recorded discussions, reflections, and semi-structured interviews about intergroup relationships or Coburn and Russell's (2008) examination of district math reform policies that used observations and interviews to investigate the qualities of teachers' networks. Qualitative data can also provide information as to the organizational culture and climate that facilitate or hinder underlying relations (see Finnigan et al. 2013and Finnigan and Daly 2012 for examples).

of the use of SNA in educational policy research. Finally, we offer recommendations to novice and emerging scholars including how to collect and analyze SNA data and useful resources to consult.

Social Network Analysis

A social network is a set of actors (also referred as nodes, vertices, or points) that can be connected to each other through relationships (also known as edges, links, arcs, lines, or ties). Actors can be a set of persons (e.g., students, principals, policy makers), organizations (e.g., firms, schools, school districts), objects (e.g., policies, documents), or even events (e.g., school meetings, political campaigns). As mentioned above, examples of relationships can include friendships, professional interactions, power structures, or the flow of resources between people or organizations.

The smallest possible social structure in which an actor can be embedded is a dyad, which has two actors that have a relationship or are connected through a "tie." In turn, the smallest social structure in which a dyad can be embedded is a triad, defined as three actors and the possible relationships among them. Figure 12.1 illustrates the ways that two or three people can be connected through ties.

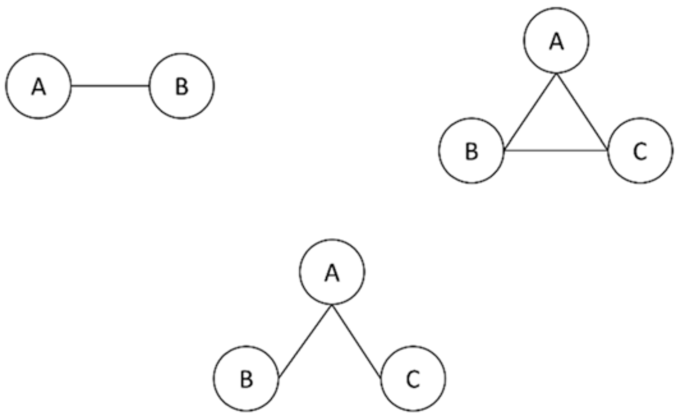

Fig. 12.1 Basic social structures: dyad and triad

Graphs or Sociograms SNA uses graphs and matrices to represent actors and summarize or present the patterns of social relations in an efficient and comprehensive manner. A graph of actors and their relationships is called a sociogram in the SNA literature. In a graph or sociogram, actors are visually represented by ***nodes*** and their relationships by ***lines***. For example, let's suppose we are studying the relationship between four teachers: Lisa, John, Mary, and Paul. We have collected data through a survey that asked each teacher to indicate who they consult for professional advice at least once a month. Lisa selected John and Paul, John selected Paul, Mary also selected Paul, and Paul selected John. This information could be represented in an ***undirected graph*** such as Fig. 12.2, Panel A. This graph shows whether a relationship between two teachers exists or not, without considering directionality (i.e., the graph does not distinguish the sender or the receiver). We could further specify the information using a ***directed graph*** by drawing an arrow from the sender to the receiver (with sender in this case meaning who they turn to for advice and receiver meaning who gives the advice) as in Fig. 12.2, Panel B.

In addition, it is possible to add more information to a graph. For example, Fig. 12.2, Panel C shows a ***valued graph*** that indicates the strength of the relationship between actors. In this case, the thickness of the tie indicates the frequency of the relationship between two teachers (a thicker line indicates a more frequent relationship). Finally, we could add information about the attributes or characteristics of the actors by changing the shape, size, and color of the nodes as in Fig. 12.2, Panel D. In this case, the color of the node indicates the sex of the teacher (gray=female, black=male), the shape shows the subject they teach (circle=math, triangle=language), and the size of the node represents how well connected a particular teacher is to the rest of the teachers within the network (a bigger node size indicates more connections with other teachers).

