© *Academy of Management Annals*
2022, Vol. 16, No. 2, 853–897.
https://doi.org/10.5465/annals.2020.0369

INTRAORGANIZATIONAL NETWORK DYNAMICS: PAST PROGRESS, CURRENT CHALLENGES, AND NEW FRONTIERS

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Social networks are dynamic by nature. While network research has typically treated relationships between social actors as static, there has been a surge in literature extending a dynamic lens to intraorganizational networks. Critically, there is no comprehensive and systematic review of intraorganizational network dynamics studies. Moreover, the field lacks programmatic coherence, clear and consistent terminology, and methodological clarity. This review attempts to resolve these issues. To foster a common language, we provide an integrative definition and clarify the scope of intraorganizational network dynamics. This allows us to distinguish four domains of dynamic network theorizing. Building on this, we develop an encompassing framework that maps the multiple facets of this literature and apply it to organize our summary and synthesis. We then take a bird's-eye view of the full body of research and discuss four foundational areas in which network dynamics research can be conceptually and methodologically extended. We end by elaborating on the issue of interdependence in network data and providing an overview of leading statistical approaches for modeling longitudinal network data that explicitly account for dependence among observations. We see this review as an entry point for researchers interested in intraorganizational network dynamics and as a way to spark new scholarship on questions that remain open in this literature.

Social networks are dynamic by nature. Over time, they emerge, evolve, and dissolve. Understanding the dynamic nature of interconnections among social actors has been of interest since the field's infancy (e.g., Heider, 1946; Newcomb, 1961; Sampson, 1969). For many years, however, the available conceptual tools, instruments for data collection, and analytical methods have favored static conceptions of social structure and led most network scholarship to treat networks as fixed and enduring entities (Kitts & Quintane, 2020; Moody, 2018).

Yet, in the past few decades, longitudinal network data has been increasingly accessible (e.g., de Nooy, 2011; Kitts & Quintane, 2020) and significant advances in analytical methods now allow researchers to draw statistical inferences from such data (Schaefer & Marcum, 2021). In tandem with these developments, network scholars have progressively returned their focus to the dynamic nature of networks and investigated how network changes come about and with what outcomes. Such work can be referred to as "network dynamics" research, and its applications to intraorganizational phenomena is the focus of this review.

With the rapid increase in research on intraorganizational network dynamics across disciplines, the literature does not lack for diversity of perspective. What it does lack, however, is a comprehensive and systematic review, clarity and consistency in how network dynamics is conceptualized and modeled,

We would like to thank the journal editors Stuart Bunderson and Carrie Leana for supporting our proposal, and our two anonymous reviewers for their helpful comments. We are particularly grateful for the editorial guidance of associate editor Bill McEvily, who deeply engaged with our work and provided invaluable advice throughout the editorial process. We also thank Selorm Agbleze, Nicolai Foss, Balázs Kovács, Eric Quintane, and Olav Sorenson for their helpful comments on previous versions of this manuscript. All remaining errors are our own.

and an encompassing framework with which to comprehend the rich and evolving landscape of intraorganizational network dynamics scholarship. The lack of these elements makes it difficult to extend conversations within the field and is thereby a core barrier to progress.

The overall purpose of this review is therefore to provide researchers with the means to move intraorganizational network dynamics scholarship forward. To this end, we take four steps. We begin by providing much-needed clarity to the terminology and scope of intraorganizational network dynamics. We then develop an encompassing framework that organizes and clarifies the multiple facets of intraorganizational network dynamics. Using that framework as a point of departure, we summarize and synthesize the existing research on network dynamics that unfolds at the intraorganizational level of analysis. Last, following from the summary and synthesis, we take a bird's-eye view of the full body of research on intraorganizational network dynamics and identify four areas in which this literature can be conceptually and methodologically extended.

Specifically, in the first area, we outline the research themes that we see as most promising to move the field forward and which have thus far been under-researched. In the second, we bring attention to the distinction between relational events and relational states and outline opportunities for research that considers both events, states, and their temporal interrelationship. In the third, we highlight two ways in which temporality can be uniquely incorporated into dynamic network studies and point out how a more explicit focus on the timing (as opposed to the occurrence) of network change can meaningfully broaden our understanding of network dynamics. In the fourth, we point to a number of important methodological considerations, offering suggestions that we believe can foster new discoveries and theoretical progress and enhance methodological rigor in the field. We complement these considerations with a methodological discussion of the issues of interdependence in network data and then summarize the leading statistical approaches for modeling longitudinal network data that explicitly account for dependence among observations.

INTRAORGANIZATIONAL NETWORK DYNAMICS: AN INTEGRATIVE DEFINITION

Current Situation

In spite of a long-standing interest in the topic, a precise definition of network dynamics has remained elusive. In particular, in the course of reviewing the literature, it became apparent that the concept of network dynamics suffered from a lack of conceptual clarity. We identified three key indicators reflecting this issue. First, out of our sample of 134 journal articles, only a handful offered a clear definition. This issue extends beyond the articles included in our review to prior conceptual work covering issues related to network dynamics, in which we observed the same lack of explicit definitions (e.g., Brass, Galaskiewicz, Greve, & Tsai, 2004; Soltis, Brass, & Lepak, 2018).

A second indicator of the lack of conceptual clarity was the range of terms used to refer to network dynamics. For example, the interrelated yet distinct terms "network emergence" (e.g., Maclean & Harvey, 2016), "network genesis" (e.g., Quinn & Baker, 2021), "network origins" (e.g., Shah et al., 2021), "network evolution" (e.g., Doreian & Conti, 2017), "network change" (e.g., Parker, Halgin, & Borgatti, 2016), and "network dynamics" (e.g., Berends, van Burg, & van Raaij, 2010) tended to be used interchangeably and without a clear specification of what they exactly meant, both within and across journal articles.

A final indicator was variance in whether the concept of network dynamics extended to predictions of network change, outcomes of network change, or both. Over time, most conceptual and empirical accounts have converged toward conceiving of network dynamics as analysis of the causes of changes in networks (e.g., Ahuja, Soda, & Zaheer, 2012; Schaefer & Marcum, 2021; Snijders, van de Bunt, & Steglich, 2010). Yet, there are also studies that explicitly refer to network dynamics in relation to models predicting nonnetwork outcomes of changes in networks (e.g., Bravo, Squazzoni, & Boero, 2012; Soda et al., 2021).

Taken together, rather than convergence toward a coherent conceptualization of network dynamics, we encountered avoidance and divergence: most scholars either do not define the concept or use idiosyncratic definitions. This lack of conceptual clarity within the field makes it difficult to navigate the literature, which, in turn, hampers cumulative knowledge growth.

A Proposed Definition

To address this issue and further stimulate the development of a coherent body of network dynamics research, we propose an integrative definition of the concept. Specifically, building on commonalities in our reviewed material and across prior conceptual work (e.g., Ahuja et al., 2012; Doreian & Stokman, 1997; Schaefer & Marcum, 2021), which we further discuss below, we derived the following:

> "Network dynamics" refers to the processes by which network change is related to its antecedents and outcomes.

Put differently, network dynamics is concerned with processes underlying *how* and *why* networks change and *how* and *why* that change translates into certain outcomes. This definition entails three jointly necessary and sufficient constitutive elements: (a) an instance of network change, (b) an antecedent or outcome of that change, and (c) a statement of relations between them. We elaborate on each of these next.

Three Constitutive Elements

Network change. In a network setting, change consists of a modification of either the nodes or the ties that make up the network (e.g., Ahuja et al., 2012), manifesting as the emergence (addition), evolution, and dissolution (removal) of ties (nodes). These changes can be both objective, as when a node exits the network (e.g., Stuart, 2017), and subjective, as when an individual modifies their perception of a colleague's position in the social space (see Brands, 2013). Whether subjective or objective, nodal and/or tie change can unfold at four different but interrelated loci: (a) node, (b) tie, (c) ego network, and (d) whole network. Nodal change is an instance in which the change rests in the node itself (Ahuja et al., 2012), such as changes in an individual's satisfaction and commitment (Krackhardt & Porter, 1985) or perceived leadership (DeRue, Nahrgang, & Ashford, 2015). Change at the locus of the tie occurs when ties between nodes are created or terminated or are modified in terms of their properties or content (e.g., Dahlander & McFarland, 2013). Ego-network change captures change in a focal node's network, such as a change in its volume, composition, or pattern (e.g., Sasovova, Mehra, Borgatti, & Schippers, 2010). Whole-network change unfolds at the locus of the entire network, such as a change in whole-network composition (e.g., Stuart, 2017).

Antecedents and outcomes. Like Ahuja et al. (2012), we classify network change at all loci as driven by four foundational antecedents: (a) agency, (b) inertia, (c) opportunity, and (d) exogenous and random factors. By "antecedents," we mean the basic explanatory logics invoked to link an empirical phenomenon to an instance of network change. The first such antecedent, "agency," represents an individual actor's motivation and ability to modify their nodal, relational, or structural state (e.g., Emirbayer & Mische, 1998; Sewell, 1992); for example, by intentionally creating beneficial ties or dissolving unprofitable ones (Stea et al., 2021). "Inertia" captures the pressures for persistence that result from routines and norms or habits (e.g., Kim, Oh, Swaminathan, & Kim, 2006); for example, when the relational attachment inherent in strong ties constrains the focal actors from terminating the relationship (Dahlander & McFarland, 2013). "Opportunity" reflects the forces that drive changes in networks according to logics of convenience and proximity (e.g., Blau, 1994), as when attendance at a social event increases the likelihood of creating new friendship relationships (Giese, Stok, & Renner, 2020). Lastly, network change can result from "exogenous factors" beyond the network or from "random processes," such as random assignment of network partners (Hasan & Bagde, 2015).[1]

Additionally, network changes can produce a variety of outcomes. Generally, these outcomes can be "economical," such as payoffs (Eguíluz, Zimmermann, Cela-Conde, & Miguel, 2005), productivity (Marion, Christiansen, Klar, Schreiber, & Akif Erdener, 2016), and creative performance (Mannucci & Perry-Smith, 2021); "psychological," such as job motivation (Ng & Feldman, 2014), job satisfaction (Krackhardt & Porter, 1985), and leader charisma (Balkundi, Kilduff, & Harrison, 2011); and "sociological," such as interpersonal trust (Frey et al., 2019), internal status order (Skvoretz & Fararo, 1996), and collective affect (Quinn & Baker, 2021).

Processes. While necessary to the definition of network dynamics, the constitutive elements described above—instances of network change and antecedents and/or outcomes of that change—are not sufficient in isolation. When they are used in isolation, our understanding of network change is necessarily descriptive, in that one can, at best, answer the question of what network change is. Instead, we view network dynamics as being concerned not

[1] While any given empirical phenomenon does not necessarily belong unequivocally to a specific antecedent of change (e.g., both agency and inertia could be invoked as explanatory logics linking tie strength to termination of ties), we believe that these foundational sets of antecedents are theoretically distinct, in that they capture profoundly different explanatory logics causing network change, which makes distinguishing them useful in informing our development of theories about network change.

merely with what network change is, but, rather, with understanding the processes explaining change and/or its temporal outcomes. Thus, the final constitutive element of our definition is the explanation of the temporal processes that link an instance of network change to its antecedents and/or outcomes. The temporal lens embedded in our definition of network dynamics is grounded in the idea that time is a precondition for change (Kunisch, Bartunek, Mueller, & Huy, 2017), where such a processual and dynamic view has been said to be one that "explicitly incorporates temporal progressions of activities as elements of explanation and understanding" (Langley, Smallman, Tsoukas, & van de Ven, 2013: 1).

A Theory about Change

Its constitutive elements taken together, our conception of network dynamics bears resemblance to that of theory as "a collection of assertions, both verbal and symbolic, that identifies what variables are important and for what reasons, specifies how they are interrelated and why, and identifies the conditions under which they should be related or not related" (Campbell, 1990: 65), where the "what," "how," and "why" provide "the essential ingredients of a simple theory: description and explanation" (Whetten, 1989: 491).

As outlined by Whetten (1989), in his synthesis of earlier work by Kaplan (1964) and Dubin (1976, 1978), the "what" of a theory is concerned with specifying the factors necessary to comprehensively understand a phenomenon of interest. For network dynamics, these factors involve instances of network change along with related antecedents and/or outcomes. The "how" of a theory captures the specification and causal ordering of the relationships between its focal factors. For network dynamics, this consists of explicitly delineating the uni- or bidirectional patterns between the factors—network change and its antecedents and/or outcomes—as they unfold over time. The "what" and "how" of a theory are necessarily descriptive. The final ingredient—the "why" of a theory—adds explanation and constitutes "the theoretical glue that welds the model together" (Whetten, 1989: 491). Specifically, this final ingredient is concerned with explaining the underlying dynamics that relate the factors in the ways proposed by the theory—in other words, the "why" adds plausible accounts of the proposed relationships. Given the inherent processual nature of network dynamics, this implies that the "why" incorporates an explanation of the links between network change and its antecedents and/or outcomes as they unfold over time. The central role of temporality in our definition of network dynamics resonates with the established idea that time is crucial for processual theories of change, in which the purpose is to go beyond a surface description of change in order to penetrate the logics underlying its temporal progression (Dawson, 2014; Langley et al., 2013; van de Ven & Poole, 1995, 2005).

Key Differences from Previous Definitions

In conclusion, what is most important about our definition is that it focuses on *explanations* rather than *descriptions* of change as it unfolds over time and that these explanations pertain to the *antecedents* leading to network change and to the *outcomes* of such change. These two aspects of our definition set it apart from prior views on what network dynamics encompasses.

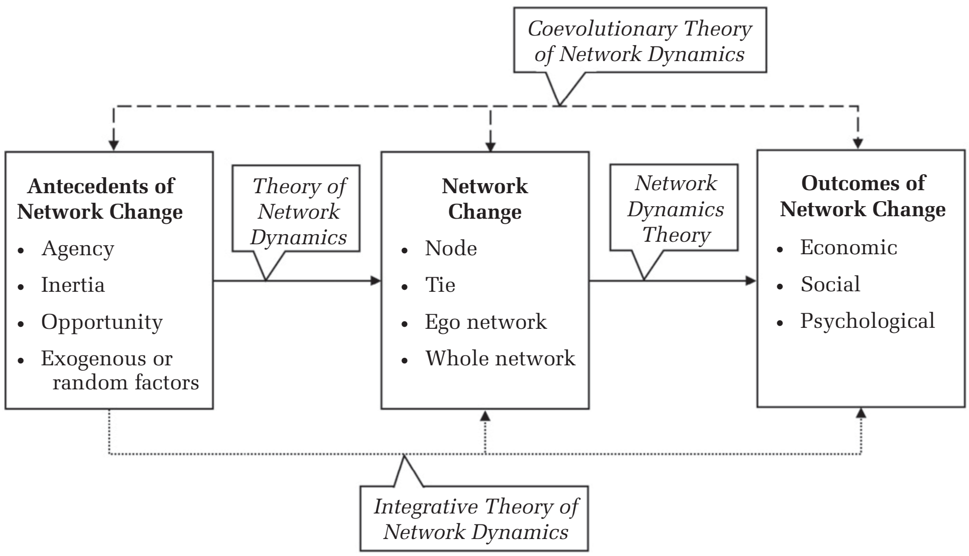
As we noted above, network dynamics is often merely invoked as a general notion, without an associated definition, and, when it is defined, it is given a variety of meanings. The differing definitions of network dynamics indicate that scholars attribute to the concept a variety of underlying ontological assumptions, which has important implications for which research questions are asked and, in turn, what theory is developed.

