1 Levels of Analysis and the Multilevel Network Framework

Much of our social, political, and professional lives are motivated and influenced by the relationships we form with others. Networks play a critical role in shaping beliefs and behaviors as they provide the context through which information is acquired, shared meanings develop, activity is coordinated, and norms are established (Coleman, 1990; Friedkin & Johnsen, 2011; McLean, 2017). Given the fundamental role networks play in our lives, researchers have advocated that fields of inquiry adopt a network perspective (Considine et al., 2009; Krackhardt & Brass, 1994; Robins, 2015). A network perspective highlights the importance of social and organizational relationships in shaping individual and collective outcomes. Inherent in the network perspective are micro–macro linkages between social actors and social structures that determine how actors create and are constrained by their social relations (Kilduff & Tsai, 2003, p. 66).

Based on our experiences teaching and conducting network research, we have observed several roadblocks to applying the network perspective. These roadblocks include conceptualizing the specific hypothesis one wants to test, identifying the relevant theory, and selecting the appropriate analytic strategy. These challenges often result in (or are derived from) several sources of confusion prevalent in network studies: (i) a misunderstanding between the unit and level of analysis, (ii) a lack of clarity on the number of observations available for analysis, and (iii) a limited consideration of the mechanisms that influence the relationship of interest.

Consider the following research questions. Why are some nodes more central than others in the network? Which self-organizing behaviors helped produce the observed network's shape? How does an actor's position in the network influence their outcomes? How does the shape of a network affect its overall success? Across these questions, the network serves as both the independent and dependent variable, and the phenomena of interest reside at the nodal, dyadic, and network levels. Just as important, each question draws on a potentially different set of theories linking network phenomena to other individual and group behaviors and outcomes. As Robins (2015, p. 13) notes, one of the strengths and challenges of network research is balancing discussions of individual actors and the social systems they comprise.

We wrote this Element to help scholars and practitioners think more deeply and clearly about networks. This element makes two major contributions. First, this Element contributes to social network research through the development of the Multilevel Network Framework. The framework provides network scholars and practitioners in various fields with an integrated conceptual model to explore how networks form and produce changes in behaviors and outcomes. The framework addresses multiple levels of analysis (nodal, dyadic, and network) and emphasizes the theoretical mechanisms connecting network phenomena within and across those levels. It encourages researchers to articulate more explicitly how different network phenomena of interest are related and reveals gaps in the underlying processes assumed to be at work. This ultimately provides insight into the appropriate data and modeling strategies needed to test theory.

Second, this Element contributes to the fields of public administration, management, and policy more specifically by applying the Multilevel Network Framework as a diagnostic lens. We conduct a systematic review and use the Multilevel Network Framework to categorize and take stock of the existing empirical literature on networks. The framework serves to categorize the extant scholarly research into micro and macro relations, types of variables, and classes of theories and mechanisms applied. Thus, we reveal the range of network relationships our field has emphasized and the significant gaps that remain. This application of the framework leads to the identification of several important areas for future research. Other fields of science can also use the Multilevel Network Framework to explore their progress and identify gaps in their literature. Overall, the framework provides several important roles. It serves as (i) a conceptual tool to help us think more deeply about the nature of network relationships; (ii) a research tool to assist in connecting data, theory, and empirical models; and (iii) a diagnostic tool to analyze and categorize bodies of literature.

This section will describe the development of the Multilevel Network Framework. The framework is based on Coleman's bathtub model (Coleman, 1990) and connects different levels and directions of analysis in network research with relevant mechanisms and theories. Given the framework established in this section, Section 2 provides an overview of the systematic review we conducted of the empirical network literature. Using the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) we identified 196 articles in 40 public administration and policy journals between 1998 and 2019. Of the 196 articles that met our search criteria, 107 focused on understanding and modeling the determinants of network formation. The other 89 examined how the composition and structure of the network influenced network effects. Sections 3 and 4 review these articles and integrate the existing network scholarship across various forms and levels.

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1.1 What Are Networks?

Before proceeding further, let us begin by defining a network. A network consists of a set of actors or nodes and the links or ties among those actors. The actors in the network can be various entities, including individuals, workgroups, organizations, local governments, and nations. The links connecting the actors can represent a wide range of possible relations. For example, the relations can be (i) social, such as a friend, (ii) interactions, such as advice seeking or communication, as well as (iii) flows, such as the movement of trade, information, or disease (adams, 2020; Borgatti et al., 2013). Networks are most often represented by an adjacency matrix or a graph. For example, Figures 1a and 1b provide both forms of representation for a simple network of ten actors. The actors are labeled A through J.

