CHAPTER 18

Emergence of Multidimensional Social Networks

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Each edition of the *Handbook of Organizational Communication* has contained a chapter on communication networks. In the first edition, Monge and Eisenberg (1987) reviewed literature on the antecedents and outcomes of communication networks. In the second edition, Monge and Contractor (2001) reviewed ten families of theories that explained the emergence of communication networks. The third edition of the *Handbook of Organizational Communication* reenvisions the study of communication networks, beginning with its definition. In the second edition, Monge and Contractor (2001) define *communication networks* as "the patterns of contact between communication partners that are created by transmitting and exchanging messages through time and space" (p. 440). Although patterns of contact are a type of communication network, the current chapter expands the scope of this definition. In particular, we define *communication networks* as *relations among various types of actors that illustrate the ways in which messages are transmitted, exchanged, or interpreted.* This definition extends the previous one in three important ways. First, it includes multidimensional networks (Contractor, 2009; Contractor, Monge, & Leonardi, 2011) that are composed of a variety of types of actors including, but not limited to, individuals, groups, organizations, artifacts, concepts, and technologies. Second, the definition highlights that communication networks are multiplex, meaning that it is useful to simultaneously consider multiple types of relations. Finally, it suggests that networks capture communication processes that are more complex than message exchange.

This chapter focuses on the various types of relations that constitute multidimensional communication networks. As such, it provides an important alternative to other ways in which the literature has been reviewed (Borgatti & Foster, 2003; Krackhardt & Bass, 1994; Monge & Contractor, 2001; Monge & Eisenberg, 1987). We begin with an overview of multidimensional networks and their importance for organizational communication research. The core of the chapter then focuses on the various types of communication relations that constitute or support communication networks. These relations include flow, affinity, representation, semantic, technological, physical, and affiliation. We review both the theoretical frameworks that scholars utilize and the key empirical findings for each type of relation. The section concludes with a discussion of *multiplexity*, or the various ways in which these relations may interact with one another and the implications of these interactions for the study of multidimensional networks. The chapter ends with a discussion of four trends that suggest now is an opportune moment to theorize the emergence of multidimensional networks.

Multidimensional Networks

Multidimensional networks consist of different types of nodes and relations that are embedded in the same network (Contractor, 2009; Contractor et al., 2011). They are an extension of two previously studied types of social networks, multimodal networks and multiplex networks. Multimodal networks include more than one type of node. For example, a network in which individuals are members of multiple voluntary organizations is a multimodal network. In this example, there are two types of nodes: individuals and voluntary organizations. Multiplex networks are single modal, meaning they have only one type of node but have multiple types of relations. For example, individuals who dislike one another but communicate with each other about work can be modeled as a multiplex network. Multidimensional networks contain a variety of different types of actors as nodes (e.g., individuals, documents, organizations) and different types of relations among them, making them both multimodal and multiplex.

Multidimensional networks are therefore better suited to capture the complexities inherent in organizational life. The network perspective has been criticized for failing to take into account the context and content of communication. Multidimensional networks embrace the challenge of this critique by bringing the context and content into focus; that is, communication context elements can become nodes in the network. Various concepts or networks formed by discourse, in which the nodes are words, can also be included.

Such a move has the important benefit of enabling researchers to explain the interdependencies across multidimensional nodes and relations. As illustrated by Contractor et al. (2011), the emergence of multidimensional networks can be explained by extending the multitheoretical, multilevel model approach (MTML; for an overview, see Contractor, Wasserman, & Faust, 2006; Monge & Contractor, 2003). Including different types of nodes creates theoretical contingencies; for example, unlike individuals, words do not engage in social exchange with one another, making that mechanism irrelevant to the emergence of links between words. Further, mechanisms such as reciprocity or transitivity can apply across multiplex relations. For example, one organization may provide financial resources to another organization and, in return, receive public affirmation; here, multiplex reciprocity would have occurred based on exchange theory mechanisms. Finally, multidimensional networks allow communication researchers to explore the dynamics of networks and, indeed, specific relational events within these systems. Longitudinal analysis of these dynamics, especially given the affordances that technology allows for in data collection, is within reach.

To understand the various types of relations among different types of actors that compose multidimensional networks, this chapter extends the work done by Contractor and colleagues (2011) on an MTML model for multidimensional networks. In particular, this chapter introduces a new taxonomy for classifying various relation types. We then use the taxonomy to review the current research in organizational communication and draw conclusions about the theoretical families that are used to study particular relation types. These patterns provide the groundwork for advancing an MTML approach to multiplex relations in multidimensional networks.

Network Relations

Network relations describe the ways in which actors of various types are connected to one another. Relations that appear in the organizational communication literature include communication mediated via technology (Cho, Trier, & Kim, 2005), collaboration among organizations (Doerfel & Taylor, 2004; Taylor & Doerfel, 2003), and hyperlinks (Shumate & Dewitt, 2008; Shumate & Lipp, 2008), to name a few. We contend that the relation among actors is the primary mechanism for organizing sets of findings in organizational communication network research. This claim is motivated by two studies. First, Faust and Skvoretz (2002) note that the vast majority of social network research can be characterized as case studies of individual communities. They suggest that these case studies can and should be compared to one another. In doing so, researchers might address the question as to whether networks are structured in similar ways, despite their surface differences on dimensions, such as type of actor, size, time and space of observation, and type of relation. To illustrate, they compare the structural characteristics of 42 social networks that vary considerably on these dimensions. These types include advice networks among managers, licking behaviors of cows, communication among monastic novices, and grooming patterns among chimpanzees. They found that types of relations better explained similar patterns in networks than types of actors. This study offers two intriguing possibilities that lie at the core of this chapter: (1) that organizational communication network research can collectively generalize findings across individual case studies and (2) that models based on similar types of relations may offer more generalizable explanations than models that focus on levels of analysis (e.g., individual, group, organization).

Second, Leskovec, Kleinberg, and Faloutsos (2007) provide additional insight into the nuanced ways in which relations may influence the emergence of networks. They report evidence of positive link growth rates (i.e., the relationship between the rate in which links and nodes are added to a network) across 12 networks of seven types. However, the relationship between the addition of nodes and the addition of relations was much stronger for the citation networks than for the communication networks (e.g., communication via e-mail). Monge, Heiss, and Margolin (2008) suggest that Leskovec and colleagues' (2007) findings indicate that various type of relations have different carrying capacities or limitations. To push this idea further, communication relations based on message exchange among human actors differ fundamentally from relations such as citations networks. This chapter explores this possibility by highlighting the different types of network relations that compose multidimensional networks. Each of these relational types has certain logical limits because of the nature of the communication linkage. In addition, patterns of theoretical investigation and empirical research become evident when they are organized by type of relation.

