

*Annual Review of Sociology***Social Networks and Cognition**

Edward Bishop Smith,¹ Raina A. Brands,²
Matthew E. Brashears,³ and Adam M. Kleinbaum⁴

¹Kellogg School of Management, Northwestern University, Evanston, Illinois 60208, USA;
email: ned-smith@kellogg.northwestern.edu

²London Business School, London NW1 4SA, United Kingdom

³Department of Sociology, University of South Carolina, Columbia, South Carolina 29208, USA

⁴Tuck School of Business, Dartmouth College, Hanover, New Hampshire 03755, USA

Annu. Rev. Sociol. 2020. 46:159–74

First published as a Review in Advance on
April 13, 2020

The *Annual Review of Sociology* is online at
soc.annualreviews.org

<https://doi.org/10.1146/annurev-soc-121919-054736>

Copyright © 2020 by Annual Reviews.
All rights reserved

ANNUAL
REVIEWS **CONNECT**

www.annualreviews.org

- Download figures
- Navigate cited references
- Keyword search
- Explore related articles
- Share via email or social media

Keywords

social networks, cognition, social capital, network perception, evolution, sociobiology

Abstract

Social network analysis, now often thought of simply as network science, has penetrated nearly every scientific and many scholarly fields and has become an indispensable resource. Yet, social networks are special by virtue of being specifically social, and our growing understanding of the brain is affecting our understanding of how social networks form, mature, and are exploited by their members. We discuss the expanding research on how the brain manages social information, how this information is heuristically processed, and how network cognitions are affected by situation and circumstance. In the process, we argue that the cognitive turn in social networks exemplifies the modern conception of the brain as fundamentally reprogrammable by experience and circumstance. Far from social networks being dependent upon the brain, we anticipate a modern view in which cognition and social networks coconstitute each other.

INTRODUCTION

Network analysis has gone mainstream. Once the domain of social scientists, network analysis has in recent decades become an essential tool for physicists, chemists, biologists, and computer scientists, among others seeking to understand structures and complex systems that reach well beyond the human, social world. As a result of this expansion, network analysis, broadly defined, now routinely includes studies of millions of connections among hundreds of thousands of nodes, or more. Moreover, those nodes no longer represent just people but now correspond to organizations, countries, computers, pages on the web, tweets, and even neurons in the brain.

Yet, with this success comes a significant risk: As data get “bigger,” there is a natural (and growing) temptation to regard networks of many kinds as similar across a variety of contexts. This tendency presents a problem for social network analysis, as social networks are no ordinary networks (Small 2017). Social networks are composed not only of vertices but also of agents that respond to environmental stimuli and initiate actions of their own. In no place is this observation more apparent than in the recent swell of research examining the cognitive foundations of social networks. What happens in the minds of network actors—both neurologically and cognitively—matters for the unfolding of network relations and, consequently, for the accumulation (and destruction) of social capital.

In this article, we review research at the intersection of cognition and social networks. Though the range of topics covered in this review is broad, what ties all of the research together is the notion that social networks are not only social structures but also structures that exist in the mind. This distinction, while obvious to some (after all, what area of human knowledge does not exist in the mind?), has profound implications for the study of social networks. In short, a person’s ability to benefit from his/her social network is heavily affected by the person’s ability to perceive that social network; to encode and recall network ties accurately; and to translate that knowledge into the ability to build, maintain, and mobilize the right ties at the right times.

To accomplish this set of tasks, the brain must first encode, organize, and store social information. The methods of this encoding are complex, drawing on both automatic and motivated cognitive processes that are further affected by situational and psychological cues or frames. People do not respond to the social world as it is, but as they see it (and, sometimes, as they want to see it). To complicate matters further, how people see the social world depends in large part on what is salient to them at a given point in time. The importance of this complex set of processes cannot be overstated, as it affects the fidelity of the encoded structure and, in turn, the availability of network contacts.

As we describe this growing cognitive turn in social network analysis, we emphasize that human behavior is not reducible simply to biology. The study of neuroplasticity has confirmed that our brains are indeed plastic, capable of physical changes in response to stimuli. Dedicated practice on the piano enlarges the area of the somatosensory cortex that is devoted to the hands and fingers, just as practice on the tightrope expands the area devoted to the legs and feet. In addition, humans are highly social creatures, and as we discuss below, our high intelligence may well have evolved to enable us to solve social problems. Therefore, by exploring how cognitive architecture influences networks, we investigate not how we are constrained or controlled by our biology but rather how our biology empowers and supports our behavioral flexibility. Much like our ubiquitous digital computers, our brains are computational engines that can be reprogrammed and repurposed to serve a vast array of functions. Thus, herein we distinguish between the neurological behavior of the human brain and its algorithmic behavior. The former refers to the physical structures that support cognition, including the encoding, processing, and recall of social network information. The latter refers to the sequence of operations performed on this

information. Given that humans are able to learn a wide variety of skills, many of which were entirely unknown in the evolutionary environment (e.g., driving a car, using a smartphone), the same neurology is able to support a wide variety of algorithms that shape both perception and action. By understanding the cognitive processes that support our mental and behavioral flexibility, we gain a better understanding of our true capabilities as well as when, and how, these capabilities are unleashed.

In the following sections, we review a broad range of publications that have contributed to research on cognition and social networks. We organize this review according to three questions that underlie much of the existing research and provide guidance for future research: (a) How do social networks get into the brain? (b) How is network cognition employed? (c) How do social networks affect cognition? We believe that, taken together, the studies reviewed here strongly indicate that a general theory of social networks cannot be complete without considering cognition. This finding leads to a provocative but inevitable conclusion: The origin of social capital rests not only in the social structures surrounding us but also in our minds.

HOW DO SOCIAL NETWORKS GET INTO THE BRAIN?

The Neural Basis of Network Cognition

Our large and metabolically expensive brains (e.g., accounting for 2% of adult body mass but 20–25% of calorie expenditure; Dunbar 1992) must serve a key function, but environmental (i.e., physical) problems can typically be solved without a high level of problem-solving intelligence. The “social brain hypothesis” (Humphrey 1976) argues that intelligence evolved to help humans deal with social rather than physical challenges. Social life confers a number of advantages upon a species, including shared defense and cooperative food gathering. But individuals living in social groups are constantly surrounded by competitors for the same preferred food, shelter, and mating opportunities. Social living thus requires preserving the group, which is essential for survival, while also pursuing individual benefit. The most intelligent individuals will be most successful at balancing these demands, leaving the most offspring as a result. As long as intelligence is at least partly genetic, this ensures that the most intelligent and socially capable fraction of each generation will leave the most offspring, producing a self-reinforcing increase in intelligence.