The most foundational ontological difference reflected in prior definitions is whether network dynamics is a descriptive representation of *what* network change is or involves *explanations* for the relationship between change and its antecedents. For instance, to Doreian and Stokman (1997: 234), "dynamics refers to change and is, in the main, purely descriptive."[2] In contrast, Ahuja et al. (2012) saw network dynamics as an analysis of the causes of changes in networks and therefore generally concerned with explaining the "*process* by which features of networks change over time" (Schaefer & Marcum, 2021: 254, emphasis added).

The definition we proposed above aligns with the view that network dynamics is concerned with *explanations*—rather than *descriptions*—of network change as it unfolds over time. At the same time, our definition affords an opportunity to expand the

[2] Doreian and Stokman (1997) also acknowledged the importance of understanding the process of network change, but did so under the different label of "network evolution."

FIGURE 1
Organizing Framework



Notes: Organizing framework with the four distinct domains of network theorizing. Solid lines represent unidirectional theorizing that uses network change either as *explanans* or *explanandum*, dotted lines represent unidirectional theorizing that uses network change both as *explanans* and *explanandum*, and dashed lines represent bidirectional theorizing that examines the coevolution between antecedents and network change or outcomes and network change.

construct to further capture its full richness. Specifically, we believe that network dynamics is concerned with both deriving an understood process of network change *and* understanding the consequences of such change, rather than being constrained to either of the two.

ORGANIZING FRAMEWORK AND REVIEW STRUCTURE

Drawing from our definition, the population of reviewed articles, and prior conceptual work (Ahuja et al., 2012; Borgatti & Halgin, 2011; Salancik, 1995), we developed an organizing framework (Figure 1) that holistically interrelates the antecedents, instances, and outcomes of network change. The framework constitutes a mutually exclusive and collectively exhaustive map of the necessary elements and related domains in which intraorganizational network dynamics can be studied. We use it to organize our review, increase conceptual precision, synthesize extant research, and provide guidance on how to move this literature forward.

Specifically, building on our discussion in the previous section of the constitutive elements, our framework shows how network change can be used as *explanans*, *explanandum*, or combinations of both, which in turn allows us to distinguish four domains of network theorizing.

The first two domains are characterized by theorizing that causally and unidirectionally either links certain antecedents to network change or links network change to certain outcomes. In the terminology of Borgatti and Halgin (2011), these domains are referred to as "theory of networks" and "network theory," respectively. In line with our focus on network dynamics, we are interested in the *dynamic* subsets of these domains, which we accordingly refer to as "theory of network dynamics" and "network dynamics theory," respectively.[3] As an illustration, a paper that explains an increase in network size as a function of ego's power would belong to the *theory of network dynamics*, while a paper that explains ego's performance as a function of a change in their

[3] Borgatti and Halgin (2011) further distinguished a third domain, "network theory of networks," in which both the independent and dependent variables involve network properties. In our conceptualization, this domain is embedded in the "dynamic theory of networks" domain (or, when modeled as the joint evolution of multiple networks, in the "coevolutionary theory of network dynamics" domain).

brokering position would belong to *network dynamics theory*.

The third domain is characterized by unidirectional theorizing that uses network change both as *explanans* and *explanandum*; in other words, theorizing that considers the full chain, causally linking certain antecedents to network change and, in turn, this change to certain outcomes. For instance, a paper that explains how an individual's self-monitoring personality increases their brokerage opportunities and how this in turn increases their creativity would be in this domain, which we refer to as "integrative theory of network dynamics."

The fourth and final domain, "coevolutionary theory of network dynamics," is characterized by bidirectional theorizing on the coevolution of antecedents and network change, or of outcomes and network change, or both. What distinguishes this domain is bidirectional theorizing, in which the network change and its antecedents and/or outcomes reciprocally affect each other. For instance, a paper in which linguistic similarity and relationship formation simultaneously coevolve—in that linguistic similarity drives relationship formation and at the same time relationship formation drives linguistic similarity—would be in this domain.

We propose this framework as useful to map and navigate the rich and evolving landscape of intraorganizational network dynamics scholarship. Accordingly, we structure our review by these four domains of network theorizing.

REVIEW METHODOLOGY

Demarcation of the Concept

In developing our review, we used a multistep procedure that drew on the systematic review approach of Denyer and Tranfield (2009). First, we specified the conceptual boundaries of network dynamics, which, in line with our discussion above, we defined as the processes through which network change is related to its antecedents and outcomes, where change can unfold at the locus of the node, tie, ego network, or whole network.

Keyword Selection

Second, we executed an iterative process to develop an inclusive string of relevant search terms. In this step, we searched the major scholarly database, Web of Science, for the following tentative list of search terms: "network dynamic*," "network evolution*," "network change*," and "network formation*." We executed this initial search in the titles, abstracts, and keywords of all papers published by seven outlets commonly regarded as the top management journals.[4] We examined the resulting articles to begin a process to develop a comprehensive list of search terms. This process was complicated by the fact that, as noted earlier, "network dynamics" does not represent a single area of research and lacks a common terminology. To ensure that our list of keywords comprehensively captured the broad conceptual scope of network dynamics, we progressively improved the set of search words. This involved an iterative process of adding new keywords and new papers until we reached saturation. Our final list of search terms consists of 123 keywords and is reported in Appendix A.

Journal Selection

Third, we defined a list of relevant journals to search. In order to cast a wider net (Short, 2009), we extended our search to the 52 journals rated 4 and 4* in the Chartered Association of Business Schools' (2008) Academic Journal Guide that fell within the disciplinary fields of management, sociology, and psychology. To ensure that all relevant papers were captured, we also included two specialty journals (Short, 2009) that were not captured in the Academic Journal Guide's 4 and 4* list: *Social Networks* and *Network Science*.

Search Execution

Fourth, we searched the identified search terms in titles, abstracts, and keywords in the 54 (seven top management, 45 "wider net," and two specialty) journals. The publication date was unrestricted (as of April 2021) and, as in prior reviews (Aguinis & Glavas, 2012; Foss & Saebi, 2017; Saebi, Foss, & Linder, 2019), we excluded book chapters, book reviews, interviews, case studies for teaching, replies, methodological papers, and proceedings papers. We conducted our final search in two major scholarly databases—Web of Science and Scopus—which identified 616 articles, after omitting overlap.

[4] *Academy of Management Journal*, *Academy of Management Review*, *Administrative Science Quarterly*, *Journal of Management*, *Management Science*, *Organization Science*, and *Strategic Management Journal*.

TABLE 1
Overview of Journals in Sample[a]

Name of journal	Journal classification	Number of articles
Social Networks	Specialty journal	33
Organization Science	Top management journal	24
Administrative Science Quarterly	Top management journal	10
Network Science	Specialty journal	8
Journal of Applied Psychology	Wider net	7
Academy of Management Journal	Top management journal	6
American Journal of Sociology	Wider net	6
Management Science	Top management journal	5
Strategic Management Journal	Top management journal	5
Human Relations	Wider net	5
Organization Studies	Wider net	4
Journal of Organizational Behavior	Wider net	3
Social Forces	Wider net	3
Journal of Management Information Systems	Wider net	2
Leadership Quarterly	Wider net	2
Psychological Science	Wider net	2
Journal of Management	Top management journal	1
Academy of Management Discoveries	Wider net	1
American Sociological Review	Wider net	1
British Journal of Management	Wider net	1
Human Resource Management	Wider net	1
Journal of Business Venturing	Wider net	1
Journal of Vocational Behavior	Wider net	1
MIS Quarterly	Wider net	1
Science	Wider net	1
Total		134

[a] Ordered by "Number of articles."

Inclusion Criteria

Fifth, we examined each article to determine appropriateness for inclusion in the review. We applied three criteria. First, the article had to study phenomena of relevance for management scholars and practitioners. That is, during the filtering process, we paid close attention not only to management contributions on network dynamics, but also to non-management contributions with implications for management researchers and practitioners. Second, it had to study network dynamics. In line with our definition, this entails theorizing about processes underlying how and why networks change and how and why network change translates into certain outcomes.[5] Third, the article had to study phenomena at the intraorganizational level of analysis. That is, relationships had to unfold within a single "organization," broadly defined as an entity (such as a company, an institution, or an association) comprising multiple people and having a particular purpose. This broader definition allowed us to include studies using empirical settings that, although not strictly speaking firm specific, were informative for management theory and practice. This includes, for example, Stuart's (2017) study of relational experimentation and performance in professional hockey teams and Argote, Aven, and Kush's (2018) work on transactive memory and group performance in a student-based experiment. Disagreements regarding exclusion were discussed until consensus was reached (Payne, Moore, Griffis, & Autry, 2011). We focused our review on empirical papers using quantitative, qualitative, or mixed methods design. The resulting final sample consisted of 134 journal articles (reported in Appendix B).[6] Table 1 gives an

[5] We observed a few papers that did not explicitly model network change, but were discussed by their authors in terms of change (see, e.g., Brennecke, 2020). Given their theoretical focus, we included these papers in our review.

[6] Six articles included in this final sample did not result from the search. These articles appeared in outlets that are typically regarded as less relevant for management scholars and therefore were not included in the search, but were frequently cited by articles that did appear in the search.

TABLE 2
Levels, Antecedents, Loci, and Outcomes of Network Change across Domains

	Theory of network dynamics	Network dynamics theory	Integrative theory of network dynamics	Coevolutionary theory of network dynamics	Total
Total articles	85 (63%)	20 (15%)	15 (11%)	14 (10%)	134
Level of analysis					
Individual	78	14	11	12	115 (86%)
Team	3	4	3	2	12 (9%)
Organization	2	2	0	0	4 (3%)
Multi-level	2	0	1	0	3 (2%)
Antecedents of change					
Agency	76	n/a	12	8	96 (58%)
Inertia	17	n/a	1	0	18 (11%)
Opportunity	26	n/a	9	9	44 (27%)
Random/Exogenous	7	n/a	0	0	7 (4%)
Loci of change					
Node	5	0	5	2	12 (8%)
Tie	50	6	6	9	71 (46%)
Ego network	30	10	8	7	55 (35%)
Whole network	10	5	1	1	17 (11%)
Outcomes of change					
Economic	n/a	19	14	1	34 (79%)
Social	n/a	5	3	1	9 (21%)
Psychological	n/a	0	0	0	0 (0%)

Note: Percentages may not sum to one hundred due to rounding.

overview of the number of included articles per journal.

Coding Scheme

Lastly, we split these 134 journal articles among this review's coauthors to code them along key dimensions, including key findings, core theoretical framework(s), methodology, setting, type of network data, unit of analysis, antecedent(s) of network change, locus (loci) of network change, and outcome(s) of network change. We then cross-checked each other's coding and the few cases of disagreement were discussed until consensus was reached. Building on our key coding criteria, Table 2 shows the prevalence of levels of analysis, antecedents, loci, and outcomes of network change across the four domains of network theorizing.

Figure 2 depicts a rapid increase in the number of articles published on intraorganizational network dynamics, organized by domain of network theorizing. Although interest in network dynamics dates back to the earliest days of the field (e.g., Heider, 1946; Moreno, 1934; Newcomb, 1961), the surge in papers in the past two decades may be driven by the increased availability of longitudinal network data (e.g., de Nooy, 2011; Kitts & Quintane, 2020) and by advances in methods of modeling network dynamics (see our methodological note in the end of the review.) The surge in scholarship is primarily driven by a stark increase in studies within the theory of networks domain, a point to which we return in the next section.

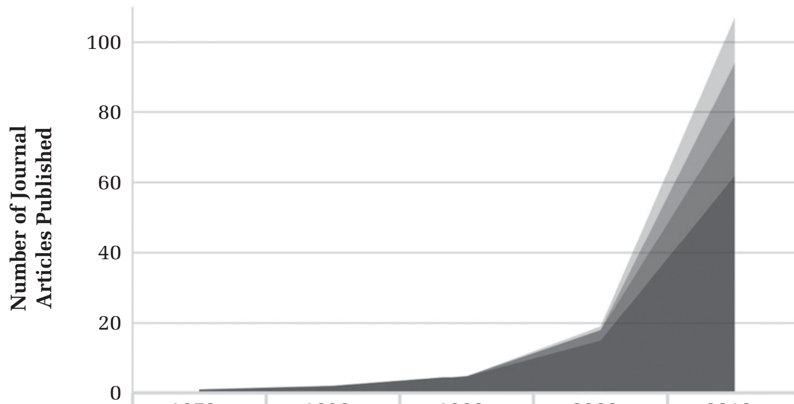
Building on our coding of the 134 journal articles in our sample, the following sections provide a review of the literature on intraorganizational network dynamics, starting with the *theory of network dynamics* domain. For each domain, after reviewing the literature, we identify domain-specific insights and suggest promising directions for research.

THEORY OF NETWORK DYNAMICS

Current Research Themes

Network research in the social sciences has largely been concerned with the consequences of networks (e.g., Borgatti & Halgin, 2011; Borgatti, Mehra, Brass, & Labianca, 2009). This focus has been suggested to be the result of a logical progression as the field matures (Borgatti, Brass, & Halgin, 2014), in which the first order of business was to establish that its constructs and mechanisms drive important outcome variables (Borgatti & Foster, 2003), and has led to calls for research that moves beyond the study of network structure and its outcomes to account for

FIGURE 2
Number of Articles by Domain of Network Theorizing



	1970–1979	1980–1989	1990–1999	2000–2009	2010–2021
Coevolutionary Theory of Network Dynamics	0	0	0	1	13
Integrative Theory of Network Dynamics	0	0	0	0	15
Network Dynamics Theory	0	0	0	3	17
Theory of Network Dynamics	1	2	5	15	62

Year Range

how networks themselves emerge, evolve, and dissolve (Salancik, 1995). As the field has progressively achieved this aim and solidified the importance of networks for a broad variety of outcomes (e.g., Borgatti & Halgin, 2011), work that investigates the relationship between antecedents and instances of network change has increased and amounts to 85 papers (63% of our sample).

In reviewing this body of work, we organize the subsections by the type of network change (i.e., the outcome variables, such as tie formation) and, within each subsection, by the constructs used to explain the focal type of network change (e.g., status or homophily). These constructs do not unequivocally belong to any specific antecedent of change—agency, inertia, opportunity, or exogenous/random factors—as the theoretical perspective that can be used to link a certain construct to an outcome of change can differ. For instance, strong relationships may be more likely to be sustained over time both because of the normative pressures against their termination (i.e., inertia) and because of a means–end rationalization intended to preserve the accumulated social capital (i.e., agency).

Tie formation. We begin our review by taking stock of the literature on drivers of network change at the locus of the tie, which occurs when ties between nodes are formed, terminated, or modified. Among studies of network change involving dyadic relationships, the most frequent topic is what drives the formation of new ties.

Status. It is well known that an actor's status influences their opportunities and constraints (Fiske, 2010; Ridgeway, Backor, Li, Tinkler, & Erickson, 2009; Sauder, Lynn, & Podolny, 2012). In an influential paper on the origins of status hierarchies, Gould (2002: 1143) argued that "actors reproduce status hierarchies by adjusting their own status-conferring gestures according to collective attributions." By this logic, we should expect low-status individuals to seek out high-status colleagues, but less so the other way around. In line with this reasoning, evidence from our review suggests that individuals are more likely to seek advice from their higher-status colleagues (Lazega, Mounier, Snijders, Tubaro, & Norms, 2012) than the other way around (Agneessens & Wittek, 2012). There is a similar finding for negative tie formation. Rubineau, Lim, and Neblo

(2019) showed that the likelihood of negative tie formation is a function of status differences between the focal actors. The greater the difference, the higher the likelihood of a negative tie, and negative ties tend to target low-status individuals. The latter finding was confirmed by Yap and Harrigan (2015), who found higher-status individuals more likely to reciprocate a positive tie with a negative one.