This section explores four types of communication and three types of infrastructure relations (see Table 18.1). The following sections describe the different types of communication relations and the theoretical perspectives used to study them.

Flow relations depict the exchange or transmission of information or resources among nodes. Flow can occur among different types of nodes, including individuals, technologies, or other artifacts. For example, flow occurs when individuals exchange messages or a person retrieves information from a website.

In contrast, *affinity relations* refer to socially constructed relationships that may have either a positive or negative valence. Although one might assume that these relations imply flow, they do not explicitly focus on the exchange or transmission of, say, information among actors.

Examples of affinity relations include friendship, collaboration, and alliances. Affinity relations can occur between individuals and other types of nonhuman actors, but in these cases, the networks are constructed in the minds of actors that exert agency (i.e., human actors can form positive attachments to computer systems, but the computer systems do not form positive attachments to the human actors). In cases where multiple actors have agency, the affinity relation can be mutual or perceived only by one party.

Representational relations involve messages about an association among actors communicated to a third party or to the public. Specifically, these relations focus on messages about one node's affiliation with other nodes that are communicated to others. Examples of representational ties include hyperlink networks[1] (e.g., Tateo, 2005) and bibliometric networks[2] (e.g., So, 1998). These relations differ from flow relations because no messages are exchanged between nodes. Additionally, they differ from affinity relations because they do not necessarily entail enduring relationships among actors. Consider, for example, the contrast between conversing with a friend (a flow relation), having a friend (an affinity relation), and name-dropping (a representational relation). In the representational relation, the person whose name is dropped does not necessarily receive a message. Additionally, the person whose name is dropped may not even have an enduring relationship with the person who is dropping his or her name.

Semantic relations focus on shared meaning or symbol use. Researchers examine semantic relations on two levels: (1) the shared meanings that result from the patterns of word usage in text or discourse and (2) individuals' cognitive maps of shared meanings. In the first type of semantic network, researchers examine word frequencies and patterns of usage. In the second type, individuals are asked about their interpretation of, say, an issue (Monge & Eisenberg, 1987). The degree to which individuals share an interpretation forms the relation.

Infrastructure Networks

Scholarship from the perspective of communicative constitution of organizations (see Putnam & Nicotera, 2008, for a review) argues that we cannot ignore materiality in explaining symbolically constructed relationships and structures of an organization. We note three types of infrastructure networks that enable and constrain the configuration of various types of communication networks. These include technological networks, physical networks, and affiliation networks.

Technological networks describe the supporting path along which flows, affiliations, or representational networks are manifested. If a technology only permits messages to be exchanged among certain users, then the infrastructure networks would only link actors who use that technology. For example, in Cooper and Shumate's (2012) study, the lack of infrastructure to support communication and collaboration among nongovernmental organizations (NGOs) concerned with gender-based violence in Lusaka, Zambia, significantly hindered the development of both the communication and affinity networks among these organizations. Lack of consistent telephone service, spotty Internet service, and disruptions in power made such network connections difficult.

Physical networks describe the proximity of actors to one another. Research on flow and affinity networks has consistently shown that physical proximity plays an important role in network structuring. For example, Van den Bulte and Moenaert (1998) demonstrated that changing the physical network, or the distance between individuals, resulted in a reconfiguration of the communication flow network. At a macro level, analyzing the evolution of the global network of intergovernmental organizations since 1820, Beckfield (2010) found the network to be increasingly influenced by regional proximity.

Affiliation networks are two-mode networks (i.e., networks in which connections are only permitted among actors of two different types), in which actors are affiliated with entities, such as organizations, social movements, online communities, events, documents, or technologies. Affiliation networks describe how individuals identify with various entities and may provide a supporting condition for flow and affinity relations among individuals. An example is interlocking boards of directors, in which individuals are affiliated with the various boards in which they serve (e.g., Haunschild & Beckman, 1998). Researchers then study how messages flow across companies through the cross-affiliation of individuals on common boards.

These seven types of relations constitute the taxonomy for discerning patterns of network research—an important element in the development of a MTML approach to multidimensional networks. In the next sections, we examine these four types of communication networks in more detail. In particular, we identify families of theoretical mechanisms that are often used to explain the emergence and outcomes of each of the four types of relations. To decipher the prevalent theories and types of research for each communication relation, we conducted an exhaustive review of empirical social network research using organizational communication concepts from the 1990s to 2012. We searched communication, sociology, and management journals to find articles that examined at least one of the four types of communication networks. We included articles that utilized network analytic techniques to empirically analyze organizational communication phenomena. This search excluded articles that presented only new theories or articles that offered rich metaphorical descriptions of networks but did not operationalize them. This review yielded

Table 18.1 A Taxonomy of Relation Types for Communication Networks

Relation Type	Definition	Examples
Communication Networks		
Flow	The transmission or exchange of messages among actors	E-mail messages sent among a group of college students (Postmes, Spears, & Lea, 2000), communication to retrieve and allocate information among experts (Palazzolo, 2005)
Affinity	A socially constructed relationship that has either a positive or negative valence	Joint ventures among companies (Ahuja, 2000), collaboration among NGOs (Taylor & Doerfel, 2003), generic friendship relations (Pollock, Whitebred, & Contractor, 2000)
Representational	A message about an association among actors communicated to a third party or the public	Hyperlinks among organizational actor websites (Tateo, 2005), public communication of the relationship between a NGO and corporation (Shumate & O'Connor, 2010a)
Semantic	Co-occurrence of words in text or shared meaning that individuals give to concepts or organizational fields	Shared meaning surrounding employee participation (Stohl, 1993), common usage of words in organizational websites (Shumate, 2012)

(Continued)

Table 18.1 (Continued)

Relation Type	Definition	Examples
Infrastructure Networks		
Technological	The supporting path for messages to flow among technologies	Connections among distributed database systems, telephone networks, Internet connectivity
Physical	Proximity of agents in time and space	Physical distance between employees' offices (Corman, 1990)
Affiliation	Relation between agents and organizational entities	Organizational identification with multiple organizational targets (Scott, 1997), nation-states that belong to intergovernmental organizations (Beckfield, 2010)

214 articles that we categorized by type of relation(s) and node(s), family of theoretical mechanisms, whether the communication network was an independent or dependent variable, source of data, and analytic method. The patterns of theory development and testing described in the subsequent sections stem from this classification. For the complete list of articles and their classification, including simulation-based studies not reviewed in this chapter, please visit http://www.michelleshumate.com/resources.