In line with the social brain hypothesis, research has identified a potential limit on the number of relationships that human beings can maintain. Dunbar (1992) identified a consistent positive relationship between the neocortical ratio (i.e., neocortex volume divided by the remaining volume of the brain) and primary group size in primates and, extrapolating from this pattern, predicted that human primary groups should contain roughly 150 individuals (i.e., Dunbar’s number). Subsequent research has generally supported this link (Barton 1996; Dunbar 1993, 1995; Gonçalves et al. 2011; Kudo & Dunbar 2001; Stiller & Dunbar 2007) and has identified cognitive limits on social network size (Roberts et al. 2009).¹ Bickart et al. (2011) identified correlations between social network size and the volume of the amygdala, a brain region that plays a role in social and emotional processing, in humans. This result was later replicated using online social networks (Kanai et al. 2012, Von Der Heide et al. 2014). Powell et al. (2012) analyzed a structural equation model in which the effect of orbital prefrontal cortex (i.e., outermost portion of the brain behind the eyes) volume on social network size was fully mediated by mentalizing competencies (i.e., the ability to explain and predict the behavior of others by accurately assessing their mental

¹This finding may have more to do with how humans recall alters in network surveys than with factors that determine the size or structure of actual networks (Bell et al. 2007, Marin 2004).

states and intentions). They concluded that “the neocortex provides the computational power to manage the complex web of social relationships needed to give a social group its cohesion and stability through time” (Powell et al. 2012, p. 2157). Together, these studies support the social brain hypothesis among humans: Brain anatomy enables social cognition, which in turn facilitates the formation of large, complex social networks.

Encoding of Social Behavior

One of the core functions that supports social behavior is memory: In order for information to influence behavior, it must be cognitively available in some form. Memory depends upon a confederation of semispecialized processes and brain regions (Atkinson & Shiffrin 1968, Baddeley 1986). For example, conditioned fear responses rely on the amygdala (LaBar et al. 1995); positive associations are stored in the basal ganglia (Bartels & Zeki 2000); and memory for specific events (e.g., episodic memory) depends on the medial temporal lobe, while memory for facts or general knowledge (e.g., semantic memory) relies on the inferior temporal and lateral cortex (Garrard & Hodges 1999). Working memory, or memory focused on the task at hand, can also be distinguished from long-term memory, or memory available for use but not currently active (Reisberg 1997). Research has consistently shown that humans have heightened memory for social information, rather than general facts. When presented with identical network structures built from social (e.g., people connected through friendship ties) or nonsocial (e.g., locations linked by roads) elements, humans recall the social networks more accurately (Janicik & Larrick 2005, Simpson et al. 2011, Van Kreveld & Zajonc 1966). Therefore, there is something unique about the human response to social information.

Research comparing the brain’s response to strangers versus familiar faces finds that merely viewing the face of someone personally known to an individual engages neural activity in the anterior paracingulate cortex and posterior superior temporal sulcus, regions associated with affective processing and theory of mind (Gobbini & Haxby 2007). This automatic activation of person knowledge is thought to facilitate the adaptation of an individual’s own thoughts and behaviors to interact productively with others.

More recent research has started to move beyond the coarse distinction of stranger versus acquaintance to consider how neural activity varies as a function of the relationship between the perceiver and the perceived. One study found that, just as we use spatial metaphors to talk about social relations (a “close” friend, a “distant” relative, etc.), the brain encodes social distance between self and other in an area of the parietal cortex known to be involved in the encoding of physical distance (Parkinson et al. 2014). While Parkinson et al. (2014) asked subjects to consider close friends versus more distant acquaintances during fMRI (functional magnetic resonance imaging), later research by Parkinson et al. (2017) imaged the brains of a subset of participants from an MBA program while showing them short video clips of classmates at different geodesic (i.e., shortest path through a network) distances from themselves. Across both studies, differences in social distance were correlated with the activity in the parietal cortex. These results suggest that over the course of human evolution, neural activity originally devoted to analysis of physical space was repurposed to process data about the social domain (Parkinson & Wheatley 2015). If the social brain hypothesis is correct, it implies that some of our habits of thought in nonsocial domains may reflect a similar repurposing of neural hardware originally developed for social tasks (e.g., the tendency to learn abstract information in network-like structures or to anthropomorphize complex devices like engines or computers).

A small but growing area of research in social neuroscience explores how the brain encodes information about the network structure surrounding familiar others (defined here as people whom

one knows and with whom one may or may not have a social relationship). Researchers collect whole-network data on a bounded population, then recruit some or all members of the population and record their neural response when prompted with photos or videos of others from their real-world social networks. Zerubavel et al.'s (2015) study of two student groups found that sociometric popularity (measured as indegree centrality) is encoded in brain regions known for their role in tracking the value of rewards (e.g., the ventromedial prefrontal cortex and ventral striatum), as well as in neural systems that play a role in understanding the mental states of others (e.g., the dorsomedial prefrontal cortex and temporoparietal junction).

Furthermore, the relationship between another's popularity and the observer's neural activity is mediated by activity in reward systems. Parkinson et al. (2017) collected network data from a complete cohort of MBA students and neuroimaging data from a subset of them. They found that viewing short video clips of popular classmates (i.e., those with high eigenvector centrality) engages activity in the dorsomedial prefrontal cortex and posterior cingulate cortex, regions implicated in social cognition; in a follow-up study, Hyon et al. (2019) showed that the spatiotemporal patterns of neural similarity are further predictive of network proximity. In addition, Parkinson et al. (2019) collected social network and gaze-cuing data in a college sorority and found that popular individuals exert a stronger effect in directing the attention of their peers. Together, these findings suggest that humans attend more to popular others and, as a result, are more motivated to understand their social cues.