Homophily. Another powerful and pervasive driver of tie formation is "homophily," or the principle that similar people—both in terms of demographic characteristics and in terms of beliefs, attitudes, and personality (Williams & O'Reilly, 1998)—are more likely to establish a connection with one another than are dissimilar people (Lazarsfeld & Merton, 1954). In a landmark review, McPherson, Smith-Lovin, and Cook (2001) found that people display a strong tendency toward homophily; the authors called for more network dynamics research to examine the "extent to which network patterns, including homophily, are created by selective tie formation or selective tie dissolution" (McPherson et al., 2001: 437–438). Numerous papers in our review provide evidence of homophilous selection in tie formation in terms of both "status homophily"—in which similarity is based on informal, formal, or ascribed status—and "value homophily," based on values, attitudes, and beliefs (Lazarsfeld & Merton, 1954).

Two studies have examined the effects of both status and value homophily. Dahlander and McFarland (2013) studied research collaborations at Stanford University and found that both similarity in gender, ethnicity, educational background, and tenure (i.e., status homophily) and reference similarity (i.e., value homophily) significantly explain coauthorship in publications and grant applications. Whereas similarity in gender, ethnicity, and educational background positively affect tie formation, similarity in tenure has a negative effect and reference similarity has an inverted U-shaped relationship with tie formation. In another study, Schaefer and Kreager (2020) used network data from a prison-based therapeutic community to show that residents are more likely to form ties with other residents to the extent they are of similar race, age, or tenure, (i.e., status homophily) and that these effects decrease over time. Only weak support was found for effects of similarity in religion and treatment engagement (i.e., value homophily).

The remaining studies exclusively consider the effects of status homophily. Weber, Schwenzer, and Hillmert (2020) showed that similarity in gender, academic ability, and social background drives the formation of study partnerships among university students in a large German university. Wimmer and Lewis (2010) found that tie formation among American college students is driven by a psychological preference for same-race alters and that this racial homophily effect is amplified by reciprocity and triadic closure. Further, Harrigan and Yap (2017) found that the formation of positive ties is driven by homophilous effects on several demographic dimensions, including age, income, and race.

In contrast, two studies found no evidence linking status homophily to tie formation. In a study of the socializing behavior of a relatively homogenous group of business people at a mixer, Ingram and Morris (2007) concluded that, in the average encounter at the mixer, participants do not engage significantly more with people similar to them in sex, race, education, and job. In another study, Kossinets and Watts (2006) found no effect of homophily on tie formation in terms of status, gender, age, and time in the community. Harrigan and Yap (2017), looking at negative ties, also found only limited support linking status homophily to tie formation.

Elementary structural effects. Tie formation is also known to be driven by a set of elementary structural effects. Two basic examples are "reciprocity" and "triadic closure," which capture the tendency to reciprocate directed ties and to form closed triplets. Studies in our sample confirm the presence of those and several other structural effects. Harrigan and Yap (2017) found that the formation of both positive and negative ties is driven by popularity, activity, and entrainment and that positive ties are also driven by reciprocity, closure, and homophily. Similarly, Kossinets and Watts (2009) found support that triadic closure and "focal closure" (dyads sharing an interaction focus) drive the formation of new communication ties. In an analysis of email communications in a knowledge-intensive organization, as well as in a replication study, Quintane and Carnabuci (2016) investigated when brokers intermediate the flow of information between the brokered parties ("gaudens strategy") or facilitate direct exchange between them ("iungens strategy"), and found that brokers tend to adopt a gaudens strategy with short-term contacts and a iungens strategy with long-term contacts. Schaefer and Kreager (2020), in their study of network data from a prison-based therapeutic community, showed that tie formation among residents is driven by mechanisms of reciprocity and transitivity and that these effects become generally more influential over time. Jonczyk, Lee, Galunic, and Bensaou (2016) found that the likelihood of forming a professional relationship high in cognitive (but not relational) trust is greater when an actor has earlier had a sparse, nonredundant network. In a study of tie formation between organizational units in a large multinational company, Tsai (2000) showed that a unit with greater prior network centrality is likely to form a new interunit tie more quickly. Dahlander and McFarland (2013) showed that centrality is an important determinant of tie formation among scientists in publication and grant application networks. In both networks, collaboration centrality has an inverted U-shaped relationship with tie formation and the difference in collaboration centrality between two nodes in a dyad negatively affects the likelihood of tie formation. Kossinets and Watts (2006) found that the likelihood of tie creation between the two unconnected members of an open triad increases with the tie strength between the two unconnected members and their mutual acquaintance.

Psychological constructs. One widely adopted perspective within network research has tended to focus on social structure as being irreducible to the individual attributes of actors (e.g., Emirbayer & Goodwin, 1994; Mayhew, 1980). Such a perspective tends to "ignore the attributes of actors (such as personality) because outcomes are assumed to derive from embeddedness in systems of relations" (Kilduff & Tsai, 2003: 65).

In contrast to this radical structuralist view, research in our sample also finds support for the individualist perspective that acknowledges the importance of individual-level characteristics as antecedents of network change (Kilduff & Krackhardt, 1994). To this end, three articles have examined how a variety of psychological constructs relate to tie formation. Feiler and Kleinbaum (2015) studied the effect of extraversion on the formation of friendship ties. They found that being more extraverted increases the likelihood of citing others as friends, as well as being cited by them as a friend. Further, similarity in extraversion between any two nodes increases the likelihood of friendship tie formation. Baker and Bulkley (2014), in a study of reputational effects in an MBA program at a large U.S. university, found that, the more help an individual receives from others, the more likely they are to manifest organizational citizenship behavior and respond to a new request for help. Also, the more an individual helps others, the more likely they are to receive help when they request it. In a study of working adults during the COVID-19 crisis, Yang, Soltis, Ross, and Labianca (2021) found that individuals are more likely to reactivate a dormant tie when experiencing job insecurity and that individuals who are performing more remote work post-COVID than they did before are less likely to reactivate a dormant tie than those who are not.

Propinquity. Many of the underlying mechanisms for tie formation we have considered so far—such as the tendency to go after the most sought-after individuals (e.g., Lazega et al., 2012)—have assumed considerable agency by the focal actors, actively seeking to form ties with people who are desirable to them. However, tie choices are constrained, at least in part, by factors—external to the actors involved—that enable or inhibit tie formation (e.g., Blau, 1994). Consistent with this logic, a number of studies in our sample have shown how tie formation is affected by being near in the social or physical space, which we refer to as "propinquity." In their study of a prison-based therapeutic community, Schaefer and Kreager (2020) found that residents are more likely to form ties with other residents with whom they share a cell. In a study of the spatial configuration of offices, Sailer and McCulloh (2012) showed that the likelihood of two people interacting depends on the physical distance between them, such that shorter distance increases the likelihood of an interaction. Dahlander and McFarland (2013), in their study of research collaborations at Stanford University, found that belonging to the same department or research center significantly explains coauthorship of publications and grant applications. Kossinets and Watts (2006) showed that the probability of tie formation in the form of email communication between members of a university community increases with the number of shared classes. In a study of a friendship network among first-year psychology students, Giese et al. (2020) found that early exposure to prospective friends from attending an event increases the likelihood of new friendship tie formation.

Tie termination and maintenance. *Elementary structural effects.* Another commonly researched aspect of network change is what happens to a tie after it is formed: what drives its maintenance or termination? Much of this literature examines elementary structural explanations of when and why ties are maintained or terminated and broadly indicates that more involving relationships are more resistant to decay. In addition to their insights on tie formation, Dahlander and McFarland (2013) showed that multiplex and strong ties are more likely to be maintained over time. In his study of bankers in a large financial organization, Burt found that tie decay is slower for strong and embedded ties (Burt, 2000) and faster for network bridges—an effect that is less pronounced for those experienced with bridge relationships (Burt, 2002). Supporting these findings, Jonczyk et al. (2016) found that more multiplex and embedded ties are less likely to be terminated. They also found that ties between more redundant actors are more likely to be terminated, indicating that, although embeddedness and redundancy might be empirically correlated, they are conceptually distinct and can have opposing effects. Kleinbaum (2018), studying the effect of corporate reorganization on tie decay, found that individuals maintain reciprocated ties (especially with highly empathic others) as well as embedded ties (especially individuals with a low self-monitoring personality). Stea, Pedersen, and Soda (2021), studying a Danish chemical firm, showed that, the lower an individual's knowledge acquisition, the higher the likelihood that they will terminate strong, embedded, and brokered ties.

Status. Three papers consider how status drives tie termination. In line with the intuition that ties to people high in the social status hierarchy provide access to valuable resources and can engender status transfer from the more prominent actor (e.g., Podolny, 2001), studies in our sample find that: service professionals are less likely to drop a contact who is a partner in their respective firm (Jonczyk et al., 2016); individuals (especially those with Machiavellian personalities) are more likely, in the face of a reorganization, to maintain ties to valuable contacts (Kleinbaum, 2018); and ties with prominent colleagues decay more slowly than ties with peripheral colleagues (Burt, 2000).

Homophily. Another explanatory variable that has been shown to drive tie stability is homophily. In line with their finding on tie formation mechanisms, Kossinets and Watts (2009) found that dyadic similarity along the dimensions of gender, age, status, field of study, year in school, and home state lowers the probability of tie dissolution. Burt (2000) showed that within-division ties decay more slowly than ties with colleagues in other divisions. Dahlander and McFarland (2013) found that reference similarity has an inverted U-shaped relationship with the maintenance of coauthorship ties in publications and grant applications.

Psychological constructs. Little empirical work has examined how psychological constructs relate to tie stability. However, there are several reasons to believe that such constructs should be important determinants of the stability of network ties. For example, research indicates that social actors' networking behavior is influenced, at least in part, by how others in their network perceive them (Kleinbaum et al., 2015). Thus, changes in interpersonal perceptions should influence the trajectories of dyadic relationships.

In our sample, only two studies have examined how psychological constructs relate to tie stability. In a study of a large military organization during a two-week training exercise, Fitzhugh, Decostanza, Buchler, and Ungvarsky (2020) theorized and found support that, to preserve access to valuable knowledge sources in the network, individuals with greater situational awareness are more likely to maintain outbound communication ties. In their study of professional service firms, Jonczyk et al. (2016) theorized that the quality of a relationship in terms of its relational trust is a critical determinant of tie maintenance. Consistent with their theorizing, they found that tie dissolution is less likely for ties high in emotional and cognitive-based trust.

Tie property change. The least-investigated type of change at the locus of the tie involves tie properties, including how network ties strengthen, weaken, or change in attributes—for instance, becoming more pleasant or useful.

Homophily and propinquity. Two papers in our sample that investigate this type of change show that homophily and propinquity appear to be important predictors of stronger and more vital ties. In a study of teachers in five public schools, Reagans (2011) showed that age similarity and propinquity positively impact tie strength and that proximity in space amplifies that effect. Maloney, Shah, Zellmer-Bruhn, and Jones (2019) focused on "tie vitality"—that is, the durability and accessibility of team member connections after a team has disbanded. They found that, after disbandment, ties among dyads similar in terms of gender and student origin are more vital. Further, teams with higher relational capital and with higher advice density have higher tie vitality. The effect of team relational capital on tie vitality is amplified by higher advice density.

Social networking site. In addition to the focus on homophily and propinquity as drivers of change in tie properties, a single study in our sample investigates how the implementation of a social networking site influences dyads' shared cognition, or similar perceptions of what and whom colleagues know. Specifically, in a quasi-natural field experiment in a large financial services firm, Leonardi (2018) found that the implementation of an internal social networking site leads employees who use it to have more shared cognition, developed through three interrelated processes—network expansion, content integration, and triggered recalling.

Ambiguity. Lastly, Srivastava (2015a) reasoned that the ambiguity arising from organizational change could trigger transitory shifts in intraorganizational networks. The results support this prediction: when ambiguity increases, individuals com municate more frequently with colleagues within the boundaries defined by the formal organization (i.e., departments) than with those outside those boundaries.

Ego-network size change. We now move from tie- to ego-level change, which involves change that pertains to a focal actor's (i.e., ego's) network, consisting of ego, ego's alters, and all the ties between them. The most commonly studied type of change is in network size.

Feedback. Organizations frequently use feedback processes to provide employees with insight into their work behavior and to stimulate improvement (Murphy & Cleveland, 1995). The importance of feedback for facilitating learning and motivation is widely accepted (Ashford & Cummings, 1983; Herold & Greller, 1977; Ilgen, Fisher, & Taylor, 1979). But what effect does it have on an individual actor's network? Three studies in our sample have examined the thesis that receiving feedback from other organizational members can increase an actor's network size. Findings suggest that, the more positive the performance feedback and the more formal mentoring an individual receives from their supervisor, the greater their network size increase, although the effect of formal mentoring may be contingent on its duration.

In a study of the global IT department of one of the world's largest engineering consulting firms, Parker et al. (2016) showed that, the more positive the performance feedback an individual receives from their supervisor, the more information-getting ties they form. Srivastava (2015b) conducted an intervention study in a software development laboratory in Beijing and found that individuals who receive formal mentoring experience greater network size increases than comparable individuals who do not participate in targeted formal mentoring. The author also found that this effect is contingent on gender; women experience greater increases in network size from targeted formal mentoring than men do. In contrast, Feeney and Bozeman (2008), in a study using data from the National Administrative Studies Project (NASP-III), found no evidence that formal mentoring in an organization increases the number of a mentee's intraorganizational ties in general, but did find weak evidence that longer-lasting mentoring relationships do increase the mentee's network's size.

Network structural properties. Past network structures are regarded as offering opportunities, as well as constraints, that can influence the evolution of future network structures (e.g., Zaheer & Soda, 2009). In line with this logic, three studies in our sample have shown how network structural properties relate to change in network size. In the context of MBA students completing internships in business and law, Sterling (2015) studied how the existence of network ties before individuals join an organization relates to the development of the size of their networks after they join. She found that, when the quality of the individuals is uncertain to incumbent organizational members, individuals with pre-entry social ties exhibit a larger increase in size post entry than those without such pre-entry social ties, and that, when certainty about quality is high, this effect depends on the quality attributes of the new entrants, such that individuals benefit more from initial structural advantages the greater their own quality attributes. Balkundi, Wang, and Kishore (2019) studied how an individual's brokerage position in a knowledge-seeking network relates to changes in their network size; they found that brokerage has a significant effect on size, but that the effect varies for intra-team brokers and inter-team brokers. Intrateam brokers form fewer ties both within and outside their teams and terminate more ties in their teams but fewer outside. Inter-team brokers form more and terminate fewer ties inside their teams, and terminate more ties outside their teams. Building on data derived from a natural experiment at an engineering college in India, Hasan and Bagde (2015) showed that interacting with random but well-connected roommates causes exogenous growth of an individual's network, compared to interacting with random and less-connected roommates.

Personality. As noted earlier, the structuralist perspective that characterizes much network research in organizational settings deemphasizes (Wellman & Berkowitz, 1988) or denies altogether (Mayhew, 1980) the role of network actors' individual and psychological characteristics. However, two papers offer evidence of the importance of individual-level characteristics as antecedents of network change (Kilduff & Krackhardt, 1994) by showing that individuals with high self-monitoring personalities are more likely to have a greater increase in network size over time. Sasovova et al. (2010) showed that self-monitoring personality relates to network size in a friendship network, such that, over time, high self-monitors exhibit higher increases in network size than low self-monitors. Similarly, Kleinbaum, Jordan, and Audia (2015) established a positive effect of self-monitoring personality on network size and showed that this effect is contingent on whether an individual's colleagues perceive them as empathic, such that those who are perceived to be higher in empathy increase their size more than those perceived to be lower in empathy.