Theories to Explain the Outcomes of Communication Network Relations

This chapter focuses on the types of relations that compose multidimensional networks. However, we would be remiss if we ignored findings on the outcomes of the types of relations. There is only a modicum of organizational communication research that focuses on the outcomes of representational or semantic networks. As such, this section exclusively reviews the research on flow and affinity relations.

Most research that utilizes flow relations as an explanatory variable invokes theories of self-interest, contagion theories, cognitive/semantic theories, and theories of exchange and dependency. At the core of each of these theories is a similar logic; that is, information or messages that flow through a network give some actors advantages because of their network roles. The most popular version of this explanation derives from the family of theories of self-interest. Theories of self-interest posit that individuals and organizations rationally decide to enter into network relationships to maximize their gains and minimize their losses (Monge & Contractor, 2001). Social capital theory (Burt, 1982) and transaction costs economics (Williamson, 1975) are both theories of self-interest. When applied to flow relationships, the core argument of this research is that actors seek to gain advantages through their position in the message flow (e.g., occupying a structural hole or being highly central in the network). For example, Cross and Cummings (2004) find that the higher an employee's centrality in their information and awareness networks, the more positively they are rated in their performance.

Mechanisms based on the family of contagion theories are also used to explain outcomes of flow relations. Contagion theories suggest that exposure to messages from the network lead to attitude or behavior changes. These theories include social information processing theory (Fulk, Steinfield, Schmitz, & Power, 1987; Salancik & Pfeffer, 1978), institutional theory (DiMaggio & Powell, 1983), and the diffusion of innovation theory (Rogers, 1995). Flow relations, in this view, are the channels for attitude and behavior changes. For example, Yuan, Cosley, Welser, Ling, and Gay (2009) reported that interpersonal exposure, tie homophily, and network cohesion increased the likelihood of adoption of SuggestBot, a software that recommends contributions one can make to Wikipedia.

Cognitive/semantic and exchange/dependency theories are also utilized to explain the outcome of flow relations. Research from the cognitive/semantic family focuses on the outcomes of knowledge-sharing networks. Such research reports that centrality in knowledge networks is related to productivity with new technology (Papa, 1990) and work group performance (Cummings, 2004). Research from the exchange/dependency perspective utilizes flow networks as explanations for trust. Specifically, individuals who are central in communication networks (Prell, 2003), who have advocates with dense communication networks (Wong & Boh, 2010), and who are embedded in reciprocal relationships (Molm, Collett, & Schaefer, 2007) are treated as trustworthy.

Across these theories, flow relations are the mechanism through which information is shared. They provide explanations for actor differences based on their positions in the social network. Actors with advantageous positions reap benefits, such as better performance, higher productivity, greater innovativeness, and high levels of trustworthiness.

Despite differences between affinity and flow relations, they use similar families of theories to explain the outcomes of communication networks. In particular, contagion, exchange/dependency, and self-interest theories are the most prevalent frameworks for research about affinity networks. The one difference is that cognitive/semantic theories are not frequently utilized to understand these networks.

Research utilizing contagion and self-interest theories to explain outcomes based on implicit information exchange is assumed to take place in affinity relations. The vast majority of studies that use this relation type focus on alliances. Although alliances create opportunities for collaboration and information sharing, communication researchers recognize that alliances do not necessarily result in either of these processes (Heath & Sias, 1999). However, alliances may provide opportunities for organizations to monitor their partners in ways not available to them without an alliance. For example, Pek-Hooi, Mahmood, and Mitchell (2004) demonstrate that firms are aware of the product awards that their partners receive. The number of these awards has an inverted–U relationship with subsequent research and development (R&D) investment.

Research that utilizes exchange/dependency theories appear better suited for affinity than flow relations. Much of this research seeks to explain trust. For example, Shane and Cable (2002) demonstrate that affinity relations increase the likelihood that investors will fund ventures. In this case, affinity relations (namely friendship and social relations) provide a better explanation for trust than flow relations. In particular, affinity relations create a structure in which violating agreements creates significant costs, and the loss of information flow does not necessarily lead to a similar disruption in one's social world.

Theories to Explain the Emergence of Communication Network Relations

Although, as discussed above, research investigating the influence of communication networks on outcomes is important, this chapter primarily focuses on research that seeks to explain the emergence of multidimensional networks. Our review indicates that there are systematic patterns in the families of theories that scholars use to explain the emergence of flow, affinity, representational, and semantic networks. In examining these families, this section lays the groundwork for applying different theories to the various types of relations embedded in multidimensional networks.

Flow

Flow relations depict the patterns of message exchange or transmission among nodes. In this section, we classify them based on two factors: whether the network is observed or perceived and whether the actors are engaged in joint or individual goal-oriented activities. We categorize studies based on their theoretical families into a two-by-two table (Table 18.2).

Whether a communication is observed or perceived is one of the most significant differences in flow relations (Faust & Skvoretz, 2002). Indeed, communication researchers have long been aware that observed and self-reported networks are fundamentally different and often bear little to no relationship to one another (Bernard & Killworth, 1977; Corman, 1990). Scholars suggest that rather than seeing this as a problem, communication researchers should consider perceived communication networks as objects worthy of study in their own right (Corman, 1990; Richards, 1985). In many cognitive theories, individuals' perceptions of flows are more relevant than some objective measure of flow. It therefore follows that different patterns of relations may occur in these two types of flow networks.

Further, flow relations differ based on the type of collective activity in which the actors are involved (see Poole & Contractor, 2011, for a more nuanced typology). We categorize the existing literature into two groups: (1) networks in which the goals of an individual actor dominate communication flow and (2) networks in which joint goals characterize communication patterns.

Observed Flow Networks

Perhaps because digital trace data are more prevalent in cases in which individual goals dominate, only one study examines observed communication networks in the context of joint goals. Oh and Jeon (2007) have investigated two open source communities, Linux and Hypermail, using both empirical and simulation data to identify the factors that influence average participation. In general, they find that as outside influence increases, average participation declines. In comparison, research on observed flow networks when individual goals predominate is more common. This research is derived from three of the 10 theoretical families: homophily, cognitive/semantic theories, and theories of self-interest. As appropriate for an examination of individual-goal networks, these theories emphasize psychological processes and individual choice in the emergence of flow networks.

Homophily-based research on observed flow generally focuses on e-mail networks and the ways in which similarity leads to high rates of exchange. For example, Kossinets and Watts (2009) examine the dynamic interaction of choice homophily and induced homophily. *Choice homophily* refers to the selection of others derived from individual psychological preference, while *induced homophily* depicts the selection of others based on similarity of opportunities, or triadic closure in this case. They find that both types of homophily operate together over time and create a network in which highly similar others exchange messages.

