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The Origins of Cognitive and Action Errors in Communication Networks

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ABSTRACT

The Origins of Cognitive and Action Errors in Communication Networks

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This dissertation explores cognitive and action errors that occur in communication networks. I leverage theories on organizational errors and social networks to develop a novel, conceptual, and empirically testable framework to understand how individuals make errors when using their networks to share information. Here, I argue that information sharing is not only *what* to share but also *with whom* to share, and mistakenly sharing information with unintended members has consequences. Despite the prevalence of this type of network error, little is known about its origins.

In this dissertation, I propose a conceptual framework for differentiating between two levels of network errors: (a) cognitive network errors and (b) action network errors. Prior scholarship on social networks has predominantly focused on cognitive network errors that occur when people incorrectly perceive their network. But this prior research provides little insight into action network errors that take place as individuals act on their networks. Organizational error literature has extensively studied action errors (*e.g.*, unintentional deviations from plans, goals, or feedback processing), yet few studies consider action network errors. I argue that integrating organizational error and social network perspectives will provide pivotal insights into how and why organizational communication, such as information sharing, often fails.

Based on the conceptual framework, my research objective is to empirically examine how individuals make cognitive and action network errors. To address this research question, I conducted two empirical studies. Drawing on data from 23 network sessions (N = 212

participants), the first empirical study examines how people overestimate and underestimate the presence of communication links by comparing the observed network with their perceived network. Comparing the actual communication networks (who was actually connected to whom) and perceived networks (who was perceived by others to be connected with whom), I observe that participants tend to overestimate the presence of communication links between people who are members of the same formal group or embedded in informal structures (*e.g.*, reciprocity and social distance) and underestimate the presence of links between people who are in different groups and who are farther from them in the social network. These findings provide insight into how people's perceptions of "who knows whom" hinder their ability to share information effectively.

In a laboratory study, including 23 pre-existing group networks (*N* = 405 participants), the second empirical study investigates who commits action network errors and who is more likely to learn from them. In the study, each group engaged in a network routing task, similar to Milgram's small-world task. Results show that individuals' errors and their ability to learn from errors are explained by dispositional factors (who individuals are), positional factors (where they are in the network), and the interplay between these factors. Taken together, these findings of the two empirical studies expand the focus to explore network errors that occur within communication networks. Hence, this dissertation contributes to theoretical advancement in the study of social networks, organizational errors, group processes, and organizational communication.

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CHAPTER 1. INTRODUCTION

Errors—unintentional deviations from truth, accuracy, or standard of behavior—are of great practical and scientific interest since they prevail in groups and organizations. They tend to have a negative connotation because significant incidents and accidents often stem from errors. For example, Korean Air Flight 801 crashed on August 6, 1997, because the flight officer and engineer did not challenge the captain's error of misjudging the aircraft's altitude. Conversely, errors can also bring positive outcomes, such as learning and innovations. For instance, chlorinated sugars—artificial sugars—came from an error of communication between two scientists when one mistakenly heard the other asking him to "taste it" instead of "test it" (Gratzer, 2004). By tasting it, they discovered innovative artificial sugars, which are widely used these days. Thus, scholars have long paid attention to mechanisms of human errors in groups and organizations (Frese & Keith, 2015; Hofmann & Frese, 2011a; Lei et al., 2016; Reason, 1990).

However, until recently, errors in information sharing have garnered little attention, despite the fact that information processes are prone to errors (Bell & Kozlowski, 2011). The two examples above illustrate that errors occur not only at the individual level, but also at the interpersonal level. Few studies have begun to explore interpersonal-level errors (Brashears & Gladstone, 2016; Pearsall et al., 2008; Sieweke & Zhao, 2015). Nevertheless, we have relatively little knowledge of the origins of interpersonal level errors, especially in information sharing. This is an essential subject to study because organizations are built around teams and networks that enable people to leverage diverse expertise; information sharing is the central process through which we learn what others know (Mesmer-Magnus & DeChurch, 2009). Specifically, we have overlooked what goes wrong with information sharing. This dissertation proposes three common organizational communication problems that arise from information sharing and tackles these problems.

According to Dale Carnegie, “90% of all management problems are caused by miscommunication.” Consistent with this notion, prior research on information sharing has focused on *what* to share rather than *with whom* to share. In other words, it highlights miscommunication as the primary communication problem of information sharing. Miscommunication refers to an unintentional consequence of misinterpreting the content of a message. This type of problem is, in fact, prevalent in groups and organizations. For example, Lingard and her colleagues (2004) report that 35.7% of medical mistakes stem from miscommunication in an operating room. Similarly, Byron (2008) illustrates that miscommunication is a considerable challenge in digital information and communication technologies. Errors of miscommunication in terms of what to share are costly.

However, I argue that, just as critical as the errors associated with “what to share” are errors associated with “with whom to share.” Prior research has suggested that information sharing processes are prone to errors regarding not only the content being transferred (*e.g.*, the telephone game) but also the connections used to transfer them (Ellis, 2006; Ghosh & Rosenkopf, 2015; Singh et al., 2010). The majority of prior research focuses on errors as content modification and distortion during information transfer (Bell & Kozlowski, 2011; Brashears & Gladstone, 2016; Huber, 1982; Miller, 1972). However, Hollingshead notes that “information may be transferred or explicitly delegated to the ‘wrong’ individual in the system, *e.g.*, one who does not have responsibility for that type of information or is unlikely to remember it due to a lack of expertise” (1998, p. 427). In other words, people sometimes route information or queries to someone who is not equipped to handle it, rather than to the most appropriate person in the network.

Based on this notion, there are other common types of communication problems in who receives information within or between groups and organizations: (a) information leakage and (b) information loss. Information leakage is a failure in which information reaches unintended recipients who may or may not use it in unintended ways. This phenomenon is increasingly widespread in digital contexts. Verizon (2020) reports that 10% of cybersecurity incidents are caused by misdelivered messages in recent years; in other words, someone who is not supposed to receive a message receives it (*i.e.*, action network errors).

Information loss refers to a process in which information never reaches its intended recipient due to delays, blockages, and distortion along the network route to the intended recipients. This is another serious negative consequence since intended recipients never receive the information. In the case of the Space Shuttle Challenger incident, two engineers conducted a simulation and found that O-rings—a seal part identified as a root cause of the incident—did not properly work under a certain temperature, yet their evidence never reached the management who made the final launch decision (Presidential Commission, 1986).

Despite the prevalence and significance of information leakage and loss, we have paid less attention to these communication failures than to miscommunication. Consequently, I argue that we have a less systematic understanding of the mechanisms behind network errors that are among the underlying causes of information leakage and loss. Specifically, I will focus on information loss through empirical investigations. Since these communication failures require two or more members of a group or organization to be involved, a network perspective sheds light on both the fundamental mechanisms of these dire phenomena and organizational errors.

Specifically, I argue that network errors consist of two levels: (a) cognitive and (b) action. Cognitive network errors occur when individuals perceive their contacts. I define them as misalignments between perceived and observed ties. Action network errors happen as individuals use their network contacts. More formally, they refer to unintentional deviations from achieving the goal of sharing information or queries with someone to whom they are only indirectly connected via their social network and where this deviation was potentially avoidable.

In my framework, I also differentiate between errors and failures. Errors happen during the process of achieving certain outcomes. Failures are outcomes resulting from actions. In other words, not all errors result in failures. For instance, you might have accidentally told your boss a piece of inaccurate information as an error for financial trading. Nonetheless, your boss still managed to make a successful financial decision (*i.e.*, an outcome), avoiding failure. That being said, the focus of this dissertation is on uncovering the mechanisms behind errors rather than failures.

Similarly, organizational error literature makes a distinction between errors and violations (Frese & Keith, 2015; Reason, 1990). We *unintentionally* make mistakes. These are errors. However, there are cases where people *deliberately* make mistakes. In the aforementioned example, you accidentally told your boss inaccurate information, yet some people may deliberately give wrong information. If there is the intent behind the action, it is not an error because it intentionally violates a rule or standard. In my dissertation, I focus solely on errors, not violations, because these two concepts clearly have different underlying mechanisms.

In summary, we have failed to pay attention to two levels of errors in communication networks: cognitive errors and action errors. Here, I study the origins of cognitive and action network errors in communication networks. The study mainly aims to address a perceptual gap between observed and perceived networks (Lee et al., 2019) and a knowing-doing gap between what people know and what they actually do (Kuwabara et al., 2018) when it comes to people perceiving and using their networks. To do so, this dissertation proposes a conceptual framework and conducts empirical research.

RESEARCH OBJECTIVES

The purposes of this dissertation are to (a) conceptualize errors in communication networks by theorizing network and processing errors and (b) examine the origins of these errors—particularly network errors—that explain how people misperceive and inefficiently act on their communication network, based on two laboratory studies. More specially, the dissertation is motivated by three primary research questions:

1. What factors impact cognitive and action network errors in information-sharing processes within communication networks, and how do these errors result in information sharing failures?
2. Why and how do individuals make cognitive network errors in the presence of formal and informal structures of communication networks?
3. Why and how do individuals commit action network errors and learn from them in information sharing via communication networks?

THESIS OVERVIEW

To answer research questions, this dissertation employs a three-study strategy. Each standalone study is closely connected through the overarching theme of this dissertation. Chapter 2 sets out foundational issues that this dissertation tackles. Then, Chapters 3 and 4 empirically address some of the fundamental issues raised in Chapter 2. Next, I describe each of the three studies.

Chapter 2 develops a conceptual framework of cognitive and action network errors in communication networks. In the framework, I introduce a typology of errors and communication outcomes, as well as which antecedent factors impact errors. Specifically, the framework differentiates between processing and network errors. While processing errors refer to an unintentional misunderstanding of content between a sender and an intended recipient, network errors are an unintentional and potentially avoidable deviation from achieving the goal of sharing information or queries with someone to whom they are only indirectly connected via their social network. Furthermore, network errors include two levels: (a) cognitive and (b) action. Specifically, I identify the antecedents, consequences, and management of these errors based on the integrated literature review of organizational errors and social networks.

Chapter 3 examines the role of formal and informal social structure on cognitive network errors. Specifically, I examine how formal and informal structures in groups impact errors that members make by comparing the actual communication network with their perceived network. Building on the literature on relational schemas, I develop hypotheses regarding errors of omission and commission. I define errors people make in communication networks as errors of commission and errors of omission. Commission errors are defined as ties that people falsely perceive to exist, while omission errors refer to ties that do exist but that people perceive as nonexistent. To test the series of hypotheses regarding errors of omission and commission, I collected data from 23 networks (N = 212 participants), measuring both the actual communication networks (who was actually connected to whom) and perceived networks (who was perceived by others to be connected to whom).

Chapter 4 focuses on social network routing errors (a type of action network error), which is defined as potentially avoidable actions by individuals that unintentionally fail to achieve the goal of routing information or queries to someone with whom they are only indirectly connected via their social network. This chapter investigates who commits social network routing errors and who is more likely to learn from them. To address these research questions, I conducted a laboratory study where 23 pre-existing groups (N = 405) were recruited at a midwestern U.S. university. In the study, each group engaged in a network routing task similar to Milgram's small-world task. Results show that individuals' errors and their ability to learn from errors are explained by dispositional factors (who individuals are), positional factors (where they are in the network), and the interplay between these factors. Taken together, these findings of the two empirical studies expand the focus to explore errors that occur within organizational communication networks.

Chapter 5 discusses the main findings of this dissertation and their contributions and implications, limitations, and future directions for research on errors in communication networks.

CHAPTER 2. NETWORK AND PROCESSING ERRORS IN COMMUNICATION NETWORKS: AN INTEGRATIVE REVIEW AND FUTURE DIRECTIONS

Organizations are built around teams and networks that enable members to leverage diverse forms of expertise via the central process of information sharing. A body of research has underscored the importance of information sharing—the act of transferring information from one to another (Mesmer-Magnus & DeChurch, 2009). For example, when each team member shares their unique information with other teammates and they process it accurately, the team can function better by integrating their respective expertise, which, in turn, improves team performance. Nevertheless, research on information sharing has predominantly focused more on *what* to share (content) than *with whom* to share (people). While delivering the accurate content of a message is the goal of information sharing, we often fail to successfully deliver a message to the intended recipient in the first place. Based on these essential components of information sharing, I propose that there are three common organizational communication problems that arise from information sharing: (a) miscommunication, (b) information leakage, and (c) information loss.

Scholars have focused on miscommunication as the primary communication problem of information sharing (Brashears & Gladstone, 2016; Byron, 2008; Kruger et al., 2005; Lingard et al., 2004; Moussaïd et al., 2015). Put simply, it is about *what* to share. I define miscommunication as an unintentional consequence of misinterpreting the content of a message. Specifically, I emphasize unintentionality. If recipients *deliberately* interpret the content of a message in a way that differs from a sender’s intended meaning, the outcome of this case is not miscommunication. This is because this outcome is intended. Conversely, miscommunication occurs without well-intended misinterpretation through information sharing. This type of problem is prevalent in groups and organizations. For example, Lingard and her colleagues (2004) report that 35.7% of medical mistakes stem from miscommunication in an operating room. Similarly, Byron (2008) illustrates that miscommunication is a considerable challenge for organizations through digital information and communication technologies because of the lack of visual and vocal cues.

However, the key point here is that miscommunication assumes that information sharing occurs between the *right* individuals who are supposed to communicate with each other. This assumption is not met in many communication instances. In other words, information is often shared with individuals who are *not* the intended recipients of the information in groups and organizations, or information sharing does *not* happen between target individuals (Hollingshead, 1998; Hollingshead et al., 2011). These types of communication problems commonly occur in information sharing within and between groups and organizations. I classify these problems regarding “with *whom* to share” as information leakage and information loss.

Information leakage occurs when information reaches unintended recipients who may or may not use it in unintended ways. This phenomenon is especially prevalent in digital contexts. Verizon (2020) reports that 10% of cybersecurity incidents are caused by misdelivered messages; that is, someone who is not supposed to receive a message receives it (*i.e.*, network errors).

Information loss occurs when information never reaches its intended recipient, due to processing and network errors. This is a serious negative consequence since intended recipients never receive the information. Milgram’s small world experiment (1969) shows that 74% of the packages never reach the intended recipient. This finding is well-replicated (Schnettler, 2009b).

Furthermore, information loss often occurs within and across organizations as they engage in knowledge transfer (Bae & Koo, 2008; Ghosh & Rosenkopf, 2015). That being said, information loss is another prevalent and significant issue of information sharing.

Despite these widely observed communication failures, it is unclear how errors of “with whom to share” result in information leakage and loss. To advance our understanding of these information sharing failures, I propose a conceptual framework to examine errors in communication networks. Since communication failures involve two or more members of a group or organization, I argue that a network perspective sheds light on the fundamental mechanisms of these dire phenomena.

This chapter begins by defining errors in communication networks. Then, I propose a conceptual framework of network and processing errors. Based on the framework, I discuss antecedents, consequences, and error management of network and processing errors. Specifically, my discussion of antecedents and management focuses on network errors. Finally, I conclude by discussing future directions of errors in communication networks.

DEFINING ERRORS IN COMMUNICATION NETWORKS

I differentiate between errors and failures. Errors are unintentional mistakes that happen during the process of seeking or achieving certain outcomes. Failures are negative outcomes as a consequence of actions. In other words, not all errors result in failures. For instance, you might have accidentally told your boss a piece of inaccurate information as an error. But, your boss still may have managed to make a successful decision (*i.e.*, an outcome). In this case, there is an error, yet it does not lead to a failure.

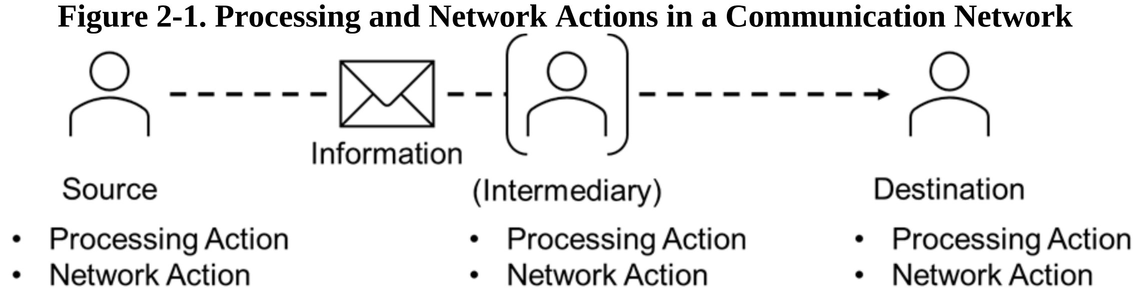
Similarly, errors and violations are different. Organizational error literature makes a clear distinction between error and violations (Frese & Keith, 2015; Reason, 1990). If we *unintentionally* make mistakes, these are errors. However, there are cases where people *deliberately* make mistakes. If there is intent behind a mistake, it is a violation because it violates a rule or standard. This dissertation focuses solely on errors, not violations, since these two concepts clearly have different mechanisms and assumptions.

Here, I argue that information sharing failures stem from processing and network errors in communication networks. Communication networks refer to "the patterns of contact that are created by the flow of messages among communicators through time and space" (Monge & Contractor, 2003, p. 3). Accordingly, errors in communication networks mean that intended information is *not* transmitted from a sender to the intended recipient through network contacts.