The Adjacency Matrix Although graphs are useful to represent relational information, if the amount of data is too large (i.e., too many nodes and relationships among them), it may become difficult to interpret using simple visual inspection. Representing the network data in matrices allows computer programs to summarize the information efficiently and find patterns in the data. Usually, social network data is stored in an ***adjacency matrix***. In most cases, this is a binary and square matrix with as many rows and columns as actors in the social network. This type of network data is called a one-mode network because it involves person-to-person connections. The matrix is filled with zeros or ones, with a 1 indicating

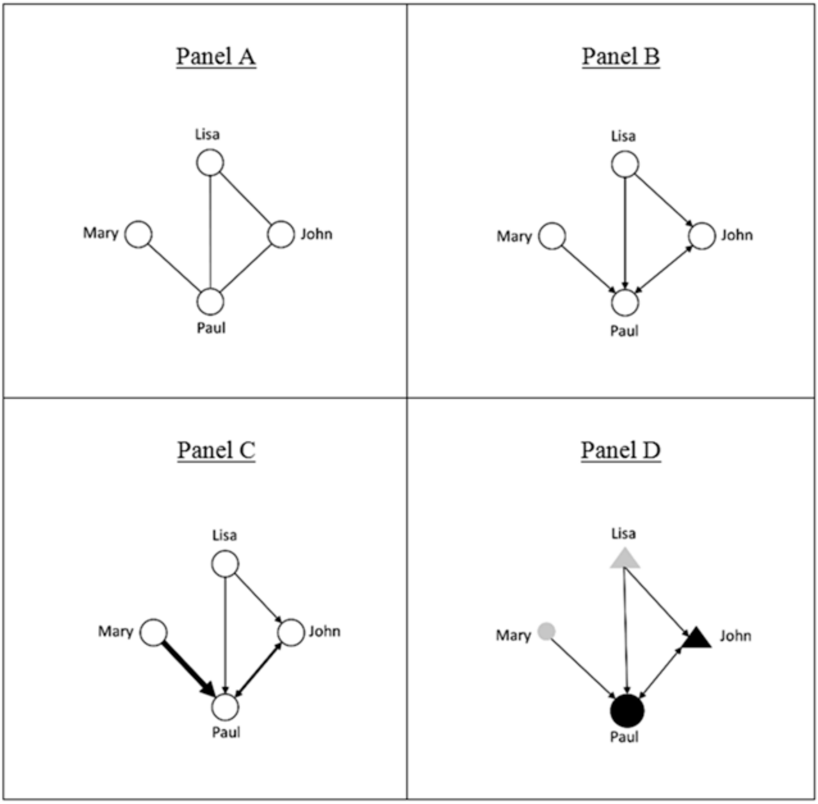

Fig. 12.2 Different ways of representing relationships using sociograms

that a relationship between two pairs of actors exists; while a 0 shows that this relationship is absent (see Table 12.1, Panel A). An adjacency matrix can be ***symmetric*** or ***asymmetric***. In a symmetric adjacency matrix we do not distinguish who nominated whom, we only know whether a relationship between two actors exists. An asymmetric adjacency matrix represents directed relationships and as seen in Table 12.1, Panel B this results in a different set of data—e.g., you can see that Panel B is different from Panel A in the Lisa/John cells with Lisa getting advice from John (1), but John not getting advice from Lisa (0). In Panel B, the shaded gray numbers are those that changed when switching from a symmetric to asymmetric data representation.