Research drawing on the cognitive/semantic family of theoretical mechanisms focuses largely on patent citations[3] as indicators of knowledge flow among inventors and organizations. Research reports that interfirm mobility of inventors (Almeida & Kogut, 1999; Rosenkopf & Almeida, 2003), interfirm alliances (Rosenkopf & Almeida, 2003), geographic localization (Almeida & Kogut, 1999; Singh, 2005), and relations among inventors (Singh, 2005) influence the flow of knowledge. In short, research from

Table 18.2 Types of Flow Networks and Theoretical Families

	Joint Goals Predominate	**Individual Goals Predominate**
Observed	Contagion (Oh & Jeon, 2007)	Homophily (Kleinbaum, Stuart, & Tushman, 2011; Kossinets & Watts, 2009) Cognitive/Semantic theories (Almeida & Kogut, 1999; Rosenkopf & Almeida, 2003; Singh, 2005) Theories of self-interest (Burt, 2011a, 2011b)
Perceived	Homophily (Klein, Beng-Chong, Saltz, & Mayer, 2004; Salk & Brannen, 2000; Yuan & Gay, 2006) Cognitive/Semantic theories (Borgatti & Cross, 2003; Casciaro & Lobo, 2008; Klein et al., 2004; Palazzolo, 2005; Yuan, Fulk, Monge, & Contractor, 2010) Exchange and dependency theories (Klein et al., 2004; Sosa, Eppinger, & Rowles, 2004) Theories of mutual self-interest and collective action (Baldassarri & Diani, 2007; Stevenson & Greenberg, 2000; Taylor & Doerfel, 2003) Theories of physical and electronic proximity (Van den Bulte & Moenaert, 1998) MTML (Contractor et al., 2006)	Homophily (Ibarra, 1995) Theories of self-interest (McDonald, Khanna, & Westphal, 2008; Mehra, Kilduff, & Brass, 2001; Shah, 1998)

the cognitive/semantic perspective examines how geographic localization restricts knowledge flow and how multiplex relations among firms enable it.

Burt's (2011a, 2011b) research has applied his social capital theory to the online gaming and virtual world contexts. He finds that individuals tend to build the same types of networks across the games that they play. However, it is their network *role*, not network *personality*, which determines their ultimate success. Consistent with findings in offline networks, Burt finds that brokers accrue significant benefits.

In sum, research on observed flow networks suggests that actors' attributes, network roles, and multiplex network embeddedness influence the patterns of communication. The MTML perspective indicates that theories in each of these areas might complement one another, providing a richer explanation in combination than in isolation. Moreover, case studies in each of these areas might be fruitfully combined through the use of meta-analysis to examine the degree to which systematic differences exist across networks. Faust and Skvoretz's (2002) work suggests that many of the apparent differences across these networks are minimal in comparison to studies that examine perceived flow, which is discussed next.

Perceived Flow Networks

Research on perceived flow networks is more prevalent than research on observed flow networks. Such research tends to focus on circumstances in which *joint goals* predominate. This research draws from five families of theories—homophily, cognitive/semantic, exchange/dependency, theories of mutual self-interest/collective action, and theories of physical/electronic proximity—and generally falls into two logics: (1) the impact of endogenous factors and attributes on the pattern of networks relations and (2) the impact of exogenous factors on the network itself.

Endogenous network factors and attributes are explained on the basis of homophily and cognitive/semantic theories. This research investigates the psychological inducements that lead to particular configurations in perceived communication networks, specifically, the network environment and individual perception of others in it. For example, Salk and Brannen's (2000) research, based in social identity theory, focuses on the differences in network formations among Japanese and German managers. Drawing from homophily theory, they suggest that managers from the same country utilize similar logics in developing their self-reported, task-related, advice-related, and private communication patterns. Yuan and Gay (2006) similarly examine instrumental and expressive communication among student teams and report that gender-based and race-based homophily has no impact on perceived flow patterns in these groups. Instead, location and previous collaboration explains the majority of variance in these relationships. Research from cognitive/semantic theory also studies the conditions in which self-reported information exchange, task communication, or advice occur. This research indicates that individuals are more likely to seek information from experts (Borgatti & Cross, 2003; Palazzolo, 2005), especially when the costs for seeking information are low (Borgatti & Cross, 2003) and when team level task interdependence and communication density are high (Yuan et al., 2010). However, Casciaro and Lobo (2008) observe that personal affect overrides the impact of expert or competence-related information seeking on network patterns. In short, if a person is liked, despite their level of competence, they are sought out for task-related information.

The impact of exogenous network factors on perceived flows is explained on the basis of exchange/dependency, mutual self-interest/collective action, and physical/electronic proximity. This research addresses how various types of exchange, either across subgroups, network regions, or teams, influence the ways that groups work together and the outcomes of their coordination. For example, Baldassarri and Diani (2007) focus on the different roles that social bonds and transaction relations play in collective action. They demonstrate how social bonds shape solidarity and unite organizations that are pursuing the same type of actions. Transactional relations, however, coordinate subgroups of actors who have less interest similarity. Drawing from exchange/dependence and electronic/physical proximity theories, Van den Bulte and Moenaert (1998) focus on the types of relations that connect actors across subgroups. They note circumstances that induce subgroups to form relationships, specifically, colocation to the same physical space. In short, research on perceived flows when joint goals predominate suggests that both endogenous network factors (e.g., homophily, perceived attractiveness) and exogenous factors (e.g., multiplex network relations) influence network configurations. The MTML approach goes further and suggests that these two sets of factors should be used in combination to predict the configuration of these networks.

Research that examines perceived flow networks in conditions when *individual goals* predominate utilizes homophily and self-interest theories. The research in this cell focuses on how individuals seek information in order to advance their careers. For instance, Shah (1998) investigates how employees use referents in job-related information seeking. She reports that employees monitor structurally equivalent actors and use them for social comparison, but they seek out organizational information from cohesive relations (e.g., those with whom they share a personal relationship). Further, to enhance opportunities for advancement over time, high self-monitoring employees strategically maneuver themselves into the central locations of a firm's networks (Mehra, Kilduff, & Brass, 2001).

In summary, two conclusions emerge from an examination of Table 18.2. First, researchers study perceived communication networks in the same ways that they examine networks of observed flow. This conclusion is somewhat troubling, since organizational communication researchers have long known that these two networks barely correlate with one another (Bernard & Killworth, 1977; Corman, 1990). Communication researchers have yet to take seriously the call to theorize about perceived communication networks in a way that is different from observed communication networks (Richards, 1985).