This definition is based on communication process models. In particular, there are three dimensions regarding communication (Shannon, 1948): a source, a destination, and information. A source transmits a message including information to his or her recipient (destination). He or she sometimes does not have a direct connection to the destination, so he or she might use an intermediary who may connect with the destination. Berlo (1960) extends Shannon's model of communication to human communication. His model includes four factors that determine the effectiveness of communication attempts by adding the channel. In the model, senders encode messages verbally or nonverbally using their choice of channels to receivers who decode them. Senders affect the communication process since they possess different communication skills, often come from different cultures, and have different attitudes toward receivers. Messages and channels also impact the communication process because senders decide how to encode and send the message. Finally, receivers affect the communication process because they have different communication skills, prior information about or attitudes toward senders, and preconceived beliefs based on their socio-cultural context (Byron 2008, p.311).

In sum, there are some essential action components in information sharing through interpersonal communication. Namely, each individual engages in two types of core actions in communication: processing and network action. On the one hand, processing action includes perceiving (encoding/decoding) messages and deciding to respond to them. On the other hand, network action entails deciding whether and to whom this information should be routed in the network. Network actions include channeling decisions (to whom the source sends a message) as well as non-sharing decisions (withholding a message). Figure 2-1 shows each action during the processes of communication in a network.

Figure 2-1. Processing and Network Actions in a Communication Network



Each action can be a source of errors. In information sharing, there is a tension between a “need to know” paradigm and a “need to share” network culture (Dawes et al., 2009). In organizations, members often face expectations of handling their own expert issues by themselves without coordinating with others. In other words, experts are not expected to share their problems, but in reality, information sharing among experts is essential to solving issues. By extending this tension model, Crowther (2014) argues that members need to balance between open networks of sharing information and closed proprietorship to compartmentalize information in modern organizations. Because of this tension, there is a likelihood that members make mistakes regarding what information to share and with whom.

Specifically, two types of errors emerge when members of a group or organization engage in information sharing: (a) processing errors and (b) network errors. While this dissertation focuses on network errors, in order to delineate them from processing errors, I provide a brief overview of the latter. Processing errors (more explicitly, information processing errors) refer to an unintentional misunderstanding of content between a sender and an intended recipient. There are two key aspects in the definition. One is unintentionality, in which individuals commit processing errors *without* intending to do so. In other words, if either a sender or an intended recipient deliberately distorts information, it is a violation, not a processing error. The second aspect in the definition is that a sender communicates the wrong information with the *right* recipient, resulting in processing errors. For example, "[t]he operators misidentified the Airbus A300 as an Iranian Air Force F-14 and mistakenly claimed that the aircraft was descending when it was actually climbing." This is an example of a processing error (Bell & Kozlowski, 2011, p. 117). In processing errors, a sender transmits information to the intended receiver. In the case of the USS Viennese, the operators passed the information to the commander (the right recipient). However, the information included a mistake, and the mistake stemmed from information processing. Therefore, this incident of *miscommunication* occurred partly due to processing errors, not network errors.

Network errors refer to an unintentional deviation from achieving the goal of conveying information or queries with someone with whom they are only indirectly connected via their social network and where this deviation was potentially avoidable. There are two dimensions of network errors: (a) cognitive errors and (b) action errors. The key here is the distinction between cognition and action. This distinction aligns with the organizational error literature that differentiates between cognitive/judgment and action errors. Frese and Keith (2015) argue that action errors "imply the nonattainment of a goal and nonconformity to some plan, whereas judgment errors are usually ascertained in relation to logical and statistical norms of rationality" (p. 663). My typology aligns with these cognitive and action error definitions.

Cognitive network errors occur when individuals incorrectly *perceive* contacts among others in the network. I define them as misalignments between perceived and observed ties. Social network research has long shown that cognitive network errors are widely prevalent since people's perceptions of their network are poor (Brashears, 2013; Brashears & Quintane, 2015; Corman & Scott, 1994). Famously, Bernard, Killworth, and Sailer (1979) find that the reality of who communicates with whom in the network differs significantly from the participants' perception of communicating with one another in the network. This type of misalignment is common in social and communication networks. Byron and Landis (2020), in particular, call for research to investigate how cognitive network errors impact information sharing.

Action network errors occur when individuals incorrectly *use* or activate their contacts to relay messages to someone with whom they perceive to be connected. More formally, they refer to unintentional deviations from achieving the goal of sharing information or queries with someone to whom they are only indirectly connected via their social network and where this deviation was potentially avoidable. Until recently, action network errors have garnered less attention from social network researchers than cognitive network errors have. A couple of exceptions are Killworth and his colleagues (2006) and Singh and his collaborators (2010).

Killworth et al. (2006) found that 50% of information sharing activities in a bureaucratic institution are not optimal, compared to the expected shortest path. In other words, employees frequently make action network errors as they engage in an information sharing task. Similarly, Singh et al. (2010) demonstrated that women and those with lower tenure and poor connectedness are more likely to commit action network errors regarding access to information than well-connected male employees with longer tenure. Aside from these studies, social network research has generated a relatively scant understanding of action network errors. In addition, research on organizational errors calls for a further understanding of action network errors as interpersonal errors (Bell & Kozlowski, 2011).

Overall, it is still unclear how cognitive and action errors play a role in information-sharing failures. This is especially important because, even though both cognitive and action errors matter in terms of information sharing consequences, the distinction between these two dimensions of network errors has not been made clear. As a result, we have little knowledge of how cognitive and action network errors impact the consequences of information sharing through network contacts given processing errors.

CONCEPTUAL FRAMEWORK OF NETWORK AND PROCESSING ERRORS

Here, I review the antecedents, consequences, and moderators within an overarching conceptual framework of processing errors, cognitive network errors, and action errors (see Figure 2-2). The framework integrates existing evidence regarding antecedents, consequences, and error management.

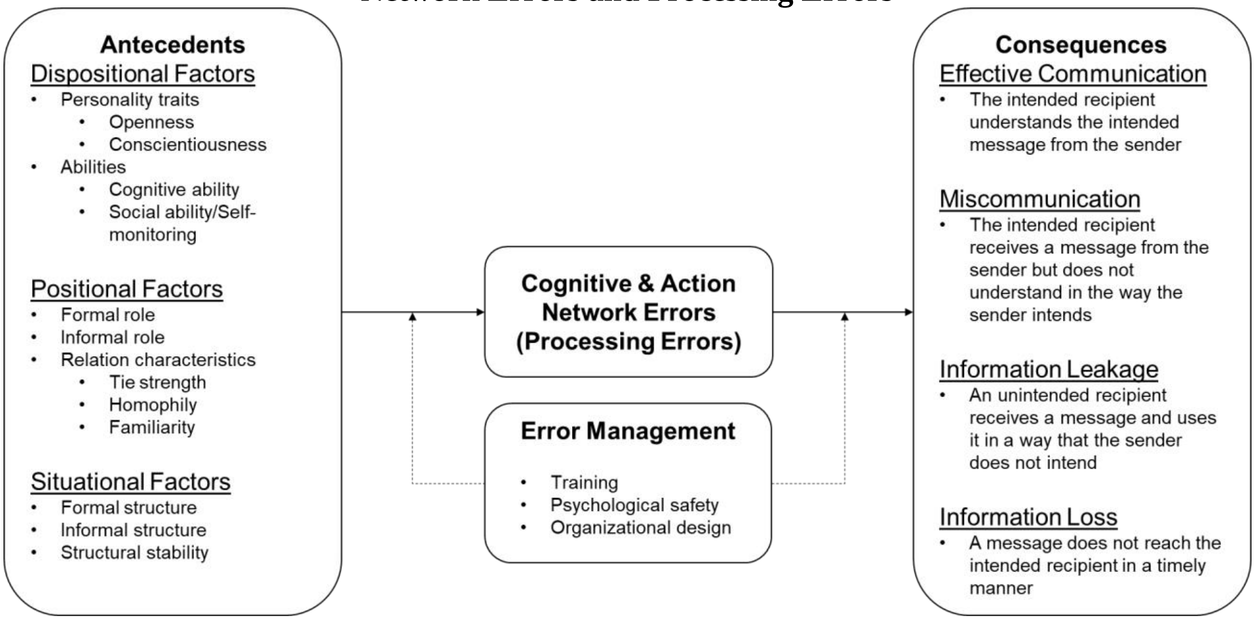
This framework extends previous approaches in three ways. First, my framework considers both cognitive and action network errors. As discussed above, network research has predominantly focused on cognitive errors (Brands, 2013), while research on organizational errors has mainly investigated action errors (Frese & Keith, 2015). I argue that the integration of both types of errors is essential to advancing our understanding of information sharing failures since cognitive and action errors have intertwined effects on communication consequences. Thus, this framework allows us to unpack these intricate effects.

Second, my framework focuses on information sharing rather than other types of organizational phenomena (*e.g.*, coordination, organizational effectiveness, and organizational safety). This focus corresponds to a call for understanding information sharing failures in teams and organizations (Crowther, 2014; Mesmer-Magnus & DeChurch, 2009; Schippers et al., 2014). For example, Mesmer-Magnus and DeChurch (2009) point out that "teams fail to share information when they most need to do so" (p. 544). This framework enables me to address how this failure occurs from an error perspective.

Finally, because of this focus, the framework is also distinct from the knowledge-sharing errors in transactive memory systems (TMS) proposed by Hollingshead and colleagues (2011). In my framework, I focus on network-related errors associated with "who knows whom" and "who knows who knows whom." In contrast, Hollingshead et al. (2011) focused on errors associated with "who knows what" in TMS, not "who knows whom." Therefore, my framework complements their conceptual framework by investigating an additional error associated with TMS.

I next examine the consequences of processing errors, which include cognitive errors and action network errors. Then, I identify the antecedents of these errors. Finally, I discuss the ways in which learning can prevent these errors (*i.e.*, error management).

Figure 2-2. Conceptual Model of Antecedents and Consequences of Cognitive and Action Network Errors and Processing Errors



CONSEQUENCES OF NETWORK AND PROCESSING ERRORS

In this section, I turn to a discussion on how processing and network errors impact organizational outcomes. Particularly, I focus on information-sharing outcomes in groups and organizations.

Table 2-1 depicts my typology of information sharing outcomes based on network and processing errors. The consequences in the framework are aligned with existing work. For instance, Lingard et al. (2004) defined a communication failure as “an event that was flawed in terms of one or more of these rhetorical factors.” In other words, they categorized a communication failure based on errors. I extend this notion to identifying four types of consequences.

First, effective communication refers to successful information processing in which the intended information reaches the intended recipient, and the recipient accurately comprehends the intended information. This is an ideal information-sharing outcome. The second communication outcome is miscommunication, which refers to an unintended consequence in which information reaches the intended recipient, yet the recipient does not comprehend the information in the way that the sender intends. Third, information leakage refers to sharing information with unintended recipients (Anand & Goyal, 2009). Specifically, information reaches the unintended recipient, and the recipient then uses the information in ways unintended by the sender. The final outcome is information loss, which refers to losing a portion of the information during the transfer between a sender and an intended recipient due to network and processing errors (Bae & Koo, 2008). In other words, the information does not reach the intended recipient, and as a result, the recipient does not receive the information.

Table 2-1. A Two by Two Matrix of Network and Processing Error Consequences

<table>
<tr><td colspan="2" rowspan="2"></td><th colspan="2">Network</th></tr>
<tr><td>Accurate</td><td>Error</td></tr>
<tr><th rowspan="2">Processing</th><td>Accurate</td><td>Effective Communication
Information reaches the intended recipient, and the recipient accurately comprehends the intended information.</td><td>Information Leakage
Information reaches the unintended recipient, and the recipient uses the information.</td></tr>
<tr><td>Error</td><td>Miscommunication
Information reaches the intended recipient, yet the recipient does not comprehend the information in the way that the sender intended.</td><td>Information Loss
Information does not reach the intended recipient, and as a result, the recipient does not receive the information.</td></tr>
</table>

Effective Communication

Not all errors necessarily lead to miscommunication, information leakage, or information loss. Rather, in spite of errors in information sharing, communication is usually effective, meaning that the intended recipient receives and understands the intended message from the source in group and organizational settings. For example, despite processing errors that lead to altering the content, the intended recipient might be able to comprehend the intended message from altered content. Or, when information goes to the wrong person (*i.e.*, a network error), that person often gets back to the sender to correct the destination. That being said, despite processing and network errors, information sharing often results in effective communication.

Miscommunication

Miscommunication is a prevailing information-sharing consequence. It emerges primarily from processing errors, not network errors. For example, Brashears and Gradstone (2016) conducted an experiment in which participants passed text messages through the predefined chain of contacts, similar to a telephone game. They found that processing errors accumulated as messages passed through a network, and message formats impacted the error rate when longer messages were more likely to preserve their meaning than shorter ones. They suggested that these results indicated that the redundancy of message content was key in preventing miscommunication, and digital communication may increase miscommunication due to shorter message formats (*e.g.*, Twitter). Other studies have also suggested that digital communication can raise the chance of miscommunication, due to processing errors between a sender and recipient, due to egocentric interpretations (Kruger et al., 2005), and emotional misjudgment (Byron, 2008).

Information Leakage

These days, information leakage has been an enormous concern for firms. In corporate information leakage, employees play a considerable role in spite of other factors, such as technological security and corporate governance (Wong et al., 2019). According to a Verizon report (Verizon, 2020), 10% of cybersecurity threats come from human errors, such as misdelivery. Employees accidentally share sensitive information with those who are not supposed to receive it. That is, employees commit an action network error by sending information to the wrong person. This type of accidental mistake has been increasingly prevalent in digital communication since technology enables us to easily share information with anyone in the world. Hence, network errors have become an increasingly significant issue in organizations.

Information Loss

Information loss is another undesired outcome of information sharing. It often impacts the quality of decision-making and organizational dysfunction—and, at worst, leads to accidents. Information loss is characterized as a result of network and processing errors when information does not reach the intended recipient; in other words, it is “the portion of knowledge lost during the transfer process” (Bae & Koo, 2008, p. 229). This often results in communication breakdowns across organizations. The authors specifically articulate the case of information loss due to processing errors. That is, information loss takes place “because persons do not always understand fully what others say, nor express clearly what they know” (p. 230). However, they do not pay attention to information loss due to network errors, even though they consider how senders and receivers evaluate their social relations for information transfer.

As Ghosh and Rosenkopf (2015) claimed, information loss occurs due to network errors in addition to processing errors. The authors assigned the term “friction” to the phenomenon in which information does not always go through a network connection. As an example of friction, 78% of letters did not reach the intended destination in a small-world experiment (Travers and Milgram, 1978). Moreover, Bryon and Landis (2020) argued that cognitive network errors play a crucial role in information loss, due to network errors, since people often think they relay information to their intended recipient. But in reality, they do not; cognitive network errors are a source of friction between people for "why people … fail to share knowledge with people who could use it (*e.g.*, people who they overlook as friends)" (p. 229). Thus, cognitive network and action errors can both lead to information loss.

Dilemma among Consequences

Even though every organization ideally obtains effective communication in information sharing, it is almost impossible to achieve, given our human cognitive limits and behavioral tendencies. In other words, processing and network errors are unavoidable. Thus, organizations face dilemmas of which unintended consequence they accept, because if they minimize one error, they increase the risk of the other type of error.

There is a dilemma, for instance, between information leakage and loss. To minimize information loss, organizations decompartmentalize silos of information. In the case of the Space Shuttle Challenger incident, two engineers experimented and found that O-rings did not properly work under a certain temperature, yet the evidence never reached the management who made the final launch decision (Presidential Commission, 1986). This exemplifies how tight security and control can sometimes backfire in terms of information sharing. However, by loosening tight information controls, they increase the risk of information leakage. Although information leakage is mainly a thread for firms, it also has unintended consequences, such as inventions. Consequently, it generates a dilemma: For instance, "knowledge sharing among R&D alliance partners can both benefit the focal firm with access to external knowledge and skillsets and expose it to potential risks of knowledge leakage and misappropriation" (Zhang et al., 2019, p. 2635). In other words, this is another version of the dilemma between a "need to know" paradigm and a “need to share” network culture (Dawes et al., 2009), as we discussed above. Hence, organizations need to balance this trade-off.

Similarly, effective communication and miscommunication also present a dilemma. Although not all miscommunication results in organizational outcomes, miscommunication is hugely problematic in the group and organizational contexts since it is the origin of many tragedies. While most studies suggest that miscommunication leads to adverse outcomes, few studies and anecdotal evidence show unintended positive consequences of miscommunication, such as innovative ideas and breakthroughs (Frese and Keith, 2015). For example, sucralose, an artificial sugar substitute, was discovered due to a miscommunication between two scientists. When Leslie Hough and Shashikant Phadnis were searching for new uses of chlorinated sugars, Phadnis was told to “taste” a chlorinated sugar compound. To be clear, Phadnis thought Hough asked him to “taste” it instead of “test,” so he did. He found the compound to be exceptionally sweet by “testing” it (Gratzer, 2004, p. 32). This example illustrates that miscommunication is unintended but not necessarily undesirable for some contexts. Thus, whereas effective communication is the desired outcome for most cases, miscommunication can sometimes produce a positive consequence.

In sum, since errors are unavoidable, organizations need to determine to what extent they manage each error, taking into consideration their goals and the implications of errors and communication outcomes. To mitigate errors in communication networks, we need to understand what factors can lead to processing and network errors. In the following section, I focus on cognitive and action network errors, and I specifically discuss the underlying factors of network errors and their management strategies.

ANTECEDENTS OF NETWORK COGNITIVE AND ACTION ERRORS

Based on the literature review, I identify three types of antecedents for cognitive and action network errors: (a) dispositional, (b) positional, and (c) situational factors. I arrange antecedent factors from micro to meso to macro levels. Even though the different levels of factors are interrelated with each other, I argue that understanding each level of factors clarifies current frontiers and future directions of cognitive and action network errors. Thus, I next discuss how each type of antecedent factor affects cognitive and action network errors.