In Figure 1a, the matrix representation, the rows and columns identify the actors. The intersecting cell for any given row and column indicates the status of the relationship between the corresponding actors. The value of "1" in the matrix means the relationship is present and "0" indicates it is absent. The information contained in the matrix can also be displayed graphically, as seen in Figure 1b. The actors are now represented as nodes, and actors who have a relationship present are connected by an edge or tie in the graph. In Figure 1a, we see that actor E has a tie with actor G, as there is a "1" at the intersection of their row and column. In the graph representation, a corresponding edge connects node E to node G. Networks can be undirected (as in Figures 1a and 1b) or directed, and they can be weighted or binary. In an undirected network, ties are symmetric, such as with collaboration or coauthorship. In a directed network, ties do not need to be symmetric or reciprocal, such as with advice seeking or trade. Weighted networks assign a value to the relationship under study. For example, rather than an advice tie being present or absent, information on the frequency of advice seeking may also be available.

(a)

	A	B	C	D	E	F	G	H	I	J
A	0	1	1	1	0	1	0	0	0	0
B	1	0	0	1	1	0	1	0	0	0
C	1	0	0	1	0	1	0	0	0	0
D	1	1	1	0	1	1	1	0	0	0
E	0	1	0	1	0	1	1	0	0	0
F	1	0	1	1	1	0	1	1	0	0
G	0	1	0	1	1	1	0	1	0	0
H	0	0	0	0	0	1	1	0	1	0
I	0	0	0	0	0	0	0	1	0	1
J	0	0	0	0	0	0	0	0	1	0

(b)

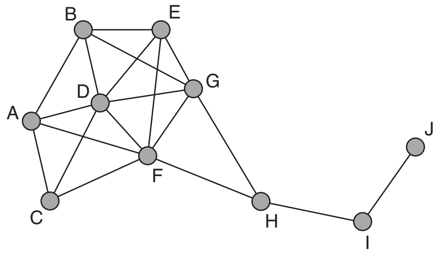

Figure 1 (a) Network represented as an adjacency matrix; (b) Network represented as a graph

Networks in public administration and policy take on various forms, from interpersonal relationships among street-level workers (Nisar & Maroulis, 2017; Siciliano, 2017) to collaborative agreements among governments (Hugg, 2020; Thurmaier & Wood, 2002). Networks in our field are often described through a variety of names. These names may focus on their function or policy domain, such as a service delivery network (Bunger, 2013; Provan & Milward, 1995) or an economic development network (Lee, 2011). The names may emphasize the nature of the relationships among the actors, such as a communication or advice network (Siciliano, 2015a). Finally, the names may stipulate the presence or absence of an over-arching authority or goal, such as purpose-oriented networks compared to serendipitous ones (Carboni et al., 2019; Nowell & Kenis, 2019; Nowell & Milward, 2022).

Regardless of the name, individual actors (whether humans or organizations) maintain agency over the relationships they form with others. For example, consider the Continuums of Care mandated by the US Department of Housing and Urban Development. The Continuums of Care establish community-wide planning and coordination among nonprofits, government agencies, housing authorities, and school districts. Despite their common origins and mandates, Continuums of Care across the country have been found to vary in their overall structure, the form of governance, size of membership, frequency of advocacy, and strength of relationship with policymakers (Hambrick Jr. & Rog, 2000; Mosley & Jarpe, 2019). Mandates to form networks by an external party (usually a government) may identify sets of actors needed to participate. However, such mandates cannot force those actors to share advice or trust one another (Siciliano, Wang et al., 2021).

Consequently, networks are emergent phenomena, and scholars applying a network perspective often consider the factors that influence tie formation and the implications of those ties. As Krackhardt (2003, p. 330, italics in original) remarks on organizational networks, "An inherent principle of the interactive form is that networks of relations span across the entire organization, unimpeded by preordained formal structures . . . These relationships can be multiple and complex. But one characteristic they share is that they *emerge* in the organization, they are not preplanned." Aligned with a network perspective, scholars argue that emergent structures provide greater insight into the functioning of systems and organizations when compared with formal structural variables (Monge & Contractor, 2003, p. 9).