Second, although homophily and cognitive/semantic theories are prevalent across both perceived and observed communication networks, there are clear theoretical distinctions between joint and individual goal-oriented networks. Studies of joint goal-oriented networks rely on theories of mutual self-interest/collective action and exchange/dependency. Research on individual goal-oriented networks draws from the self-interest family, primarily social capital theories. As such, researchers can now draw conclusions about the typical patterns expected across network case studies, ones that could aid in developing a contingency-based MTML theory for the emergence of flow networks. Such a theory could also consider expected patterns in affinity networks as researchers embrace the study of multidimensional networks.

Affinity Relations

The study of affinity relations focuses on socially constructed relationships among actors that may have either a positive or negative valence. As illustrated by the perspective on the communicative constitution of organization (Putnam & Nicotera, 2008), researchers must rely on individual or organizational reports to determine whether socially constructed relationships, such as friendship or collaborations, exist among parties. As such, affinity relations are perceived communication networks. However, researchers can apply a more stringent criterion to affinity relations. Instead of relying on a single report as evidence of the relation, each party can confirm the relational connections. The reviewed studies, however, do not treat perceived and confirmed affinity relations differently. Instead, the research typically falls into two categories: studies of forming alliances and studies of developing interpersonal relationships.

The research on individual goal-oriented affinity relations typically examines patterns of alliances or collaborative relationships across organizations that are included in a sector. The primary explanation for alliance formation or collaborative relations among organizations derives from exchange/dependency theories. This work shows that alliance relationships are more prevalent among organizations that are embedded in multiplex relationships (Gimeno, 2004; Rosenkopf, Mentiu, & George, 2001; Stuart, 1998), are both high-status or unconstrained incumbents (Jensen, 2008), are central in the network (Gulati & Gargiulo, 1999), have previously had a relationship (although that decreases with each subsequent partner), and have common mutual partners (Atouba & Shumate, 2010; Gulati, 1995b; Gulati & Gargiulo, 1999). In addition, research that focuses on alliances investigates their evolution over time

(Lavie & Rosenkopf, 2006; Powell, White, Koput, & Owen-Smith, 2005; Shumate, Fulk, & Monge, 2005), their contractual nature (Gulati, 1995a), how patterns differ by region (Owen-Smith, Riccaboni, Pammolli, & Powell, 2002), and alliance withdrawal (Greve, Baum, Mitsuhashi, & Rowley, 2010).

The remaining studies of affinity relations generally focus on interpersonal cooperative relationships and friendships. Almost half of these studies investigate the circumstances in which individual goals predominate, including academic collaboration on papers (Hughes, Peeler, & Hogenesch, 2010), friendship networks in schools (Conti & Doreian, 2010; Moody, 2001), work collaborations (Bacharach, Bamberger, & Vashdi, 2005), cooperative relations among entrepreneurs (Vissa, 2011), and friendships based on coappearances on Facebook[4] photos (Wimmer & Lewis, 2010). In contrast, studies of networks when joint goals predominate focus on workgroups (Balkundi, Kilduff, Barsness, & Michael, 2007; Milton & Westphal, 2005). A theme that appears across these studies is greater contact among different individuals can override homophily-based influences on individual affinity relationships. Although individuals tend to form affinity relations with others like them, they can be influenced to form heterogeneous relationships through contact with diverse others, including through workgroup formations (Balkundi et al., 2007) or school integration (Moody, 2001). In short, diverse interactions can induce birds of a feather not to flock together.

The reviews of the research on flow and affinity relations point to two interesting implications. The first is that studies of perceived flow and those on affinity relations may have more in common than do investigations of perceived and observed flow. The research based in homophily theory provides a compelling case. Research that examines observed communication networks finds homophily-based effects (Kleinbaum et al., 2011; Kossinets & Watts, 2009). In contrast, research on perceived communication networks (Yuan & Gay, 2006) and affinity networks (Balkundi et al., 2007) find little support for homophily-based explanations and instead point to the role of colocation and previous collaboration on networks. One possible explanation for this finding is that an individual's communication behavior is driven by homophily and that the recognition of such behavior causes dissonance for participants; hence, individuals may socially construct communication networks that embrace diversity. Alternatively, individuals may think about their social worlds based on those with whom they are colocated and are in similar social and/or task groups, but they have a broader set of communication contacts that are relatively homogenous.

Second, although cognitive/semantic theories and homophily theory account for both affinity and flow relations, some theoretical families provide more dominant explanations for one type of relation than others. Theories of mutual self-interest/collective action explain flow relations; evolutionary theory accounts for affinity networks. Cognitive/semantic theoretical explanations are prevalent in flow networks, while exchange/dependency explanations appear in studies of affinity networks. Such patterns suggest that different families of theories may explain some types of relations in multidimensional networks better than others.

Representational Relations

Representational relations describe messages about affiliations among a set of actors that are communicated to a third party; hence, they are by definition self-reported communication relations. The properties of flow versus the characteristics of representational communication networks are logically different. For the receiver, the cost of receiving flow relations increases with each link, assuming that message is received and processed. Receiving too many flow links can result in information overload and therefore present a practical cap on indegree centrality (i.e., the number of links coming to an actor). In contrast, receiving additional representational communication links has no corresponding costs. As such, the structure of networks composed of representational relations and flow relations are likely to differ. Networks composed of representational relations often contain a few actors with relatively high indegree centrality in comparison to other actors in their network. Networks possessing this pattern are said to follow a scale-free indegree distribution (Barabási, Albert, & Jeong, 2000). In contrast, because of the cost of receiving a multitude of flow relations, the degree centrality of actors in flow networks is likely to be constrained, making the differences between the degree centrality of actors in these networks smaller than between actors in networks composed of representational relations. The study of representational networks is new to organizational communication. Even though other types of representational relations exist, organizational communication research has focused on two types: hyperlink networks and the public communication of corporate-NGO relations.

Hyperlink Networks. As Shumate and Lipp (2008) and Lusher and Ackland (2010) note, hyperlinks are connections based on public affiliation or representation instead of flow. Indeed, electronic communication can hyperlink to websites without the author(s) of that website becoming aware of the link. Through representational communication, hyperlinks seek to socially construct the relationship among actors for third parties. For organizational communication researchers, hyperlinks among websites provide insights into the varied relationships among government, for-profit, and nonprofit institutions. However, the majority of studies focus on nonprofit organizations, NGOs, and social movement websites.