Dispositional Factors

Human errors are generally committed by individuals. Each individual has innate traits and abilities that encompass individual tendencies to act in a particular way (*e.g.*, personality traits and abilities). Here, I call them dispositional factors. Research has shown that dispositional factors play an essential role in errors (Lei et al., 2016). For instance, the Big Five personality traits and abilities are, in general, predictive of committing errors. Based on this notion, I discuss how personality traits and abilities have a significant effect on cognitive and action network errors.

Personality Traits

Personality traits are some of the dispositional factors that affect network errors. The Five-Factor Model or Big Five consists of (a) openness to experience (openness), (b) conscientiousness, (c) extraversion, (d) agreeableness, and (e) neuroticism (Goldberg, 1993). A meta-analysis study indicates that low conscientiousness and agreeableness are associated with work accidents in which individuals are involved in organizations (Clarke & Robertson, 2005). Errors are no exceptions. In their review paper, Lei and her colleagues (2016) identify that personality traits, such as openness and conscientiousness, are moderators of how individuals successfully learn from error training. Moreover, a systematic literature review of the relationship between personality traits and social networks finds that personality has a significant impact on personal network size and structure, even though its effects are not yet conclusive across different studies (Selden & Goodie, 2018). Although all the traits can impact network errors, prior research on organizational errors has shown that openness and conscientiousness have a particularly high association with errors. The prior work has not focused on network errors. Therefore, I discuss below how these two traits—openness and conscientiousness—can impact network errors.

Openness is an individual trait of intellectual curiosity and imagination. Gully et al. (2002) reported that high openness is related to high effectiveness in error-encouragement training when subjects are encouraged to commit errors. By contrast, Naveh and his colleagues (2015) found that people with high openness commit fewer errors than ones with low openness in a low learning environment, while the opposite relationship occurs under a high learning circumstance. As noted in the study by Naveh et al., their finding was contrary to that of Gully et al. (2002), and the expectation was that more open individuals make fewer errors in an environment that emphasizes error-making. This is because more open individuals tend to be training-ready and willing to learn from experiences (Naveh et al., 2015). Hence, these findings suggest that high openness can be related to cognitive and action network errors.

Conscientiousness is also relevant to network errors. It is a characteristic of individuals who are disciplined and diligent (McCrae & John, 1992). Specifically, to accurately perceive a network, people need to diligently observe and learn “who talks to whom” not only regarding “to whom they talk" but also "to whom others talk." As prior studies indicate (Brashears & Quintane, 2015; Janicik & Larrick, 2005), observing and learning a social network are not easy tasks. They require diligent and thorough observation. Accordingly, conscientiousness is an essential trait to fulfill this requirement. For instance, Colquitt and Simmering (1998) demonstrate that conscientiousness is related to the rate of learning for individuals. Because developing network awareness requires careful observation and learning, I expect that high conscientiousness plays a crucial role in making fewer cognitive network errors.

In addition to how people perceive their networks, conscientiousness has been shown to be related to how people use their networks. Anderson (2008) suggested that high conscientiousness can also be key in effectively gathering information in organizations since it enables them to search their network more diligently and thoroughly. Lee et al. (2010) reported that conscientious people are more likely to be seen as effective network mobilizers by their colleagues. Thus, I expect high conscientiousness to be related to low cognitive and action network errors.

Abilities

Individual abilities are also vital dispositional characteristics in explaining network errors. I focus on two types of abilities: cognitive and social. Cognitive ability is the individual capacity to process information, whereas social ability is related to an individual ability to understand social situations. Research suggests that these two constructs are distinctive (Goleman, 2006). While cognitive ability is strongly linked with intellectual capability (*e.g.*, working memory and computation speed) (Kanfer & Ackerman, 1989), social ability is based on the notion of mind-reading in social settings, which is also known as theory of mind (Baron-

Cohen et al., 2001). I argue that both abilities affect cognitive and action network errors through different mechanisms.

Storing and using social information regarding “who knows whom” is a cognitively intensive task for humans. Research on Cognitive Social Structures (CSS) suggests that people cannot remember every dyadic relation, even in a small, 15-person network (Brashears & Quintane, 2015). Consequently, memory capacity plays an essential role in the accuracy of network cognition. For example, Stiller and Dunbar (2007) report that cognitive ability measured by a short-term memory task is positively associated with the size of a social group in which an individual interacts during a given time. They explain that, to maintain social contacts, individuals need to perform a network recall; therefore, it is crucial to have certain cognitive capabilities to remember prior social interactions. Thus, I predict that high cognitive ability is related to fewer cognitive network errors.

Similarly, small-world experiments have pointed out that human navigation of social and information networks requires high cognitive ability (Adamic & Adar, 2005). Since networks encompass complicated structures, it is not easy for people to navigate complex networks. Nevertheless, high cognitive ability can help people understand and quickly process their complex environments. Thus, I expect that those with high cognitive ability are more likely to navigate a social network effectively than those who are low on cognitive ability.

Recently, *social ability* has garnered attention from scholars. Based on social capital literature, Kuwabara and his colleagues argue that a malleable mindset toward networking fosters the social ability of individuals and, more broadly, builds a diverse network structure. Self-monitoring is one of the social ability measures, referring to how much people are aware of their self-presentations, expressive behavior, and nonverbal affective displays (Snyder, 1974). It is a powerful predictor of an individual's career success, partly because individuals who are strong self-monitors tend to end up in desirable positions in social networks (Fang et al., 2015). Research has shown that self-monitoring is correlated with brokerage positions (Oh & Kilduff, 2008; Sasovova, Mehra, Borgatti, & Schippers, 2010) and fewer cognitive network errors (Flynn et al., 2006).

Additionally, self-monitoring is related to the ease of social interactions. Specifically, strong self-monitors are more likely to have solid social skills than poor self-monitors (Furnham & Capon, 1983). Their social skills allow them to navigate the social world easily. Thus, I expect that high self-monitoring is associated with low network errors.

Positional Factors

Positional factors are based on relational characteristics rather than an individual's innate dispositional characteristics. Relational characteristics could be based on formal and informal roles in a group and organization. Roles are related to positions: namely, where a person is in the network. Thus, positional factors refer to a person's location or role in the informal or formal network, or to the characteristics of their relationship with others. I discuss three types of positional factors: formal role, informal role, and relational characteristics.

Formal Role

In groups and organizations, members are generally affiliated with assigned roles, such as managers and specialists. These assigned roles are an essential factor in information sharing because they determine how information flows within the group or organization.

Formal roles usually reflect the prior experience and qualification of members in groups and organizations. These characteristics influence how information flows through formal positions. According to Morrison (1993), new employees seek information from both their peers and managers, and they rely more heavily on their boss for technical information than their peers. That is, the existence of formal roles based on prior experience makes employees change their information-seeking and sharing behavior. This can lead employees to misjudge to whom they need to reach out.

Expertise is also associated with formal positions. Individual expertise impacts the occurrence of individual errors. For example, based on observation of human-computer interactions in 12 different companies, Prümper and collaborators (1992) illustrate that, although novices are more likely to commit knowledge errors related to a lack of relevant knowledge than experts, they tend to make fewer habit errors (*i.e.*, correct actions that are performed in the wrong situations) than experts. This is because experts rely heavily on routinized actions with limited attention (Lei et al., 2016, p.1320).

Marineau et al. (2018) posited that this phenomenon occurs in cognitive network errors as a result of power. People in formal roles of power commit errors because of "inattentiveness or employing automatic processing to rely on cognitive maps that are not updated frequently" (p. 146). Pfeffer (1994, p. 69) mentioned that power comes from being in the "right" place. CSS studies have shown a negative association between power and accuracy in perceiving the whole network of relationships in an organization. For instance, in his field study controlling for formal power, Krackhardt (1990) found no significant relationship between being a manager and the cognitive network errors of advice and friendship ties. Casciaro (1998) argued that individuals in higher hierarchical positions have a greater interest in and access to work-related ties (such as advice ties) than friendship ties. However, in her field study, she found that power is positively related to cognitive network errors in both friendship and advice networks. In an experimental study, Simpson et al. (2011) posited that individuals primed to experience low power would make fewer errors when learning social networks than high-power individuals. They found that high- and low-power participants do not differ statistically when considering only ties that are present, but low-power participants are more accurate about absent ties. Thus, even though the evidence is somewhat mixed, these studies suggest that power has some influence on how individuals perceive social information, specifically when it comes to social networks. Overall, powerful individuals make more cognitive network errors than low-power individuals.

Informal Role

Because each member of a group and organization has unique dispositions and interactions with others, informal roles emerge from these interactions, which are usually different from formal roles. Social network research has illustrated that informal roles are as important as formal roles (Cross & Parker, 2004). It measures informal roles based on network positions through centrality scores. Prior research has shown that the structural positions of individuals (*e.g.*, centrality) dictate their behavior (Burt et al., 2013). Here, I focus on two informal roles, such as popularity and brokerage, since these two roles seem to have particularly strong connections with cognitive and action network errors.

Popularity is one of the informal positions in social networks. Popularity is defined as a position in which individuals are nominated by many others in the network. Krackhardt (1987) found that those who are more popular in the network tend to have accurate perceptions—fewer cognitive network errors—of the friendship network, compared to those located in the periphery. This is because the popularity position provides them with more opportunities to observe “who is connected to whom” in the network. Similarly, Bondonio (1998) and Casciaro (1998) report that popularity is positively associated with fewer cognitive network errors.

Furthermore, popularity influences action network errors. While small-world research has shown that a high-degree strategy—sending a letter to popular people—is not as effective as sending to non-popular individuals to complete a small-world task (Adamic & Adar, 2005), I argue that popular people can navigate their network effectively, even though they may not always be able to send all the messages, sometimes due to information overload. Note that I differentiate between sending to popular individuals and popular individuals sending to others here. Consequently, I expect that a popularity position enables people to commit fewer cognitive and action network errors.

Brokerage is a network position in which individuals occupy a conduit location between others in their network. In other words, members rely on those who occupy a brokerage position to serve as intermediaries in the flow of information. Research has shown that this brokerage position is positively associated with individual outcomes (such as creativity and career success) because it enables the access and facilitation of diverse and novel information (Burt, 1992). These advantages come, in part, from their network awareness. For instance, Krackhardt (1987, 1990) showed that brokerage is positively correlated with the accuracy of a friendship network. As a result, individuals in brokerage positions gain informal power by making fewer cognitive network errors.

Moreover, because of their positions, brokers tend to not only perceive their network accurately but also use their network effectively. They have a so-called vision advantage where they can observe “who talks to whom” in different parts of the network (Burt, 1992). This vision advantage is particularly crucial in a small-world task in which people need to send packages to contacts who are in different communities from the previous senders to reach the final destination (Dodds et al., 2003; Milgram, 1967). Hence, I posit that brokers will be better at sharing information.

Relational Characteristics

The nature of relations between a sender and recipient also impacts the likelihood of cognitive and action network errors. According to social network research, three relational characteristics are key in information sharing: (a) tie strength, (b) homophily, and (c) familiarity.

Tie strength that captures the extent to which the relationship between two individuals can be characterized on a spectrum from close friends to acquaintances to strangers. Granovetter (1973) demonstrated that acquaintances possess more useful information for job search than close friends because acquaintances tend to hold new information that is not shared among close friends. Subsequent studies have confirmed this notion of “the strength of weak ties” in which acquaintances (*i.e.*, weak ties) bring more new and useful information to job seekers than close friends (*i.e.*, strong ties) (Burt, 1992; Montgomery, 1992). More recently, Brashears and Quintane (2018) theorized the notion of “weak” ties with three dimensions: capacity, redundancy, and frequency. The capacity of a tie refers to “the amount of information that a tie can transfer” (p. 107), redundancy refers to the extent to which people can reach out to the same individual using different pathways, and frequency represents how often a tie is used during a given time. In an empirical analysis of email communication among employees at a company, the authors showed that redundancy has a significant and positive correlation with capacity and frequency, though capacity and frequency are not correlated. This suggests that people reach out to others using different pathways that are high capacity and frequently used, and they often use pathways that are not capable of reliable information transfer. For instance, a global small-world experiment by Dodds and colleagues (2003) showed that frequently used pathways are less likely than weak ties to be in successful message chains. Hence, tie strength impacts whether people can share information with the *right* person based on their contacts' capability (*i.e.*, network errors).

Homophily is the principle of "birds of a feather flock together." In other words, it is a relational characteristic ascribing similarity between two individuals on some attribute. For example, those of similar gender, political belief, or expertise are more likely to be connected with each other than those who differ. This is one of the most consistent findings in social networks (McPherson et al., 2001). Based on a small-world experiment in a company, Singh, Hansen, and Podolny (2010) report that employees tend to gather information from those who are similar to them, even though these people are not the optimal sources to contact for information. More specifically, employees are more likely to seek those who share the same characteristics (*e.g.*, connectedness, tenure, and gender), irrespective of whether the search is effective. As a result, this homophily search leads to action network errors.

In addition to tie strength and homophily, another relational characteristic is *familiarity* between two people. Familiarity is the extent to which two people spend time together. Unlike tie strength, which characterizes the quality of the relationship, familiarity characterizes the quantity of the interactions. The more individuals work together, the more likely they are to infer what the other does. Having said that, people tend to infer the content of messages that they receive from familiar individuals. This familiarity effect can increase the chance of committing cognitive network errors when they process information with little attention. This is because people develop habitual routines when they work together over time. As a result, they pay less attention to their interactions (Gersick & Hackman, 1990). Familiarity also influences action network errors. For instance, Sieweke and Zhao (2015) reported that there is an inverted U shape relationship between familiarity and coordination errors within National Basketball Association teams. This result demonstrates that, once a team develops habitual routines, network errors increase among teammates. Accordingly, familiarity leads to action network errors when people share information.

Situational Factors

Situations play a significant role in organizational errors. Because each employee is embedded in an organization, organizational rules and structure have a considerable impact on how each acts in the organization (Goodman et al., 2011). This chapter focuses on the structural aspects of situational factors.

Formal Structure

Formal structure, such as organizational charts and task units, exists in organizations. It usually determines the information flow of organizations. Allen and Cohen (1969) reported that most technical information sharing aligns with workgroup structure within a research laboratory. Also, members of an organization follow procedural requirements. For instance, subordinates must report task progress to a designated supervisor or manager on a regular basis in organizations. Subsequently, the supervisor needs to provide updates to the top management level. This chain of command is procedural, meaning that deviations from it are a violation, not an error. However, the procedure can also include errors. For example, engineers discussed the potential risk of technical issues during a meeting before the Space Shuttle Challenger's launch, but a senior NASA manager unintentionally missed the meeting. As a result, engineers assumed that the senior manager knew about the issues, but he was not aware of them, which led to the root cause of the accident later. Formal structure tends to endanger cognitive network errors when people think they share information with an intended recipient, but in reality, they do not. This type of error is difficult to avoid when there is an event (*e.g.*, a formal meeting) in which people do not often meet each other, and a number of people attend because they have a lack of understanding of who needs information and who is at the meeting (*i.e.*, ambiguity for the intended recipient).

Furthermore, many modern organizations are based on a top-down pyramid structure in which all the information goes to the leader (*e.g.*, CEO) of the organization. While the advantage of this structure is that members know where to seek and share information, the problem is that information is always gathered towards the top. As a result, the structure often generates information overload (Huber, 1982; Oldroyd & Morris, 2012). Thus, there is a trade-off between fewer network errors and information overload in setting a formal pyramid structure. Taken together, the formal structural relationship between two individuals increases the chance of action network error.

Informal Structure

Despite the existence of formal structure in groups and organizations, informal structure always emerges from interactions and communication between members. In my discussion of relational characteristics in a previous section, I focused on informal ties among pairs of individuals influencing an individual's network errors. Here, I focus on the effect of the overall informal network's structure on shaping network errors. In particular, when members of an organization face a high degree of task uncertainty, they tend to engage in informal networks rather than formal networks (Van De Ven et al., 1976). Because of the nature of emergence, informal structure often creates unintended network patterns, such as centralized and decentralized structures. Bavelas and his research group conducted network experiments in which participants solved a puzzle as a five-person group in different network structures. Bavelas (1950) and Leavitt (1951) reported that centralized networks (*e.g.*, a person in the center is connected to the other four who do not have connections among each other) had faster task completion times with fewer errors—specifically regarding completion switches, which participants pressed when they completed a task—and fewer message exchanges than decentralized networks (*e.g.*, all the people are fully connected to each other), even though each participant was less satisfied with the task. However, Shaw (1964) showed that, in complex tasks (compared to a simple task in Bavelas-Leavitt's experiment), decentralized structures performed better in terms of time, errors, and participant satisfaction, although the number of messages was still fewer than in centralized structures.

Centralized networks can prevent members from learning and developing "who knows whom" and "who knows what." Within centralized networks, the structure of communication networks hinders members from directly interacting with one another, except via the one who is in the star position. As a result, this type of communication network requires certain members to relay information to others. This limited number of communication pathways also prevents members from learning "who knows whom" and "who knows what," which in turn prohibits the development of a shared mental model (Argote et al., 2018). Consequently, depending on their network locations and task types, members make higher or lower rates of network errors in centralized and decentralized network structures.