A large body of organizational research has examined the consequences of brokerage—that is, the linking of otherwise disconnected actors in social networks—for facilitating a range of organizational and individual outcomes (e.g., Burt 1992). Social neuroscience has found that thinking about others who are brokers in real-world social networks prompts neural activity in brain areas (e.g., superior temporal and supplementary motor regions) widely implicated in motion processing and action understanding (Parkinson et al. 2017), suggesting that perceivers attributed particular social importance to brokers (Parkinson et al. 2017). This finding is paralleled by research by Brands and colleagues that has linked brokerage to the masculine qualities of agency and heroic charismatic leadership (Brands & Kilduff 2013, Brands et al. 2015); thus, the fact that perceivers attend more to and attribute more social meaning to the movement of brokers could be the neural signature of attributions of charisma.

Beyond exploring the role of specialized brain regions in recognizing, encoding, and storing information about social networks, emerging research in social neuroscience suggests that the brain plays a role in actually shaping our social networks. Sociologists have long studied homophily, the tendency for “birds of a feather [to] flock together” (McPherson et al. 2001). Homophily is substantially a result of the tendency for similar individuals to find themselves in the same contexts due to larger structural forces (e.g., individuals of similar socioeconomic status live in the same neighborhoods), but recent research suggests that people whose experiences of the world are similar on a neural level are more likely to be friends. Parkinson et al. (2018) measured the social network among a cohort of MBA students, and then imaged a sample of them while presenting them with a series of naturalistic video clips. Their results indicated that aggregate dyadic similarity in subjects' neural response to the stimulus set was associated with greater geodesic proximity in the network and with a higher probability of being friends—that is, the patterns of brain activity in two individuals were more similar in proportion to the closeness of their relationship. Exploratory analyses suggest that similarity in neural response in the ventral and dorsal striatum (including the right nucleus accumbens, right and left caudate nucleus, and left putamen), right amygdala, right superior parietal lobule, and left inferior parietal cortex seems to be especially predictive of friendship. Furthermore, preliminary evidence is consistent with a selection effect: that *ex ante* neural similarity drives subsequent friendship formation.

Cognition and Network Recall

In addition to understanding how the brain neurologically manages social information, we must understand how humans algorithmically manage social information. Two main strategies have been used to address the algorithmic quality of network memory: self-report and experimental measurement. The self-report approach asks subjects to tell researchers with whom they interact, usually through the use of a question meant to elicit a list of names fitting some set of relational criteria (e.g., Brashears 2014, Marsden 1987). Researchers then compare these reports to respondents' observed patterns of interaction (e.g., Bernard & Killworth 1977) to determine recall accuracy.

Unfortunately, this approach has shown that recollections of specific interactions do not match observed behavior at dyadic (i.e., person to person; Bernard & Killworth 1977), triadic (i.e., three-person groups; Bernard et al. 1980, Killworth & Bernard 1979), or clique (i.e., larger saturated groups; Bernard et al. 1979, 1980) levels. Evidently, these self-report data tend to capture typical patterns of interaction and can accurately replicate factions or alliances, but they are not good indicators of specific realized interactions (Freeman et al. 1987, 1988, 1989; Freeman & Romney 1987; Romney & Faust 1982). Humans do appear to produce valid social information in self-reports of their networks, but not in a way that is easy to correlate with observed interactions.² Given these limitations, relationships obtained via free recall methods are likely to be biased in favor of closer/stronger ties; thus, this method remains useful when research interest is focused on these areas (Marin 2004). Prompting respondents has also been shown to improve the responses to name generator items (Hsieh 2015).

The second strategy for assessing human recall of social information, experimental measurement, has focused largely on the critical role of schemas. Schemas, or frameworks for processing information, are well documented across many domains (e.g., Brewer & Treyens 1981, Martin 1993) and accelerate the learning process (Bartlett 1932, Neisser 2014). The earliest research applying schemas to network learning (De Soto 1960) used an experimental design in which subjects attempted to learn small four-person networks that were presented one dyad (i.e., relationship) at a time. Subjects recalled networks more quickly when a given schema was appropriate for the task (e.g., hierarchies were learned more rapidly when nodes were “influenced by” other nodes, rather than “friends with” other nodes). Subsequent research has supported these findings (e.g., Freeman 1992) using schemas based on kinship (Brewer & Yang 1994), context (Brewer & Garrett 2001), and geographic location (Brewer & Garrett 2001, Killworth & Bernard 1982).

Schemas also appear to function as “compression heuristics” (Brashears 2013), allowing the brain to use shortcuts, or rules, to compress large quantities of network information into relatively easy to recall structures. As a result, we can cognitively maintain networks that are larger than our neocortex size might suggest. In a series of studies, Brashears and colleagues presented subjects with a vignette describing a novel 15-person network. Because these networks were experimenter generated, it was possible to assess recall accuracy unambiguously, and because they were novel to participants, network characteristics that facilitated encoding and recall could be distinguished from frequency of contact and rehearsal effects. Participants were asked to memorize and then report on these novel networks, separated by a distractor task. Brashears and colleagues found that triads and kin relations function as compression heuristics (Brashears 2013, Brashears et al.

²A variation on this approach, the cognitive social structure method, asks all members of a bounded group (e.g., an academic department) to report on their own relationships and the relationships of all others, creating a three-dimensional data structure of perceived ties (Krackhardt 1987). Responses can be combined to create a baseline for judging accuracy, but cannot confirm network structure independent of individual recall, and thus cannot be said to speak directly to accuracy.

2016), that the default unit of relationship encoding appears to be the triad (Brashears & Quintane 2015), that females exhibit superior network recall relative to males (Brashears et al. 2016), and that affective balance operates as a compression heuristic (Brashears & Brashears 2016).

Simulation research with experimentally derived data further suggests that compression heuristics primarily enhance recall (i.e., extraction from memory), rather than encoding (i.e., insertion into memory), though this has not been shown directly (Omodei et al. 2017). Brashears (2013) also argues that compression heuristics can be distinguished into structural heuristics, which are microstructures of a specific network graph (e.g., triads), and cultural heuristics, which are systems of connection that are learned (e.g., kinship systems). In both cases, these heuristics are not continually active but rather are activated when signs in the environment suggest that they are appropriate, and inappropriate activation can degrade rather than enhance recall (e.g., Brashears 2013). Thus, the specific schemas learned (often via experience; Enemark et al. 2014, Kashima et al. 2013) and activated by an individual can powerfully influence the effectiveness of the underlying neurological hardware on network encoding and recall.