Table 12.1 Representing relationships using matrices

Panel A: symmetric adjacency matrix

	Lisa	John	Paul	Mary
Lisa	–	1	1	0
John	1	–	1	0
Paul	1	1	–	1
Mary	0	0	1	–

Panel B: asymmetric adjacency matrix

	Lisa	John	Paul	Mary
Lisa	–	1	1	0
John	0	–	1	0
Paul	0	1	–	0
Mary	0	0	1	–

When relationships are studied with people across events or affiliations, SNA moves from the traditional ***one-mode network*** structure to a ***two-mode network structure*** (2MN). One often used data set, called *Deep South,* demonstrates how events can be used to understand how actors—in this case, 18 southern women—were connected through 14 social gatherings (see Davis et al. 1941). In this case, or others that look at affiliations in terms of attendance at events (e.g., memberships on boards, etc.), inferences are made about underlying patterns of ties or groupings based upon these affiliations. If two of the women in the Deep South data set attended the same social gathering, we now assume a relationship between these two women. Importantly, affiliations are considered broadly and thus two-mode networks may involve any connection between two different groups, such as researchers and journals (in terms of where they have published), donors and initiatives, voters and candidates, readers and magazines, etc. For two-mode networks, matrices are usually rectangular in shape because the number of people and events are no longer required to be the same.

Most of the discussion we include in this chapter focuses on the structure of whole networks, whether across people or agencies, because these seem particularly well-suited to educational policy research; but it is important to mention a different unit of analysis—the ego level or personal level of a network—which could also be considered. Ego network studies can provide rich detailed information about a policy in terms of knowledge around it, influence over decisions, or implementation of a policy on the ground, and is local to the person(s) versus examining more global patterns. For example, in considering how a particular policy became supported by a school board member one might consider the structure and quality of that board member's ego network—meaning all of the connections that board member has to other board members, higher education faculty, policy makers, or teachers. Additional details about differences in collecting and analyzing whole network versus ego network data can be found in Borgatti, Everett, and Johnson (2013).

Social Network Analysis in Education Research

While SNA is not entirely new to education research it is still a burgeoning area of work.[3] Within education, scholars have been concerned with the importance of connections, ties, and attributes of formal and informal networks, which can be important to building collaborative communities, student interest and support groups, and staff agency and efficacy (see Kezar 2014; Lubbers 2003; Lubbers and Snijders 2007; Siciliano 2016). Most of the scholarly work employing SNA in education focuses on three main areas: peer networks, teacher networks, and leader or administrator networks (predominantly at the K-12 level). In addition, some higher education research has employed SNA methods in studies of change in higher education, research collaboration, student activism, and campus social and cultural capital in peer and staff networks (see Kezar 2014). We briefly discuss some examples of this work to provide the reader with an understanding of the variety of uses of SNA at the K-12 and higher education levels before turning our attention to applying SNA in education policy research.

General Applications: Peers, Teachers, and Leader Networks Peer network studies have focused on the role of peers in students' educational outcomes (e.g., academic effort, dropout rate), health outcomes (e.g., weight control, alcohol and drug consumption), or socio-emotional outcomes (e.g., social integration, homophobic behavior). Friendship networks are thought to be a rich source of resources that students can accrue or exchange in order to shape their future opportunities and outcomes. One example of this type of research is Frank et al.'s (2008) examination of how high school students' math course-taking was influenced by friendship groups, finding that girls take into account the decisions of their friends in course selection. Similarly, Grunspan et al. (2014) used SNA to investigate whether and how learning outcomes were related to classroom networks in an undergraduate biology course.

[3] For more details of SNA in education, see Carolan (2014) and Daly (2010).

Networks among teachers have also been identified as a critical area of research. Work in this area has identified patterns relating to teachers' professional interactions, including the extent to which they exhibit collegial relationships, and the ways in which these impact social capital acquisition and teacher learning (e.g., Penuel et al. 2009). In addition, teacher networks have been found to be a leverage point for the diffusion of instructional expertise through professional development (e.g., Sun et al. 2013), impacting feelings of teacher efficacy (e.g., Siciliano 2016), influencing the reform-related attitudes of teachers (Cole and Weinbaum 2010), and impacting student achievement (Pils and Leana 2009; Siciliano 2015).

Recent scholarly work has focused on the leadership networks (including school and central office administrators) within the educational system as a crucial factor for educational change and improvement. For example, Daly and Finnigan's longitudinal study of social networks within and across low-performing schools and districts found that sparse networks across leaders limits access to research evidence as leaders undergo new strategies in response to policy sanctions (Finnigan et al. 2013) and that weak and uni-directional connections between principals and central office staff in low-performing districts are particularly problematic to district-wide reform efforts (Finnigan and Daly 2012).[4] These authors also found high levels of leadership churn in low-performing districts, with the most sought after leaders for advice leaving the district (Finnigan et al. 2016), and called attention to the underlying politics that inhibited improvement given the network structure of leaders (Daly et al. 2014).