1.2 Units Versus Levels of Analysis

This Element develops a framework for thinking about the micro- and macro-level factors that impact the emergence of ties among actors and how those ties and the resulting network structure produce effects. Underlying the myriad of actors and relations that can comprise networks are multilevel theoretical constructs and mechanisms that help to explain network formation and network effects (Monge & Contractors, 2003). Because networks are multilevel phenomena, research on the same set of actors can operate at different levels of analysis. For example, when studying network performance, at what level does the performance outcome reside? Is it the individual actor's success? Or the community or residents the network is designed to serve (Provan & Milward, 2001)? At the same time, at what level do the factors influencing these outcomes reside? Is it the position of individual nodes that matters? The overall structure of the network? These questions force researchers to understand the distinction between the level of analysis and the unit of analysis in network scholarship.

Traditionally, research does not distinguish between units of analysis and levels of analysis. For example, when we conduct research at the organizational level, this is equivalent to saying our units of analysis are organizations (not individuals in the organization). However, network analysis is different in this regard. Because networks focus on the relationships among entities, not simply their attributes, there is a profound difference between units of analysis and levels of analysis (Krackhardt, 2010). To illustrate this difference, consider Figure 1b, which is a classic "Kite" network (Krackhardt, 1990). Each of the ten nodes in the graph is arbitrarily labeled with a letter. But each node could easily represent a different type of entity. For example, each node could be a person (and the eighteen ties could represent communication ties). Alternatively, each node could be a firm (and each of the eighteen ties could represent interlocking directorship ties). Or, each node could be a country (and each of the eighteen ties could represent bilateral trade agreements). We refer to those different entity types as the units of analysis for the network. The unit of analysis defines the specific scope and content of the nodes in the network.

In contrast, the level of analysis speaks to the structural feature of the graph that corresponds to the research question one is interested in exploring. There are several levels represented in the graph in Figure 1b. For the sake of discussion, let us assume that the unit of analysis is the individual and the ties among those individuals represent "daily communication" links within the team that these ten people belong to. We could be interested in knowing why person H has a tie to person F but not to person D. Or, we could be interested in knowing how H's position in the network gives rise to particular advantages, over and above the advantages enjoyed by D in their position. Or we could be interested in knowing whether the shape of the network, as a whole, contributes to the team's performance. Each of these interests represents a different level of analysis of this one network.

To be specific, the *Level of analysis* in a network study is given by an integer L in the term N^L, where N is the number of nodes in the network and N^L is the potential number of observations that the network provides to address the question. A Level 1 study of this network in Figure 1b would indicate that the primary focus is on the individual node, perhaps the advantages or constraints they experience by occupying their particular position in the network. The number of pertinent observations for such a research question at Level 1 is $N^1 = 10$ in this case; one observation per node in the network. A Level 2 study of this same network might ask the dyadic question, what seems to predict who will communicate with whom in this network? In all, at Level 2, there are N^2 dyadic relations that could be studied. However, as in the case of Figures 1a and 1b, we have imposed symmetry on the ties and do not consider self-relations (people talking to themselves), which reduces our number of observations to $(N^2 - N)/2$. This restriction on the number of possible observations at Level 2 is not unusual, but it still may be thought of as approximating N^2, at least as an order of magnitude estimate.

This same network also permits us to ask another Level question, as mentioned earlier: What is the consequence of the shape of the network as a whole? This is a Level 0 question, where the number of observations provided to address this question is $N^\circ = 1$. Thus, despite gathering information on each of the ten actors and their relations, we still have only observed the properties of a single network. Of particular note here is that this Level 0 question is not simply an average of the attributes at the more micro level, Level 1. Rather, the network's shape is defined by a characteristic of the pattern or structure of the network as a whole and cannot be reduced to some sum of its constituent parts.

Finally, to complete our typology of Levels of analysis,[1] we consider that network ties themselves are often perceived differently by different occupants of the system. For example, the fact that H has a tie to I in the Kite network may not be observed by all the other members of the network. If one were to misperceive this critical link, this could affect how they operate within the system. In this context, as Krackhardt (1987) argued, sometimes how people perceive the network can be more critical in terms of their behavior than the actual network in which they are embedded. Level 3 studies allow us to pursue such claims. For example, individuals who are perceived to be central or tied to

[1] In addition to the levels mentioned here, network scholars may engage in the analysis of subgroups. Subgroups in networks are defined and calculated in a variety of ways. In general, they can be thought of as sets of actors who are more tightly connected with one another than they are to others in the network. Such groups are identified through the application of detection algorithms, like Girvan–Newman. Subgroup analysis is often conducted as part of an analysis at a particular level. For example, scholars in public administration have used subgroups as a contextual variable in models of nodal behavior (Maroulis, 2017).