Research additionally demonstrates a variety of influences on the quality of network memory. For example, Hlebec & Ferligoj (2001) found that individual mood (relatively durable affective state) affects recall processes and that this impact is moderated by the nature of the task (e.g., free recall versus roster method). These findings are consistent with later research (Shea et al. 2015) suggesting that emotional states can affect the neurological function of social recall, the selection of compression heuristics, or both. Recently, Welles & Xu (2018) examined the performance of a variety of stimulus tasks (e.g., network graphs and textual descriptions), finding that diagrams are more effective at conveying network information than alternatives (e.g., lists). This result is important because it is one of the few that unambiguously points to impacts at the encoding stage, rather than at the recall stage. Moreover, the superiority of diagrams for conveying social information is consistent with the finding, discussed above, that social closeness is processed by some of the same neural regions as physical proximity (Parkinson et al. 2014, 2017). In short, spatial representations of networks are effective because social information is processed, at least partly, by regions of the brain that evolved to deal with physical proximity. Therefore, while the neural and algorithmic behaviors of the brain are separable, they are nevertheless intermingled and coconstitutive.

HOW IS NETWORK COGNITION EMPLOYED?

People differ not only with respect to the social networks they come to inhabit but also in their ability to capitalize on their networks in order to get ahead. One explanation for these differences might be underlying individual differences in network cognition. Researchers have examined whether individuals might differ in their abilities to perceive and remember social networks accurately, with consequences for their outcomes (Krackhardt 1990). However, with few exceptions (e.g., Flynn et al. 2010), research has yet to uncover significant individual difference variables that explain differences in network cognition. For example, self-monitoring is a powerful predictor of individuals' career success, partly because individuals who are high self-monitors tend to end up in desirable positions in social networks (Fang et al. 2015). Yet, high self-monitors do not arrive at these positions because they have a superior ability to accurately perceive social networks (Casciaro 1998) but, rather, because of their superior social skill (Flynn et al. 2006, Mehra et al. 2001).

In contrast to individual differences perspectives, social psychological perspectives emphasize the power of situations in explaining differences in network cognition (Cao & Smith 2020). According to these perspectives, cognition is situated in the sense that it is an adaptive response to the situations that surround individuals (Schwarz 2009, Semin & Garrido 2015). In any given

social situation, individuals engage in purposeful action to meet their goals, whether they be to get along or get ahead. Network cognition assists individuals in understanding their social world and selecting appropriate responses in order to meet their goals (i.e., network cognition is in service of action). From this view, individuals' network cognitions are dynamic, emerging as a product of both the situation (e.g., social structure, organizational context, and external stimuli) and the cognitive states that are salient to the individual at the time (e.g., emotion, belief, expectation, goal, schema, or script) (Brands & Mehra 2019). More generally, humans have evolved substantial cognitive capacity in order to enable flexibility, so we should not be surprised to find that our cognition is situationally contingent.

One of the first models to formalize a situational approach to network cognition is that by Smith et al. (2012). Their model differentiates among an individual's potential network (i.e., everyone that person knows), cognitively activated network (the people who are brought to mind in any particular situation), mobilized network (the people whom the individual reaches out to in a given situation), and realized network (the people who respond, i.e., those who are successfully mobilized). These stages are highly distinct and highly inclusive in that they involve different cognitive systems as well as different actors. The jump from the potential network to the cognitively activated network relies largely on schemas and heuristics that operate unconsciously, guiding which individuals and relationships (stored in long-term memory) will be made available to the conscious mind (in working memory). The transition from the cognitively activated network to the mobilized network often involves decision making and preplanning (though this is not always the case; Small 2017), and thus tends to be substantially more deliberative. Finally, the transition from the mobilized network to the realized network involves not only the social capabilities of individuals (e.g., their ability to make requests of others gracefully) but also the social capabilities and decisions of their alters (i.e., associates), which shape the outcomes of the individual's social maneuvering (Cao & Smith 2020).

The Smith et al. (2012) model therefore provides a means of integrating automatic, deliberative, and structural/dyadic factors into a common framework. Within this framework, several individual-level factors identified by previous research are relevant for the activation, mobilization, and realization of networks: status, power, and emotions; goals and motivations; and stereotypes.

Status, Power, and Emotions

To date, the predominant aim of the dynamic network cognition approach has been to identify what factors produce individual differences in the activated network. A key theme to emerge from this research is that experiencing low status and negative emotions induces people to activate smaller, denser networks (i.e., a winnowing response) whereas experiencing high status and positive emotions induces people to activate larger, sparser networks (i.e., a widening response). For example, a seminal study in this area showed that individuals respond differently to job threats depending on whether they have low or high status (Smith et al. 2012). Individuals with low status respond to job threats by activating smaller, denser sections of their potential network, while individuals with high status respond to job threats by activating larger, sparser sections of their potential network. In parallel to these findings, Shea et al. (2015) found that when individuals experience positive emotion they activate larger and less dense network structures, while those who experience negative emotion activate smaller, denser networks. Likewise, following social exclusion (a negative emotional experience), people activate denser social networks (O'Connor & Gladstone 2015).

Power also affects network cognition. Individuals who are primed with low power tend to engage in more deliberative, controlled social network cognition than those primed with high power,

who tend to be more schematic in their thinking (Landis et al. 2018). When people are primed to have low power, they tend to be more accurate in their recall of social networks than high-power individuals (Simpson et al. 2011). In particular, low-power individuals are less susceptible to “filling in the blanks” (Freeman 1992) in that they are better at perceiving—or more likely to attend to—absent ties. As a result, low-power individuals are more likely to see opportunities for brokerage (i.e., structural holes) than high-power individuals (Landis et al. 2018). In contrast to low-power individuals, high-power individuals tend to rely more heavily on network schemas to make sense of their social network; they assume that their surrounding influence networks are arranged into a hierarchy, with the individual at the top being universally influential and the person at the bottom being universally influenced (Simpson et al. 2011).

Status and power themselves interact to produce differences in network cognition. One study manipulated sense of power in individuals of different status, meaning that individuals were either in a situation where their sense of power matched their status (i.e., high status/high power or low status/low power) or in a situation where they experienced a mismatch between their sense of power and status (i.e., high status/low power or low status/high power) (Menon & Smith 2014). The results show that individuals who experienced concordance between their status and power tended to activate larger, sparser, and more diverse networks whereas those who experienced discordance (low status/high power or high status/low power) activated smaller, denser, and less diverse networks. The authors of this study speculate that a stable sense of self produces feelings of comfort and control, providing a secure emotional base from which to explore more expansive social worlds via the activation of larger, more diverse networks. Conversely, individuals who experience conflict between their sense of self as high or low status and the environment (being primed with low or high power, respectively) may respond by activating familiar networks that can restore their lost sense of self (Menon & Smith 2014).