While there has been some attention to social networks in education research at the higher education level, this remains an underexplored area (Kezar 2014). Higher education researchers have focused on faculty networks and productivity and peer networks and student outcomes, but there is not yet research that studies university systems as a whole or higher education network actors as discussed by Biancani and McFarland (2013). A few studies that focus on college student peer networks include Thomas' (2000) study which examined ties among college freshman to predict college persistence; Rios-Aguilar and Deil-Amen's (2012) study of Latina/o college students' networks which found that ties that helped students to enroll were not as useful in supporting them during college and with post-college planning; and Gonzalez Canché and Rios-Aguilar's (2015) study of the influence of community college peers on credit attainment.

[4] For more results from this longitudinal study, see (Daly and Finnigan 2011, 2012; Finnigan and Daly 2014).

Applications to the Study of Education Policy Above, we provided examples of the limited attention to SNA in education research, to date. Perhaps more important has been the dearth of research using SNA methods at the educational policy level. Yet every stage of the policy cycle (problem definition and agenda setting, design, implementation, and evaluation) involves a social process. According to Knoke (2011), "policy network analysis seeks to identify the important actors – governmental and non-governmental organizations, interest groups, and persons – involved in policymaking institutions, to describe and explain the structure of their interactions during policymaking processes, and to explain and predict collective policy decisions and outcomes" (p. 210). Thus, SNA provides researchers a valuable tool especially well-suited to study policy (Hermans and Thissen 2009; Penuel et al. 2006; Song and Miskel 2005). Despite its potential, SNA has not been as commonly used in educational policy as it has been in other realms such as public health (Carolan 2013).

In this section, we illustrate the potential of SNA for studying policy issues in K-12 and higher education by offering two recent empirical examples. Each of these focuses on a specific stage of the policy cycle though it is important to note that there are many more ways to study policy using SNA.

Policy Advocacy SNA can be used to study policy issues in the early stages of the policy cycle. It is particularly well suited to studies that focus on underlying politics, including policy influences, agenda setting, and policy advocacy. For example, Au and Ferrare (2014) used SNA to examine how the network of relationships among policy actors influenced the passage of a charter school initiative in Washington. Although, voters had opposed charter school legislation in three previous referendums in 1996, 2000, and 2004, they approved I-1240 in 2012. Critical to understanding the passage of any policy is to recognize the influence that advocacy groups exercise over the public vision and political discourse. In this case, Au and Ferrare (2014) examined the influence of policy advocates within the context of the "Yes On 1240 WA Coalition for Public Charter Schools" campaign by using a social capital perspective where policy advocates transferred material (e.g., donations or volunteers) or symbolic resources (e.g., prestige) through their social connections to shift the public vision and political discourse.

Using various data sources—including tax returns, institutional reports, and public disclosures—Au and Ferrare (2014) uncovered connections among organizations and individuals and the Yes Campaign, and generated a binary adjacency matrix of the directed relationships among the policy actors. From this matrix, a directed graph was constructed that traces the transference, or flow, of resources among policy actors and organizations supporting the "Yes On 1240" campaign.

Using social network analysis methods, Au and Ferrare (2014) identified key influencers over this policy process, finding that the Bill & Melinda Gates Foundation was the most central transmitter of resources. Almost all the transferred resources were material instead of symbolic; and philanthropic foundations acted as channels directing resources toward the policy actors to influence the charter school policy adoption. SNA was an innovative way to trace the influence of private individuals and different types of organizations including philanthropic foundations and advocacy groups over the adoption of the charter school policy.