In general, interorganizational hyperlink research focuses on three related but distinct issues. The first is to decipher the pattern of hyperlink relations based on the overall network structure. Shumate and Dewitt (2008) and Shumate and Lipp (2008) describe particular patterns that are prevalent in these hyperlink networks, including reciprocal relations, relations to two unlinked other websites, relations from two unlinked websites, and transitive relations. A second, more prominent focus has been on organizational attributes that influence the prevalence of relations. The most prominent theoretical explanation in this work is homophily, whereby various types of similarities influence the likelihood of a hyperlink among organizational actors; these similarities include same goals (Bae & Choi, 2000), same global region (Shumate & Dewitt, 2008), and same political party and committee affiliation (Park & Kluver, 2009). However, a second explanation, based on resource dependence theory, also receives attention. Gonzalez-Bailon (2009a, 2009b) observes that groups with greater economic resources are significantly more likely to receive hyperlinks than groups with fewer economic resources.

A third focus centers on the ways that hyperlinks intersect with other relations. Pilny and Shumate (2011) suggest that NGO hyperlinks are an extension of offline instrumental collective action behaviors. They report that offline relations, including financial relations, membership relations, and collaborative relations, influence hyperlinking. However, the relation that has received the most interest is issue networks, particularly the ways that they align with hyperlink networks. Issue networks depict political entities (Kim, Barnett, & Park, 2010) or NGOs (Rogers & Ben-David, 2008) who are engaged in similar policy discourses; such networks link together the politicians or NGOs who address the same social issues. Researchers have found that issue networks correlate with hyperlink networks (Kim et al., 2010; Menczer, 2004; Shumate, 2012).

Relationships Between Corporations and NGOs. A second example of representational communication comes from research associated with the Symbiotic Sustainability Model (Shumate & O'Connor, 2010b). The Symbiotic Sustainability Model focuses on the public communication of relationships between corporations and NGOs.

It asserts that such relations are part of the institutional positioning of communication (McPhee & Zaug, 2000). Such representational relations are the constitutive elements through which organizations mobilize capital and convince stakeholders of their legitimacy and character. Shumate and O'Connor (2010a) examine the portfolio of NGO partners identified by corporations. Practically, the research reports the types and numbers of social issues that are likely to be salient in corporate-funded communication.

In effect, research on representational relations is relatively scarce in the organizational communication literature. These studies rely on theoretical families such as homophily (Bae & Choi, 2000), resource dependency (Gonzalez-Bailon, 2009a), collective action (Pilny & Shumate, 2011), and evolutionary theory (Shumate & O'Connor, 2010a). Clearly, more work is needed before conclusions can be drawn. In particular, more attention needs to be paid to the ways that impression management (Schlenker, 1980) influences these relations, especially since they stem from messages communicated to third parties in a public venue. Moreover, because representational networks have a few actors that receive significantly more links than others in their network (Barabási et al., 2000), the formation of links is likely driven by social influence. Hence, both social influence and impression management theories may provide robust explanations of the patterns that depict representational relations.

Semantic Relations

Communication scholars were among the first researchers to conduct semantic network analysis (Danowski, 1988; Monge & Eisenberg, 1987). In their early book, Rogers and Kincaid (1981) suggest, "We need to combine the research method of content analysis of communication messages with the technique of network analysis to better understand how individuals give meaning to information that is exchanged through communication processes" (p. 77). However, since 1990, our survey of organizational communication network research reveals only one article that conducted a semantic network analysis of individuals (Stohl, 1993). Based on a content analysis of unstructured interviews, Stohl derived a network of the extent to which 60 managers shared their interpretations of the term *participation*. Overall, her study supports the use of Hofstede's (1980) cultural dimensions, using data that were not subject to common methods bias or quantitative reduction through survey-based items. Stohl's study illustrates Rogers and Kincaid's (1981) claim regarding the potential of combining social network analysis and content analysis methods.

However, the lack of studies that use this combined approach may stem from the need for theories to guide semantic network researchers. Stohl (1993) notes some difficulty in interpreting the meaning of measures, such as centrality, in semantic networks. Carley and Kaufer (1993), in perhaps the only theoretical work on semantic networks, suggest that the concepts of conductivity and consensus provide helpful interpretations or directions for research. *Conductivity* is a concept's ability to trigger other concepts or its ability to act as a gateway to other concepts. In contrast, *consensus* describes the degree to which people agree on the structure of the semantic network. Carley and Kaufer draw researchers' attention to two important elements of semantic network analysis: (a) understanding the relationships between words or concepts within the network and (b) understanding the ways in which individuals' cognitive maps of semantic networks vary. Both elements are ripe areas for future research, especially with access to digital texts.

Even though other types of communication network relations may exist, the four presented in this chapter account for most of organizational communication network research to date. *Flow networks* focus on the exchange of messages among actors while *affinity networks* describe the socially constructed relations among actors that may imply flows but are conceptually distinct from flows. *Representational networks* signal actors' affiliations to third parties. *Semantic networks* describe shared meanings among people and concepts.

Foundations of Multiplexity in Multidimensional Networks

The explanatory power of multidimensional networks lies in their ability to capture both the variety of nodes that make organizing possible (e.g., individuals, organizations, concepts, technologies) and the relations that constitute organizing. The above sections highlight the theoretical families that are frequently used to examine these types of communication networks. In this section, we draw this work together and discuss seven issues undergirding the foundations of a MTML approach to multidimensional networks.

First, by creating a taxonomy for classifying relations among types of networks, we address a first hurdle in the MTML approach to multidimensional networks. Communication relations such as information seeking, sharing information on various topics, and receiving unsolicited information fall within the same category. As such, these networks should be explained by the same set of theoretical families. For example, perceived relations when individual goals predominate are most commonly, and perhaps best, explained by theories of self-interest. In contrast, different types of relations (i.e., confirmed friendship and observed communication about a topic) are guided by different theories. Specifically, when individual goals predominate, theories of homophily, exchange/dependency, and physical proximity apply to the confirmed affinity relation, and theories of self-interest guide studies of observed flow relations.

Second, certain logical patterns arise in particular relation types. Observed flow relations have a logical ceiling on the expected degree centrality, because time constrains the number of individuals with whom one can communicate. In contrast, representational relations bear no direct cost to the recipient. As such, the indegree centrality of these relations is likely to be relatively unconstrained, perhaps explaining preferential attachment to a few nodes in such networks. Further, since affinity networks describe the social construction of enduring relationships, cognitive consistency is likely to drive the creation of triangles in positively valenced networks, a pattern explained by balance theory (see Monge & Contractor, 2003). Although more work is needed to empirically validate these logical patterns, this taxonomy underscores the importance of incorporating differences into a MTML approach to multidimensional networks.