prominent actors in the network are also perceived to be higher performers, regardless of their true position (Kilduff & Krackhardt, 1994). Further, individuals with more accurate perceptions of the network have been shown to have greater power and reputations (Kilduff & Krackhardt, 2008; Krackhardt, 1990; Krackhardt & Kilduff, 1999). Thus, analyses of people's perceptions matter because one's view of the broader network shapes their decisions and behaviors. Level 3 analyses focus not on the actual ties between actors but consider all the possible perceptions of ties that could occur between those N actors. The number of observations at Level 3 is N^3 (1,000 in this case, although again, we might only consider the perceptions on symmetric and non-self-communications, which would reduce the number of observations to $N(N-1)N/2 = 450$).

The numeric categorization of the level of analysis is not simply a numeric labeling to separate the different types of research questions that can be posed about a network. The numbers associated with each of the levels create a connection between the structural feature of interest (i.e., nodes or dyads or whole networks) and the number of those structural features available to the researcher for analysis. Another way to summarize this connection is to consider that the level of analysis is also the number of subscripts necessary to refer to the particular observation being referenced. If one is looking at aspects of a whole network, X, then no subscripts are needed to reference it. However, if an analysis is examining the properties of the nodes within the X network, then one needs to identify each of those nodes via a single subscript i, as in X_i. A dyadic, Level 2 analysis likewise requires two subscripts to identify each of the nodes (i and j) involved in a dyad, and thus X_{ij}. Finally, a Level 3 study requires the use of three subscripts as such analyses consider the perception each actor has of the i–j tie, and thus an observation would be referenced as X_{ijk}, where k is the perceiver of the i–j tie.

1.2.1 Methods of Analysis

Each Level of analysis associated with network data requires paying attention to how the individual observations at that level should be treated. While many statistical assumptions can be made at each Level, violations of these assumptions abound and affect the feasibility of particular analytical methods and model choices. In some ways, Level 0 analysis is the easiest, and in some ways, it is the hardest level at which to conduct scientific research. It is easiest because the primary assumption of independence of observations is the most tenable. Most whole networks are treated as if they are independent systems without a structure between the units (i.e., between different networks) that would create an autocorrelation in errors in the models. For example, Crespi

(2020) analyzed a set of over 1,000 hospitals in the United States to show that the average path distance between doctors in their patient-sharing networks within the hospital was significantly related to the hospital's efficiency in delivering health care, controlling for a host of possible confounds. Sarkar et al. (2010) demonstrated across fifty-two bank branches that the shape of the communication networks between informal leaders and other employees explained almost 90 percent of the variance in profitability across those branches. Both studies used traditional statistical tools in their analyses, assuming these organizational units (hospitals and bank branches, respectively) constituted independent observations. The difficulty at this level of analysis is that the data requirements are severe. In the smaller case of the Sarkar et al. study, each of the fifty-two branches required collecting complete network data among each branch's twenty to fifty employees. In the Crespi (2020) study, complete network data were collected for each of the over 1,000 hospitals. This is a cumbersome task, often prohibitively so as the average size of the organizational units increases.

While pursuing network questions at Level 0 is both scientifically interesting and valuable to practitioners, the scope of such studies makes them daunting. Thus, another common approach to dealing with analysis at Level 0 is to conduct case studies, comparing a smaller number of units but fleshing out in detail what is going on in each unit. An excellent example of this is the classic Provan and Milward (1995) study of four community health care systems, wherein they showed that the shape of the networks within each system was related to their overall functioning. Of course, with only four observations, no statistical tests would be sensible. However, their rich description of each system and how these networks related to their daily operations provided compelling evidence and logic for their claims.

For Level 1 analysis, each actor (unit) is ascribed a score based on their position in the network. An immediate advantage that Level 1 studies have is that there are N observations for each network, making such studies much more amenable to statistical inferential tests than Level 0. Within the study of organizations, Burt's (1992) development of "structural holes" is a prominent concept, both theoretically and empirically. In Level 1 studies, each actor's structural position is measured, along with other variables that can also be attributed to the actor. Again, traditional econometric methods are frequently used in such analyses, treating each actor in the network as an independent observation.