Goals and Motivation

Research has begun to explore how network cognition serves goal pursuit, examining how goals and motivations shape both network activation and mobilization. Shea & Fitzsimons (2016) contrasted the network activation and mobilization of individuals who had affiliation goals (the desire to improve and maintain relationships with others) with those of individuals who had advancement goals (the desire to enhance their careers). They found that individuals with advancement goals tended to see others through an instrumental lens, focusing on others’ utility in helping them reach their goals. Consequently, these individuals activated sparser networks (Shea & Fitzsimons 2016). In contrast, individuals with affiliation goals activated denser networks. One possible explanation for these findings comes from research examining motivational styles and network cognition. Individuals who are motivated by a need for achievement are better able to accurately discern the connections and disconnections in their surrounding networks, relative to individuals with a low need for achievement (Casciaro 1998). Given that individuals overestimate the connectivity of their surrounding networks (Freeman 1992), it may be that those with achievement goals activate less dense networks because they are more attuned to the actual pattern of relationships around them (relative to those with affiliation goals). This explanation is also consistent with the assertions of the social brain hypothesis: Those who do not feel a pressing need for personal achievement may be more inclined to focus on the maintenance and support of the group as a whole.

Stereotypes

Another burgeoning stream of research in network cognition has focused on gender stereotypes. Stereotypes are person schemas that contain beliefs about the characteristics and attributes of

social identity groups (Hilton & Von Hippel 1996). Since stereotypes also govern perceptions of social behavior (Eagly & Crowley 1986), it follows that stereotypes should affect social network cognition as well. Research has shown that gender stereotypes affect individuals' perceptions of the friendship networks around them such that they overestimate the extent to which women's networks are interconnected while underestimating the connectivity in men's (relative to the actual density of men's and women's networks) (Brands & Kilduff 2013). This bias arises from the stereotyped expectations about men as agentic, powerful, and dominant and women as communal (Eagly & Steffen 1984). These expectations about the personal characteristics of men and women extend to expectations about their social behavior, in that people tend to assume men will be surrounded by less dense networks that afford them with power and opportunities for action, while women will be surrounded by close, dense networks that are communal and cohesive (Brands & Kilduff 2013).

However, gender stereotypes not only shape expectations about how men and women will behave but also govern expectations about how men and women should behave (Heilman & Eagly 2008). As a result, women who are perceived to build counterstereotypical networks incur reputational penalties (Brands & Kilduff 2013). For example, the connectivity of the networks surrounding women leaders—regardless of their own position in the network—affects attributions of charismatic leadership to women; women who are surrounded by dense, interconnected networks are seen as more charismatic than men (Brands et al. 2015). One might expect this perception of charisma to influence the likelihood that networks mobilized by the leader will be realized (i.e., the likelihood that individuals will respond positively to the leader's efforts to mobilize them).

Gender stereotypes about typical and appropriate social network roles are, of course, internalized by women themselves. When women see themselves as having violated stereotypical expectations by occupying networks that are less dense, they perform worse on intellectual tasks (Brands & Mehra 2019). This result is due to stereotype threat, a phenomenon that occurs when stereotypical expectations about a group's performance in a particular domain are salient to members of that group and serve to paradoxically undermine their performance by diverting working memory resources from task execution (Spencer et al. 2016). There is a stereotype that women will perform worse than men in less interconnected networks. As a result, women experience heightened anxiety when they see themselves as surrounded by less interconnected networks; thus, this stereotype is salient to them, taxing their working memory and disrupting their performance (Brands & Mehra 2019).

HOW DO SOCIAL NETWORKS AFFECT COGNITION?

Above, we consider how the brain encodes information about the social network and thereby shapes network behavior. But if the brain affects network behavior, we must also ask whether and how the network may affect the brain. For many years, neuroscientists believed that the brain was formed during childhood and adolescence and was largely static afterward. Consequently, it was assumed that the direction of causality flowed from brain structure to network structure and not in the other direction. However, research over the last two decades has overturned that conventional wisdom, instead demonstrating that neuroplasticity (i.e., the ability of the brain to change, forming and reorganizing its synaptic connections) is present throughout the life course (Pascual-Leone et al. 2005). In a classic study, Maguire et al. (2006) showed that London taxi drivers had a larger posterior hippocampus (associated with spatial navigation) compared with a control group of bus drivers, whose physical tasks were largely similar to those of the taxi drivers but who follow a fixed route with no navigation required (London taxi drivers are required by law to memorize the city's streets and may not use electronic aids like GPS devices). Furthermore, the difference between

groups increased with driving tenure, suggesting a treatment effect rather than a selection effect. This and other research has convincingly shown that experience affects the physiology of the brain throughout the entire life course; the outstanding question is whether one's social network can be the source of such brain-altering experience.

We know of no studies in humans that directly address this question, but we can learn a great deal from studies of our highly social primate relatives. Most primate studies of the social brain draw comparisons across species (Dunbar 1992), but in one within-species study, Sallet et al. (2011) quasi-randomly assigned rhesus macaques to live in either small or large social groups. Those in large groups developed more gray matter in brain regions associated with social and emotional processing (their superior temporal sulcus, temporal pole, amygdala, and rostral prefrontal cortex) and greater connectivity between these regions, compared with those in smaller social groups. The results of this randomized experiment suggest that the size of the social group exerted a causal effect on the anatomical structure and function of individual monkeys' brains. In effect, experience and the demands of circumstance reprogrammed the brain via physical changes in its structure.