Structural Stability

Both formal and informal structures play an essential role in information sharing, yet these structures are not stable in groups and organizations (Edmondson, 2004). Instead, they are usually quite dynamic, and the dynamic structural change impacts network errors in organizations for two primary reasons: restructuring and turnover. *Restructuring* is an organizational determination of a reinvented structure of work and organizational practices, including relocation (Hirsch & Soucey, 2006). It is often used to change formal structures in organizations. For example, using the internal audit data of a banking institution, Ramanujam (2003) found that changes including structure in units increase the chance of latent errors, which refer to deviations from procedures and policies that may have adverse consequences of organizational significance. I argue that this structural change also impacts cognitive and action network errors because members of an organization must adjust their mental model and routine habits per the change.

The other reason is *turnover*. It is common that members of a group change by quitting and adding. Turnover is generally a much more spontaneous and individual action than restructuring because members themselves decide it. This membership change significantly impacts communication patterns since members of a group develop the patterns over time and space. For example, Argote and her colleagues (2018) demonstrated that membership turnover is more likely to increase group-level errors in fully connected groups than in centralized groups. This is because members in centralized groups rely on dyadic communication to develop transactive memory systems. After membership turnover, they increase the frequency of dyadic communication more than those in fully connected groups. This difference leads to a number of errors between the two group conditions. Particularly, people tend to make fewer cognitive errors in centralized groups than in fully connected groups, due to the limited number of pathways. Therefore, the effect of turnover on network errors in groups is larger for fully connected groups than for centralized groups.

ERROR MANAGEMENT

The literature review of organizational errors enables me to identify three strategies (*i.e.*, training, psychological safety, and organizational design) that affect how people manage and reduce future errors over the course of an activity by learning from their past errors. I argue that, like other types of errors, network errors are also preventable and manageable. Error management involves “coping with errors to avoid negative error consequences, controlling damage quickly (including reducing the chances of error cascades), and reducing the occurrence of particular errors in the future (secondary error prevention)” (Frese & Keith, 2015, p. 665). It is critical, given that errors inevitably occur in tasks involving humans. Information sharing is no exception, and it is notoriously difficult not to make any errors (Bell & Kozlowski, 2011). Error management in information sharing is particularly challenging because of causal identification issues. For instance, it is often unclear who originated an error and how the sequence of error events unfolded between a pair of individuals while they were communicating. Despite these challenges, the importance of identifying effective error management strategies remains. This is because it helps mitigate the risk of network errors that can lead to unintended consequences. Therefore, I review three common methods for error management that can overcome these challenges associated with network errors.

Training

Training is designed for individuals to learn how to execute tasks. It typically occurs before errors happen and includes strategies to manage errors when they happen. Training generally induces learning or uses learning as a mechanism. Different types of training are designed based on learning styles. There are two types of learning in error training: (a) error *avoidance* training (EAT) and (b) error *management* training (EMT) (e.g., Bell & Kozlowski, 2008). Keith and Frese (2005) differentiated them as error avoidance and management training. On the one hand, EAT focuses on preventing individuals from committing errors. On the other hand, EMT emphasizes how individuals make errors during training and use them as learning exercises. As a result of EMT, individuals can enhance their capability to cope with errors. EMT also provides individuals with opportunities to make errors and to receive feedback on tactics to avoid repeating errors. This training process is necessary for network errors. For instance, Liang, Moreland, and Argote (1995) show that group training improves task performance, thereby increasing coordination of “who knows whom” and “who knows what” within a group, compared to an individual training condition in which an individual needs to join a newly formed group. Thus, the ability to learn from errors during training enables individuals to actively develop a mental map of “who knows whom” and, in turn, reduce action network errors.

Through training, organizational members also learn about a set of rules and strategies for organizational communication. These rules and strategies prevent an error of processing or networking from information sharing failures. For instance, to avoid both network and processing errors, many organizations have fixed formats of reporting for critical issues (Weick & Sutcliffe, 2007). Particularly, through engaging in training, people can learn by doing. Learning by doing leads members to learn and internalize these rules or standards. Consequently, training enables members to reduce the risk of making network errors in the first place and to correct them by learning, even if they make errors.

Hence, at the individual level, training is a primary tool for error prevention and management. This tool alleviates the risk of network errors leading to negative communication outcomes.

Psychological Safety

Psychological safety is a concept in which members of a group share their belief in safety for interpersonal risk-taking (Edmondson, 1999). This concept has been found to be one of the most significant factors in predicting and learning from errors (Edmondson & Lei, 2014) and explains why members of an organization share knowledge and information (Collins & Smith, 2006). Therefore, I argue that psychological safety is a catalyst for both antecedents and consequences of network errors; it affects the extent to which people report and learn from network errors.

One of the main concerns about network errors in organizations is error reporting. This is because network errors have an interpersonal nature—errors require at least two people. Prior research has shown that people tend to hide errors because of negative feelings associated with errors (Edmondson, 2004). This tendency can be stronger in interpersonal contexts. As a result, psychological safety plays a crucial role in reporting network errors.

The second point is learning from network errors. For error learning, psychological safety is necessary. Particularly, learning from network errors requires a safe space because the nature of network errors is interpersonal. For example, Dahlin et al. (2018) stated, “when the environment is ambiguous and changing, team information processing becomes complicated, which hampers learning” (p. 255). Besides, as sharing information of errors is not a part of existing group routines (Lawton et al., 2012), or members of a group do not have enough autonomy to collect critical information (Kerr, 2009), learning may not occur. Thus, establishing psychological safety to share error information within a team is critical to reduce cognitive and action network errors and mitigate their impact by learning from them.

Organizational Design

At the macro level, organizational design is essential to mitigate the rate and impact of network errors. Organizational error literature, in particular, has studied high-reliability organizations (HROs), such as naval aircraft carriers, air traffic control systems, and nuclear power plants. HROs are characterized by the mindfulness infrastructure that enables them to operate as adaptive organizational forms (Weick et al., 1999). This mindfulness infrastructure consists of (a) preoccupation with failure, (b) reluctance to simplify interpretations, (c) sensitivity to operations, (d) commitment to resilience, and (e) deference to expertise. These characteristics become particularly salient when faced with unexpected situations. For instance, many HROs follow a typical communication hierarchy during routine operations but defer to the person with the expertise to solve the problem during upset conditions. During a crisis, decisions are made at the front line, and authority migrates to the person who can solve the problem, regardless of their hierarchical rank. This means that formal roles and the line of command change by organizational design.

Additionally, recent HRO research has underscored mindful organizational culture where collective errors, including network errors, can be avoided through individual and collective vigilance that helps create robust yet flexible processes (Weick & Sutcliffe, 2007). In particular, the mindful organizational culture can be achieved by cultivating four subcultures: reporting culture, in which people share their accounts of what goes wrong; just culture, in which organizations treat people fairly; flexible culture, in which organizations determine authority and decisions independently of a hierarchy; and learning culture, in which people increase their capacity by sharing information.

Relatedly, the main argument of the mindful organizational culture in HROs has a strong connection to error management culture (EMC) in the organizational error literature. EMC refers to norms and common practices that encourage error detection, communication, analysis, and quick correction at the organizational level (van Dyck et al., 2005). Notably, van Dyck and colleagues asked their participants about the types of errors they think of when they respond to the survey. The types of errors included misplacing a finished product, ordering wrong supplies, mis-planning and mis-budgeting a project, and not sharing a piece of information. The researchers found that companies that have a culture to positively manage these errors perform better than companies that do not. Thus, I posit that network errors can be reduced by cultivating organizational efforts to develop a mindful organizational culture.

CONCLUSION

This chapter has offered three main sets of conclusions by developing a conceptual framework for cognitive, action network, and processing errors in communication networks and identifying their antecedents, consequences, and error management. First, my framework clarifies how different dimensions of factors affect cognitive and action network errors, as well as how these errors impact information sharing outcomes and what error prevention and management strategies can play a moderating role in the relationship. Since information sharing problems are prevalent yet often consequential, I believe that this framework opens new directions for future research to solve theoretical and practical problems of errors in communication networks.

CHAPTER 3. ERRORS OF OMISSION AND COMMISSION IN GROUP COMMUNICATION NETWORKS

For groups to perform effectively, members need to know “who knows whom” and “who talks to whom.” This is because people act based on their *perception* of “who knows whom,” rather than “who actually knows whom” (Kilduff & Krackhardt, 2008). Yet, people often fail to accurately perceive the social structure of relations among members in their groups (Bernard et al., 1979; Bernard & Killworth, 1977; Killworth & Bernard, 1976, 1979). Specifically, the existence of formal structure makes this phenomenon more complicated and leads to unintended consequences. A notable example of this comes from the Space Shuttle Columbia disaster:

> [T]he Mission Management Team failed to disseminate information to all system and technology experts who could be consulted. Issues raised by two Langley and Johnson engineers led to the development of “what-if” landing scenarios of the potential outcome if the main landing gear door sustained damaged [sic]. This led to behind-the-scenes networking by these engineers to use NASA facilities to make simulation runs of a compromised landing configuration. These engineers—who understood their systems and related technology—saw the potential for a problem on landing and ran it down in case the unthinkable occurred. But their concerns never reached the managers on the Mission Management Team that had operational control over *Columbia* (National Aeronautics and Space Agency, 2003, p. 169).

From my perspective, two things are particularly relevant in this quote. First, the report reveals that there was an assumption of a communication channel between the managers and engineers, but in reality, there was none. Second, until the report came out, the managers did not know that the two engineers—who were located in different locales while being in the same functional unit—communicated with each other, even though they did. These fundamental problems in perceptions of communication networks led the NASA management team to eventually make a poor decision based on “incomplete and misleading information” (National Aeronautics and Space Agency, 2003, p. 100). How was it possible that a group of managers and engineers misperceived the existence of communication channels?

Prior research demonstrates that misperceptions of the structure of social relations are a root cause of communication errors (Byron & Landis, 2020; Heath & Staudenmayer, 2000; Hollingshead et al., 2011). There are two types of misperceptions. First, people can fail to perceive relations that do exist, leading to *errors of omission*. Second, people can perceive relations that do not exist, leading to *errors of commission*. These misperceptions can reduce the quality and efficiency of information sharing in groups (Hollingshead et al., 2011). For example, as a consequence of omission errors, groups might miss opportunities to leverage untapped communication channels. This underscores the recognition that, to improve group performance, groups need to learn from both types of errors.

Research on misperceptions has suggested that relational schemas—pre-existing expectations about social relations—are key in understanding why and how people make errors of omission and commission (Baldwin, 1992; Brashears, 2013; Brashears & Quintane, 2015). In social networks, relational schemas are used to categorize members of their networks into groups. Although the use of relational schemas helps people accurately store and encode social information with efficiency and generalization (Sun et al., 2021), it might create biases that lead individuals to incorrectly attribute connections among people they group together and incorrectly perceive connections among people not grouped together. Some of the work in social networks shows that people make errors of omission and commission based on the frequency of colloquium attendance (Freeman et al., 1987; Freeman & Romney, 1987), social network patterns (Brashears & Quintane, 2015), and social exclusion (O'Connor & Gladstone, 2015). Despite these studies, it remains unclear why and how relational schemas impact both errors of omission and commission in work contexts where both formal and informal structures exist.

In this paper, I propose a theory of relational schemas explaining why and how formal and informal structures contribute to both omission and commission errors by comparing the actual network (who was actually connected to whom) with the perceived network (who was perceived to be connected to whom). I advance a relational schema model of how members in a network make sense of their communication patterns. Since formal and informal structures significantly influence communication patterns in networks (Monge & Contractor, 2003; Sosa et al., 2015), I seek to unpack the role that formal and informal structures play in the errors made by members when perceiving their communication networks. Results support the theory that there is an accuracy trade-off in using relational schemas to inform perceptions of communication networks.

To theorize the role of formal and informal structure in errors of omission and commission, I aim to make two main contributions. First, this study contributes to the recent advancement of relational schema literature. Although research on relational schemas has long been of scientific interest (Baldwin, 1992; de Soto, 1960; Freeman, 1992; Freeman et al., 1987; Zajonc & Burnstein, 1965a, 1965b), recent studies have theorized and empirically tested more nuanced views of the processes by which schemas shape perceptions of communication networks

(Brashears, 2013; Brashears & Quintane, 2015; Carnabuci et al., 2018; Sun et al., 2021). However, many of these studies were conducted in non-work settings where there was no formal structure. Consequently, they missed the importance of formal role schemas. Additionally, the networks that participants perceived were designed by researchers and hence were imposed and contrived, rather than emerging organically from participants' interactions. Therefore, my study advances this line of research, leveraging a novel context in which members work together for a specific task within formal group constraints. As such, my theoretical and empirical insights are particularly relevant to work contexts.

Second, my research also contributes to our understanding of communication failures in networks, based on the interplay between formal and informal structures. Until recently, the literature has focused on the *streams* of communications through the formal and informal structure rather than *perceptions* of them (McEvily et al., 2014). For example, a NASA investigation report featured communication failures as one of the key causes of the Challenger incident (Presidential Commission, 1986). Yet, history repeated itself when the Columbia accident occurred subsequently. Despite all the structural changes made to mitigate communication failures, based on the recommendations from the Challenger report, the internal report of the Columbia pointed to the same cause: communication failures. To this end, my theory provides an alternative yet powerful explanation for communication failures. That is, the same relational schemas provide reasonable sensemaking aids to perceive the structure of communication networks, yet simultaneously lead people to make specific types of errors. Acknowledging this trade-off helps organizational designers pay closer attention to members' potential errors of omission and commission in their perceptions of the communication network. I discuss these next.

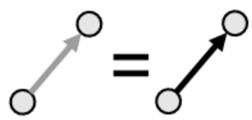
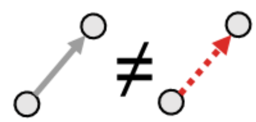
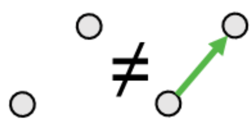
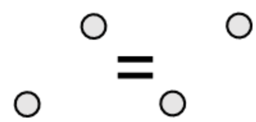
THEORETICAL BACKGROUND AND HYPOTHESES

Errors of Omission and Commission in Communication Networks

I define errors people make in communication networks as errors of omission and errors of commission. I define omission errors as ties that do exist, but that people do not perceive to exist. These are also referred to as Type II errors or false negatives. On the other hand, commission errors are defined as ties that do not exist, but people perceive that they do exist. These are also referred to as Type I errors or false positives.

A series of informant accuracy studies by Bernard, Killworth, and Sailer (Bernard et al., 1979; Bernard & Killworth, 1977; Killworth & Bernard, 1976, 1979) demonstrated that people's perceptions of communication networks are generally inaccurate. In addition to observing communication networks among people in different settings, researchers asked participants to self-report with whom they had communicated. Their results indicated that people's self-reports were at variance with the observed communication behavior patterns. This "informant inaccuracy" in self-reports has appeared repeatedly in social and communication networks (Brands, 2013; Kilduff & Krackhardt, 2008). In addition to inaccuracy in their self-reports of communication with others, people report inaccurate perceptions of communication patterns among others in experimental settings (Flynn et al., 2010; Janicik & Larrick, 2005; Simpson et al., 2011; Simpson & Borch, 2005). Brashears (2013) postulates that even a 15-person network exceeds a person's working memory to remember others' faces and connections.

Table 3-1. The Concepts and Consequences of Accurate Perceptions and Misperceptions

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="2">Perceived Network</th></tr>
<tr><th>A person perceives there is a tie</th><th>A person perceives there is not a tie</th></tr>
<tr><td rowspan="2">Actual Network</td><td>There is a tie</td><td>Accurate:
• a person accurately perceives a tie that exists
Outcome:
• a group has a distributed communication system & people know how to route information
</td><td>Errors of Omission:
• a person fails to perceive a tie that exists
Outcome:
• untapped resource: a group has communication channels that are not used
</td></tr>
<tr><td>There is not a tie</td><td>Errors of Commission:
• a person perceives a tie that does not exist
Outcome:
• breakdown: a group tries to use communication channels that do not exist
</td><td>Accurate:
• a person accurately perceives that no tie exists
Outcome:
• a group has a distributed communication system & people can efficiently route information
</td></tr>
</table>

Note: Actual ties are gray, accurately perceived ties are black, commission errors are green, and omission errors are red and dashed.

Errors of omission and commission in a communication network have palpable potential repercussions. First, when members make commission errors, they assume that network links exist among members who are not connected. This leads them to assume that critical information is being conveyed to or gleaned from certain members when, in fact, it is not. These communication breakdowns can result in costly errors. Second, omission errors lead members to engage in redundant communication because they assume a link does not exist between people when, in fact, it does. This leads to avoidable inefficiencies that impede the group's attempt to accomplish its goals. I summarize my concepts and consequences of omission and commission errors in Table 3-1.

Although it is essential to understand how people develop accurate perceptions of social relations (Casciaro, 1998; Krackhardt, 1990; Michaelson & Contractor, 1992), given the adverse consequences, there is a growing interest in understanding the mechanisms that explain the errors people make. Cognitive research indicates that human beings exhibit systematic error patterns (Freeman et al., 1987; Tversky & Kahneman, 1974), which influence how social networks are structured (Brashears et al., 2016; Brashears & Quintane, 2015). For instance, Freeman, Romney, and Freeman (1987) investigated systematic patterns of omission and commission errors among people participating in university events. They found that the more individuals attended the events, the more likely they were to make commission errors, but the less likely they were to make omission errors. More recently, O'Connor and Gladstone (2015) demonstrated that, in small group networks, social exclusion makes individuals perceive ties that, in fact, do not exist (*i.e.*, commission errors). Further, Brashears and his colleagues conducted a series of network recall experiments with different imposed network structures and found that people use specific memory schemas—compression heuristics—to store and recall information regarding social relations (Brashears, 2013; Brashears et al., 2016; Brashears & Quintane, 2015). Their findings suggest that people make systematic errors as they encode and recall social information.