Other drivers. A few papers have investigated, in relative isolation, how propinquity, status, incentive redesign, job performance, and the introduction and diffusion of a new technology relate to change in network size. In a study of social network change and race in a police academy, Conti and Doreian (2010) found that propinquity, in the form of workgroups and fixed seating arrangements, relates to increases in network size, and that this effect is stronger within than between races. Smith, Menon, and Thompson (2012) investigated how status differences influence the cognitive activation of social networks under job threat and found that individuals of varying status activate different subsections of their networks when faced with job threat. One dimension in which this happens is network size. When individuals who perceive themselves to be of lower status encounter job threat, they activate smaller subsections of their networks, whereas individuals who perceive themselves to be of higher status activate larger subsections of their networks. Mitsuhashi and Nakamura (2022) found that, after a firm introduces performance-based incentive schemes, employees are more likely to develop smaller networks. Wu, Antone, Srinivas, DeChurch, and Contractor (2021) found that, during a crisis, job performance drives inter-team tie creation and reactivation, but not intra-team tie creation and reactivation. Last, Burkhardt and Brass (1990) showed that the introduction and diffusion of a new technology in an organization leads to change in network size, such that early adopters of the new technology increase their network size following its introduction, whereas the networks of late adopters become smaller.

Ego-network brokerage change. One of the most influential ideas in social network research is "network brokerage," a structural network position that presents opportunities for a network actor (broker) to mobilize information or resources across "structural holes" between two or more otherwise disconnected actors (Burt, 2005). Individuals who occupy such brokerage positions in organizations tend, for instance, to come up with better ideas (Burt, 2004), receive higher performance ratings (Mehra, Kilduff, & Brass, 2001), and get promoted sooner (Brass, 1984; for a recent review, see Kwon, Rondi, Levin, DeMassis, & Brass, 2020).

Network structural properties. Given these benefits, one pressing question for researchers has been to understand what makes certain individuals occupy more brokerage positions than others. A few studies have examined how various structural properties relate to change in brokerage. In addition to their findings relating to change in network size, Hasan and Bagde (2015) showed that interacting with random but well-connected roommates increases an individual's brokerage score, compared to interacting with random and less-connected roommates. In a study of career history data for 30,000 employees in a large information technology and electronics firm, Kleinbaum (2012) found that, compared to following the organization's well-established career path, following an atypical career path is related to an increase in brokerage. Focusing on boundary-spanning roles, Friedman and Podolny (1992) found, analyzing data collected during labor negotiations, that different individuals perform different boundary-spanning roles. Individuals who broker socioemotional flows are less likely to also broker task flows, and vice versa. Similarly, individuals who broker ties toward their opponents (representatives) are less likely to also broker ties from their opponents (gatekeepers), and vice versa. Lastly, Shah (2000) found that, in the aftermath of a downsizing, the loss of friends decreases the betweenness centrality of survivors.

Personality. There is good reason to believe that a multitude of personality profiles might relate to changes in brokerage over time (e.g., Burt, Jannotta, & Mahoney, 1998). One personality construct that has been systematically linked with brokerage is that of "self-monitoring," or the "active construction of public selves to achieve social ends" (Gangestad & Snyder, 2000: 546). Scholars have reasoned that, due to their chameleon-like approach to social interactions, highly self-monitoring personalities tend to be absorbed into different social circles, making them more likely to span structural holes (e.g., Mehra et al., 2001). As in much previous research, however, the cross-sectional nature of those studies precluded examining the evolution of new structural holes over time. Two studies in our sample apply a dynamic lens to the relationship between self-monitoring personality and brokerage, finding support for the prediction that a self-monitoring personality facilitates brokerage evolution over time. Using data on friendship networks in a radiology department, Sasovova et al. (2010) showed that, over time, high self-monitors increase their brokerage score more than low self-monitors do. Also, high self-monitors have a higher rate of formation of new structural holes through gaining new friends and are more likely to maintain their brokerage positions. Kleinbaum et al. (2015) showed that the effect of self-monitoring on brokerage is contingent on whether an individual's colleagues perceive them as empathic; those seen as higher in empathy increase their brokerage more than those seen as lower in empathy.

Status. Status differences have been suggested to influence the extent to which actors can occupy structural holes. Because of their prominence in the social hierarchy, higher-status individuals are more likely to attract disconnected alters and to have selection power over whom to connect with (Kwon et al., 2020; Sauder et al., 2012). Consistent with these ideas, Smith et al. (2012), in their study of status differences and the cognitive activation of social networks under job threat, reasoned that higher status makes individuals more protective of their identities, such that they become more outwardly focused, activating more diverse networks, and thereby reinforcing their status as well-connected and competent individuals. In line with this reasoning, results indicate that, when encountering job threat, individuals who perceive themselves as lower status activate more closed, redundant (i.e., more constrained) subsections of their networks, whereas those who perceive themselves as higher status activate more open and relatively diffuse (i.e., less constrained) subsections of their networks.

Incentive redesign. Mitsuhashi and Nakamura (2022) used intraorganizational copatenting data to analyze the effect of incentive redesign in two Japanese electronics firms in the 1990s, and found that, after the introduction of performance-based incentive schemes, employees are more likely to develop more constrained networks.

Ego-network density change. Another fundamental perspective in social network research concerns "network density," a structural network feature that captures the extent to which a focal actor's partners are connected to each other. According to this view, closely knit networks are facilitative for ego, promoting a normative environment that favors trust and cooperation (Coleman, 1988, 1994; Granovetter, 1985). Individuals in densely connected networks have been shown to be more productive (Reagans & Zuckerman, 2001), to better attain their goals (Balkundi & Harrison, 2006), and to more easily engage in knowledge transfer (Reagans & McEvily, 2003).

Despite its importance, we observe only one study in our review that considers drivers of change in an individual's network density. In a series of experiments, Shea, Lee, Menon, and Im (2019) studied how, during ethical decision-making, individuals engage in "strategic cognitive network activation"—that is, bringing to mind a subset of the potential network that may be more beneficial for them under the circumstances. Findings indicate that individuals preparing for and recovering from unethical behavior tend to strategically seek out distinct resources from their social networks. When individuals are preparing to behave unethically, they tend to cognitively activate lower-density networks. In contrast, when recovering from unethical behavior, they cognitively activate more dense networks.

Ego-network composition change. The final ego-network-level change that has been studied relates to individuals' "network composition," or "the metrics that summarize the characteristics of network members (e.g., percentage of kin and diversity of race)" (Dhand et al., 2021: 2). Four papers have examined this type of change, though along very different dimensions. In a simulation-based study of *preferential attachment by diversity*, Watts and Koput (2014) showed that, when individuals prefer diversity in their tie formation, this creates networks in which the basic characteristics and functioning are maintained when nodes or ties are being added or dropped.

In addition to insights on how a self-monitoring personality induces an increase in network size and brokerage over time, Sasovova et al. (2010) showed that it alters the overall composition of an individual's network, in that the friends attracted tend to be unconnected with previous friends and come from functional groups other than one's own.

In another study, Aven (2015) used a data set consisting of the email communication within Enron prior to its demise to show that individuals' network composition changes as a function of their *membership in corrupt versus noncorrupt projects*. Compared to members of noncorrupt projects, members of corrupt projects communicate less frequently and have fewer reciprocal ties. Both effects are contingent on project tenure, such that, over time, communication frequency decreases more and communication reciprocity increases more for members of corrupt information networks than for members of noncorrupt information networks. Also, the corrupt project members increasingly embed their communication within triadic relations as project tenure increases, whereas the opposite is true for noncorrupt project members. Aven (2015) proposed that this might be because members of corrupt projects wish to preserve secrecy by obstructing or limiting relations between connections among others with whom the focal actor shares a connection.

Mitsuhashi and Nakamura (2022), in their study of the effect of *incentive redesign* in two Japanese electronics firms, also found partial evidence that, after a performance-based incentive scheme is introduced, employees are more likely to develop networks with others who have similar expertise.

Mollica, Gray, and Treviño (2003), studying the composition of friendship ties among a cohort of MBA students, found that *racial homophily* significantly influences the composition of friendship networks. Despite having fewer same-race ties to choose from, the networks of racial minorities exhibit greater racial homophily than those of Whites, both in the formation phase and over time. This effect is greater in networks of individuals whose race is their most salient social identity. While those tendencies exist during the formation of the networks, over time, there is no significant change in racial homophily in the networks of racial groups.

Whole-network structure and composition change. Studies focusing on "whole-network change"—also called "macro-level network change" (e.g., Ibarra, Kilduff, & Tsai, 2005)—are concerned with changes that pertain to the structure or composition of the entire network (Provan, Fish, & Sydow, 2007).

Optimization behaviors. Most studies have examined how social actors' optimization behaviors aggregate to either stability or change in the global network structure. The broad conclusion here is that network stability may be a function of incentives affecting the social actors who make up the network, such that, when local incentives for change in network composition are higher (or lower), the network composition is less (or more) stable. In a simulation-based study, Smaldino, D'Souza, and Maoz (2018) showed that, when the benefits of maintaining current ties, triadic relations, and "spillover ties" (i.e., ties with the same individuals across contexts) remain, networks can be generally stable over time. This happens despite a change in the cost of tie formation, even if the underlying network structure could not have arisen after the change in tie cost. Do'an, van Assen, van de Rijt, and Buskens (2009) also studied network stability, and found that, since network structure has a large impact on the network's benefits for its members, individual actors tend to change their networks when they are free to choose their exchange partners, such that few networks are stable over a wide range of tie costs. Burger and Buskens (2009) used an experimental setup to show that different global network structures can emerge as a direct byproduct of the conscious, goal-directed actions of individuals in the network trying to optimize their positions, depending on the underlying social context in which there are various incentives. In another study taking into consideration local optimization by individuals, Zeggelink (1994) used a simulation-based approach to show that macro-level outcomes are often not globally optimal, due to the local optimization by individuals.

In addition to these studies of how network actors' agentic motives drive network structure, a single study has focused on how such motives affect network composition. In a simulation-based study, Quinn and Baker (2021) demonstrated a considerable increase in collective affect when individuals choosing interaction partners decide to trade off the acquisition of instrumental resources to avoid a decrease in positive emotion.

Trust. Many scholars acknowledge the importance of trust in shaping dyadic interactions (e.g., Blau, 1964; Macy & Skvoretz, 1998), but how does trust at the local level aggregate to shape the network structure at the global level? One study in our sample considers this question. In a study of the stability of communication networks in 24 patient care units (PCUs) in three southwestern U.S. acute care hospitals, Brewer, Carley, Benham-Hutchins, Effken, and Reminga (2020) reasoned that the extent to which actors' information is trusted—for instance, as a result of experience, education, or specific knowledge of the situation—should influence the frequency with which their information is sought by other actors, thus influencing the communication network structure and, potentially, the stability of network metrics. Findings indicate that, over time, PCU networks tend to be highly stable along the dimensions of node set size, average distance, clustering coefficient, density, weighted density, diffusion, total degree centrality, betweenness centrality, and eigenvector centrality. They are unstable, however, along the dimensions of hierarchy, fragmentation, isolate count, and clique count. The stability of PCU networks depends on the confidence that staff members have in the information obtained from their colleagues (trust), such that, when confidence is high, the stability persists, and, when confidence is low, it does not.

Demographic crisscrossing. A single study has considered how demographic crisscrossing—actors in one demographic subgroup sharing one or more demographic attribute with another subgroup and thereby bridging across the subgroups—can influence global network structure. Specifically, in a study of opinion polarization in work teams, Mäs, Flache, Takács, and Jehn (2013) used a formal modeling approach to show that, if there is high initial congruency between demographic attributes in a work team and opinions on work-related issues, and homophily is sufficiently strong, then strong fault lines can give rise to subgroup opinion polarization in the short run. However, this effect can be overcome in the long run for teams that comprise demographic crisscrossing actors who share some demographic attributes with multiple subgroups. This allows such actors to develop opinion consensus independent of the strength of homophily and initial congruency and thus to function as a bridge across the fault line.

Perceived warmth and competence. People constantly make judgments about their own psychological attributes (such as personality, emotions, and attitudes) and those of others (Kenny, 2020), with wide-ranging implications for social actors' networks and the resulting outcomes (e.g., Kleinbaum et al., 2015; Porath et al., 2015). Whereas the role of perceptions as an antecedent to network change has traditionally been studied at the individual (i.e., ego-network) level, a single study in our sample develops a multilevel theory of how interpersonal perceptions cause the emergence of different leadership structures in groups (i.e., whole-network level). Using a sample of 255 MBA consulting teams, DeRue et al. (2015) examined the role of interpersonal perceptions as drivers of denser and more centralized leadership structures over time. They found that, at the whole-network level, density of "perceived warmth" (the extent to which members see the group as warm) and centralization of "perceived competence" (the extent to which one person is seen as the most competent on the team) positively determine the emergence of denser and more centralized leadership structures, respectively. At the individual level, the authors unpacked micro-level processes by which these group-level leadership structures emerge. For the emergence of denser leadership structures, the effect is driven by individuals' perceptions of the group's warmth; those who perceive it as warm are more likely to identify with it, and, in turn, to emerge as leaders. For the emergence of more centralized leadership structures, the effect is driven by the groups' perception of an individual's competence, such that those perceived by the group as competent are more likely to engage in more leader-prototypical roles, and, in turn, emerge as leaders.

New technology. Factors that emanate from random processes or from beyond the network may enable or inhibit the evolution of social networks (Ahuja et al., 2012). Burkhardt and Brass (1990) showed that the introduction and diffusion of a new technology affects not only ego-level outcomes, but also the global network structure, in that, when early adopters are those who had been less central than late adopters, a structural change in terms of the whole-network density and the distribution of central nodes occurs. For the distribution of central nodes, when early adopters are individuals who were previously less central, they are sought out by others at the expense of the centrality of late adopters, resulting in a redistribution of central nodes in the network. Also, late adopters significantly decrease their in-degree centrality, resulting in a decrease in whole-network density after the introduction of the new technology.

Change in nodal attributes. Just as attributes of social network actors influence network evolution, those attributes may themselves be the loci of network change. The last set of studies in this domain explicitly focuses on the attributes of the nodes in a network and analyzes the attributes' transformation.

Leadership. Although the psychological study of leadership dates back more than 100 years and has produced an enormous literature (Kaiser, Hogan, & Craig, 2008), Brass et al. (2004) observed that there has been little empirical work on leadership and social networks. Our review indicates, however, that, since Brass et al.'s observation, researchers have started to extend understanding of the subject. To this end, five studies in our review examine the drivers of leader emergence or continuity—the factors that cause a change or persistence in the extent to which a social network actor is seen as leader-like (Kaiser et al., 2008).

Three studies show that social cognition plays an integral role in leadership emergence. In their study of MBA consulting teams, DeRue et al. (2015) also found two determining factors that drive an individual to emerge as a leader. When an individual perceives the group as being warm, they are more likely to identify with it, and, in turn, to emerge as a leader. Further, when an individual is perceived by the group as competent, they are more likely to engage in more leader-prototypical roles, and, in turn, emerge as a leader. However, Kalish and Luria (2016) showed that the criteria by which people perceive leadership in others change over time, such that individuals are at first more likely to be perceived as leaders due to their higher levels of noticeable, leadership-relevant attributes, but, over time, they are more likely to be perceived as leaders due to their higher levels of covert, leadership-relevant attributes. Actors also rely on their own leadership-relevant attributes to inform their perceptions of leadership in others. In a study of undergraduates involved in a study abroad program, Emery (2012) found that individuals are more likely to emerge as relationship leaders if they are good at perceiving and managing emotions, and more likely to emerge as task leaders if they are good at using and understanding emotions. Carnabuci, Emery, and Brinberg (2018) combined experimental and observational data to show that individuals use a "linear ordering schema"—a default expectation that a given relational structure should form a linear order or ranking—to process information about leadership relations. When a leadership network around a focal individual is incongruent with the linear ordering schema, he or she changes their leadership attributions toward restoring linear ordering—that change often being driven by transitivity and popularity mechanisms.