An ongoing study by Parkinson and colleagues (C. Parkinson, A.M. Kleinbaum & T. Wheatley 2020, unpublished research) aims to test the hypothesis that the social network affects the human brain directly. To do so, the authors replicated their 2018 study (Parkinson et al. 2018), but with a longitudinal design. Neuroimaging studies were performed at the inception of an MBA program; the social network unfolded over a period of 19 months, and follow-up neuroimaging studies will be performed on the same subjects at the conclusion of the program. This study has the potential to identify evidence of both selection effects (in which *ex ante* neural similarity predicts network formation) and treatment effects (friendship induces neural convergence over time). A related study centers on the fact that, while neural activity captures how the brain experiences the world, language captures how an individual talks about the world. Kovacs & Kleinbaum (2020) present evidence that people whose use of language reflects underlying psychological similarity are more likely to become friends and, furthermore, that friendship increases linguistic similarity over time. Thus, while it is premature to draw any definite conclusions, the preliminary evidence from social neuroscience suggests not only that the brain shapes the social network but also that the social network may shape the brain.

The relative paucity of research on network effects on the brain is understandable, albeit unfortunate. It is understandable because presenting strong evidence of such a link requires both careful designs that are able to provide evidence of causality, as well as imaging capabilities to identify changes in the physical structure of the brain; it is unfortunate because until such studies are complete, it will be easy for researchers within and beyond the social sciences to fall back on antiquated notions that the arrow of causality runs in one direction, from the biological to the social. Yet, our growing understanding of the brain's operation demonstrates that it is highly plastic, and the social brain hypothesis implies that it should be especially sensitive to social experiences. Therefore, the potential for future studies to explore the links running from social experiences to brain structure is tremendous. We anticipate a future in which studies are able to explain how the physical structure of the brain and algorithmic mechanisms of the mind are coconstitutive rather than superior and subordinate.

CONCLUSIONS

A growing body of research indicates that cognitive processes influence the size, structure, and use of human social networks. At a basic level, the brain appears to have structural capacities for identifying individuals and relationships as well as for encoding social distinctions similarly

to physical distance. Its capability to encode and recall social information is not simply driven by biology but also responds to the use of schemas and heuristics, which function to improve the speed and quality of information processing while also giving rise to characteristic patterns of errors. Moreover, the nature of processing is contingent on context, with circumstances (including power, goals, context, and emotions) helping to shape the types of networks that become available in the conscious mind, and the ways that those networks are used by individuals. Finally, there is preliminary evidence that our social environments and social networks reciprocally affect our brains. In short, the new cognitive turn in social network analysis is making dramatic progress that only seems to accelerate with time.

One of the key insights to emerge over the last several decades is that conceptions of social behavior being dictated by the physical structure of the brain are overly simple. Although it is true that we do our thinking with our brains—and thus all of our behavior is, in some sense, rooted in brain function—it is also true that our brains evolved to be flexible and adaptive in response to circumstance, rather than fixed and static. Humans are able to develop new behaviors not simply from one generation to the next, but within a single lifetime, a single year, a month, or even a day, and the range of behaviors exhibited by modern humans is stunningly different from those common in our evolutionary environment.³ It is by studying the physical structure of the brain and the algorithmic behavior of the mind that we can understand how humans are capable of such impressive flexibility in the face of changing circumstances.

By way of analogy, both a mechanical clock and a digital electronic computer are computational devices, but whereas the former is able to execute only a single program with minimal input from the user (beyond setting the time), the latter is capable of a practically unlimited variety of behaviors and outputs. While older, antiquated models tended to view the brain as akin to a clock, executing constant programs with only a few variables open to change, proponents of the modern cognitive turn view the brain as changeable, programmable, and in constant dialogue with the environment, thereby enabling nearly limitless adaptability.

With so much work yet to be done, the potential directions for future study are virtually boundless. We need substantial progress on all parts of the problem—from identifying the structures in the brain that support social activity to uncovering the algorithms and heuristics that have been (and are being) developed to guide our social behavior to improving our understanding of how context impacts these processes as well as the brain itself. Yet, as neuroimaging technologies become more sophisticated, more portable, and less expensive, the potential to achieve these goals has never been greater. We are presented with a singular opportunity: As the tools of brain science become more accessible, there is an increasing need for the substantive and theoretical knowledge possessed by social scientists. By engaging with this effort, we help ensure the continued quality of the cognitive turn, rather than embracing our own obsolescence.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

This review benefited from discussions and debates with a diverse set of colleagues, coauthors, and friends, without whose insights our own work would be less complete and less interesting.

³ Although attendees at major academic conferences may find themselves drawing on traditional competencies in hunting and gathering.

Any errors are ours alone. We are especially grateful for the vision of the first author, who forged us into a team and guided this project to a beautiful conclusion.