Policy Implementation Beyond policy advocacy, SNA can also be useful in studying policy implementation and its effects on education systems. To illustrate this application, we turn to a recent study by Hodge, Salloum, and Benko (2016). These researchers examined Common Core State Standards' (CCSS) implementation by focusing on secondary ELA resources (e.g., professional development or curricular resources for teachers) that were sponsored and shared by 51 state educational agencies (SEAs) and other intermediary organizations (i.e., non-system actors such as research institutes, nonprofits, and policy or advocacy organizations, to name a few). The authors investigated the types of resources SEAs were recommending and which SEAs supported these resources—as well as how resources tied these groups together—to consider what CCSS messages were being spread throughout the system (and would ultimately reach ELA teachers). SNA allowed the researchers to examine the *structure* of the two-mode resource sharing network to understand CCSS implementation.

Using public information available on SEA homepages, the authors catalogued 2001 resources, which included 2644 ties or *edges* across 313 agencies (51 SEAs and 227 organizations) or *nodes*. The researchers examined the centrality of SEAs as well as their connectedness to other organizations (see Fig. 12.3). The results illustrate a *core-periphery network*, meaning certain agencies that are highly connected remain in the center,

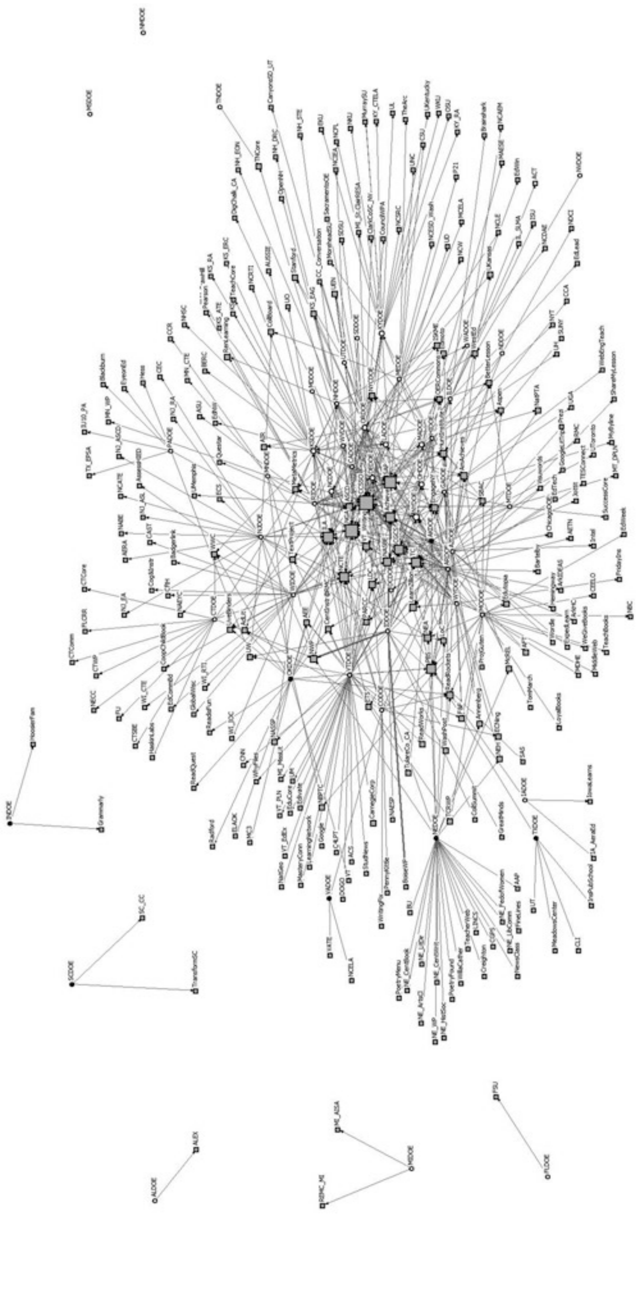

Fig. 12.3 Social network of state education agencies and intermediary agencies' connections around common core ELA resources. (Note: SEAs are circles; white are CCSS SEAs, and black are non-CCSS SEAs; grey squares are intermediary organizations, tie thickness represents number of resources used from an agency and node size represents a measure of the agencies' centrality in the network. Source: Hodge et al. (2016, p. 7))

or "core" (e.g., SEAs such as Massachusetts, North Carolina, Ohio, and New York as well as education policy membership organizations like CCSSO, general membership organizations like ACSD (formerly the Association for Supervision and Curriculum Development) and membership organizations focused on literacy like the National Council of Teachers of English known as NCTE). For-profit companies were also central in the network. Those with fewer connections were located toward the periphery (e.g., Iowa and Iowa Learns).