Two studies show that structural positions in the network also matter for leader emergence. Fleming and Waguespack (2007) studied careers within the Internet Engineering Task Force community from 1986 to 2002 and found that both brokering and boundary-spanning roles significantly increase the likelihood of emerging as an open innovation community leader, and that these effects are strongly contingent on physical presence within the community. Cohen, Rosner, and Foerst (1973) showed that leadership continuity is contingent upon the communication network structure, in that wheel networks produce highly centralized structures conducive to leadership continuity whereas completely connected networks produce decentralized structures more likely to lead to leadership discontinuity.

Status, satisfaction, and commitment. Only two studies have examined dimensions of nodal attribute change that are not related to leader emergence or continuity. Skvoretz and Fararo (1996) presented a dynamic model for the formation of status orders in small task groups, highlighting that participation of actors in group discussion is structured by external status differences, and that these differences inform the formation of internal status attributions. In a study of employee turnover in fast food restaurants, Krackhardt and Porter (1985) showed that, the closer the employees who stay are to those who leave, the more satisfied and committed the remaining employees become subsequent to the turnover of their coworkers. The authors reasoned that the increase in satisfaction with and commitment to the job were a means to cognitively justify individuals' own decision to stay.

Discussion

One of the great lessons from the last half century of research is that embeddedness in social networks is a root cause of several crucial ends, including individual achievement and social stratification. As awareness of the importance of networks has grown, scholars have increasingly sought to explain how networks themselves emerge, evolve, and dissolve. This tendency has been boosted both by influential calls for research that expands our understanding of the antecedents of network change (Salancik, 1995) and by the development of statistical models for social networks as outcome variables (Snijders, 2011).

In line with these tendencies, our review highlights an abundance of work in the theory of network dynamics domain. In this regard, scholars have focused predominantly on explaining changes at the tie and ego-network levels and shown convincing evidence that distinct theoretical logics explain these changes (or lack thereof), including normative pressures, means–end rationalization, and logics of convenience and proximity.

Whereas research in this domain exhibits generally high theoretical maturity, there is still ample room to improve our understanding of the drivers of network change. One promising avenue for future work is to develop a better understanding of what leads nodes to have distinctly composed networks. For example, rather than merely considering what makes an individual become more or less of a broker or more or less central in a network, future work could investigate what causes certain individuals to broker between or to be central among certain types of colleagues. In turn, this would enable a more granular understanding of the possible outcomes of structural positions such as brokerage and centrality. For example, an increase in centrality resulting from ties formed with a given set of actors could produce very different outcomes than would the same increase in centrality but with different actors.

As a second illustration, we point to causes of node-level network change. In intraorganizational network research, the social actors are the least expansive unit of analysis and are nested in dyads, which are nested in groups, which are nested in departments, which are nested in business units, and so forth (Hitt, Beamish, Jackson, & Mathieu, 2007). One important implication of this is that changes at the nodal level are prone to induce bottom-up effects with consequences that span the entire network (Moliterno & Mahony, 2011). A first step in being able to appreciate the potential cross-level effects of change in actor attributes is to understand how and why changes in nodal attributes come about.

NETWORK DYNAMICS THEORY

Current Research Themes

As we noted earlier, the bulk of network research in the social sciences has focused on the consequences of networks (e.g., Borgatti & Halgin, 2011; Borgatti et al., 2009). Although an impressive and convincing body of work confirming the significance of networks for a wide variety of important outcomes has accumulated, it has by and large been characterized by a "static bias" (Harrington & Fine, 2006), with network properties assumed to be fixed in time (Watts, 2004). Indeed, our review finds only a relatively small amount of work—20 papers (15% of our sample)—concerned with the outcomes of network change. In reviewing these papers below, we organize the subsections by the type of network outcome as depicted in our framework, and, within each subsection, we group the material by the specific outcomes studied in the papers (e.g., creativity, collaboration).

Economic. *Performance.* The most frequently researched outcome of network change in our sample is, perhaps unsurprisingly, performance. In explaining variation in performance, most papers in this domain contribute dynamic insights to the foundational debate on social capital that recognizes the contrasting benefits of dense and sparse network structures (Burt, 1992; Coleman, 1988, 1994; Granovetter, 1985; Obstfeld, 2005). For example, Parise and Rollag (2010) drew on the classic idea that embeddedness in dense networks facilitates cooperation, coordination, trust, and mobilization of knowledge (Coleman, 1988; Reagans & McEvily, 2003), theorizing and finding that density in preexisting work and friendship networks has a direct and positive carryover effect on initial group performance for newly formed teams. Similarly, Lee, Bachrach, and Lewis (2014) found that an increase over time in network density has an overall positive effect on group performance. Other studies have applied a dynamic lens to examine the conditions under which dense or sparse network are more beneficial. For example, Burt and Merluzzi (2016), focusing on time-varying enactments of different network structures, found that engaging over time in network oscillation between closure and brokerage enhances network advantage, as captured by enhanced status or access to structural holes. Using an experimental design, Argote et al. (2018) showed that highly dense groups perform better in the absence of membership turnover, whereas highly brokered networks perform better with turnover. A single study focuses on the performance implications of a shock in the network due to the removal of a central node. Specifically, in a study of professional hockey teams in the National Hockey League, Stuart (2017) showed that the injury of central players negatively affects team performance.

Creativity and knowledge. An extensive body of work based on a static network conception has documented how various features of informal networks can affect the creativity and knowledge mobilization of network actors (for a review, see Phelps, Heidl, & Wadhwa, 2012). Several studies in our review extend the knowledge in this domain by showing some of the complexities that arise when approaching the topic from a dynamic viewpoint. In a study of the core artists behind the TV series *Doctor Who*, Soda, Mannucci, and Burt (2021) showed that, over time, network stability weakens the creative advantages provided by open networks and heterogeneous content, whereas less stable networks (i.e., networks whose composition changes over time) strengthen those advantages. Mannucci and Perry-Smith (2021) conducted a set of experiments to better understand the dynamics and creativity implications of network activation during idea generation and elaboration. One core insight of this work was that individuals with large networks are less likely than individuals with small networks to activate and switch to the most beneficial type of tie across idea generation and elaboration phases, with negative implications for creativity enhancement. Relatedly, in a study of two central R&D labs of a large multinational company, Kijkuit and van den Ende (2010) showed that, among other things, different levels of density are conducive to successful idea adoption, depending on the specific phase of the front-end of the new product development process: low density is beneficial for idea generation, medium density for idea development, and high density for idea refinement.

With respect to knowledge mobilization, Levin, Walter, and Murnighan (2011) found that reconnecting to a dormant strong tie (a former strong tie that is now out of touch) provides more efficiency, novelty, and trust and—as a result—more useful knowledge than a current strong tie. In a study of the value of new ties, Levin and Walter (2019) found evidence that we can predict which advice relationships will be most valuable even before the focal individuals ever meet. Specifically, the authors showed that individuals receive more valuable knowledge from advice relationships when a third party recommends the new contact and when there are no common connections between the focal individuals and the new contacts. Scholars have also shown how changes in network density can impact a group's transactive memory system. In the aforementioned study by Argote et al. (2018) on membership turnover, the authors also showed that dense groups develop stronger transactive memory systems in the absence of membership turnover, and that highly brokered groups develop stronger transactive memory systems when turnover does occur. Lee et al. (2014) found that, over time—absent considerations of turnover—a more dense network structure has a negative direct effect on transactive memory system development in groups and a simultaneous positive indirect effect on transactive memory system development via an increase in transitive triads.

Social. *Social assimilation.* Disentangling the effects of selection and influence remains a fundamental endeavor in the social sciences (Lewis, Gonzalez, & Kaufman, 2012): Do people connect with others who are similar to them? Do they, over time, become more similar to the people they are connected with? Or, are the two processes interrelated and coevolve over time? As we saw earlier, substantial evidence from dynamic network research highlights social selection, or homophily, as a fundamental driver of tie formation. At the same time, studies in our review highlight the importance of social influence from a dynamic network perspective. In a study of managers of a multiunit organization, Tasselli, Zappa, and Lomi (2020) found that, within (but not across) subunit boundaries, a communication tie between two managers enhances their likelihood of developing similar vocabularies over time. In another study, de Klepper, Sleebos, van de Bunt, and Agneessens (2010) showed that individuals adjust their level of discipline to that of their friends, such that an individual who has more friends is more influenced by their overall level of discipline than an individual who has fewer friends—an effect driven primarily by social influence rather than social selection.

Cooperation. Cooperation is an important theme for organizations (Schalk & Curşeu, 2010). From a network perspective, cohesion is a structural property commonly associated with enhanced cooperation. A close-knit network structure is presumed to induce more mutual monitoring and sanctioning of norm violations and, in turn, to establish effective norms and increase trust and collaboration in the network (Coleman, 1988, 1994; Fleming, Mingo, & Chen, 2007; Obstfeld, 2005; Podolny & Baron, 1997). However, contrary to these ideas, two papers in our review indicate that increased network cohesion may be detrimental to cooperation. Using agent-based simulations, Zschache (2012) showed that the cost of network change affects the level of cooperation, such that cooperation is more likely when group cohesion is low instead of high, and actors can effortlessly change interaction partners. Relatedly, in a study of a new special unit within the Italian subsidiary of a multinational computer manufacturer, Gargiulo and Benassi (2000) found that managers with cohesive communication networks are less likely to adapt the composition of those networks in response to a change in coordination requirements, which, in turn, jeopardizes their role as facilitators of horizontal cooperation within the focal business unit.

Discussion

In this domain, studies extend a dynamic perspective to network effects in order to explain how *changes* in networks produce a variety of important outcomes. By so doing, these studies deviate from most of the literature on network outcomes, which has largely overlooked the dynamic nature of networks (Harrington & Fine, 2006).

By explicitly incorporating network change as a driver of various outcomes, these studies make two fundamental contributions. First, our review highlights that several well-documented effects from studies taking a static perspective replicate when analyzed longitudinally. These replications are important, given the limited ability of cross-sectional designs to address questions related to causal ordering.

Second, these studies reveal new theoretical insights and add nuance to our understanding of network effects. One example of this is Burt and Merluzzi's (2016) study, which, by characterizing brokerage and density as episodic, showed that network advantage is enhanced for actors who engage in sequenced transitions in and out of closed networks—an insight that would have been impossible to derive from a static setup.

In this regard, the most immediate priority for future research in this domain is to derive additional theoretical insights about processes underlying how and why changes in networks produce certain outcomes. As we see it, there is ample room to extend understanding in this domain, both with respect to the types of network change and the types of outcomes under investigation. By way of illustration, promising avenues in terms of types of network change include changes in individual's networking behaviors, in their ability to learn to recognize and leverage given structural opportunities, and in how nodes are perceived by their colleagues. With respect to outcomes, we particularly encourage investigations of psychological consequences which, as our review shows, have been largely overlooked despite repeated calls to bring the "person back in" to the study of social networks by integrating network and psychological perspectives (e.g., Kilduff & Krackhardt, 1994).

INTEGRATIVE THEORY OF NETWORK DYNAMICS

Current Research Themes

In the two domains reviewed so far, research has considered the underlying drivers of network change and the consequences of such change. The third domain takes a more holistic approach. It integrates the aforementioned two domains, seeking to elucidate both how a network reached a given structure and how that structure, in turn, breeds certain outcomes. Below, we review this body of work, which, with 15 papers, accounts for 11% of our sample.

Antecedents informing the outcome of network change. Two papers in our sample develop integrative theories of network dynamics building on the assumption that, to better understand the effects of a network change on a given outcome, it is worth investigating what drove the network change in the first place.

In one study, Frey, Buskens, and Corten (2019) ran a laboratory experiment with 342 participants and showed that an increase in network embeddedness promotes both trustfulness and trustworthiness. However, when taking into account the antecedents that lead to the increase in embeddedness, the authors found that the effect on trustfulness is stronger if the increase resulted from actor's endogenous choices than if it was imposed exogenously.

In another study Shah, Peterson, Jones, and Ferguson (2021) leveraged mixed- and multi-methods to show that both task and relationship intragroup conflict predominantly originate from individuals, dyads, or subgroups, and remain where they originate rather than spreading to other teammates or eventually concentrating to a smaller set of team members. When considering the consequences of intragroup conflict for team performance, the authors reasoned that "traditional compositional measures of intragroup conflict are not sufficient to fully understand how conflict affects team outcomes," suggesting that "precision in where conflict originates may provide greater insight on … when conflict benefits or undermines team performance" (Shah et al., 2021: 436, 436– 437). Consistent with this line of reasoning, the authors found that, whereas, for relationship conflict, the locus of origin has no effect on team performance, task conflict that originates at the locus of the individual or dyad positively predicts team performance.

Elucidating causal pathways. The two papers reviewed above showed that, sometimes, knowing what leads to a given network change informs our understanding of the change's specific outcome. We saw, for instance, that an increase in embeddedness promotes trustfulness more if it results from actors' endogenous enactment of their networks than if it was imposed exogenously (Frey et al., 2019). Most papers within this domain, however, are less concerned with how the antecedent might differentially affect the outcome through a change in the network itself, but, instead, focus on elucidating the pathways through which a given antecedent leads to an outcome by inducing a change in a network variable.

Predominantly, studies have investigated *pathways to performance*—that is, the pathways by which certain antecedents lead to performance outcomes by stimulating network change. In a first group of papers, such change unfolds at the individual level of analysis. In a study that uses both a social network analysis of an R&D department of a biotechnology firm and an experiment, Porath, Gerbasi, and Schorch (2015) showed that, the more an individual is perceived as civil by their colleagues, the more they turn to him or her for advice and the more they perceive them to be a leader, which, in turn, enhances that individual's performance. Çelen and Hyndman (2012) studied social learning and show that the cost of forming new ties determines which ties are formed and how useful they end up being. When there is a small positive cost of forming ties—as opposed to no cost—individuals form more informative ties, which, in turn, enhance social learning and lead to increased predictive power and higher expected payoffs. Clement and Puranam (2018) used simulations to show that, even if randomly selected, weak top-down enforcement of a formal structure in an organization facilitates bottom-up emergence of informal communication networks, which, in turn, improves organizational performance. In contrast, whereas formal structure regenerates interactions, in its absence, those interactions tend to disappear, as their maintenance requires coordination, but their termination does not. In another study, Balkundi et al. (2011) found that central individuals in advice networks subsequently encounter a nodal change, in that they tend to be seen as more charismatic by subordinates, which, in turn, boosts higher team performance. Further, Brennecke (2020) used survey and interview data collected from engineers in a large manufacturing firm to examine the antecedents and performance consequences of "dissonant ties"; that is, ties to colleagues that are simultaneously positive and negative. The author found several drivers of dissonant ties. From the perspective of a focal individual, tenure is negatively related to their use of dissonant tie. From the perspective of their colleagues, their formal hierarchical rank has a negative effect on being approached with dissonant ties and their tenure a positive effect on it. From a dyadic perspective, similarity in formal hierarchical rank and tenure are positively related to dissonant tie formation, whereas working in the same unit is negatively related. In terms of the consequences of dissonant ties, Brennecke (2020) showed that the use of dissonant ties has a positive impact on an individual's performance, in terms of both peer assessment and supervisor rating.