Third, this review provides additional insights into data collection methods that influence the object of studies. As explicated by Corman (1990), perceived communication networks are not simply the results of relying on self-reported data; they are a fundamentally different object of study than observed communication networks. Perceived flow relations may bear more resemblance to unconfirmed affinity relations than to observed communication relations. As such, this finding calls into question organizational communication researchers' decisions to use the same theoretical families to explicate perceived and observed communication relations.

Fourth, in multidimensional networks that include nonhuman nodes, particular patterns of relations are logically not possible (i.e., friendship with a repository); however, unconfirmed positive affinity relations are plausible (e.g., the positive relationship that many people have with Siri on their iPhone). Researchers should explore differences between such unconfirmed and the confirmed affinity relations.

Fifth, affinity and communication relations do not necessarily implicate each other. That is, even though individuals report a friendship, they do not necessarily communicate with each other more often via e-mail or as observed in server logs. In short, multiplexity in multidimensional networks is likely to be more complicated than simple replication of relations within the same network; instead, relation types may suppress, facilitate, or trigger complex compound interactions (i.e., where a relation of one type among actors explains relations of other types among other actors). For example, in the nonprofit-corporate partnership domain, representational linkages between corporations and nonprofits may influence both affinity relations among nonprofits in the network and the ways that semantic networks framing the social issue are construed by the community of organizations.

Sixth, our taxonomy underscores the importance of specifying the boundary of the network—an important precondition for understanding multidimensional networks. *Network boundary specification* refers to the researcher's decision about what actors and relations to include in a network and what to exclude. Researchers set up a network boundary in two ways: an open boundary approach and a positional network approach (see Wasserman & Faust, 1994, for differences from a methodological perspective). In the open boundary approach, the researcher selects nodes based on the accessibility of the data. Studies that use snowball sampling based upon interpersonal contacts rely on an open boundary approach. In contrast, positional network approaches make purposive choices about actors in the network based upon some understood grouping, often based upon a common goal or membership (i.e., all of the employees of an organization). The choice between the two influences the types of theories that should be used in a study. In open boundary networks, individual goals predominate and, as such, theories of self-interest play a larger role. In contrast, in the positional approach, joint goals predominate and theories of mutual self-interest/collective action play a large role. In the positional approach, the actors' common goal orientation and the resources they use fall within the network's boundaries.

Seventh, and finally, the taxonomy points to gaps in theorizing multidimensional networks; that is, there are relatively few theories about the emergence of representational or semantic networks. Although homophily, resource dependency, collective action theory, or evolutionary theories explain some representational relations, future research needs to explicate the conditions under which these theories apply. Similarly, although Carley and Kaufer (1993) provide two important theoretic concepts for understanding semantic networks, empirical research in organizational communication has yet to demonstrate the heuristic value of this work. Both theory development and empirical exploration are needed to develop an MTML model for the emergence of multidimensional networks.

Theorizing the Emergence of Multidimensional Networks: The Perfect Storm

This chapter has advocated for a MTML explanation for the emergence of multidimensional networks. It would be fair to ask if and why this is the right time to be advancing this research agenda. In this section, we argue that there are four factors that put us on the brink of a positive "perfect storm" to witness the ascendance of this intellectual enterprise: novel undertheorized network forms of organizing, a data deluge, advances in analytics, and the exponential growth in computational capabilities (Contractor, 2013).

Novel Undertheorized Network Forms of Organizing

The advent of new technologies has ushered in a new generation of creative thinking around novel modalities for organizing (Shirky, 2009). These new inherently network forms of organizing represent a disruptive change from the less technologically enabled forms of network organizing described just over a decade ago by Powell (1990). One overarching feature of these models of organizing is the ability to facilitate spontaneous mobilization of globally distributed individuals and resources to generate innovative solutions to problems, contribute to real-time data collection and creation, or engage in collective action. Here are just a few examples. Innocentive.com solicits external solvers for problems confronting large R&D intensive corporations (Jeppesen & Lakhani, 2010). Individuals contribute to real-time collection and curation of knowledge, such as mapping mobility patterns in the event of a disaster (Bengtsson, Lu, Thorson, Garfield, & von Schreeb, 2011). Editors team up to compose a breaking news story on Wikipedia (Keegan, Gergle, & Contractor, 2013). Programmers collaboratively develop software on GitHub.com (Dabbish, Stuart, Tsay, & Herbsleb, 2012). Publics contribute to the funding of a start-up, product, or scientific study on kickstarter.com or rockethub.com (Wheat, Wang, Byrnes, & Ranganathan, 2012).

These phenomena are not just quantitatively but also qualitatively different from conventional modes of organizing. As a result, there is a pressing need to develop new theories, or at the very least, extend existing theories, to understand and enable these novel forms of organizing. Recent theoretical contributions on collective intelligence (Malone, Laubacher, & Dellarocas, 2009; Woolley, Chabris, Pentland, Hashmi, & Malone, 2010), social movements (Castells, 2012), collective leadership (Contractor, DeChurch, Carson, Carter, & Keegan, 2012), and the emergence and equifinality of group behavior (Hackman, 2012) allude to the importance of networks in explaining these phenomena and hence pave the way for the development of a more explicitly network-based explanation.

Data Deluge: From Big Data to Broad Data

While the development of new information technologies has ushered in novel undertheorized forms of organizing, they have also opened the fire hose of data associated with these models of organizing. This has heralded the advent of computational social science (Lazer et al., 2009) as yet another arrow in the quiver of methodologies used by social network researchers alongside field studies, experiments, and ethnography.

The emergence of digital trace data as a method of data collection has important implications for the study of some of the types of social network relations highlighted in the previous section. *Digital trace data* refers specifically to the logs of actions, interactions, and transactions that were created in digital spaces. Examples include e-mail interactions (Kossinets & Watts, 2009), hyperlinks between webpages (Lusher & Ackland, 2010), and activities in Wikipedia (Yuan et al., 2009). Digital trace data is distinct from archival data, which refers to the use of any secondary data that was previously recorded such as archival patent citation data (Singh, 2005). Research using digital trace data is relatively new, and only 17 of the 241 studies examined in this review use it. In contrast, archival data is the most commonly used data source in our review, with almost 35% of studies using it ($n = 84$).