Recent studies have called for studying both omission and commission errors in work organizations (Byron & Landis, 2020; Krackhardt, 2014; McEvily, 2014). Specifically, Byron and Landis (2020) pointed out that not seeing and incorrectly seeing a network tie between individuals lead information sharing to fail at critical moments. Whereas research on omission and commission errors focused on friendship and advising relations (Brashears & Quintane, 2015; Flynn et al., 2010; Freeman et al., 1987; Freeman & Romney, 1987; Krackhardt, 2014; McEvily, 2014; O'Connor & Gladstone, 2015), it has overlooked misperceptions of communication links that play a vital role in information sharing. I argue that addressing underlying mechanisms of omission and commission errors in communication networks in work contexts is especially important since it provides more practical insights. Therefore, I propose a theory explaining how both omission and commission errors emerge in work communication networks.

Mechanisms of Omission and Commission Errors

In work contexts, it is well established that emergent communication networks arise when individuals informally communicate with others outside their formal structure. For example, Cross and Parker (2004) described significant differences between the formal structure of the organizational chart and informal network coming from the frequency of information exchange among members in a larger corporation's division. Further, there are tensions between the extent to which formal and informal structures impact members' behaviors (Monge & Contractor, 2001). The salience of informal structures is particularly underscored in new, technologically enabled forms of organizing, such as distributed groups (Hinds & Bailey, 2003; Zaccaro et al., 2012), peer production communities (Faraj et al., 2011), and flash organizations (Valentine et al., 2017; Valentine & Edmondson, 2015). While these new forms of organizing tend to have a fluid structure, they still self-organize into formal roles and structures (consider Wikipedia). Therefore, it is important to recognize the ongoing tension between the formal, albeit increasingly fluid, structures and emergent informal structures in light of the ascendance of these new forms of organizing. Hence, I argue that the lens of the formal and informal structures as types of schemas both play key roles in understanding how people make sense of communication networks in organizations while also leading to “omission and commission errors.” In the next section, I discuss how formal organizational structures shape members' perceptions of communication networks. In the section after that, I discuss how people’s perceptions of the informal communication network are endogenously deployed to impute the presence or absence of links within the same communication network.

Formal Structure

A formal structure, such as hierarchy and subgroups, is commonly used to coordinate tasks efficiently. The division of labor enabled by a formal structure helps individuals to not only enhance their task coordination and the efficiency of communication, but to also reduce their cognitive load by providing relational schemas (Clement & Puranam, 2018; Simon, 1962). Relational schemas are defined as pre-existing knowledge structures for processing and organizing social information in the human mind. Relational schemas enable us to simplify the social world and compress social information. That is, they improve the efficiency of storing and recalling social information. However, this simplification diminishes the accuracy with which individuals view the social world. Thus, the formal structure, while providing people with simplifying schemas, can lead people to make errors in recalling social relations.

Functional units are a particular type of formal structure. Frequently, an organization uses such units to improve the efficiency of task completion and coordination (Kittur et al., 2009). Since the units are designed for members to work closely together, having such units sets an expectation in which members within a unit are more likely to communicate with each other.

Understandably, people might expect members in different units to have less communication with each other. For instance, Kilduff, Crossland, Tsai, and Krackhardt (2008) demonstrated that when individuals were asked to report friendship relations within their organization, they exaggerated the relations based on group boundaries. In other words, they assumed that there were more links within a group than actually existed. Likewise, research on social network learning shows that people remember social relations based on kinship labels more quickly than those based on non-kinship labels (Brashears, 2013). Additionally, Heald, Contractor, Koehly, and Wasserman (1998) found that those within the same department tend to develop perceptions of the social structure that are similar to each other's views but different from those in other departments. Hence, people are more likely to perceive that those within a functional unit are more likely to communicate even though they might not, while those who are in different units are less likely to communicate even though they might be perceived to be communicating.

Hypothesis 1a (H1a): Holding other factors constant, errors of omission are less likely to occur in a dyad between members in the same functional unit than between those in different units.

Hypothesis 1b (H1b): Holding other factors constant, errors of commission are more likely to occur in a dyad between people in the same functional unit than between those in different units.

Alongside functional units, a *divisional unit* offers another organizing mechanism for formal structures. Divisional units are often grouped on the basis of geographic locations (Moon et al., 2004). The proximity of unit members plays a key role in facilitating communication among them. Even though new technologies enable us to communicate across geographically dispersed locales, research shows that proximity is still a significant factor in explaining "who talks to whom" (Rivera et al., 2010). For instance, Kleinbaum, Stuart, and Tushman (2013) reported that geographic colocation overpowers the non-spatial effects of technology-enabled communication on email interactions between individuals in an organization. In other words, organizational members are more likely to talk with those in the same location than those in different locations. Therefore, I expect that members use divisional units as a relational schema to make sense of communication network patterns.

Hypothesis 2a (H2a): Holding other factors constant, errors of omission are less likely to occur in a dyad between members in the same divisional unit than between those in different units.

Hypothesis 2b (H2b): Holding other factors constant, errors of commission are more likely to occur in a dyad between people in the same divisional unit than between those in different units.

Informal Structure

In the preceding section, I theorized on how formal organizational structures (functional and dividual units) shape members' perceptions of the communication network. In this section, I direct our attention to a more endogenous process of sensemaking. Specifically, I posit that people rely on their perceptions of the communication network to infer and impute the presence (or absence) of links within that same communication network. For instance, people often use the heuristic that communication is *reciprocal*. A reciprocal tie means that A reports a tie to B (A → B), and B reports a tie to A (B → A). However, in group and organization contexts, communication is often non-reciprocal. This is especially true when considering communication advice ties (Krackhardt & Hanson, 1993) or communication information flow ties (Ghosh & Rosenkopf, 2015; Podolny, 2001). For example, A relays a message to B (A → B), but B does not necessarily reply to A (B ↛ A). This unidirectional or asymmetric communication is frequently observed in group and organization contexts (Carley & Krackhardt, 1996; Corman & Scott, 1994). However, reciprocity is a ubiquitous norm in interpersonal communication (Berger & Calabrese, 1975). Indeed, Newcomb (1979) theorized that reciprocity via communication is a common emergent structure in social settings and found empirical evidence supporting his theory. Previous studies provide evidence that individuals assume reciprocal social relations more quickly than non-reciprocal ones because people are cognitively attuned to the reciprocal structure (de Soto, 1960; Janicik & Larrick, 2005). Thus, I expect that people tend to develop a relational schema based on reciprocity and perceive a reciprocal relation, even when such relations do not actually exist. On the other hand, people are less likely to miss a reciprocal relation when such relations do exist.

Furthermore, because reciprocity is a strong social norm and schematic structure when communication between individuals is not reciprocated, people might mistakenly assume that there is no relation between them in either direction. Indeed, Zajonc and Burnstein (1965a) found that people had more difficulty recalling a four-person network that lacked reciprocal ties than they did recalling a network *with* reciprocal ties. Hence, I posit that individuals tend to miss non-reciprocal relations, even though such relations exist. That is, if they assume (correctly or incorrectly) the presence of a tie from A to B, they are also likely to assume (correctly or incorrectly) the absence of a tie from B to A. I call this the reciprocity hypothesis. Furthermore, suppose they assume (correctly or incorrectly) the absence of a tie from A to B. In that case, they are also likely to assume (correctly or incorrectly) the absence of a tie from B to A. That is, they tend to underestimate the presence of non-reciprocal relations, even when such relations do exist.

Hypothesis 3a (H3a): Holding other factors constant, errors of omission are less likely to occur in a reciprocal dyad than in an asymmetric dyad.

Hypothesis 3b (H3b): Holding other factors constant, errors of commission are more likely to occur in a reciprocal dyad than in an asymmetric dyad.

Alongside reciprocity, another common structure in informal networks likely to be used as a heuristic for inferring and imputing the presence or absence of links in communication networks is transitive closure, or *transitivity*. The closure is a triadic structure of relations in which three people are all connected with each other. This is a fundamental structure of social relations (Faust, 2008; Granovetter, 1973). Communication patterns often demonstrate this triadic structure. Transitivity is a triadic structure in which A talks to B and C, and B also talks to C. Newcomb (1961) argues that the transitive structures emerge through communication—friends of friends are likely to become friends and communicate. This suggests that individuals might assume the presence of triadic structures in social networks, even when they are not present. In fact, previous research shows that people tend to "fill in the blanks," even if the triadic structure is not closed (Freeman, 1992). Namely, when A talks to B (A → B) and B talks to C (B → C), people tend to assume that A also talks to C (A → C). I call this the closure hypothesis.

Furthermore, recent literature has shown that the triadic structure is a basic schema, and people chunk social networks based on this structure (Brashears & Quintane, 2015; de Soto, 1960; Janicik & Larrick, 2005; 1965b). Interestingly, emerging evidence also suggests that this triadic closure schema, particularly the “filling in the blanks” phenomenon, is unique to social networks, and is not found in non-social networks (O’Connor & Gladstone, 2015). Thus, when we use the triadic closure schema, we tend to overestimate the existence of a closed tie, even if it does not exist, as opposed to underestimating the absence of such tie when it exists.

Hypothesis 4a (H4a): Holding other factors constant, errors of omission are less likely to occur in closed transitivity than in unclosed transitivity.

Hypothesis 4b (H4b): Holding other factors constant, errors of commission are more likely to occur in closed transitivity than in unclosed transitivity.

On the other hand, when people fail to recognize the triadic structure, they might miss all triad relations, even if some do exist. A dominant idea of schemas is that people have multiple distinct schemas to make sense of the social world (Janicik & Larrick, 2005; Neisser, 1976; Sun et al., 2021). Once people fail to use the closure schema, they might use a different schema (*e.g.*, the reciprocity schema) to make sense of their surrounding environment. Namely, they might miss relations relevant to their activated schema, even if those relations exist.

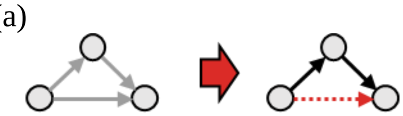
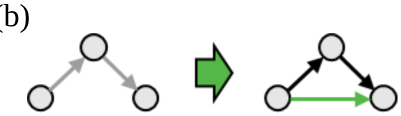
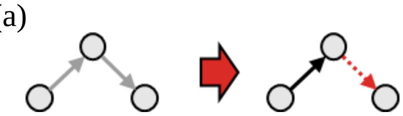
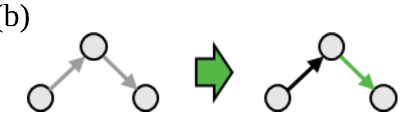
Two-path is a sequential structure in which information flows from A to B to C as another informal property. It is an unclosed triad structure (A → B → C but A ↛ C). In other words, A talks to B (A → B) and B talks C (B → C), but A does not talk to C (A ↛ C). In this case, if someone does not perceive one of the existing ties (B → C), their triadic schema might result in a failure to perceive the other. Furthermore, according to prior research (Krackhardt & Kilduff, 1999), people have poor perceptions of friends’ friends because of the difficulty of directly observing how friends are connected to others. Friedkin (1983) proposed *horizons of observability* referring to “a distance in a communication network beyond which persons are unlikely to be aware of the role performance of other persons" (p. 54). He empirically demonstrated that people have limits to accurately infer indirect social relations. Hence, I predict that when people perceive an unclosed triadic structure, they tend to miss a relation that actually exists. Similarly, the two-path structure also increases the chance of errors of commission when people overestimate the existence of a tie that may not exist. Even though a two-path structure exists in communication networks (Sosa et al., 2015), people have difficulty recognizing it. Thus, I hypothesize that the two-path structure results in more errors of commission when individuals perceive a tie that is part of an unclosed triad.

Hypothesis 5a (H5a): Holding other factors constant, errors of omission are more likely to occur in a two-path dyad than in a non-two-path dyad.

Hypothesis 5b (H5b): Holding other factors constant, errors of commission are more likely to occur in a two-path dyad than in a non-two-path dyad.

I summarize my hypotheses and the associated structural signatures in Table 3-2.

Table 3-2. Summary of the Hypotheses and Associated Structural Signatures

	Errors of Omission		Errors of Commission	
	Actual Network	Perceived Network	Actual Network	Perceived Network
Functional Unit (H1)	(a) 		(b) 	
Divisional Unit (H2)	(a) 		(b) 	
Reciprocity (H3)	(a) 		(b) 	
Transitivity (H4)	(a) 		(b) 	
Two-path (H5)	(a) 		(b) 	

Note: The red box arrows signify the omission-error process, whereas the green box arrows indicate the commission-error process. Actual ties are gray, correctly perceived ties are black, omission errors are dashed red, and commission errors are solid green.

METHODS

Data

Intergroup Communication Context

To examine my hypotheses, I use a unique dataset from NASA's Human Exploration Research Analog (HERA; Neigut, 2015) at the Johnson Space Center in Houston. I conducted my study within HERA Campaigns 3 and 4, a 30- to 45-day simulated space mission in which four-person astronaut crews conduct tasks in an environment that emulated isolated, controlled, and confined conditions that they would encounter on a mission to Mars. One task they conducted is called Project RED (**R**ed planet **E**xploration and **D**evelopment) and required the four-person HERA crew to work with an eight-person "mission control" on Earth in a multiteam system (team of teams) that was tasked with deciding where to construct a well to support a human colony on Mars. The multiteam system was made up of four teams (or functional units): planetary geology, space human factors, extraterrestrial engineering, and space robotics (see Figure 1). Each of these four units included one member from the four-person HERA crew and two from the eight-person mission control. After spending about an hour negotiating and deciding on a location for the well, the four-person HERA crew and eight-person mission control engaged in a second activity, Project RED Relay. Project RED Relay was tasked with getting data from the Jet Propulsion Laboratory (JPL, in Pasadena, CA) to specific recipients in the 12-person multiteam system to help them execute plans for drilling the well. Due to bandwidth limitations in space communications, each of the 12 participants was required to select only two contacts from the 11 other individuals in the activity to whom they could directly route messages. They then attempted to route messages they received directly from JPL (or indirectly from JPL via others who chose them as a direct contact in the activity) to the final recipient. They accomplished this by relaying the messages to one of the two contacts they believe to be most likely to efficiently deliver those messages to the final recipient. Everybody engaged in two rounds of this activity, each lasting 10 minutes. The system recorded the two contacts selected by each participant for each of the two rounds. After completing the activity, all 12 participants reported their perception of the other 11 members' choices for direct contacts.

Sample

I collected data in 23 sessions from eight, four-person HERA crews paired with 23, eight-person mission controls. HERA crews completed the task two to four times throughout their 30-

to 45-day mission, each time with a different mission control group (for a total of 24 possible sessions). Due to personnel and technical issues, one session was dropped, leaving a total sample of 23 sessions and 212 individuals (12 participants who did not participate in the survey were dropped). Of those 212 individuals, 29 were HERA crew members who were recruited and selected by NASA. In contrast, 183 university students and individuals in the surrounding community were recruited as mission control members through fliers and department subject pool email lists.

Figure 3-1. Formal Structures of 12-Person Roles in Project RED Relay

Note: The red color indicates the HERA crew. Participants are divided into four functional units.

Measures

Formal Structure

During the task, each participant was assigned to a specific role in one of the four specific *functional units*: planetary geology, space human factors, extraterrestrial engineering, and space robotics (see Figure 3-1). The roles and units are meaningful because participants were provided instructions for their roles and units before starting the task. They performed the task based on their roles in an attempt to maximize both their units' goals and the overall performance of the multiteam system. Hence, participants were well aware of this formal structure when they participated in the Project RED Relay activity.

In addition to functional units, participants were placed in different locations. They were assigned by location to five specific *divisional units*: HERA at the Johnson Space Center (*i.e.*, Sedimentologist, Martian Meteorology Specialist, Biochemical Engineer, and Drilling Specialist), Mission Control Center 1 (*i.e.*, Hydrogeologist and Structural Geologist), Mission Control Center 2 (*i.e.*, Martian Terrain Specialist and Maintenance Specialist), Mission Control Center 3 (*i.e.*, Mechanical Engineer and Fluid Engineer), and Mission Control Center 4 (*i.e.*, Materials Specialist and Operations Specialist) (see Figure 3-1). Similar to functional units, every participant was aware of these divisional units because their units are related to their tasks.

Actual Networks

Actual networks were constructed based on whom participants selected as their two contacts in each Project RED Relay session. Therefore, I define my actual networks as "who actually chose whom in Project RED Relay." Since I asked participants to engage in the activity twice and choose two new contacts at the end of the first session, each person could choose up to four total contacts. I collected these actual networks from 23 sessions.

Perceived Networks

To measure perceived networks, I asked the 12 participants after the two rounds of Project Red Relay activity to report on “the people you think each person chose as their contacts (select up to four names and at least two names).” In doing so, I adopted a well-established method to measure perceived networks called Cognitive Social Structures, or CSS (Krackhardt, 1987). CSS is a “cognitive representation of social networks” (Brands, 2013). It requires a set of people in a group or organization to report their cognitive representations of social relations among all pairs of other members within the group or organization. Operationally, it generates 23, 12-person networks, each of which captures the cognitive representation of the 12-person network by each of the 12 individuals.

Dependent Variables

Omission Error Tie

My dependent variable is an omission error. It is based on whether an omission error happened. It takes the value of 1 if a communication link exists in the actual network, yet members do not perceive it in their perceived network; otherwise, it takes the value of 0.

Commission Error Tie

The other dependent variable measures whether a commission error occurred, taking the value of 1 if there is no communication link in the actual network, but members perceive such a link in their perceived network; otherwise, it takes the value of 0.