A second group of papers models network change at the level of the team or organization. Briscoe and Tsai's (2011) analysis of a large law firm's acquisition of two smaller firms examined the antecedents and consequences of post-acquisition integration through client sharing. They found interunit client sharing influenced by the closure of a partner's referral network before an acquisition event, such that greater closure leads to more—and lower closure to less—interunit sharing. Higher levels of pre-merger referral network closure also lead to the termination of fewer intraunit client-sharing ties, whereas lower closure leads to the termination of more such ties. These effects, in turn, matter for a variety of outcomes. Compared to intraunit client sharing, interunit sharing leads to greater revenue generation but less human capital development. Melamed, Sweitzer, Simpson, Abernathy, Harrell, and Munn (2020) showed that homophily drives cooperation and tie formation, which result in higher clustering and segregation between groups at the global network level and, in turn, to higher group-level performance. This happens because individuals in homophilous clusters cooperate more, which allows them to earn more. In a study of intrafirm inventor networks, Argyres, Rios, and Silverman (2020) found that centralization of R&D budget authority leads to greater connectedness of the intrafirm coinvention network, which, in turn, increases the breadth of both innovation search and impact.

Besides studies focusing on performance outcomes, three studies have examined *pathways to new attitudes and behavior*. In a sample of 338 employees from multiple organizations, Ng and Feldman (2014) showed that an increase in community embeddedness leads to an increase in organizational embeddedness, which in turn improves job motivation, social networking behavior, and organizational identification. In a study of recently promoted service professionals, Bensaou, Galunic, and Jonczyk-Sédès (2014) considered what networking strategies individuals use. They found three: (a) "devoted players" are highly dedicated and active networkers open to meeting and engaging with many people; (b) "selective players" enjoy networking, but are not nearly as focused on it as the devoted players and do not regard it as paramount for career success; and (c) "purists" show little enthusiasm for networking and regard it as comprising superficial encounters. Selection into either strategy depends predominantly on the underlying agency invoked by individuals, above and beyond prior network structure. The strategies are, in turn, associated with different outcomes. Devoted players tend to have larger networks than both purists and selective players. Devoted players have the densest internal networks of close relationships, but also connect with many external contacts, resulting in a less dense overall network. Overall, selective players have the densest networks, devoted players have medium-dense networks, and purists have the least dense networks. Devoted players tend to be much more active than purists in social integration with peers. Purists tend to be much less committed to the organization than devoted players and selective players. In another study, Melamed and Simpson (2016) used a simulation-based approach along with a laboratory experiment to show that the value of ties positively affects their strength, which, in turn, promotes cooperative behaviors. Woehler et al. (2021) found that, in the context of a corporate merger, employees with high formal power (rank) and high informal status (in-degree centrality) widen their networks by connecting with those in the counterpart legacy organization, which, in turn, reduces their likelihood of turnover after the merger. The authors also found that personally felt threat in the form of merger-related job insecurity reinforces the relationship between formal power and network widening.

Discussion

In his review of Burt's (1992) influential book *Structural Holes*, Salancik (1995: 345) called for a "good network theory of organization" that moves beyond the study of network structure and its outcomes to account for how networks themselves emerge, evolve, and dissolve. An interesting discussion that derives from the critique by Salancik (1995) and others (e.g., Emirbayer & Goodwin, 1994) is whether our "understanding of network outcomes is incomplete and potentially flawed without an appreciation of the genesis and evolution of the underlying network structures" (Ahuja et al., 2012: 434) or whether such integrative theorizing is merely "satisfying and elegant" but yet not necessary (Borgatti & Halgin, 2011: 11), because "it is not the actors' intentions and actions leading to occupying a certain position that creates the outcome but the actual occupation of the position" (Borgatti & Halgin, 2011: 11).

This debate has important implications for how we should study social networks. By integrating the previously discussed two domains of network theorizing, the papers in this third domain are poised to elucidate whether it is the case that, if one wants to better understand the effects of a network change on a given outcome, it is informative to investigate what drove the network change in the first place. Nevertheless, only two papers in our review explicitly contribute empirical insights to this discussion by testing whether knowing the antecedents of a given network change helps us understand its outcome (Frey et al., 2019; Shah et al., 2021; see Antecedents Informing the Outcome of Network Change section above). While these papers provide preliminary support for the view that integrative theorizing is important for a complete understanding of network outcomes (Ahuja et al., 2012), drawing such a conclusion with confidence will require more empirical evidence that replicates and extends their findings.

Our review of this domain also prompts an important methodological consideration. Although research questions in this domain lend themselves naturally to a formal test of mediation (see, e.g., Aguinis, Edwards, & Bradley, 2017), relatively few studies have applied that approach (for exceptions, see Balkundi et al., 2011; Ng & Feldman, 2014; and Porath et al., 2015). Rather, work has commonly used multiple studies answering different aspects of the research question in a stepwise fashion (e.g., Shah et al., 2021). While informative, it is important to bear in mind that these approaches have important shortcomings in comparison to a formal test of mediation. Most importantly, the latter allows researchers to directly model their causal assumptions, to understand if the effects are full or partial, and—for studies hypothesizing on multiple effects—to gain insight into the relative importance of each mechanism.

COEVOLUTIONARY THEORY OF NETWORK DYNAMICS

Current Research Themes

In the three domains reviewed so far, research has relied on the assumption of a clear causal direction between the focal network and its antecedents and outcomes. In many cases, however, the causal direction might be open for discussion (Agneessens, 2020). Scholars are therefore increasingly engaging in bidirectional theorizing, in which the network change and its correlates reciprocally affect each other. In the past decade, work in this domain has particularly benefited from advances in methods for modeling network coevolution (Snijders, Steglich, & Schweinberger, 2007; Steglich, Snijders, & Pearson, 2010). It has progressed along two dimensions: (a) the coevolution of a network and behavior and (b) the coevolution of multiple networks. Below, we review this evolving literature, which, with 14 papers, makes up 10% of our sample.

Coevolution of networks and behavior. The largest share of the studies investigating a coevolutionary theory of network dynamics examines the joint evolution of networks and behavior over time. Most of these studies have shown that networks coevolve with psychological constructs. In a study of a two-day assessment boot camp for an elite Israeli military unit, Kalish, Luria, Toker, and Westman (2015) showed that communication networks coevolve with perceived stress. Individuals who experience higher stress form fewer new communication ties and are more likely to maintain existing ties. At the same time, the smaller the focal individual's communication network, the more their stress increases over time. In another study, Schulte, Cohen, and Klein (2012) found that perceptions of psychological safety in teams and the formation of network ties coevolve. On the one hand, the more psychologically safe team members perceive their team to be, the more likely they are to ask their teammates for advice and to see them as friends and the less likely they are to report difficult relationships with them. On the other hand, team members also adopt their friends and advisors' perceptions of the team's psychological safety and reject the perceptions of those with whom they report a difficult relationship. Elmer, Boda, and Stadtfeld (2017), in a study of a housing community for university affiliates and their partners, found evidence that emotional well-being and friendship ties coevolve; on the one hand, individuals select others as strong-tied friends based on similar levels of emotional well-being, and, on the other hand, individuals' emotional well-being converges to the emotional well-being of their strong-tied friends.

Other studies have shown how networks coevolve with other variables, including linguistic style, market selection orientation, and status. Kovács and Kleinbaum (2020) showed, in two studies, that friendship ties and linguistic style coevolve: people with similar linguistic styles are more likely to form and maintain friendship ties, while friends experience linguistic convergence over time. Ebbers and Wijnberg (2019) found that individuals' "market selection orientations" (capturing the perceived importance of commercial success) coevolve with friendship ties. The strength of an individual's market selection orientation relates negatively to friendship tie formation, while friendship ties converge over time in the strength of market selection orientation. In a study involving a full cohort of MBA students, Torlò and Lomi (2017) showed not only that social status and network ties coevolve, but also that the effects vary between friendship and advice networks. In terms of social influence, students assimilate to the status of their friends rather than to the status of their advisors. For status-based social selection, status makes students more active in their friendship networks, but more popular in their advice network.

There were also two papers that theorized about coevolution between networks and behavior, but found no empirical support for it. Tröster, Parker, Van Knippenberg, and Sahlmüller (2019) studied the coevolution of tie change and thoughts of quitting in advice and friendship networks. Findings indicate that, while individuals with more thoughts of quitting have a higher tendency toward change in their advice network and toward stability in their friendship network, the changes in network ties do not relate back to thoughts of quitting. Similarly, in a study of a cohort of psychology students at a German public university, Thiele, Sauer, Atzmueller, and Kauffeld (2018) investigated how developmental peer relationships and career aspirations coevolve. Findings indicate that students form ties with peers with similar career aspirations, but no evidence was found that students' career aspirations become similar to those of their developmental peers.

Coevolution of multiple networks. Three studies investigate the joint evolution of multiple networks. In one study, Ellwardt, Steglich, and Wittek (2012) investigated the coevolution of friendship and gossip networks, using data from a medium-sized Dutch nonprofit organization. Whereas the formation of gossiping ties facilitates friendship formation between employees, the authors did not find support that friendship ties led to new gossip ties. Labun, Wittek, and Steglich (2016) investigated the coevolution of friendship and power networks in a Dutch childcare organization and found that individuals form friendship ties with the colleagues they perceive to be powerful, and also tend to regard as powerful the people that their powerful colleagues consider as friends. In a group of MBA students, Snijders, Lomi, and Torlò (2013) examined how friendship and advice networks coevolve with employment preferences. With respect to advice ties, agreement on employment preferences leads to the formation of advice ties, and vice versa. The same was found for friendship ties, although the support was weak.

Discussion

Separating the effects of social influence and selection is one of the greatest unsolved puzzles in the social sciences (Lewis et al., 2012; Steglich et al., 2010). By studying how network change and its correlates influence one another, the papers in this domain contribute to the solution of this puzzle.

Although coevolutionary theory of network dynamics is the least populated of our four domains, preliminary evidence that selection and influence are not independent processes over time is accumulating. This conclusion pertains particularly to the joint evolution of networks and psychological constructs and, to a lesser extent, the joint evolution of networks and other networks.

Whereas the work we reviewed here provides significant insights into the selection and influence debate, much can still be done to further understanding on this important matter. For example, recent research has pointed out that, on the one hand, personality is likely to influence networks, and, on the other hand, networks are likely to influence individuals' personalities (Tasselli, Kilduff, & Landis, 2018). However, our review clearly indicates that scholars investigating the relationship between networks and personality have approached the topic assuming a unidirectional causal link.

Since misattribution of selection effects to social influence—or of social influence to selection—leads to wrong conclusions about the social mechanisms underlying the observed dynamics (Steglich et al., 2010), we see high potential in future work that challenges the commonly made but increasingly questioned assumption that there is a clear causal direction linking a focal network to other networks or to attribute variables (Agneessens, 2020).

AN AGENDA FOR FUTURE RESEARCH

A bird's-eye view of the full body of research on intraorganizational network dynamics provides the opportunity to identify new insights that are not readily apparent with only a partial outline of the literature. In this section, we move beyond the domain-specific considerations that we raised after discussing each domain of network theorizing and discuss four broader fundamental areas in which network dynamics research can be conceptually and methodologically extended. For each, we point to a number of general directions that we consider particularly important for shaping research on the topic.

Under-Researched Themes

Our review shows that some research themes have reached higher levels of theoretical maturity than others. Below, we outline four themes that we see as most promising to help scholars tackle new and important questions for intraorganizational network dynamics research.

Alter-centric perspectives. Most studies in our review apply an ego-centric perspective to the study of network dynamics, focused on ego's attributes and structural network positions (Grosser, Venkataramani, & Labianca, 2017; Kleinbaum et al., 2015). Few studies adopt an alter-centric approach acknowledging that the attributes and structural characteristics of ego's network alters are also critical factors affecting changes in ego's network and related outcomes. Such an approach, however, is important, as it allows researchers to improve the predictive power of their dynamic network theorizing by relaxing the implicit assumption that alters behave as passive agents (Kleinbaum et al., 2015). To do so, network scholars need to better account for the "objective functions" of multiple social actors, acknowledging that tie choices result from a matching process between both sides of a dyad (Ahuja et al., 2012). Accordingly, we see much promise in complementing the ego-centric perspective with more work that takes into account the attributes and structural characteristics of ego's network alters. Such work could include analysis of how alters' evaluations of ego's personality or network properties affect ego's ability to shape their network. For example, future research could focus on the alter-centric conditions that may affect the likelihood of brokerage creation, persistence, or termination.

Cognitive view. A closely related priority for future research is to enrich our understanding of the role of cognition for network dynamics. Such a view takes into account that individuals form and continuously adjust their perceptions of nodal, relational, and structural characteristics about both themselves and their alters and use those perceptions to inform their behavior in the social setting (e.g., Brands, 2013; Byron & Landis, 2020; Casciaro, 1998; Kleinbaum et al., 2015). The cognitive view is thus an additional layer that shapes the social dynamics in networks and is integral to our ability to better understand the complexity of social relations. However, despite calls for work that extends the cognitive perspective in networks to dynamic settings (e.g., Brands, 2013), our review found only limited scholarly effort in this direction. Particularly promising areas in this regard include examinations of the coevolution of perceptions and networks, of the drivers and consequences of changes in perceptions of egos and alters, and of (a)symmetries in how nodes perceive each other (e.g., in terms of personality traits or structural characteristics) and the relationships linking them (e.g., in terms of strength or type and content of flows).

Dynamic multilevel research. Virtually all papers in our review focus on change at a single level of analysis (i.e., node, tie, ego network, or whole network). This approach fails to account for the fact that change at one level necessarily influences change at other levels (Moliterno & Mahony, 2011). Dynamic network analysis is particularly well suited to a more granular understanding of multilevel phenomena and their consequences, for a number of reasons—with perhaps the most critical being that the temporal dimension allows researchers to capture how and when lower-level changes translate into higher-level changes, and vice versa. Thus, we see an opportunity for more dynamic multilevel research. One promising direction would be to study how established ego-level tendencies, such as striving for larger networks to acquire more knowledge, translate in the longer term into global network properties, such as overall cohesiveness and redundancy.

Formal and informal network change. Another promising avenue for research is the dynamic interrelationship between formal organizational design and informal social structure. While prior work has established that bridging the gap between formal organization and informal social structure is important to better understand network dynamics (McEvily, Soda, & Tortoriello, 2014), our review highlights that work on this topic is still scarce. We therefore echo McEvily et al.'s (2014) call for more research that jointly considers the formal and informal bases of network dynamics. For instance, we see great opportunity in leveraging the recent advances in coevolutionary modeling techniques (see, e.g., Agneessens, 2020; Kalish, 2020) to go beyond unidirectional analyses of how formal elements drive change in informal elements, and vice versa.

Selection of Social Ties

Relationships between social actors can be of many types, each aggregating into a corresponding network (Borgatti, Everett, & Johnson, 2018). In practice, the social ties commonly studied by network scholars can be classified as either relational states or relational events (Borgatti et al., 2018; Borgatti & Halgin, 2011). "Relational states" are continuous over time with some degree of persistence. State-type social ties can be separated into three kinds of dyadic phenomena (Borgatti et al., 2014): *similarities*, such as group comembership, physical colocation, and same gender; *relational roles*, such as friendship and advice ties; and *relational cognition*, such as avoidance and energizing ties. In contrast, "relational events" are instantaneous and discrete actions that occur periodically over time within dyads and that can be counted over periods of time. Like relational states, relational events can be distinguished into different types of dyadic phenomena (Borgatti et al., 2014): *interactions*, such as email and conversation, and *flows*, such as exchanging information and beliefs. In short, relational states can be regarded as something that a focal node *is* with another node, rather than something a node *does* with another node.

Our review highlights that the literature on intraorganizational network dynamics is concerned predominantly with networks of state-type social ties that are either instrumental (advice and work communication) or positive affective (friendship) and that are primarily studied in isolation. However, as some papers in our review highlight, different types of network are not necessarily independent of one another as they evolve (e.g., Snijders et al., 2013) and may also follow different patterns of change, possibly resulting in profoundly different outcomes (e.g., Rubineau et al., 2019). In our view, such interdependencies between different networks offer a rich opportunity for new insights. Replications with different types of network could also prove promising. Thus, we see the need for research that considers a broader variety of types of relationship—such as dormant ties, ambivalent ties, energizing ties, and negative ties—and that investigates whether and how they interact with other networks over time.