Social network analysis methods provided the tools for Hodge and her colleagues to uncover: (1) the more influential actors over Common Core implementation because of their provision of CCSS resources that were shared by a number of states; and (2) the multiple groups that may be sending conflicting messages about CCSS instruction, given their centrality in the network. They also found that CCSS states were more likely to connect with each other than non-CCSS states, but found uneven connectedness and isolation among some states, suggesting external resources may not be making their way into some states. Given the state department of education's role in building capacity among teachers, *what* they provide teachers around ELA instruction is extremely important to CCSS implementation. The SNA suggested that while many states provided conceptual resources, more practical ones appeared desirable as many groups were seeking these out from particular agencies. SNA in this case provided important empirical data that can inform policymakers as to the assumptions and challenges relating to state CCSS implementation and the diffusion of resources.

Recommendations for Novice and Emerging Scholars

At this point we have described what SNA is and how it can be used to study educational policy. Here we provide some more specific recommendations to scholars as they consider whether SNA is appropriate for their work.

Step 1: Consider Whether Relational Questions Drive Your Analysis It is important to consider whether the relationships between individuals, organizations, or events are important to your area of study. Remember that social network studies consider questions like who is affiliated with a particular group or who seeks advice from whom? In the policy realm, questions that might drive the research are questions relating to which advocacy groups may have influenced policy discourse, how connections to certain teachers or district events may have impacted implementation, or whether certain policy outcomes—e.g., increased collaboration among higher education units—were achieved. In this type of research, the connections or ties among actors are central to the analysis.

Let's consider a local policy that involves a new student assignment policy to reduce segregation in a particular district. In this case, questions relating to who (e.g., the media, groups representing communities of color, or parents) influenced the design of the policy would be particularly important and social network analysis could help to uncover the most influential actors.

Step 2: Consider What Theoretical Perspectives Drive Your Analysis Though SNA is not directly linked to any particular theoretical perspectives, we highlight a few common lenses here, including social capital, cognitive social structure theories, diffusion theories, and the advocacy coalition framework, to illustrate lenses that may be useful in policy research. Choice of perspective or lens will be closely linked to the questions asked and unit of analysis of the work.

Social Capital Network theories are central to the concept of social capital, as individuals are embedded within relationships, and these relationships are embedded in larger subgroups that eventually form a social network. This theory suggests that personal connections and interpersonal interactions are an investment just like other types of capital (e.g., human or cultural capital) (see Scott's (2017) discussion of how Bourdieu, Coleman, and Putnam contributed to these areas). Social capital is operationalized as the resources embedded in social systems and used by actors for action (Lin 2001), and these resources can vary from communication to information exchange, trust, and knowledge sharing (Scott 2017; Wasserman and Faust 1994). Relationships create a structure that determines opportunities for social capital transactions or access to these resources (Burt 1992; Coleman 1988, 1990; Granovetter 1973, 1983; Lin 2001; Putnam 1993, 2000).

Cognitive Social Structures Studies using cognitive social structure (CSS) theories (Krackhardt 1987) aim to integrate the role of cognition and meaning-making, so in this case it might be around making sense of or interpreting policy. The most common frameworks shaping CSS studies emerge from social cognition and structuralist theories that position context and social relationships as central components to meaning-making. Based on these theories, social structures influence the individual's position and exposure within the network context, social interaction leads to expectations for future interactions, and individuals' social positions then impact how they see actors in the network (Casciaro 1998). CSS can uncover whether individuals' interpretations align with intended outcomes or predict future actions (see also Brands 2013 and Pierce et al. 2014).