Independent Variables

Functional Unit

To test my functional unit hypotheses (H1a and H1b), I measure a binary variable based on whether or not a tie exists within a functional unit in the actual network. If so, I label it 1; if not, 0.

Divisional Unit

I used geological identification of the same divisional unit to test my divisional unit hypotheses (H2a and H2b). This is a binary indicator set to 1 for HERA–HERA and MCC–MCC dyads, and 0 for inter-divisional dyads in the actual network.

Reciprocity

Reciprocity is a binary measure that captures a reciprocal tie from B to A if there is a tie from A to B that is correctly perceived by a respondent in the actual network. If such a tie exists, I label it 1; otherwise, 0. I used this indicator to test Hypotheses 3a and 3b.

Transitivity

Transitivity is a binary measure of whether there is a tie from A to B when a respondent correctly perceives ties from A to B and B to C. I use this variable to test Hypotheses 4a and 4b.

Two-path

To test my two-path hypotheses (H5a and H5b), I measured two-path with a binary indicator. This was based on whether there was a tie from B to C when a respondent accurately perceived the existence of a tie from A to B and the absence of a tie between A and C.

Control Variables

HERA

I include a binary indicator of HERA crews (HERA). HERA controls for whether CSS respondents are HERA who participated in Project RED Relay at the Johnson Space Center. Because the four-person crew spent time together in the Analog, they are more likely to be aware of who talks to whom than MCC who joined Project RED Relay at a university. If individuals are HERA, they are labeled as 1; otherwise, 0.

Campaign

I control for different campaigns that participants attended (*i.e.*, Campaigns 3 and 4). This is particularly important for HERA crews because each mission in Campaign 4 was longer (45 days) than Campaign 3 (30 days). This means that crews in Campaign 4 stayed longer in the isolated, controlled, and confined module and thus engaged in one more session (four trials) than those in Campaign 3 (three trials). More importantly, the crews in Campaign 4 were severely sleep-deprived compared to those in Campaign 3. Therefore, I expect that the HERA crews in Campaign 4 will make more errors when perceiving the network. If participants attend a session in Campaign 4, they are labeled as 1; otherwise, 0.

Trials

I include a numeric variable controlling for the number of trials in which each participant was engaged during Project RED Relay. This trials term is particularly crucial for HERA participants since they participated in Project RED Relay multiple times.

Analytic Method

To test hypotheses H1 to H5, I used a multilevel generalized linear mixed model (GLMM). The reasons for the choice of GLMM are that my dependent variable is binary (*i.e.*, 0 and 1), and that participants in my data are nested in sessions and trials. Specifically, I chose the three-level growth logistic model that predicts Y_{itk}, which shows either commission or omission error ties with the following formula:

$$Level\ 1: logit[P(Y_{tik} = 1)] = \pi_{0ik} + \pi_{1ik}Trials_{tik} + e_{tik} \tag{1}$$

In Eq. (1), this model estimates the probability of an *i*'s error tie at trial *t* nested within *k*'s session as a function of formal/informal structure factors at Level 2 and Campaign at Level 3, and the error term *e*.

$$Level\ 2: \pi_{0ik} = \beta_{00k} + \beta_{01k}individual/dyadic\ factors + r_{0ik} \tag{2a}$$

$$Level\ 2: \pi_{1ik} = \beta_{10k} + \beta_{11k}individual/dyadic\ factors + r_{1ik} \tag{2b}$$

In Eq. (2a), the intercept of Level 1 is estimated based on individual and dyadic factors (*e.g.*, functional unit, divisional unit, reciprocity, transitivity, two-path, and HERA) with the error term *r* at Level 2. Similarly, in Eq. (2b) I estimated the slope of Level 1 by the same individual and dyadic factors as Level 2.

$$Level\ 3: \beta_{00k} = \gamma_{000} + \gamma_{001}Campaign + u_{00k} \tag{3a}$$

$$Level\ 3: \beta_{01k} = \gamma_{010} + u_{01k} \tag{3b}$$

$$Level\ 3: \beta_{10k} = \gamma_{100} + \gamma_{101}Campaign + u_{10k} \tag{3c}$$

$$Level\ 3: \beta_{11k} = \gamma_{110} + u_{11k} \tag{3d}$$

In Eq. (3a), the intercept of Eq. (2a) is estimated by Campaign with the error term *u*. Likewise, Eq. (3c) estimates the intercept of Eq. (2b) as a function of Campaign. Finally, Eq. (3b) and (3d) estimate the slope of Eq. (2a) and (2b), respectively. I estimated these three-level growth logistic models using the *lme4* package in R (Bates et al., 2015).

RESULTS

Data Descriptive Statistics

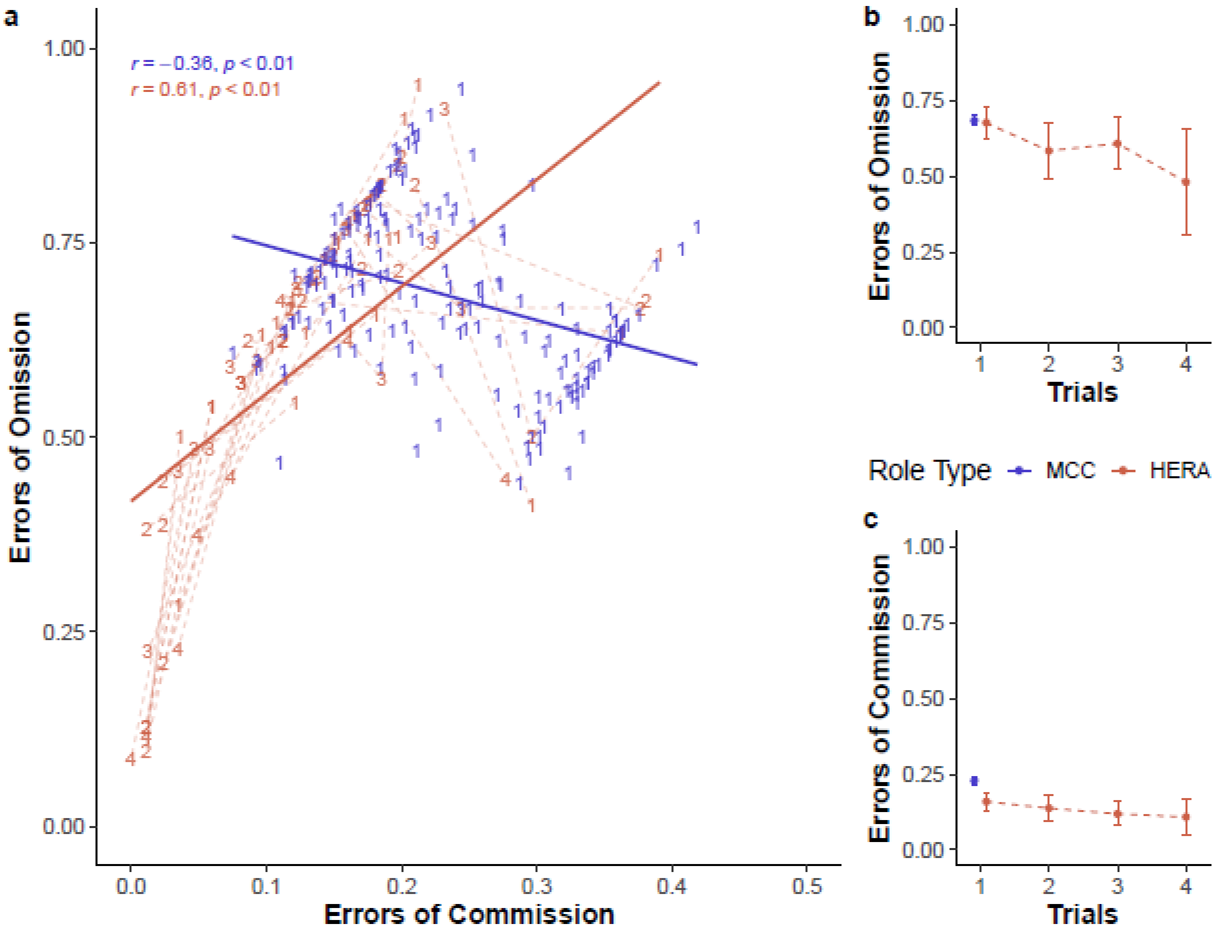
Figure 3-2 presents the omission and commission rates for HERA crews and MCC. In Figure 3-2a, omission and commission errors are positively correlated in HERA ($r = 0.61$, $p < 0.01$), but they are negatively correlated in MCC ($r = -0.36$, $p < 0.01$). To uncover the correlational differences between HERA and MCC, I created plots for each omission and commission error. Doing so was particularly essential since HERA crews engaged in the task multiple times while MCC did not.

Figure 3-2b shows the average of omission error rates for HERA and MCC. The average of omission error rates for HERA is 0.677 at the first trial, whereas the rate for the MCC counterpart is 0.685. I found no statistically significant difference between them: $t(33) = 0.267$, $p = 0.791$. My additional analysis shows that there are statistically significant differences among trials, $F(1, 80) = 6.951$, $p < 0.05$. The result suggests that HERA crews made fewer errors of omission over time.

Figure 3-2a presents the average of commission error rates for HERA and MCC. I found that HERA crews ($M = 0.159$) were less likely to make errors of commission than MCC ($M = 0.229$), $t(37) =4.249$, $p < 0.01$. Additionally, HERA crews seemed to learn from errors of commission since they made fewer errors of commission over time, even though it was not statistically significant, $F(1, 80) = 3.665$, $p = 0.059$.

Taken together, these descriptive statistics suggest that people are less accurate in identifying actual ties than in perceiving the lack of ties. The results also indicate that omission errors occur more often than commission errors. Additionally, there are different tendencies for making errors between HERA and MCC in my data. Finally, HERA crews reduced the amount of errors of omission they made by learning. In other words, the more they engaged in this type of task, the more accurately they perceived communication links in the network.

Figure 3-2. Errors of Omission and Commission by HERA vs. MCC



Note: (a) Each number indicates participants with their trials, and dotted lines connect HERA crew members (red) who participated in multiple trials. The solid lines are the best fit regression for HERA and MCC, respectively. (b) This compares the omission error rate between HERA and MCC. Only HERA crew members participated in multiple trials. The dot points represent the mean estimate, and the lines are 95% confidence intervals. (c) This compares the commission error rate between HERA and MCC.

Hypothesis Tests

The results of my tests for the hypotheses are shown in Tables 3-3 and 3-4. I present three models for my multilevel GLMM analysis in each table. This is because I gradually add hypothesized factors to the baseline model to test my hypotheses. In Table 3-3, I estimate omission errors based on the absence of perceived ties when they were reported in the actual networks. The origins of the errors include terms related to the functional unit (H1a), divisional unit (H2a), reciprocity (H3a), transitivity (H4a), and two-path (H5a). In Table 3-4, I estimate commission errors based on the occurrence of perceived ties when none were reported in the actual networks as a function of hypothesized terms; that is, the functional unit (H1b), divisional unit (H2b), reciprocity (H3b), transitivity (H4b), and two-path (H5b).

Table 3-3 shows the results of the multilevel GLMMs for omission error ties. I incrementally add key variables to the models. Model 1a is my baseline model, in which I include the terms, such as HERA, campaign, and trials. In the model, the trials term is negative and significant (π = -0.226; $p < 0.05$; odds ratio (OR) = 0.798), indicating that the more people repeatedly engaged in CSS, the less likely they were to make omission errors. Neither HERA nor campaign is statistically significant. Thus, my baseline findings are consistent with Figure 3-2's results.

Model 1b adds formal structure variables (*i.e.*, functional and divisional unit) to the baseline model. The trials term remains negative and significant (π = -0.226; $p < 0.05$; odds ratio (OR) = 0.798). The campaign trials term becomes positive and significant (γ = 0.145; $p < 0.05$; odds ratio (OR) = 1.156), indicating that those who participated in Campaign 4 were more likely than those in Campaign 3 to miss ties that exist in the actual network. The functional unit term is negative and significant (β = -0.719; p < 0.01; OR = 0.487) which supports my H1a about a negative effect of the intra-functional unit on omission errors. This suggests that people are less likely to perceive omission error ties if they are between a pair of the same functional unit individuals, rather than ties between different functional unit individuals. Contrastingly, the divisional unit term does not support my H2a about the intra-divisional unit's negative effect on omission errors since it is positive and significant (β = 0.097; p < 0.05; OR = 1.102). It indicates that people are more likely to perceive omission error ties if these ties are within the same divisional unit than if the ties are between different divisional units. This result is contrary to my H2a.

Next, I add informal structure variables to Model 1c. Results show the same signs of the variables as the previous model. The functional term has the same effect and significance, while the divisional unit term is no longer significant. Now, the reciprocity term supports H3a regarding the negative reciprocal omission error tendency since it is negative and significant (β= -0.600; p < 0.01; OR = 0.549). The result suggests that individuals are less likely to make omission errors when reciprocity exists in the actual network than when a non-reciprocal tie exists. Transitivity (β= -0.284; p < 0.01; OR = 0.753) is negative and significant. Thus, this result supports H4a, indicating that individuals do not tend to commit omission errors when a triad is closed. Contrarily, the two-path term is positive and significant (β = 0.146; p < 0.05; OR = 1.157). It supports my two-path hypothesis (H5a), suggesting that individuals underestimate the existence of ties as a part of an unclosed triad.

Table 3-3. Results of Multilevel GLMMs

	Model 1a	Model 1b	Model 1c
		Omission Error Tie	
Intercept	0.954 **	1.149 **	1.158 **
	(0.108)	(0.113)	(0.111)
HERA	-0.053	-0.071	-0.096
	(0.102)	(0.103)	(0.097)
Campaign	0.130	0.145 *	0.138 *
	(0.073)	(0.073)	(0.069)
Trials	-0.226 *	-0.226 *	-0.204 *
	(0.091)	(0.094)	(0.092)
Functional Unit		-0.719 **	-0.621 **
		(0.049)	(0.050)
Divisional Unit		0.097 *	0.054
		(0.049)	(0.049)
Reciprocity			-0.600 **
			(0.067)
Transitivity			-0.284 **
			(0.074)
Two-path			0.146 **
			(0.047)
AIC	11590.630	11378.357	11270.689
BIC	11662.038	11464.047	11377.801
Log Likelihood	-5785.315	-5677.179	-5620.344
Num Observations	9328	9328	9328
Num Individuals	263	263	263
Num Unique Individuals	212	212	212
Num Sessions	23	23	23

Note: * p < .05; ** p < .01. Standard errors in parentheses. Log-odds ratios are reported here, and standard errors are in parenthesis. *Positive* values indicate people are *more* likely to make omission errors.

In Table 3-4, I present the results of models, including errors of commission as a dependent variable. Model 2a is my baseline model that includes HERA, Campaign, and Trials. The HERA term is negative and significant (β = -0.464, p < 0.01, OR = 0.629), indicating that HERA crews are less likely to make commission errors than MCC participants. The trials terms are also negative and significant (π = -0.274, p < 0.01, OR = 0.760). This suggests that HERA crews reduced the number of commission errors when they repeated trials of the task. Finally, the campaign term is negative yet not statistically significant. My findings in Model 2a are also consistent with my observations in Figure 3-2.

In Model 2b, I test the formal structure hypotheses (H1b and H2b), adding the terms to Model 2a. The functional unit term is positive and significant (β = 0.659, $p < 0.01$, OR = 1.933). This supports my functional unit hypothesis (H1b), indicating that members are more likely to misperceive the presence of a tie between a pair of members in the same unit, even when such ties actually do not exist. Similarly, the divisional unit term is positive and significant (β = 0.097, $p < 0.05$, OR = 1.102). Thus, it confirms my divisional unit hypothesis (H2b), suggesting that individuals tend to overestimate the presence of a tie within a divisional unit more than they overestimate a tie between divisional units.

In Model 2c, I test terms that are related to informal structures, such as reciprocity (H4b), transitivity (H4b), and two-path (H5b). First, the reciprocity term is positive and statistically significant (β = 0.505, $p < 0.01$, OR = 1.657). This supports my reciprocity hypothesis (H3b) that members of a group are more likely to misperceive the presence of a reciprocal tie between a pair of members when, in fact, a tie only exists from one in the pair to the other. Second, transitive closure is not statistically significant. Thus, I do not find support for my transitivity hypothesis (H4b). Finally, the two-path term is positive and significant (β = 0.134, $p < 0.01$, OR = 1.143). This result supports my two-path hypothesis (H5b), suggesting that individuals are more likely to overestimate the existence of a tie that does not exist in the actual network if such a tie is part of an unclosed triad.

Table 3-4. Results of Multilevel GLMMs

	Model 2a	Model 2b	Model 2c
		Commission Error Tie	
Intercept	-0.910 **	-1.045 **	-1.155 **
	(0.094)	(0.096)	(0.100)
HERA	-0.464 **	-0.481 **	-0.492 **
	(0.096)	(0.097)	(0.096)
Campaign	-0.126	-0.124	-0.117
	(0.067)	(0.068)	(0.067)
Trials	-0.274 **	-0.269 **	-0.277 **
	(0.078)	(0.079)	(0.081)
Functional Unit		0.659 **	0.598 **
		(0.046)	(0.047)
Divisional Unit		0.097 *	0.104 **
		(0.038)	(0.038)
Reciprocity			0.505 **
			(0.053)
Transitivity			0.007
			(0.054)
Two-path			0.134 **
			(0.035)
AIC	21621.991	21410.996	21323.058
BIC	21702.098	21507.125	21443.219
Log Likelihood	-10800.995	-10693.498	-10646.529
Num Observations	22264	22264	22264
Num Individuals	263	263	263
Num Unique Individuals	212	212	212
Num Sessions	23	23	23

Note: * $p < .05$; ** $p < .01$. Standard errors in parentheses. Log-odds ratios are reported here, and standard errors are in parenthesis. *Positive* values indicate people are *more* likely to make commission errors.