Beyond this call for work on a wider range of state-type social ties, we see great promise in increased investigation of event-type social ties. This is important not only because event-type ties are likely to follow different processes than state-like ties do (Snijders & Koskinen, 2013), but also because event-type social network data allows researchers to test hypotheses about the timing and patterns of social interactions (Schecter & Quintane, 2021; Silk et al., 2017), which can be used, among other things, to uncover the social activity that lies beneath (and evolves within) social relationships (Butts & Marcum, 2017). For instance, researchers can use event-type social network data to investigate how individual attributes (e.g., personality) influence the likelihood and patterns of future interaction events within a work-collaboration relationship. Modeling such data is complicated by their inherent temporal and relational dependencies (Butts, 2008), an issue we return to in the next section (A Note on the Statistical Modeling of Longitudinal Observational Network Data), in which we discuss a modeling approach for event-level network data and two approaches for state-level network data.

Closely related, we see an important opportunity in exploring how events and states inform each other over time. In particular, events provide conditions and opportunities that can influence the likelihood that relational ties form, change, or dissolve—and, vice-versa, relationships can affect the pattern and likelihood of events that take place within them. For instance, if two social actors exchange valuable information (event), a deeper relationship may well ensue (state), which, in turn, could result in them engaging in more knowledge sharing (event). We see it as important for researchers to account for the fact that interaction events and state-like relationships can—and often do—influence one another, because this perspective makes it possible to derive new theoretical mechanisms underlying network change.

The Role of Time in Network Dynamics Theorizing

In line with our integrative definition of the concept of network dynamics in the Intraorganizational Network Dynamics section above, the driving force behind network dynamics studies is explanations—rather than descriptions—of the processes of network change. The cornerstone of such explanations is an appreciation of the temporal nature of network change processes.

Our review has highlighted that, with few exceptions (e.g., Burt, 2000), the intraorganizational network dynamics literature treats time simply as a medium through which substantive processes occur, with a focus on identifying predictors or outcomes of network changes. Such studies take a relatively atheoretical approach to the time element in the underlying substantive processes and provide only limited insight into the temporal processes of network change (George & Jones, 2000; Langley et al., 2013; Mitchell & James, 2001; Ployhart & Vandenberg, 2010).

We believe that a particularly fruitful avenue for future research is to theoretically address the time element in explanations of network change processes. In this regard, we reiterate Mitchell and James's (2001: 544) call to be more precise in theorizing about change processes by answering questions such as "When does the change occur, at what rate does it occur, and with what in the environment is the change associated? How, exactly, does time influence X or Y, or both, or their interrelationship? Does time moderate the X, Y relationship? Does Y cause X, as well as X cause Y? What errors are associated with time?"

Methodological Considerations

Our review highlights important methodological considerations. Below, we offer suggestions that we see as particularly useful for future study of intraorganizational network dynamics.

Causal identification. The first issue relates to causal inference. Our review highlights that only a few studies use clear identification strategies, including laboratory, field, and natural experiments. Rather, most use longitudinal observational research designs. As an approach to studying causation, observational longitudinal network analysis is generally better than the cross-sectional analysis common in nondynamic network research (De Vaus, 2001). But, experimental network analysis, by enabling control of all aspects of the process (Brashears & Gladstone, 2020), allows researchers to get at causal network mechanisms only partially inferable from observational data (Matous, Pollack, & Helm, 2021). To better understand causal network mechanisms, it is therefore important to use experimental network data collection and analysis (see also Valente, 2012).

Qualitative approaches. In addition to the use of experimental designs, the use of qualitative approaches to the study of intraorganizational network dynamics can open promising research directions. For now, our survey finds relatively few papers using qualitative methods. This is unsurprising, given the mathematical foundations of social network theorizing, but qualitative methods—when used either in isolation or in combination with quantitative approaches—have distinctive features particularly suitable to the study of certain dynamic network phenomena. Most notably, they are well fitted to address issues of description, interpretation, and explanation (Bluhm, Harman, Lee, & Mitchell, 2011), and, in turn, to uncover the underlying processes of network dynamics and generate theory (for an excellent example, see Bensaou et al., 2014)). We therefore see an opportunity for research to leverage inductive approaches to discover new network dynamics phenomena, generate novel theory, and deepen our understanding of already established phenomena.

Network interdependence. A final issue relates to the inherent interdependence of observations in social network data. Most studies in our sample adopt standard statistical methods that assume the independence of observations. This assumption is typically untenable for social network data, given its inherently relational nature, and, when it is violated, misleading inferences can result (Imbens & Rubin, 2015; Sobel, 2006). Given the importance and complexity of this point, we provide an elaborate discussion in the following section, unpacking the issue of interdependence in network data and summarizing three leading statistical approaches for modeling longitudinal network data that explicitly take into account network dependencies.

A NOTE ON THE STATISTICAL MODELING OF LONGITUDINAL OBSERVATIONAL NETWORK DATA

The vast majority of the studies in our sample that examine network dynamics adopt standard statistical methods—such as traditional logit or probit regression models—to study tie formation, with a focus on testing the effect of nodal or dyadic covariates or of some network characteristics on the likelihood that a tie is formed (e.g., Burt, 2002; Tasselli et al., 2020). However, such methods are based on an assumption of independence—typically an untenable assumption for social network data, given its relational nature (e.g., Burk, Steglich, & Snijders, 2007). Research has attempted to address this issue with a variety of corrections (see e.g., Kim, Howard, Cox Pahnke, & Boeker, 2016), such as estimating models with standard errors clustered simultaneously around ego, alter, and the undirected dyad (Cameron, Gelbach, & Miller, 2011). While useful, these techniques may be an insufficient solution (Greene, 2008; Kim et al., 2016) and do not explicitly incorporate network interdependencies (Cranmer & Desmarais, 2011; Snijders et al., 2010; Steglich et al., 2010). In response, a number of recent approaches have been developed that explicitly take into account and treat complex dependencies inherent in social network data as substantively interesting. In addition to their potential advantages for valid statistical inference, these approaches can be used to test the presence of social mechanisms, such as reciprocation and triadic closure, and to evaluate the residual effect when multiple such mechanisms are included in one model (Stadfeld & Amati, 2021). In the following sections, we elaborate on the issue of interdependence in network data, then summarize three leading statistical approaches for modeling longitudinal network data in a way that explicitly accounts for dependence among observations.

Interdependencies in Social Networks

Social networks involve a comprehensive set of interdependent processes in which an actor's behavior depends on the behavior and characteristics of others in their environment. For instance, social mechanisms such as reciprocation and triadic closure imply that a social actor's decision to form a tie is contingent, at least in part, on actions by surrounding actors. Thus, systematic dependencies among patterns of ties are a defining feature of social networks. The network approach is so useful precisely because, given its inherent relational nature (e.g., Borgatti & Foster, 2003), it can represent these interdependencies (see Huckfeldt, 2009).

However, the inescapable reality of the interdependence of social actors poses a fundamental challenge to the standard statistical approaches typically used by social scientists. These approaches often rest on the "stable unit treatment value assumption" (Rubin, 1980), which requires no interference between subjects. When this assumption is violated, standard errors may be underestimated, and confidence intervals may be anti-conservative (Lee & Ogburn, 2021), resulting in misleading inferences (Imbens & Rubin, 2015; Sobel, 2006).

A core challenge facing the development of statistical models for social network analysis has been to express dependence among network actors (Snijders, 2011). This situation has changed significantly in the past few decades, as enhanced computational power has made possible models that satisfactorily represent network dependencies (Borgatti et al., 2014; Snijders, 2020).

We discuss here three leading statistical approaches that explicitly take into account network dependencies, and are designed to model longitudinal network data (Schaefer & Marcum, 2021): (a) relational event models, (b) stochastic actor-oriented models, and (c) dynamic exponential random graph models. Table 3 summarizes these approaches, and the remainder of this section offers a detailed discussion of each.

Leading Statistical Approaches That Account for Network Interdependence

Relational event models. Inspired by survival and event history analysis, the "relational event model" (REM; Butts, 2008) is a statistical framework specifically developed to analyze sequences of time-stamped or ordinal social interactions with complex temporal and relational dependencies without requiring a priori aggregation. As such, REM allows for the estimation of statistical models with micro-level longitudinal network data without collapsing the relational data into cross-sectional panels and thus preserves a wealth of information about timing, sequence, and changes in the composition of network nodes (Kitts & Quintane, 2020; Quintane,

TABLE 3
Summary of the Three Main Modeling Approaches for Network Dynamics

	REMs	SAOMs	Dynamic ERGMs[a]
Model summary	A model for sequences of time-stamped or ordinal social interaction events (such as emails or resource transfer), used to study the social dynamics that lie beneath and evolve within existing social relationships	A model for longitudinal panel network data that uses an "agent-based approach"—where actors control their outgoing ties and make changes in those ties according to short-term goals and restrictions—to simulate the process of change that transforms an initially observed network into a subsequent observed one, and by so doing enables the estimation of parameters that drive this transformation	A model for longitudinal panel network data that shares a similar mathematical core to SAOMs. Instead of placing primacy on the actors by specifying the model from the actor's point of view, dynamic ERGMs are tie-oriented models, in that they are based on changes in tie-variables given the rest of the network
When to use	To address research questions involving the likelihood, timing, sequences, and patterns of discrete social interaction events	For research questions about the formation or termination of network ties as driven by actors weighting ties against one another, change in individual behavior, and coevolution of networks and behavior	For research questions about the formation or termination of network ties, particularly those focused on drawing tie- rather than actor-level inference
Example research questions	How do past interaction events, individual attributes, or contextual factors influence the likelihood of future interaction events? What is the expected time for a recipient to reciprocate interactions from a particular sender? Are the temporal patterns of relational interaction events different for employees with certain personality traits?	How do endogenous network (or structural) effects drive tie change (formation, termination) or stability (maintenance of status quo)? What individual traits or dyadic covariates might influence the likelihood that actors choose to form or dissolve ties? Do people with similar characteristics seek each other out as friends (i.e., selection mechanism), or do friends exhibit convergence on their characteristics over time (i.e., influence mechanism), or both (i.e., do they coevolve)?	How do relational properties (such as gender homophily between actors) affect the likelihood of a tie being formed? Are multiplex or strong ties more likely to persist? How does tie productivity influence the likelihood that a tie is terminated?
Nature of network data	Micro-level dynamic network data consisting of sequences of interaction events that may be either time-stamped or ordinal	Whole-network dynamic data consisting of longitudinal panels of binary network states, where ties between actors are recorded as either present or absent	Same as SAOMs
Data requirements	A series of relational interaction events, ordered in time, that represent a sequence of directed social actions between a given number of social actors over some window of observation	Network panel data with two or more observation waves that can be either directed or un-directed	Same as SAOMs
Outcome variable(s)	Occurrence of the next relational event (i.e., social action) in the sequence	Tie change, which can take three forms: formation of previously not existing ties; maintenance of existing ties; or the presence of ties regardless of whether they	Tie change, which can be either formation of previously not existing ties, or maintenance of existing ties

TABLE 3
(Continued)

	REMs	SAOMs	Dynamic ERGMs[a]
		were newly formed or maintained. In addition, SAOMs allow behavioral dependent variables, which can represent, for instance, actors' behavior, attitudes, or beliefs. Behavioral dependent variables can be modeled both in isolation and in studies of the coevolution of networks and behavior	
Predictor variable(s)	History of prior interaction events (e.g., inertia, reciprocity), attributes of the individuals (e.g., personality), and situational context (e.g., work environment)	Endogenous network (or structural) effects (e.g., reciprocity, transitivity); attributes of the individuals, which may be constant in nature (e.g., personality traits) or varying (e.g., attitudes); and attributes of the dyads, either generally constant (e.g., same gender) or varying (e.g., congruence in interpersonal perceptions)	Same as SAOMs
Parameter interpretation	Parameter values are estimated for each covariate and indicate the odds that a relational interaction event will happen, conditional on all other effects included in the model. The estimated parameter values can be reported as conditional log-odds, interpreted in terms of their sign and significance, and, as in logistic regression, can be converted to odds ratios or probabilities	Parameter values are estimated for each covariate and indicate the conditional log odds ratios[b] that a given change takes place (e.g., tie formation). The estimated parameter values can be interpreted in terms of their sign and significance, and, as in logistic regression, can be converted to odds ratios or probabilities	Same as SAOMs
Key references	Brandes, Lerner, and Snijders (2009), Butts (2008), Butts and Marcum (2017), Marcum and Butts (2015), Schecter and Quintane (2021)	Kalish (2020), Ripley, Snijders, Boda, Vörös, and Preciado (2022), Snijders (2001, 2005, 2017), Snijders et al. (2007, 2010), Steglich et al. (2010)	Hanneke, Fu, and Xing (2010), Krivitsky and Handcock (2014), Robins and Pattison (2001), Snijders and Koskinen (2013)

Note: REMs, relational event models; SAOMs, stochastic actor-oriented models; ERGMs, exponential random graph models.
[a] Apart from in the Model Summary, we focus here primarily on longitudinal ERGMs (LERGMs), as temporal ERGMs (TERGMs) do not allow inference about change.
[b] Formally, these are probability ratios, as SAOMs model multinomial and not binary choices.

Pattison, Robins, & Mol, 2013; Schecter & Quintane, 2021). REM thus enables researchers to use their temporally explicit data to test hypotheses about the likelihood, timing, sequences, and patterns of discrete social interaction events (Schecter & Quintane, 2021; Silk et al., 2017). With this framework, scholars might answer questions such as what is the expected time for a recipient to reciprocate interactions from a particular sender and how do individual attributes (e.g., personality) or contextual factors (e.g., work environment) influence the likelihood of interaction events.

The core element of REMs is the relational event, defined as "a discrete event generated by a social actor (the 'sender') and directed toward one or more targets (the 'receivers,' who may or may not be actors themselves)" (Butts, 2008: 159). A relational event thus involves a sender, a receiver, and an instance of interaction. A sequence of discrete relational events in continuous time, recorded as either an event order or a time-stamp, constitutes an event history of the social actions taken by a group of senders and targeted toward a group of receivers in a given observation window. Relational event data can take many forms, such as email exchanges (e.g., Quintane & Carnabuci, 2016) or radio communications (e.g., Butts, 2008).

The REM framework (Butts, 2008) is related to models used in survival and event history analysis, in which each potential event is assumed to have a piecewise constant hazard. The model estimates a hazard function for the rate of interaction events, conditional on the history of prior interaction events (capturing endogenous network effects such as reciprocity and popularity), on sender and receiver attributes (e.g., personality), and on situational contextual factors (e.g., work environment). This framework is thus useful for the study of social processes that underlie and evolve within social relationships unfolding in time.

REM produces an output comparable to that of standard logistic regression, in which parameter values are estimated for each covariate and reflect the focal variable's weight on the hazard of event occurrence. The estimated parameter values are usually reported as log-odds and can be exponentiated to yield odds ratios. The parameter values can also be used to examine expected inter-event times (see Butts & Marcum, 2017).