Diffusion Theories Diffusion theory has roots in anthropology, sociology, epidemiology, geography, and marketing, among other areas, and describes the mechanism by which new ideas, opinions, attitudes, and behaviors spread throughout a community (Bailey 1975; Rogers 2003; Ryan and Gross 1943; Valente 1993, 1995; Valente and Rogers 1995). Initially described by Ryan and Gross (1943), the basic premise is that new ideas and practices spread through interpersonal contacts and communication (see Beal and Bohlen 1955; Hagerstrand 1968; Katz et al. 1963; Rogers 1995; Valente 1995; Valente and Rogers 1995). Diffusion modeling assumes a classic S-shaped curve whereby initial growth in adopting something occurs gradually at first, then accelerates, then decelerates (Rogers 2003). Because diffusion often occurs through personal networks, and these networks are shaped by many factors, including geography, ethnicity, age, and socioeconomic status (SES), there may be different diffusion trajectories for different subgroups (Valente and Fosados 2006). Knowledge diffusion is largely influenced by interactions, which serve as conduits (Moody 2004).

Advocacy Coalition Framework (ACF) This framework suggests that actors in a particular policy subsystem (defined as a policy issue/area, usually bounded geographically, that encompasses different policy stakeholders such as government, interest groups, research organizations, and media) structure themselves into coalitions of competing policy beliefs to shift policy toward their coalition's interests (Sabatier 1988; Sabatier and Jenkins-Smith 1993). Advocacy coalitions are stable social groups over time that coordinate and share beliefs and resources within but not across the boundaries of the coalition (Sabatier 1988). According to this framework, policy change can occur through administrative organizations, which usually maintain a more moderate position regarding an issue, and thus, can act as brokers or mediators among coalitions. In addition, new scientific information can be used by coalitions to support their political views and produce policy learning. Finally, exogenous shocks or new information can also be the origin of policy change (Sabatier 1988; Sabatier and Jenkins-Smith 1993).

While these are by no means meant to be exhaustive, these four theoretical frameworks offer a few different conceptual lenses and show the variety of perspectives that might align with and inform SNA studies. Many other sociological, psychological, or political lenses could inform your work.

Step 3: Collect Network Data Collecting data for social network studies depends upon the type of analysis—one mode and two mode—and available data. Many studies involve surveys administered to individuals that involve questions relating to the existence or frequency of ties. As an example, if a researcher was concerned with the structure of organizational friendships and support, they may ask individuals to establish "Who would you consider a close friend?" In policy research, data may be collected around who someone asked advice from around a particular policy or who was at certain events when a policy was being discussed or designed. Using our example above again, we might consider two different types of studies. A one-mode study might ask all key stakeholders who they asked for advice about the policy—which would result in a matrix much like the one depicted in Table 12.1, panel B. Alternatively, a two-mode study might consider all of the individuals who were on the task force to develop the policy and what affiliations they had in the community to uncover the strength of the influence of various groups through these affiliation ties. In this case, the two-mode matrix would have individuals x community groups, as opposed to the one-mode matrix with actor x actor (for more on two-mode SNA, see Borgatti 2012; Borgatti and Everett 1997). As mentioned above, important to data collection is consideration of whether the study will examine a complete network (e.g., all of school board members and their relationship to each other), or ego networks of individuals (e.g., the network of advice for individual school board members which would include anyone they turn to for advice whether they are on the school board or not).

The use of SNA methods comes with certain ethical considerations relating to collecting this type of data (Borgatti and Molina 2003; Kadushin 2012). First, unlike traditional survey techniques and analysis, respondents' anonymity may be difficult to protect; this is especially true of intra-organizational and subunit analyses. However, inter-organizational or more nested methods move beyond the issues of anonymity. Practices like using a third party to process attribute data and other sensitive data such as value-added data that link teachers and student achievement to a unique identifier before releasing data to researchers for analysis can also help to maintain confidentiality.