Digital trace data can be used to gather observed flow, semantic, and representational communication relations. However, the study of observed flow relations may be the most important of these types. Research on observed flow relations has been scant, and much of the recent research in our review relies on digital trace data. Because we know that observed and perceived flow relations differ significantly (Bernard & Killworth, 1977; Corman, 1990), the emergence of big data is a revolutionary opportunity to understand a type of communication network we know relatively little about. Further, the "mashing" of traditional data sources with one or more digital traces moves us from utilizing *big data* to constructing *broad data* (Hendler, 2012). Broad data holds the greatest promise for developing novel research that examines multidimensional networks that contains observed flow relations and many other types of relations described in the typology.

Advances in Network Analytics

Although developing new theories and accessing large tracts of data are necessary, they are insufficient to advance our understanding of new forms of organizing without substantial advances in the development of network methodologies. In particular, we point to three methodological developments in the past decade that make analysis of such data both more effective and efficient: the creation of semantic networks from texts, inferential social network analysis methods, and methods to analyze longitudinal networks. We will briefly discuss each of these in turn.

First, recent methodological developments make future research on semantic networks both easier and more rigorous. Tools such as Automap, an assemblage of text analysis techniques (Carley, Columbus, Bigrigg, & Kunkle, 2011), provide a number of utility techniques (e.g., stemming words so that *cat* and *cats* are not treated as separate concepts) that streamline the analysis. Further, tools such as Crawdad (Corman & Dooley, 2006) implement a technique called *centering resonance analysis* that allows for the automatic creation of semantic networks from texts (Corman, Kuhn, McPhee, & Dooley, 2002). It indexes noun phrases that have the most discursive importance in texts and links them based on their co-occurrence. Along with techniques for topic modeling (Griffiths, Steyvers, & Tenenbaum, 2007), syntax analysis (Pennebaker, 2011), and sentiment analysis (Thelwall, Buckley, & Paltoglou, 2012), they have the potential for fulfilling the unrealized potential of investigating semantic networks.

Second, the move from descriptive to inferential approaches in networks research necessitated the development of new methodologies; p* or exponential family of random graph models (ERGMs) are one of the most influential inferential approaches that have emerged in the last two decades to test theoretically interesting network hypotheses. The potential of these statistical models have prompted their adoption by a small but growing number of scholars interested in empirically testing hypotheses. Twelve of the 214 publications reviewed for this chapter used p*/ERGMs. Lusher, Koskinen, and Robins (2013) offer excellent methodological and empirical examples for the use of p*/ERGMs in a variety of contexts. p*/ERGMs are also being extended to the analysis of multidimensional networks where nodes could be of more than one type. For instance, Keegan, Gergle, and Contractor (2012) used bipartite p*/ERGMs to test hypotheses about the extent to which attributes of editors on Wikipedia (experienced or novices) and attributes of the entries on Wikipedia (breaking news or average news articles) would pattern the assembly of editors working on a specific article.

Third, there have been a number of techniques recently developed for the study of longitudinal networks. To examine changes in networks from one time period to another, the most dominant model for the study of network dynamics has been the stochastic actor-oriented models (Snijders, Van de Bunt, & Steglich, 2010). These models, implemented in a software called SIENA (Simulation Investigation for Empirical Network Analysis), capture the coevolution or the mutual influence of the attributes of actors in a network (such as their attitudes and behaviors) on their relations (such as friendship and advice) and vice versa. There have been recent efforts to extend stochastic actor-oriented models to study multidimensional networks. Snijders, Lomi, and Torló (2012) test hypotheses about the extent to which friendship and advice relations among students (the first set of nodes) coevolved dynamically with their preferences for employment by a set of organizations (the second set of nodes).

However, the advent of digital trace or digitally annotated data has forced network researchers to reconsider their conceptualizations of longitudinal network data (Mathur, Poole, Peña-Mora, Hasegawa-Johnson, & Contractor, 2012). Traditional longitudinal models such as the aforementioned stochastic actor-oriented models utilize the network as it appears at one slice in time to explain the structure of the network at subsequent slices in time. However, digital trace data is often logged as the occurrence of a relational event from actor A to actor B at a particular point in time that is often recorded up to the second. For instance, a relational event would be the exact moment where an individual A began to follow the Twitter feed of an individual B. In this case, collapsing the networks into slices of time is an unnecessary aggregation resulting in loss of the richness associated with the unfolding dynamics of each relational event. The greater prevalence of relational event data captured from digital traces is motivating the development of new relational event network models that eschew the need for slices of networks at time intervals. Instead, they model the rate and weight associated with the occurrence of each relational event as a function of all prior relational events weighted by their recentness (Brandes, Lerner, & Snijders, 2009; Butts, 2008). Leenders, DeChurch, and Contractor (in press) provide a theoretical overview and an exemplar for the study of relational events in multiteam systems.

Exponential Growth in Computational Capabilities

The preceding subsections have outlined three reasons for the ascendance of a research agenda dedicated to multidimensional networks: undertheorized novel forms of organizing, a deluge of data, and advances in analytics. The final element is the exponential growth in computational capabilities. As has been immortalized in Moore's (1965) law, growth in computational capabilities has doubled every 18–24 months over the past five decades. Today, petascale computing enables us to test theoretical models using sophisticated techniques on large data sets in hours or days, rather than the months or years it would have taken a decade ago. Williams et al. (2011) describe how communication researchers can productively collaborate with computer scientists to leverage supercomputing infrastructure to analyze terabytes of network data from teams involved in online combat and quest activities within a massive multiplayer online game. A more technical discussion of those issues is beyond the scope of this chapter.

In summary, multidimensional networks are important objects of study for organizational communication researchers. They represent the complexity of organizational life and address the context and content of communication. This chapter has classified the types of communication and infrastructure relations that comprise these networks; and in doing so, it presents opportunities for both empirical and theoretical work. This chapter has also argued that the emergence of novel forms of organizing, the deluge of data, advances in analytics, and growth in computational capabilities make it a particularly opportune moment for theorizing the emergence of multidimensional networks. Hence, although it has been 25 years since a chapter in the first edition of the *Handbook of Organizational Communication* summarized social network research in the field, in many ways, the area is just entering its adolescence, with new and exciting research possibilities.

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Notes

1. *Hyperlink networks* describe the hypertext relationships that exist between websites.

2. *Bibliometric networks* describe the citation and authorship relationships that exist, often in academic papers.

3. Patent citations are created by three parties: the applicant, the patent lawyer, and the patent office. The goal of patent citations is to accurately account for all prior knowledge upon which the current patent builds. As such, it is a measure of knowledge flow.

4. In the case of copresence in photos, as argued by Wimmer and Lewis (2010), there exists documentation of an offline relationship and time spent together. As such, these relations are better classified as affinity.

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