While traditional econometrics is the most common analysis approach at Level 1, one could argue that these units are not independent of one another, an assumption that is essential to statistical testing. Indeed, the fact that critical network ties are part of the theoretical story by itself might encourage the researcher to question whether this assumption is valid. Fortunately, network autocorrelation models have been developed (Doreian et al., 1984; Leenders, 2002) to test these assumptions, assess the strength of this lack of independence, and control for it to the extent it affects the observations of interest. If the data are longitudinal, then even more sophisticated methods can be used to tease apart the various sources of influence over time (Snijders, 2017).

Level 2 questions, however, are unambiguously non-independent. No one would try to defend the N^2 observations available among N actors as statistically independent of one another. Indeed, Krackhardt (1988) showed that treating Level 2 observations as independent when in fact there may only exist a moderate degree of interdependence leads to large Type I errors in statistical testing. In a set of simulations, he demonstrated that more than half of the simulated samples "appear" statistically significant when in fact the samples were drawn from a population where the null hypothesis is true.

Two streams of work have been shown to deal with this problem with Level 2 data. The first, the Quadratic Assignment Procedure (QAP), applies a permutation test, which has been shown to be robust against the extent of interdependence among observations (Dekker et al., 2007; Krackhardt, 1988). The second is a larger body of work, called Exponential Random Graph Models (ERGM), that approaches this problem from a stochastic viewpoint (Lusher et al., 2013; Robins et al., 1999). Both methods allow the researcher to pursue Level 2 questions while explicitly acknowledging the lack of independence in the raw dyadic data. Methods for longitudinal data have been developed for ERGMs (Cranmer et al., 2021), as well as stochastic actor-oriented models (SAOM) as implemented through RSiena (Ripley et al., 2022). Depending on the granularity of the data, relation event models (REM) have been developed to deal with time-stamped dyadic data (Butts, 2008).

Level 3 questions, where there are three actors associated with each observation (a perceiver, a sender, and a receiver of a tie), compound this lack of independence problem exponentially. If we want to know the answer to the question, why does John think that Sue is a friend of Robert, there are so many sources of confound here that it is difficult to even think about how to model them. As a result, what scholars have done instead is aggregate Level 3 data to a higher level. For example, Krackhardt (1990) asked, do people with more accurate perceptions accrue more power in the organization? By comparing Level 3 data on an actor's perception of the whole network with a Level 2 assessment of the "actual" network, he computed an accuracy score for each network actor. He then used traditional econometric methods to answer the accuracy-power question. Almost all the empirical work with Level 3 data has aggregated up to either

Level 2 or Level 1 observations, as Krackhardt did, to get an answer to the question of interest. However, these aggregations leave the fundamental Level 3 questions on the table: Why do some people perceive some actors to send some ties to other specific actors? And while scholars are working on possible modeling approaches to address these questions, there is, to date, no peer-reviewed or generally accepted statistical techniques to deal with these thorny Level 3 issues.

1.2.2 Direction of Analysis

Another layer of complexity when studying networks is the direction of analysis. Like other phenomena, networks can serve as both (i) dependent variable, where the ties and overall shape of the network are to be explained, and (ii) independent variable, where the network explains some other outcome. Combining the level of analysis with the direction of analysis, we create a 4×2 table that depicts the type of research questions that can be asked at that level and direction of analysis. Table 1 provides sample research questions for each cell, along with examples of typical methods of analysis.

1.3 Framework Overview

The Multilevel Network Framework shown in Figure 2 serves to combine the level and direction of analysis along with linkages that serve as placeholders for the relevant mechanisms and theories that connect the variables under study. The model is based on Coleman's bathtub, also known as Coleman's boat (Coleman, 1990). Coleman's bathtub model has been used in a variety of fields interested in relating micro-level events to macro-level structures and outcomes. The bathtub model "provides a systematic scheme for articulating social explanations and their presuppositions" (Ylikoski, 2016, p. 3). Consequently, the model forces a researcher to be explicit about the processes and mechanisms that give rise to the phenomenon of interest.

In our adaptation, the Multilevel Network Framework combines two bathtub diagrams and situates the network (its shape and composition) at the center. The network, Point D in Figure 2, serves to connect the two bathtubs together. On the left side is a model of network formation, consisting of Points A, B, and C. This side of the framework treats the network as the dependent variable and focuses on processes of network formation. On the right side of the framework, the network functions as the independent variable and connects with Points E, F, and G. This side of the framework examines the implications and consequences of network structure. Each point in the framework is also associated with a particular level of analysis (nodal, dyadic, and network). Note, we do not include the cognitive level (Level 3) in the framework, though one could imagine extending the model