Step 4: Prepare Data for Analysis In uncovering and understanding the actors and ties of social networks, researchers pay particular attention to metrics of *density*, *reciprocity*, *centrality*, and *homophily*. Density provides information about how well connected or sparse the relationships are in a social network, and it is defined as the proportion of actual ties to all possible ties within a network. Reciprocity is the proportion of mutual connections across the network and measures the strength of a relationship. Centrality aims to quantify the relevance or influence of a particular actor within a social network. Lastly, homophily measures the desire for individuals to establish relationships with others that share similar characteristics or beliefs to themselves.

Beyond descriptive analyses and visual presentation of sociograms, some social network studies in education involve regression analysis or estimation procedures (e.g., Daly and Finnigan 2012; Sun et al. 2013; Moolenaar et al. 2014), and multi-level modeling (e.g., Siciliano 2016; Spillane and Kim 2012).[5] In these studies, the centrality of individuals for example, might be used to predict outcomes compared with more peripheral actors, or fidelity of implementation around a particular policy may predict higher levels of network centrality. In the case of our example around student assignment, more decentralized leadership networks in a community might predict more successful policy implementation (because of greater buy-in across diverse groups).

[5] Additional relevant examples outside of education that might be useful include Yu, Hao, Dong, and Khalifa (2013) which investigated knowledge sharing behaviors of individuals and within teams using a multi-level nested model.

More advanced statistical methods can also be used to look at policy research which can overcome limitations of interdependence within and across ties. Using exponential random graph models (ERGMs)—also sometimes referred to as *p** models—SNA software like Simulation Investigation for Empirical Network Analysis (SIENA) (Ripley and Snijders 2010) and its R-package version RSiena (Ripley et al. 2017) can determine whether the formation of networks (e.g., voters and policies; organizations sponsoring projects; etc.) can help to inform policy formation, implementation, and outcomes by comparing actual networks with simulated stochastic models of networks with the same characteristics to establish whether network structure is based on chance or not. In this manner, Berardo (2014) was able to determine the structure of organizations as they were linked to projects and the role that governmental actors might play in *brokering* and *bridging* inter-organizational collaboration on projects through actor by organization network analysis. Though not an educational policy-specific study, it sheds light on the complexity of SNA methods that can be applied to educational policy research agendas by considering agency and structure of networks within specific educational contexts.

Conclusion

Social network analysis (SNA) is a unique methodology, allowing researchers to examine and uncover the underlying connections among people, behaviors, events, objects, and institutions within and across social systems. Its focus on connections and relationships makes SNA ideal for studying policy—which involves a social process at every stage. As emerging and experienced researchers consider the theories and methods that best explain, uncover, and advance understandings relating to policy advocacy, policy design, policy implementation, and policy outcomes, it is worthwhile to consider the ways that SNA might expand our knowledge base in these critical areas. We hope this chapter has contributed to the larger conversation around how policy research can be advanced by innovative methodological approaches to meet the complex needs of the field and to produce rigorous results that can improve policy and practice and ultimately the outcomes and opportunities for youth.

Recommended Readings

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing social networks.* London: Sage Publications.

This practical book walks readers through all aspects of the research process from designing a study to interpreting the results. The book includes chapters on data collection and management, visualization, and analytical approaches including analyses particular to SNA such as related to subgroups, centrality, ego networks, etc. *Readers are also introduced to the software developed by the first two authors for analysis of social network data, UCINet, and Netdraw.*

Kadushin, C. (2012). *Understanding social networks: Theories, concepts, and findings.* New York: Oxford University Press.

This book covers fundamental concepts in SNA, presenting core themes, constructs, and applications. It is especially useful for researchers who are new to the social network field and particularly interested in the psychological and sociological underpinnings of SNA. The book calls attention to ethical considerations in collecting and using social network data.

Scott, J., & Carrington, P. J. (Eds.) (2011). *The Sage handbook of social network analysis.* London: Sage Publications.

This is a comprehensive text that introduces readers to SNA by systematically reviewing the concepts, theories, methods, principal topics, and discussions within the field. While it can provide introductory material to a newcomer it also will be useful to more seasoned researchers who are interested in developing stronger grounding in the underlying theories, mathematical models, and variety of applications of SNA.

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