In summary, my results support H1a, H1b, H2b, H3a, H3b, H4a, H5a, and H5b. However, I do not find support for H2a and H4b. Overall, my main findings, based on statistical tests, are as follows: (a) people make errors of commission by incorrectly perceiving the presence of communication links if A and B are in the same formal structure *(i.e.*, *functional* or *divisional* unit) and informal structures (*i.e.*, reciprocity or two-path) even if they do not exist; (b) people commit errors of omission by *missing* the existence of a communication link in the actual network if A and B are in different *functional* units or if A and B are part of an *unclosed* triad; and (c) people correctly identify the presence of a communication link if A and B are in the same *functional* unit, if communication is only one-way from A to B or from B to A (but not both), or if communication is part of triadic closure.

DISCUSSION

My empirical evidence supports the theory of relational schemas explaining how members in a group make sense of the presence of communication links in their network based on formal and informal structure. My main findings highlight that members of a group make systematic errors in their perceptions about "who talks to whom." My analyses indicate that these perceptions are inferred from relational schemas that utilize formal and informal structures in group communication networks. These results underscore the trade-off of using these schemas for inferences. Specifically, relational schemas simplify individuals' cognitive tasks to identify a large number of communication links, yet simultaneously lead them to misperceive or miss links. Hence, my results suggest that formal structural change itself as an intervention does not necessarily help mitigate miscommunication among group members. It is important for members to update their perceptions of the group communication network to function effectively.

Contributions

This paper makes contributions to the literature and implications for practice. First, I find that different mechanisms lead people to make omission and commission errors. This is theoretically important because existing theories do not distinguish between the mechanisms for these two types of errors. For example, compression heuristics help explain why commission errors occur (Brashears, 2013; Brashears & Quintane, 2015), but do not necessarily account for why people miss communication links (*i.e.*, commit omission errors). Practically, my findings also suggest that, to prevent these errors, we might need to intervene differently for errors of omission and commission.

More specifically, I find strong evidence that formal structure (*i.e.*, functional and divisional units) has strong effects on accurate and inaccurate perceptions of communication links. Brashears and his colleagues' compression heuristics provide a framework for humans encoding social network processes based on group and triadic closure (Brashears, 2013; Brashears & Quintane, 2015). Whereas my study adds evidence to compression heuristics, thereby confirming triadic closure as a relational schema, my data strongly support the group schema based on formal structures. This suggests that, although I observe commission errors based on triadic closure, the group schema has a stronger effect than triadic closure after controlling for the formal structure. I suspect this might be due to priming since my participants performed a group-based task immediately upon engaging in this activity. Given that schemas are developed through experience (Neisser, 1976) and can be primed (Simpson et al., 2011; Simpson & Borch, 2005), my findings might actually be more valid in work contexts. However, future work needs to address how priming and compression heuristics work together or separately.

Third, I find that individuals reduce errors of omission and commission by learning. Namely, individuals reduce misperceptions over time and increase the accuracy of their perceptions. Thus far, Ertan, Siciliano, and Yenigün (2019) are the only longitudinal CSS study. They found no significant increase in accuracy, based on their data from a cohort of MBA students. Although there are differences between their data and mine (*e.g.*, friendship vs.

communication links), my study provides new longitudinal CSS evidence. Given that Brands (2013) calls for understanding social and cognitive network dynamics, this is an overall valuable contribution to the CSS literature.

Fourth, I use the lens of formal and informal structures to understand the errors people make in perceiving group communication networks. This has implications for transactive memory systems since the theory assumes that members of groups or organizations act based on their accurate knowledge of other members (Ren & Argote, 2011). This knowledge is developed through communication (Palazzolo et al., 2006). My study demonstrates that members have systematic biases in accurately perceiving communication patterns. Hence, these findings have implications for the potential limits associated with the development of an effective transactive memory system.

As indicated above, my study demonstrates that members of a group make systematic errors, and that members share their misperceptions. This insight is particularly promising from a cognitive repairs perspective (Heath et al., 1998). Cognitive repairs are organizational practices that correct individuals' heuristics and, subsequently, their errors, which can be costly for groups and organizations. Cognitive repairs can help members of groups or organizations mitigate such errors. For instance, since the errors come from mental schemas, organizational practices, or communication technologies, reminding individuals of the full range of relevant information on communication links can help them to overcome their misperceptions. Of particular note is the increasing use of enterprise social media (such as Jive, Chatter, and Slack) that possesses the technological affordance of visibility to enable people to see who is communicating with whom (Leonardi, 2018; Leonardi & Vaast, 2017).

Finally, my study has substantial implications regarding space exploration, given that communication networks play a crucial role in mission failures—the Challenger and Columbia disasters being two poignant examples. My results mainly confirm qualitative evidence of communication failures on past mission disasters (Vaughan, 2016). On the one hand, an omission error means the group is not as efficient in routing information effectively. Namely, bottlenecks can result from limited or unused channels. On the other hand, a commission error means that people waste time and communicate important information that cannot go anywhere. Does this mean a commission error is more serious than an omission error? Consider the Columbia incident: There were engineers who knew about the issue, but they assumed channels existed when, in fact, they did not. The same issue surfaced in the Challenger incident. According to the Rogers Commission Report (Presidential Commission, 1986), people at Thiokol reached out to Dr. Lucas—a manager at the NASA Marshall Space Flight Center—and assumed that he passed the information to upper-level managers, even though he did not. The critical information did not get passed along, resulting in a terrible event. These were actually due to commission errors. Managers can use this framework to diagnose and make specific interventions for the problems, depending on which type of errors they would like to minimize.

Limitations and Future Directions

Despite my substantive contributions, my study has limitations that future research must address. First, my "mission to Mars" context is specific and unique, compared to prior research on this topic, and might limit my findings' generalizability. Specifically, my theory of relational schemas on the role of formal and informal structures in perceiving group communication networks should be applicable and extendable to other group and organizational contexts.

However, I only tested the theory using this unique setting of a simulated study. Although I extended a line of research on errors in perceiving social and communication networks by using a unique dataset, future research should replicate my findings in more generalizable contexts.

Second, my research uses relatively small-sized networks, not unlike previous work (*e.g.*, O'Connor & Gladstone, 2015). Because of this, it is challenging to generalize my findings to larger communication networks in organizations. For example, due to the size, I did not have an explicit hierarchy in groups. Organizations commonly include hierarchy as a formal structure. Based on prior research (Heald et al., 1998), the formal hierarchical structure might be another relational schema that lets people make omission or commission errors. Furthermore, hierarchy is expected as another type of schema (*i.e.*, the linear-order schema) that people use (Carnabuci et al., 2018; de Soto, 1960). Therefore, future studies need to examine whether my findings are extendable to large-scale hierarchical networks.

Third, I limited the choices of contacts each person could make to no more than two in each round and a maximum of four across the two rounds of Project Red Relay. This limitation in network contacts is realistic in some settings, but not all. Furthermore, consistent with other recent research (Yenigün et al., 2017), I also find omission errors occur more frequently than commission errors in perceiving group communication networks. This suggests that I should pay closer attention to omission errors than commission errors. Even though past research indicated similar findings (Siciliano et al., 2012; Yenigün et al., 2017), future research should explore the pattern of errors when there are no limits on the number of contacts.

Finally, I do not have evidence to make strong claims of causality between relational schemas and people's perceptions of social relations, even though I used a longitudinal network method, because my research is not based on a randomized experiment. However, recent studies have begun to use fMRI instrumentation to much more precisely demonstrate a causal relationship between neural brain activity and how people perceive social networks and process social information (Falk & Bassett, 2017; Meyer et al., 2012). In corresponding to Smith et al. (2020), future research should leverage randomized experimental methods and fMRI instrumentation to test for causality.

CHAPTER 4. POSITIONAL AND DISPOSITIONAL FACTORS THAT PREDICT SOCIAL NETWORK ROUTING ERRORS AND LEARN FROM THEM

"Our effectiveness is only as good as our ability to communicate." This quote—from the Assistant Chief of the New York Fire Department, Donald Burns, in the federal report on the 1993 bombing of the World Trade Center—captured his perspective on the documented communication errors among first responders (Burns, 1993). Groups and organizations increasingly face the challenges of sharing information in a timely manner, sometimes compounded by the complex environment of operating virtually and remotely (Bell & Kozlowski, 2002). To avoid issues related to information overload or the leakage of sensitive information (Huber, 1982), groups and organizations often rely on information routing (one-to-one message transmission) rather than broadcast messaging (one-to-many). The concept of routing focuses on "direction, route, and destination," which are not captured by more generic terms such as communicating and transmitting (Huber, 1982, p. 142). In the case of the World Trade Center incident, for example, firefighters routed information to selected others in command via in-person and radio channels. However, the opening quote was motivated by the frustration that, in the World Trade Center bombings, information often did not reach the intended recipient or took a longer path than expected. "Error-free routing" plays a critical role in teams of nuclear power generation (Carroll, 1998), hospitals (Tolk et al., 2015), and other high-reliability organizations (Weick & Sutcliffe, 2007).

Prior research has suggested that information routing processes are prone to errors in terms of the content being routed (a.k.a. "the telephone game") as well as the connections used to route them (Ellis, 2006; Ghosh & Rosenkopf, 2015; Singh et al., 2010). The majority of prior research focuses on content modification and distortion during information transfer (Bell & Kozlowski, 2011; Brashears & Gladstone, 2016; Huber, 1982; Miller, 1972). However, Hollingshead notes that "information may be transferred or explicitly delegated to the 'wrong' individual in the system, *e.g.*, one who does not have responsibility for that type of information or is unlikely to remember it due to a lack of expertise" (1998, p. 427). In other words, people sometimes route information or queries to someone who is not equipped to handle it, rather than to the most appropriate person in the network. I call these *social network routing errors* (SNREs). While people make SNREs, they also have the ability to learn from them.

To understand both the prevalence and antecedents of network errors and subsequent learning, I set out to answer two research questions. First, how often do individuals commit social network routing errors (RQ1a), and, relatedly, to what extent do individuals learn from their social network routing errors over time (RQ1b)? My second question seeks to answer who and why certain people make more errors, and/or better learn from errors than others. Hence, I ask: Which positional and dispositional factors explain who is more likely to commit social network routing errors (RQ2a)? And related to this, which positional and dispositional factors explain who is more likely to learn from social network routing errors (RQ2b)?

I examine SNREs in a laboratory setting involving 405 participants organized into 23 networks engaged in a network routing task. The network routing task is similar to Milgram's small-world experiment in which each participant routed information to an intended recipient who was directly or indirectly connected to them. I measured each individual's SNREs while engaging in this task. My study seeks to make three main contributions to our understanding of errors in groups and organizations. First, I focus on the conceptual development of an understudied type of error in groups and organizations: SNREs. To make fewer SNREs and learn from them, people need to be aware of "who knows whom" and "who knows what" in their groups and organizations. Towards that goal, I leverage and contribute to the literature on transactive memory systems (TMS) (*e.g.*, Ren and Argote 2011) and cognitive social structures (CSS) (*e.g.*, Brands, 2013). Second, I develop quantitative metrics to measure SNREs and learning from SNREs in groups and organizations. Third, I identify positional factors (where individuals are in the network) and dispositional factors (who they are) that explain an individual's propensity for committing and SNRE and learning from it.

THEORETICAL BACKGROUND

Social Network Routing Errors

I define social network routing errors (SNREs) as actions by individuals that unintentionally fail to achieve the goal of routing information or queries to someone with whom they are only indirectly connected via their social network. I also look at where this failure was potentially avoidable. As such, SNRE is an action error which Frese and Keith (2015, p. 662) defined "as unintended deviations from plans, goals, or adequate feedback processing, as well as incorrect actions resulting from lack of knowledge." My definition of SNRE includes three characteristics of action errors: (a) a deviation from a standard or desired behavior, (b) a deviation that is unintentional, and (c) a deviation that could have been avoided (Bell & Kozlowski, 2011, p. 116).

In this case, I identify the desired behavior as the shortest path routing. Prior studies have considered the shortest path as a standard in many contexts. For example, van Dyck and his colleagues noted that "most people hold a standard of efficiency (and certainly companies do);

thus, inefficient routes are deviations from this standard, and, from this perspective, inefficient actions are erroneous and managers sometimes report inefficiencies as examples of errors" (2005, p. 1229). In a study of 105 telephone survey interviewers, Killworth et al. (2006, p. 85) found that the average path lengths individuals used to route messages (3.23) was 40% longer than the average actual shortest path (2.30) "showing that mistakes are prevalent." While some studies have noted that longer paths lead to message distortion (Hansen, 1999, 2002; Huber, 1982; Miller, 1972), others have found that the shortest paths lead to desirable outcomes such as innovation (Fleming et al., 2007), effective search for knowledge (Singh et al., 2010), and creativity (Uzzi et al., 2007). In all of these studies, deviation from the shortest path represented SNRE with suboptimal outcomes.

While the deleterious effects of network-routing errors have been observed and lamented, SNREs remain an understudied type of error. The error literature has predominantly focused on the individual- and collective-level errors (Frese & Keith, 2015; Goodman et al., 2011; Hofmann & Frese, 2011b). Individual errors are defined as errors committed by individuals "without the participation of any other team members" (Sasou & Reason, 1999, p. 2). Collective errors refer to errors that are shared by multiple members of a team (Sasou & Reason, 1999). Research in groups and organizations from a Transactive Memory Systems perspective (see Ren & Argote, 2011 for a recent review) focused on the manifestation and consequences of these collective errors. For instance, Moreland, Argote, and Krishnan (1998) found that members who trained as a group made fewer errors when assembling a product than members who were trained individually. While this study measured the groups' errors in product assembly, the fact that they found the impact of training on performance to be fully mediated by the transactive memory systems points to the plausibility that underlying SNRE led to the manifest assembly errors. Specifically, training together facilitated members' ability to build accuracy around three social network relations within the group: who knows what, from whom to retrieve information, and to whom to allocate information. Errors in these social networks led groups with weaker transactive memory systems to make assembly errors. In contrast to this study, Pearsall et al. (2008) explicitly measured social network routing errors associated with transactive memory behaviors. In a study of 69 teams engaging in a simulated command and control activity with high task interdependence, Pearsall et al. (2008) found that team members' errors in transactive memory behaviors (expertise directory, information allocation, and retrieval coordination) negatively impacted their team's performance and mental model accuracy. However, while transactive memory behaviors were measured at the dyadic level—who do you perceive as having expertise, to whom do you allocate information, and from whom do you retrieve information—they were aggregated and analyzed at the collective level. Indeed, in their review of errors in teams, Bell and Kozlowski (2011, p. 121) noted that, in certain conditions such as sequential workflow, "collective failure is likely to stem from errors that originate not at the collective level but rather at the dyadic level, such as a breakdown in coordination or communication as work transitions from one member to the next." That said, their review points to the preponderance of errors being studied at the collective rather than the dyadic level.

Therefore, for conceptual clarity, I propose that an SNRE is neither an individual nor a collective error. Instead, it is a network error conceptualized and analyzed at the dyadic level. Because network errors bridge individual-level errors and collective errors, they serve as useful, multilevel linking mechanisms to explain, in part, how individual actions toward others collectively shape emergent collective error processes. Several studies have begun to conceptually explore network errors in various contexts, such as surgical teams and ball passing in basketball teams. Lingard et al. (2004) used ethnographic field note methods to code 421 communication events (verbal or non-verbal exchanges between two or more members) in 94 surgical teams and found that communication failures occurred in 30% of these events, and a third of those resulted in errors jeopardizing patient safety. Sieweke and Zhao (2015) investigated the antecedents and consequences of “bad passes” in the National Basketball Association (NBA) games between 2002 and 2011. In NBA parlance, “bad passes represent instances in which the ball is lost in inter-individual interactions” and hence is indicative of a dyadic network error, whereas a failed pass due to “ball-handling errors indicate errors attributed to intra-individual factors or processes” (Sieweke & Zhao, 2015, p. 387). They found evidence of a U-shaped relationship between the average familiarity among team members and the number of dyadic network errors committed by the team as measured by bad passes. While the studies of communication errors in surgical teams and ball-passing errors in basketball teams conceptually address dyadic errors, their analyses and inferences are rolled up to the collective level. Hence, their studies do not offer insights at the dyadic level about what factors explain why a specific person might make a dyadic error.

In addition to the literature on organizational errors, network research has also investigated dyadic network errors. Powell and his colleagues (1996, pp. 119–120) noted that, as innovations emerge from networks between (not just within) organizations, “firms must learn how to transfer knowledge across alliances.” These knowledge flows are prone to errors as a result of what Ghosh and Rosenkopf (2015) described as friction. They theorized four sources of friction impeding or distorting the flow of knowledge from one actor to another in a network: "(1) the characteristics of nodes composing dyads, (2) the broader structure of the network in which the dyads are embedded, (3) the types of ties composing the network, and (4) the nature of the knowledge to be transmitted" (Ghosh & Rosenkopf, 2015, p. 625). Some of the elements of friction they discussed were deliberate efforts to restrict or distort knowledge flows and would not be included in my definition of SNRE, which focuses only on instances in which individuals unintentionally fail to achieve the goal of routing information or queries. For instance, Borgatti and Cross (2003) demonstrated that potential recipients would be deterred from knowledge-seeking when they perceived high costs associated with the transfer. However, Singh et al. (2010) showed that search paths are unintentionally activated differentially by organizational members seeking relevant information: Peripheral employees (in the structural sense as well as the demographic sense) tend to commit SNRE by initiating their search paths to equally peripheral employees who are not helpful in accessing information. Their findings suggest that SNREs do not only occur, but that they vary as a function of the person's structural position in the network as well as individual characteristics. Network research on cognitive social structures offers one possible explanation for the prevalence of SNRE. Cognitive social structures refer to each individual's perceptions of who is connected with whom within a social network (Krackhardt, 1987). Research has shown that individuals vary in their ability to accurately perceive these network ties, which thereby impacts their propensity to make SNRE (see Brands, 2013 for a recent review).