LITERATURE CITED

- Atkinson RC, Shiffrin RM. 1968. Human memory: a proposed system and its control processes. In *Psychology of Learning and Motivation*, ed. K Spence, JT Spence, pp. 89–195. Amsterdam: Elsevier
- Baddeley A. 1986. *Working Memory*. Oxford Psychol. Ser. 11. Oxford, UK: Oxford Univ. Press/Clarendon
- Bartels A, Zeki S. 2000. The neural basis of romantic love. *NeuroReport* 11:3829–34
- Bartlett FC. 1932. *Remembering: A Study in Experimental and Social Psychology*. Cambridge, UK: Cambridge Univ. Press
- Barton RA. 1996. Neocortex size and behavioural ecology in primates. *Proc. R. Soc. B* 263:173–77
- Bell DC, Belli-McQueen B, Haider A. 2007. Partner naming and forgetting: recall of network members. *Soc. Netw.* 29:279–99
- Bernard HR, Killworth PD. 1977. Informant accuracy in social network data II. *Hum. Commun. Res.* 4:3–18
- Bernard HR, Killworth PD, Sailer L. 1979. Informant accuracy in social network data IV. A comparison of clique-level structure in behavioral and cognitive network data. *Soc. Netw.* 2:191–218
- Bernard HR, Killworth PD, Sailer L. 1980. Informant accuracy in social-network data V. An experimental attempt to predict actual communication from recall data. *Soc. Sci. Res.* 11:30–66
- Bickart KC, Wright CI, Dautoff RJ, Dickerson BC, Barrett LF. 2011. Amygdala volume and social network size in humans. *Nat. Neurosci.* 14:163–64
- Brands RA, Kilduff M. 2013. Just like a woman? Effects of gender-biased perceptions of friendship network brokerage on attributions and performance. *Organ. Sci.* 25:1530–48
- Brands RA, Mehra A. 2019. Gender, brokerage, and performance: a construal approach. *Acad. Manag. J.* 62:196–219
- Brands RA, Menges JI, Kilduff M. 2015. The leader-in-social-network schema: perceptions of network structure affect gendered attributions of charisma. *Organ. Sci.* 26:1210–25
- Brashears ME. 2013. Humans use compression heuristics to improve the recall of social networks. *Sci. Rep.* 3:1513
- Brashears ME. 2014. “Trivial” topics and rich ties: the relationship between discussion topic, alter role, and resource availability using the “important matters” name generator. *Sociol. Sci.* 1:493–511
- Brashears ME, Brashears LA. 2016. The enemy of my friend is easy to remember: balance as a compression heuristic. In *Advances in Group Processes*, ed. SR Thye, EJ Lawler, pp. 1–31. Bingley, UK: Emerald Insight
- Brashears ME, Hoagland E, Quintane E. 2016. Sex and network recall accuracy. *Soc. Netw.* 44:74–84
- Brashears ME, Quintane E. 2015. The microstructures of network recall: how social networks are encoded and represented in human memory. *Soc. Netw.* 41:113–26
- Brewer DD, Garrett SB. 2001. Evaluation of interviewing techniques to enhance recall of sexual and drug injection partners. *Sex. Transm. Dis.* 28:666–77
- Brewer DD, Yang BL. 1994. Patterns in the recall of persons in a religious community. *Soc. Netw.* 16:347–79
- Brewer WF, Treyens JC. 1981. Role of schemata in memory for places. *Cogn. Psychol.* 13:207–30
- Burt RS. 1992. *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard Univ. Press
- Cao J, Smith EB. 2020. *Why do high status people have larger social networks? Belief in status–quality coupling as a driver of social networking behavior*. Work. Pap., Kellogg Sch. Manag., Northwest. Univ., Evanston, IL
- Casciaro T. 1998. Seeing things clearly: social structure, personality, and accuracy in social network perception. *Soc. Netw.* 20:331–51
- De Soto CB. 1960. Learning a social structure. *J. Abnorm. Soc. Psychol.* 60:417–21
- Dunbar RI. 1992. Neocortex size as a constraint on group size in primates. *J. Hum. Evol.* 22:469–93
- Dunbar RI. 1993. Coevolution of neocortical size, group size and language in humans. *Behav. Brain Sci.* 16:681–94
- Dunbar RI. 1995. Neocortex size and group size in primates: a test of the hypothesis. *J. Hum. Evol.* 28:287–96
- Eagly AH, Crowley M. 1986. Gender and helping behavior: a meta-analytic review of the social psychological literature. *Psychol. Bull.* 100:283–308

- Eagly AH, Steffen VJ. 1984. Gender stereotypes stem from the distribution of women and men into social roles. *J. Personal. Soc. Psychol.* 46:735–54
- Enemark D, McCubbins MD, Weller N. 2014. Knowledge and networks: an experimental test of how network knowledge affects coordination. *Soc. Netw.* 36:122–33
- Fang R, Landis B, Zhang Z, Anderson MH, Shaw JD, Kilduff M. 2015. Integrating personality and social networks: a meta-analysis of personality, network position, and work outcomes in organizations. *Organ. Sci.* 26:1243–60
- Flynn FJ, Reagans RE, Amanatullah ET, Ames DR. 2006. Helping one's way to the top: Self-monitors achieve status by helping others and knowing who helps whom. *J. Personal. Soc. Psychol.* 91:1123–37
- Flynn FJ, Reagans RE, Guillory L. 2010. Do you two know each other? Transitivity, homophily, and the need for (network) closure. *J. Personal. Soc. Psychol.* 99:855–69
- Freeman LC. 1992. Filling in the blanks: a theory of cognitive categories and the structure of social affiliation. *Soc. Psychol. Q.* 55:118–27
- Freeman LC, Freeman SC, Michaelson AG. 1988. On human social intelligence. *J. Soc. Biol. Struct.* 11:415–25
- Freeman LC, Freeman SC, Michaelson AG. 1989. How humans see social groups: a test of the Sailer–Gaulin models. *J. Quant. Anthropol.* 1:229–38
- Freeman LC, Romney AK. 1987. Words, deeds and social structure: a preliminary study of the reliability of informants. *Hum. Organ.* 46:330–34
- Freeman LC, Romney AK, Freeman SC. 1987. Cognitive structure and informant accuracy. *Am. Anthropol.* 89:310–25
- Garrard P, Hodges JR. 1999. Semantic dementia: implications for the neural basis of language and meaning. *Aphasiology* 13:609–23
- Gobbini MI, Haxby JV. 2007. Neural systems for recognition of familiar faces. *Neuropsychologia* 45:32–41
- Gonçalves B, Perra N, Vespignani A. 2011. Modeling users' activity on Twitter networks: validation of Dunbar's number. *PLOS ONE* 6:e22656
- Heilman ME, Eagly AH. 2008. Gender stereotypes are alive, well, and busy producing workplace discrimination. *Ind. Organ. Psychol.* 1:393–98
- Hilton JL, Von Hippel W. 1996. Stereotypes. *Annu. Rev. Psychol.* 47:237–71
- Hlebec V, Ferligoj A. 2001. Respondent mood and the instability of survey network measurements. *Soc. Netw.* 23:125–40
- Hsieh YP. 2015. Check the phone book: testing information and communication technology (ICT) recall aids for personal network surveys. *Soc. Netw.* 41:101–12
- Humphrey NK. 1976. The social function of intellect. In *Growing Points in Ethology*, ed. PPG Bateson, RA Hinde, pp. 303–17. Cambridge, UK: Cambridge Univ. Press
- Hyon R, Kleinbaum AM, Parkinson C. 2019. Social network proximity predicts similar trajectories of psychological states: evidence from multi-voxel spatiotemporal dynamics. *NeuroImage*. In press. <https://doi.org/10.1016/j.neuroimage.2019.116492>
- Janicik GA, Larrick RP. 2005. Social network schemas and the learning of incomplete networks. *J. Personal. Soc. Psychol.* 88:348–64
- Kanai R, Bahrami B, Royle R, Rees G. 2012. Online social network size is reflected in human brain structure. *Proc. R. Soc. B* 279:1327–34
- Kashima Y, Wilson S, Lusher D, Pearson LJ, Pearson C. 2013. The acquisition of perceived descriptive norms as social category learning in social networks. *Soc. Netw.* 35:711–19
- Killworth PD, Bernard HR. 1979. Informant accuracy in social network data III. A comparison of triadic structure in behavioral and cognitive data. *Soc. Netw.* 2:19–46
- Killworth PD, Bernard HR. 1982. A technique for comparing mental maps. *Soc. Netw.* 3:307–12
- Kovacs B, Kleinbaum AM. 2020. Language-style similarity and social networks. *Psychol. Sci.* 31:202–13
- Krackhardt D. 1987. Cognitive social structures. *Soc. Netw.* 9:109–34
- Krackhardt D. 1990. Assessing the political landscape: structure, cognition, and power in organizations. *Adm. Sci. Q.* 35:342–69
- Kudo H, Dunbar RI. 2001. Neocortex size and social network size in primates. *Anim. Behav.* 62:711–22