Stochastic actor-oriented models. Another approach specifically designed to model social relationships and the nonindependence that these imply is "stochastic actor-oriented models" (SAOMs; Snijders, 1996, 2001; Snijders, Carrington, Scott, & Wasserman, 2005), commonly referred to as SIENA models after the acronym of its software implementation. SAOMs provide a flexible statistical framework for modeling longitudinal network data that has been collected in a panel design at two or more points in time. In contrast to REMs, a foundational assumption in SAOMs is that the network ties are not brief events, but are regarded as states with a tendency to endure over time. These models use an actor-oriented approach to estimate transitions in networks across observation waves, as influenced by individual traits (e.g., sex of the tie sender), dyadic covariates (e.g., same sex of the tie sender and receiver), and endogenous network effects (e.g., transitivity) (Snijders et al., 2010). With this framework, researchers can model change in one- and two-mode networks (e.g., probability of the formation or termination of network ties), change in individual behavior (e.g., levels of organizational citizenship behavior), and coevolution of networks and behavior (e.g., organizational citizenship behavior and friendship ties) and networks and other networks (e.g., friendship and work communication ties).

SAOMs assume that the observed network panel data are snapshots of an unobserved underlying process by which tie change unfolds in continuous time. These changes are decomposed into a series of mini-steps between observation waves, in which a randomly chosen actor has the opportunity to make a choice about their outgoing ties (creating or terminating one outgoing tie or maintaining the status quo) or their personal characteristics (increase, decrease, or maintain status quo) according to short-term goals and restrictions. In this sense the model is actor-oriented, and the actors base their choices on the current state of the network which they are assumed to have full-knowledge of, not on a memory of previous states (Snijders, 2001).

Since mini-steps are unobserved, SAOMs use an agent-based approach to simulate the change process as it may have unfolded across observation waves. Specifically, these models take as the starting point the observed network at a given time (e.g., observation wave 1) and, from there, simulate change over mini-steps to model the process that transforms the initially observed network into the subsequent observed network (e.g., observation wave 2). This process is specified through both the frequency by which the network actors have an opportunity to make changes (i.e., the rate function) and the probability that an actor makes a change given the opportunity (i.e., the evaluation function). The evaluation function is the heart of any SAOM and takes into account individual covariate effects, dyadic covariate effects, and network structural effects. Actors use it to assess the value of every possible change and select the change with the highest value according to short-term goals and restrictions. Changes are thus "myopic," in that they are concerned exclusively with immediate consequences.

Estimation starts by iteratively allowing randomly selected agents to make change choices according to the aforementioned functions. After the simulation run, the simulated network is compared with the subsequently observed networks, and, if these are too distinct, the parameter estimates are updated and the simulation is repeated. This updating process continues iteratively until convergence is achieved—that is, the simulated network resembles the observed network. Parameter estimates that represent the observed network change are then produced and can be interpreted in terms of their sign and significance, and, as in logistic regression, can be converted to odds ratios or probabilities.

Extensions have been made to the basic SAOM. A particularly noteworthy one is the modeling of coevolution of networks and nodal attributes (Snijders et al., 2007, 2010; Steglich et al., 2010). This family of models builds on the basic SAOM but extends the dependent variable. Specifically, in addition to network change, these models include an evolving actor-level variable that can influence the network and be influenced by it. In other words, a core assumption in these models is that both networks and actor attributes develop interdependently over time. In addition to modeling the coevolution of networks and actor attributes, this class of SAOMs allows for joint analysis of multiple networks, such as friendship and advice (Ripley et al., 2022). By permitting statistical inference on the mechanisms that drive such coevolution processes, this class of SAOMs enables researchers to unpack and model a broad range of important theoretical questions, such as how interpersonal personality perceptions coevolve with tie decay. We refer interested readers to Kalish (2020) for a recent review and tutorial on this type of SAOM.

Dynamic exponential random graph models. A third approach builds on the "exponential random graph model" (ERGM) family (Frank, 1991; Frank & Strauss, 1986; Wasserman & Pattison, 1996). ERGMs were originally formulated to model a network observed at a single point in time; they allow for modeling it as a function of both exogenous parameters (e.g., nodal attributes) and endogenous parameters (e.g., reciprocity, transitivity). The observed network is assumed to be one of a distribution of possible networks with similar core characteristics. That is, the observed network is generated through some unknown stochastic process. The objective of estimation is to derive parameter values that reproduce structural properties similar to those of the observed network. ERGMs are modified logistic regressions that predict the conditional log odds of the existence of a network tie from a set of model parameters representing exogenous and endogenous effects, with parameters indicating the importance of a given network effect for the presence of a tie.

The endogenous dependencies modeled in ERGMs tend to imply temporal processes, such as reciprocation. Such processes, however, are not explicitly considered in the model specification. A number of recent extensions to the basic ERGM have been formulated for longitudinal network data—observed at two or more points in time—to more explicitly capture the underlying temporal dynamics. We refer to this general class of model for longitudinal network data as "dynamic ERGMs" (Snijders, 2011).

These extensions come in two variants: a discrete- and a continuous-time specification. The first variant is "temporal ERGMs" (TERGMs; Robins & Pattison, 2001; see also Desmarais & Cranmer, 2012; Hanneke et al., 2010), which are discrete-time models based on the logic of panel regression, in which lagged earlier observations are used as predictors for later observations. In line with this logic, the most basic form of TERGM is a conditional ERGM that includes among the predictors an earlier observation of the network.

The second variant is "longitudinal ERGMs" (LERGMs) (Koskinen, Caimo, & Lomi, 2015; Snijders & Koskinen, 2013), which are continuous time models (like SAOMs) in which network change is decomposed into mini-steps. These models are tie oriented; the opportunity for change occurs as pairs of nodes are randomly chosen, and, once a dyad is selected, the probability of tie-level change is defined by a logistic regression model conditioning on the rest of the network. LERGMs, like SAOMs, assume that network change results from a continuous-time Markov process, with choices based on the current state of the network. But, while SAOMs place primacy on the actors by specifying the model from the actor's point of view, LERGMs are tie-oriented models in which changes occur in tie variables, given the rest of the network (Block, Koskinen, Hollway, Steglich, & Stadtfeld, 2018). And, while SAOMs can also model behavioral and coevolutionary change, LERGMs can model only tie-level change in the form of tie formation or termination.

The inferences that can be drawn from discrete- and continuous-time models are different with respect to network change (see, e.g., Block et al., 2018). On the one hand, discrete-time models, such as the basic form of TERGMs, can be applied to the study of how variables captured at an earlier time relate to the network at a later time. It follows that, despite including an earlier realization of the network, these models cannot be used to make inferences about change. On the other hand, by directly modeling the processes of change, continuous-time models, such as LERGMs and SAOMs, can answer questions about change as it unfolds.

CONCLUSION

Intraorganizational network dynamics research is burgeoning, drawing on advances in the conceptual tools, analytical methods, and longitudinal network data at our disposal. These opportunities and the rapid growth in the literature, however, have come at the cost of programmatic coherence, clear and consistent terminology, and methodological clarity. Our aspiration, with this review, is to help network scholars capitalize on the unprecedented conceptual, empirical, and methodological opportunities by resolving those challenges.

To this end, we started by clarifying the terminology and scope of intraorganizational network dynamics. We then developed an encompassing framework that maps the facets of this literature and used it to organize our summary and synthesis of the available body of work. Based on our summary and synthesis, we took a bird's-eye view of the entire intraorganizational network dynamics literature and considered four foundational areas that hold great promise in conceptually and methodologically extending network dynamics research. We ended with a methodological note on the issue of interdependence in network data and an overview of three leading statistical approaches for modeling longitudinal network data, all of which explicitly account for dependence among observations.

At a time when interest in the topic, access to longitudinal network data, and analytical advances have never been greater, network scholars should continue to pursue important theoretical and practical contributions in intraorganizational network dynamics. We hope that our review will offer them guidance and support.

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APPENDIX A

LIST OF SEARCH TERMS

"network evolution" OR "evolution of social network" OR "evolution of network" OR "evolution of organizational network" OR "evolution of organisational network" OR "network dynamics" OR "dynamics of social network" OR "dynamics of network" OR "dynamics of organizational network" OR "dynamics of organisational network" OR "network emergence" OR "emergence of social network" OR "emergenc* of network" OR "emergence of organizational network" OR "emergence of organisational network" OR "network change" OR "change in social network" OR "network changes" OR "network formation" OR "formation of social network" OR "formation of network" OR "formation of new tie" OR "creation of new tie" OR "structural dynamics of network" OR "formation of tie" OR "creation of tie" OR "persistence of tie" OR "dissolution of tie" OR "termination of tie" OR "evolution of tie*" OR "cessation of tie*" OR "origination of tie*" OR "creation of link*" OR "persistence of link*" OR "dissolution of link*" OR "termination of link*" OR "decay of link*" OR "evolution of link*" OR "cessation of link*" OR "formation of linkage*" OR "creation of linkage*" OR "persistence of linkage*" OR "dissolution of linkage*" OR "termination of linkage*" OR "decay of linkage*" OR "evolution of linkage*" OR "cessation of linkage*" OR "origination of linkage*" OR "development of network*" OR "formation of relationship*" OR "dissolution of relationship*" OR "sabm" OR "tie persistence" OR "tie dissolution" OR "tie termination" OR "tie decay" OR "tie evolution" OR "tie cessation" OR "tie origination" OR "link formation" OR "link-formation" OR "link creation" OR "link persistence" OR "link dissolution" OR "link termination" OR "link decay" OR "link evolution" OR "link cessation" OR "link origination" OR "linkage formation" OR "linkage-formation" OR "linkage creation" OR "linkage persistence" OR "linkage dissolution" OR "linkage termination" OR "linkage decay" OR "linkage evolution" OR "linkage cessation" OR "linkage origination" OR "longitudinal network data" OR "siena" OR "rsiena" OR "dynamics of organizational networks" OR "dynamic network analysis" OR "dynamic social network analysis" OR "dynamic networks" OR "longitudinal network analysis" OR "longitudinal network models" OR "longitudinal social networks" OR "multiplex network evolution" OR "network development" OR "network evolution and change" OR "network evolution models" OR "network-change" OR "networks over time" OR "longitudinal networks" OR "relationship formation" OR "relationship dissolution" OR "stochastic actor-based model*" OR "antecedents and consequences of networks" OR "antecedents of networks" OR "network antecedents" OR "consequences of networks" OR "network consequences" OR "dynamics of networks" OR "network churn" OR "cessation of tie*" OR "bridge decay" OR "decay function" OR "tie clos*" OR "tie bridg*" OR "tie form*" OR "emergence of organi?ational network*" OR "emergence of interorgani?ational network*" OR "emerg* network structure*" OR "change* in group composition" OR "forming an advice network" OR "network generation" OR "brokerage dynamics" OR "dynamic structur* of network*" OR "tie longevity" OR "change* in social network" OR "evolution of social network*"

APPENDIX B

OVERVIEW OF FINAL SAMPLE OF REVIEWED ARTICLES

TABLE B1
Final Sample of Reviewed Articles on Intra-Organizational Network Dynamics Across Domains of Network Theorizing

Theory of network dynamics	Network dynamics theory	Integrative theory of network dynamics	Coevolutionary theory of network dynamics
Agneessens and Wittek (2012)	Argote et al. (2018)	Argyres et al. (2020)	D'Andreta, Marabelli, Newell, Scarbrough, & Swan (2016)
Aven (2015)	Bravo et al. (2012)	Balkundi et al. (2011)	Ebbers and Wijnberg (2019)
Baker and Bulkley (2014)	Burt and Merluzzi (2016)	Bensaou et al. (2014)	Eguíluz et al. (2005)
Balkundi et al. (2019)	de Klepper et al. (2010)	Brennecke (2020)	Ellwardt et al. (2012)
Brewer et al. (2020)	Gargiulo and Benassi (2000)	Briscoe and Tsai (2011)	Elmer et al. (2017)
Burger and Buskens (2009)	Kijkuit and van den Ende (2010)	Çelen and Hyndman (2012)	Kalish et al. (2015)
Burkhardt and Brass (1990)	Kleinbaum and Stuart (2014)	Clement and Puranam (2018)	Kovács and Kleinbaum (2020)
Burt (2000)	Kwon, Oh, & Jeon (2007)	Frey et al. (2019)	Labun et al. (2016)
Burt (2002)	Lee et al. (2014)	Melamed and Simpson (2016)	Schulte et al. (2012)
Buskens and van de Rijt (2008)	Levin et al. (2011)	Melamed et al. (2020)	Snijders et al. (2013)
Carnabuci et al. (2018)	Levin and Walter (2019)	Ng and Feldman (2014)	Thiele et al. (2018)
Casciaro and Lobo (2015)	Mannucci and Perry-Smith (2021)	Porath et al. (2015)	Torlò and Lomi (2017)
Cohen et al. (1973)	Marion et al. (2016)	Shah et al. (2021)	Tröster et al. (2019)
Conti and Doreian (2010)	Parise and Rollag (2010)	Van Osch and Steinfield (2018)	Corten and Buskens (2010)
Dahlander and McFarland (2013)	Paruchuri and Awate (2017)	Woehler et al. (2021)	
DeRue et al. (2015)	Soda et al. (2021)		
Do'an et al. (2009)	Stuart (2017)		
Doreian and Conti (2017)	Swan and Scarbrough (2005)		
Emery (2012)	Tasselli et al. (2020)		
Feeney and Bozeman (2008)	Zschache (2012)		

TABLE B1
(Continued)

Theory of network dynamics	Network dynamics theory	Integrative theory of network dynamics	Coevolutionary theory of network dynamics
Feiler and Kleinbaum (2015)			
Feld (1997)			
Fitzhugh et al. (2020)			
Fleming and Waguespack (2007)			
Friedman and Podolny (1992)			
Friedrich, Griffith, and Mumford (2016)			
Gibson, Hoffman, La Fleur, and Buchler (2021)			
Giese et al. (2020)			
Hanaki, Peterhansl, Dodds, and Watts (2007)			
Harrigan and Yap (2017)			
Hasan and Bagde (2015)			
Hoffman, Block, Elmer, and Stadtfeld (2020)			
Hummon (2000)			
Ingram and Morris (2007)			
Jonczyk et al. (2016)			
Kalish and Luria (2016)			
Kleinbaum (2012)			
Kleinbaum (2018)			
Kleinbaum et al. (2015)			
Kossinets and Watts (2009)			
Kossinets and Watts (2006)			
Krackhardt and Porter (1985)			
Kulik, Rae, Sardeshmukh, and Perera (2015)			
Lazega et al. (2018)			
Leonardi (2018)			
Leonardi (2013)			
Li and Piezunka (2020)			
Maclean and Harvey (2016)			
Maloney et al. (2019)			
Manning (2010)			
Mäs et al. (2013)			
Mirc and Parker (2020)			
Mitsuhashi and Nakamura (2022)			
Mollica et al. (2003)			
Parker et al. (2016)			
Quinn and Baker (2021)			
Quintane et al. (2013)			
Quintane and Carnabuci (2016)			
Rawlings, McFarland, Dahlander, and Wang (2015)			
Reagans (2011)			
Rubineau et al. (2019)			
Sailer and McCulloh (2012)			
Salzinger (1982)			
Sasovova et al. (2010)			
Schaefer and Kreager (2020)			
Schecter, Pilny, Leung, Poole, and Contractor (2018)			
Shah (2000)			

TABLE B1
(Continued)

Theory of network dynamics	Network dynamics theory	Integrative theory of network dynamics	Coevolutionary theory of network dynamics
Shea et al. (2019)			
Skvoretz and Fararo (1996)			
Smaldino et al. (2018)			
Small, Deeds Pamphile, and McMahan (2015)			
Smith et al. (2012)			
Snijders and Lomi (2019)			
Srivastava (2015a)			
Srivastava (2015b)			
Stea et al. (2021)			
Sterling (2015)			
Tsai (2000)			
Watts and Koput (2014)			
Weber et al. (2020)			
Wimmer and Lewis (2010)			
Wu et al. (2021)			
Yang et al. (2021)			
Yap and Harrigan (2015)			
Zeggelink (1994)			