- LaBar KS, LeDoux JE, Spencer DD, Phelps EA. 1995. Impaired fear conditioning following unilateral temporal lobectomy in humans. *J. Neurosci.* 15:6846–55
- Landis B, Kilduff M, Menges JI, Kilduff GJ. 2018. The paradox of agency: Feeling powerful reduces brokerage opportunity recognition yet increases willingness to broker. *J. Appl. Psychol.* 103:929–38
- Maguire EA, Woollett K, Spiers HJ. 2006. London taxi drivers and bus drivers: a structural MRI and neuropsychological analysis. *Hippocampus* 16:1091–101
- Marin A. 2004. Are respondents more likely to list alters with certain characteristics? Implications for name generator data. *Soc. Netw.* 26:289–307
- Marsden PV. 1987. Core discussion networks of Americans. *Am. Sociol. Rev.* 52:122–31
- Martin CL. 1993. New directions for investigating children's gender knowledge. *Dev. Rev.* 13:184–204
- McPherson JM, Smith-Lovin L, Cook JM. 2001. Birds of a feather: homophily in social networks. *Annu. Rev. Sociol.* 27:415–44
- Mehra A, Kilduff M, Brass DJ. 2001. The social networks of high and low self-monitors: implications for workplace performance. *Adm. Sci. Q.* 46:121–46
- Menon T, Smith EB. 2014. Identities in flux: cognitive network activation in times of change. *Soc. Sci. Res.* 45:117–30
- Neisser U. 2014. *Cognitive Psychology*. New York: Psychology. Class. ed.
- O'Connor KM, Gladstone E. 2015. How social exclusion distorts social network perceptions. *Soc. Netw.* 40:123–28
- Omodei E, Brashears ME, Arenas A. 2017. A mechanistic model of human recall of social network structure and relationship affect. *Sci. Rep.* 7:17133
- Parkinson C, Kleinbaum AM, Wheatley T. 2017. Spontaneous neural encoding of social network position. *Nat. Hum. Behav.* 1:0072
- Parkinson C, Kleinbaum AM, Wheatley T. 2018. Similar neural responses predict friendship. *Nat. Commun.* 9:332
- Parkinson C, Liu S, Wheatley T. 2014. A common cortical metric for spatial, temporal, and social distance. *J. Neurosci.* 34:1979–87
- Parkinson C, Lynn B, Kleinbaum AM, Wheatley T. 2019. *Network centrality modulates social attention*. Work. Pap., Dartmouth Univ., Hanover, NH
- Parkinson C, Wheatley T. 2015. The repurposed social brain. *Trends Cogn. Sci.* 19:133–41
- Pascual-Leone A, Amedi A, Fregni F, Merabet LB. 2005. The plastic human brain cortex. *Annu. Rev. Neurosci.* 28:377–401
- Powell J, Lewis PA, Roberts N, García-Fiñana M, Dunbar RIM. 2012. Orbital prefrontal cortex volume predicts social network size: an imaging study of individual differences in humans. *Proc. R. Soc. B* 279:2157–62
- Reisberg D. 1997. *Cognition: Exploring the Science of the Mind*. New York: Norton
- Roberts SG, Dunbar RI, Pollet TV, Kuppens T. 2009. Exploring variation in active network size: constraints and ego characteristics. *Soc. Netw.* 31:138–46
- Romney AK, Faust K. 1982. Predicting the structure of a communications network from recalled data. *Soc. Netw.* 4:285–304
- Sallet J, Mars RB, Noonan MP, Andersson JL, O'Reilly JX, et al. 2011. Social network size affects neural circuits in macaques. *Science* 334:697–700
- Schwarz N. 2009. Mental construal in social judgment. In *Social Cognition: The Basis of Human Interaction*, ed. F Strack, J Förster, pp. 121–38. New York: Psychology
- Semin GR, Garrido MV. 2015. Socially situated cognition. In *Advances in Experimental Social Psychology*, ed. MP Zanna, pp. 283–304. Amsterdam: Elsevier
- Shea CT, Fitzsimons GM. 2016. Personal goal pursuit as an antecedent to social network structure. *Organ. Behav. Hum. Decis. Process.* 137:45–57
- Shea CT, Menon T, Smith EB, Emich K. 2015. The affective antecedents of cognitive social network activation. *Soc. Netw.* 43:91–99
- Simpson B, Markovsky B, Steketee M. 2011. Power and the perception of social networks. *Soc. Netw.* 33:166–71
- Small ML. 2017. *Someone to Talk To*. Oxford, UK: Oxford Univ. Press

- Smith EB, Menon T, Thompson L. 2012. Status differences in the cognitive activation of social networks. *Organ. Sci.* 23:67–82
- Spencer SJ, Logel C, Davies PG. 2016. Stereotype threat. *Annu. Rev. Psychol.* 67:415–37
- Stiller J, Dunbar RI. 2007. Perspective-taking and memory capacity predict social network size. *Soc. Netw.* 29:93–104
- Van Kreveld D, Zajonc RB. 1966. The learning of influence structures. *J. Personal.* 34:205–23
- Von Der Heide R, Vyas G, Olson IR. 2014. The social network-network: Size is predicted by brain structure and function in the amygdala and paralimbic regions. *Soc. Cogn. Affect. Neurosci.* 9:1962–72
- Welles BF, Xu W. 2018. Network visualization and problem-solving support: a cognitive fit study. *Soc. Netw.* 54:162–67
- Zerubavel N, Bearman PS, Weber J, Ochsner KN. 2015. Neural mechanisms tracking popularity in real-world social networks. *PNAS* 112:15072–77