In sum, this section has sought to demonstrate that SNRE is an understudied phenomenon with significant negative implications for group and organizational outcomes. While the majority of scholarship on organizational errors has focused on individual and collective errors, there have been a few studies, such as those in surgical and sports teams, that have examined errors at the dyadic level. However, most of these studies aggregate their insights to the collective level and hence do not offer insights about the prevalence of SNREs in specific dyads. Meanwhile, social network researchers have acknowledged that friction in knowledge flows can result in SNREs, and that some of the sources of this friction are based on individuals activating inefficient paths due to inaccurate perceptions of who is connected to whom in the network. These inaccurate perceptions might result from their own peripheral position in the network or other individual dispositional factors.

Learning from Social Network Routing Errors

Understanding the prevalence and origins of SNREs leads to the follow-up challenge of understanding the degree to which individuals are able to learn from errors over time. It is natural for individuals to start off a new task by making errors, but do they start to see patterns that enable them to improve? Even in organizations with strong formal networks, there are informal network ties that form, break, strengthen, or weaken over time. These ties are dynamic. An essential aspect of network learning, then, is the degree to which individuals are able to detect changes, understand their own misconceptions, and then reduce their error propensities by updating their mental maps of the network.

I define network learning based on Zhao's (2011, p. 436) definition of learning as "the process through which individuals (a) reflect on errors that they have made, (b) locate the root causes of the errors, (c) develop knowledge about action-outcome relationships and the effects of these relationships on the work environment, and (d) use this knowledge to modify or improve their behavior or decision making." By extension, learning from an SNRE occurs when an individual begins to see their errors and better understand social network connections, then use this enhanced understanding to adjust their actions. Because an SNRE is, by definition, potentially avoidable, I argue that people are able to learn from this type of error. Borgatti and Cross (2003) suggest that individuals learn their personal network by knowing, valuing, and accessing others. In other words, people enhance their understanding of relationships around them through observation. Thus, to reduce SNREs, people need to actively learn who is connected to whom. I conceptualize network learning as a form of active learning. Active learning is usually contrasted with passive learning, which assumes a transmission or conduit model of learning. In many cases, a formal organizational chart is the closest proxy that individuals have to a network "cheat-sheet." As such, it represents the most enduring option for passive learning of social networks in groups and organizations. Given the ephemeral and dynamic nature of social networks, it is inconceivable that it can be effectively transmitted via passive learning—beyond artifacts, such as the formal organizational chart.

Bell and Kozlowski (2008, p. 297) outlined two features of active learning. First, "the learner assumes primary responsibility for important learning decisions (*e.g.*, choosing learning activities, monitoring, and judging progress)." Indeed, these are consciously, or subconsciously the activities individuals deploy to learn about the ties within their social networks. Second, an "active learning approach promotes an inductive learning process, in which individuals must explore and experiment with a task to infer the rules, principles, and strategies for effective performance (Frese et al., 1991; Smith et al., 1997)." This feature also aligns well with individual efforts to explore the likelihood of certain ties being present in their social networks, experimenting by routing messages via those ties to test their conjecture, and inductively concluding if their conjecture is indeed borne out. Further active learning is particularly effective when learners need to transfer their development skills to real-world situations, compared to guided training (Keith et al., 2010; Zhao, 2011). In summary, my study focuses on actively learning from SNRE by oneself, through trial and error, rather than with the aid of formal instruction or guided training. Indeed, the extant literature on network learning has demonstrated that people are able to learn about relations through trial and error (de Soto, 1960; Janicik & Larrick, 2005).

Factors Related to Error Propensity and Learning

While my first research question applied to the frequency with which individuals commit social network routing errors and to what extent individuals learn from them, my second research question examines the factors that explain propensities to commit SNREs and learn from them. Individuals vary in terms of committing errors and learning from them (Gully et al., 2002). I define an individual's tendency to commit SNREs as their "SNRE (or error) propensity." In this section, I explore different factors that impact an individual's SNRE propensity and learning.

The literature suggests that intrapersonal and interpersonal factors influence individuals' SNRE propensity, as well as their ability to learn from SNREs. Intrapersonal factors include individual characteristics such as personality traits and abilities. I refer to these collectively as "dispositional" factors. Interpersonal factors include relational characteristics between individuals, specifically their position in the overall network. Hence, I refer to these collectively as "positional" factors. I posit that individuals' SNRE propensity and their ability to learn from them will be differentially influenced by both dispositional and positional factors. I discuss these factors in turn next.

Dispositional Factors

Prior research suggests two types of individual characteristics—personality and ability—are likely to affect SNRE propensity and learning.

Personality Traits

Personality traits explain individual differences based on individuals' tendencies to act in particular ways. The Five-Factor Model of personality (personality traits) encompasses five dimensions: openness to experience (openness), extraversion, agreeableness, conscientiousness, and neuroticism (Digman, 1990; John & Srivastava, 1999). Prior research has shown that openness and conscientiousness are associated with errors that people commit. Openness is a trait that is characterized by imaginativeness, creativity, appreciation of aesthetics, and intellectual curiosity, while conscientiousness consists of self-discipline, orderliness, competence, motivation, and dependability. Gully et al. (2002) reported that high openness is related to high effectiveness in error-encouragement training, while more conscientious individuals tend to perceive their capability to perform a task as lower when they are encouraged to commit errors. By contrast, Naveh and his colleagues (2015) found that people with high openness commit fewer errors than ones with low openness in a low learning environment, while the opposite relationship occurs under a high learning circumstance. As noted in their study, their finding is contrary to Gully et al. (2002), and their expectation is that more open individuals make fewer errors in an environment that emphasizes error-making. Although the directionality of the impact of personality traits on errors is not conclusive, there is evidence that personality traits have an effect on an individual's error propensity.

In addition to explaining the propensity to commit errors, personality traits explain individuals' ability to learn from errors. First, the personality dimensions of agreeableness and the sociability aspect of extraversion explain differences in individuals' tendency to attend to social information and their desire to interact with many others, respectively. Second, the personality dimensions of conscientiousness and neuroticism have been shown to affect learning and, in turn, performance (Barrick & Mount, 1991). Conscientiousness predicts learning in a variety of settings. Relatedly, Major, Turner, and Fletcher (2006) found that openness, extraversion, and conscientiousness impact motivation to learn. Furthermore, Zhao (2011) found that neuroticism negatively influences negative emotionality, which, in turn, positively impacts motivation to learn. Taken together, I expect that the aforementioned personality traits are related to network errors and learning.

Abilities

Prior research indicates that error propensity and learning from errors also depend on individual abilities. Prior work on errors finds that cognitive ability plays an important role. For example, Gully and his co-authors (2002) found that cognitive ability is positively associated with task performance (*i.e.*, low error propensity) regardless of error training conditions. Carter and Beier (2010) demonstrated that cognitive ability has a positive impact on training performance in error management training since cognitive resources affect how much individuals can allocate their attention to a given task. Moreover, Bell and Kozlowski (2008) suggested that cognitive ability regulates active learning because it supports one's ability to plan, monitor, and behave in furtherance of task goals (*i.e.*, metacognitive activities). They reported that cognitive ability moderates the positive relationship between exploratory learning and metacognitive activities, and cognitive ability also positively affects training performance. Taken together, I posit that cognitive ability negatively impacts an individual's error propensity.

Prior research also suggests that cognitive ability enables individuals to learn more and faster (*e.g.*, Kanfer & Ackerman, 1989): “attentional resources are essential for learning to occur” (Zhao, 2011, p. 437). Kanfer and Ackerman (1989) posit that cognitive ability plays a key role in complex task performance because those with high cognitive ability can allocate more attentional resources to the task. Building on this framework, Keith, Richter, and Naumann (2010) showed that high cognitive ability was associated with learning where participants were required to apply a learned task to another similar task in a guided training condition. Hence, I expect that cognitive ability has a positive association with learning from SNREs because of the perennial changes in the underlying social network. In addition to cognitive ability, emerging literature suggests that social ability shapes error propensity and learning in team contexts (Ferris et al., 2002; Kuwabara et al., 2018). The error management training literature suggests that social skills are key to determining how well people learn through errors in training since they usually work together during error training (Heimbeck et al., 2003). Therefore, I expect a positive association between social ability and an individual's error propensity and learning.

Positional Factors

Positional factors (where a person is located in the network) also play a key role in the propensity with which they commit errors and learn from them. They facilitate how people act (Burt et al., 2013) and how they access information (Reinholt et al., 2011). A review paper by

Burt, Kilduff, and Tasselli (2013) shows that those who have large and diverse connections access unique information, including about who is connected to whom in the network. In this section, I discuss how network positions impact an individual's error propensity and learning.

Popularity

To reduce SNREs, individuals need to be aware of who is connected to whom. Social network research suggests that the better individuals are connected, the better their ability to identify who is connected with whom. The classic research on the relationship between network structure and task performance demonstrated that individuals' network positions are associated with the number of errors (tapping on a wrong switch) that people made during the task (Bavelas, 1950; Leavitt, 1951). More recently, Krackhardt (1987) found that those who are more central in the network tend to have accurate perceptions of the friendship network, compared to those who are located in the periphery. Casciaro (1998) provided additional evidence that popular individuals tend to be more accurate in terms of their network perceptions than unpopular ones. This is because central (or better connected) actors tend to receive more information than peripheral ones, and, as a result, they are more likely to observe and learn who is connected to whom in the network. Consequently, I posit that popularity is negatively related to an individual's propensity for SNRE and positively related to their learning from SNREs.

Brokerage

In addition to popularity, a person's position in the network can also be described in terms of their brokerage. Brokerage describes a position where a person is connected to others who are not connected to each other in a social network. Occupants of this position are often called brokers. Brokers are regarded as having a structural advantage. For instance, those who occupy a brokerage position tend to access diverse information and, if they utilize it, produce better ideas than those who do not (Burt, 1992, 2004). Brokerage can proffer an advantage by conferring a greater and wider range of access to information, including about who is connected with whom. I, therefore, expect those in a higher brokerage position to commit fewer SNRE and to exhibit greater learning as a result of their advantageous position.

This section has outlined potential positional and dispositional factors that influence individuals' propensity to commit SNRE and learn from them. Prior research suggests that errors involving more than one person are more likely to be attributed to positional factors rather than to dispositional factors (Sasou & Reason, 1999). This is because they involve interdependent interactions; thus, an individual's position in the network can affect how often he or she commits errors. Further, Borgatti and Cross (2003) showed that individuals' positions determine the extent to which they learn to observe who is connected to whom in the network. Thus, since SNREs are, by definition, dyadic errors, I postulate that positional factors play a greater role in SNREs and learning from SNREs than dispositional factors. Yet, in the absence of extant empirical evidence, I will explore all of these expected relationships.

METHOD

Study Design

To examine my research questions, I developed a novel network routing task inspired by Milgram's small-world experiment (Milgram, 1967) and Bavelas and Levitt's network experiment (Bavelas, 1950). Participants completed the network routing task on an online platform called "Six Degrees of Separation" (6-DoS; described in the Procedure section). I recruited groups of at least 15 members each to a laboratory to perform 6-DoS.

Participants

I recruited 405 participants from 23 intact networks that each consisted of at least 15 individuals. The sample was 57% female, 42% male, and 1% other). All participants were recruited at a midsize midwestern university in the U.S., and each participant received $30 upon completion of the 90-minute study session. I recruited the intact networks from student organizations in which participants regularly interact for a common purpose (*e.g.*, music, culture, business, etc.). The criteria for selecting my sample were based on (a) individuals who are part of an entity where they have an ongoing awareness of most other members, and (b) individuals who have a common identity as a group. I recruited these groups of participants via email, online posts, and individual solicitation. Institutional Review Board approval was obtained prior to recruitment and data collection.

Procedure

Each participant first completed a battery of self-report survey questions about themselves and their social networks (described in Measures). Then, each participant selected three contacts from their group, whom they could send messages for a three-minute network routing task. Once all group members had selected three contacts, the task began, and the system presented the participants with messages to route to other group members who had been selected as a final destination. For standardization, the system was set to select a message destination that was located at exactly three degrees of separation from the participant. The participant then had to choose one of their three pre-selected contacts to send the message to so as to most effectively route it to the final message destination assigned by the system. To make this decision, the participants had to use their mental map of the network. Who among the three contacts they selected was most likely to get the message to the final message destination? The system was set to send a new message for routing every 30 seconds; hence, over the course of three minutes, each participant was required by the system to route messages at least six times. In addition, participants were also receiving messages from others who had chosen them as contacts. Participants engaged in five consecutive three-minute sessions. They were able to change their three direct contacts before each of the subsequent four sessions.

To facilitate active learning from SNRE, the 6-DoS platform enabled each participant to explore, if they chose to, information about the full pathways of messages they had routed, allowing them to see where messages had been directed before receiving them and after forwarding them. The message trail information included information about who sent the messages to whom and if they reached their final destination. Thus, the information enabled participants to engage in active learning—experimenting, and then learning from the errors—if the contact they chose to relay messages was, in fact, not on the shortest path to the final destination.

Measures

Social Network Routing Errors

I measured SNRE as the rate of errors per person at a time point. I segmented each of the five rounds into six time intervals since the system generated a message for each participant every 30 seconds: 30 seconds, 1 minute, 1.5 minutes, 2 minutes, 2.5 minutes, and 3 minutes. To calculate the rate of SNRE, I took three steps. First, I calculated the observed rate of SNRE at a given time interval in each round (Figure 4-1, observed routing error rate). Because individuals varied in overall activity (different total numbers of messages relayed per individual at a time point), I needed to ensure that my measure controlled for the total number of routing events. To address this concern, I computed a null model of routing error rates using 1,000 randomly shuffled versions of the observed routing decisions made by each individual. This generated the expected distribution of routing error rate for an individual (*i.e.*, expected routing rate) given the magnitude of their routing activity. Based on this null model (Figure 4-1, expected routing error rate), I then computed a z-score for each individual's routing error rate. Next, I describe the dispositional, positional, and control measures.

Personality Traits

I measured the Five-Factor Model of personality using the MINI-IPIP, which includes 20 items (*i.e.*, five items for each scale) (Donnellan et al., 2006). Each respondent indicated how closely each statement reflected their own belief (1 = very inaccurate; 5 = very accurate). *Openness* (openness to experience) is defined as a person's penchant for imagination, nonconformity, and autonomy. An example item is "Have a vivid imagination" (Cronbach's α = 0.74). *Conscientiousness* is a scale defined as an individual's tendency toward hard work, persistence, and organization. A sample item is "Like order" (Cronbach's α = 0.75). *Extraversion* is a characteristic of socialization and friendliness. The scale consists of five items, such as "Talk to a lot of different people at parties" (Cronbach's α = 0.80). *Agreeableness* refers to the extent to which people are pleasant, cooperative, and caring. An example item is "Sympathize with others' feelings" (Cronbach's α = 0.76). Finally, *neuroticism* is defined as a person's characteristic toward mood swings. A sample item is "Have frequent mood swings" (Cronbach's α = 0.75). I standardize each scale for a range between 0 and 1.

Cognitive Ability

To measure an individual's cognitive ability, I used the Wonderlic Personnel Test (Wonderlic & Hovland, 1939), a 50-item measure that is widely used for assessing an individual's cognitive ability. It includes verbal, mathematical, and spatial items, and studies compare it to longer and more variegated measures of cognitive ability. Individuals earned one point for each item answered correctly. I standardized the measure for a range between 0 and 1.

Social Ability

I measured a person's social ability using the "Read the Mind in the Eyes" test (Baron-Cohen et al., 2001). This test contains 37 items (one dummy item) for which participants choose the adjective that best describes a person's eyes, reading their facial expressions through a look in their eyes. This captures the extent to which individuals read the emotions of others. I standardized the measure for a range between 0 and 1.

Popularity

To obtain information about people's social networks, in the survey they completed at the start of the activity, I provided each participant with a list of all others in that network activity and asked them to nominate "Whom on this list do you know?" (Burt, 1984). This social network data allows us to examine how a pre-existing understanding of the social environment impacts SNRE and learning. I measured *popularity* using in-degree centrality, which is basically how many people nominated this person. Because the group size varied in my sample (*Min* = 15; *Max* = 26), I normalized in-degree centrality to be the ratio of the number of people who nominated a person divided by the maximum number of people that could have nominated that person. For example, in a network of 21 individuals, consider a case in which a participant was nominated by five out of a maximum of 20 (excluding the person being nominated). The participant would receive a normalized in-degree centrality (or popularity) score of 0.25.

Brokerage

Using the aforementioned social network scale survey, I computed *brokerage* using betweenness centrality (Freeman, 1978). Betweenness centrality is measured based on the number of times that a person appears as the shortest path between any other pairs in the network. Indeed, prior studies that investigated information seeking and knowledge networks used betweenness centrality as brokerage (Cross & Cummings, 2004; Hansen, 2002; Mehra et al., 2001). Following these studies, I used betweenness centrality since my purpose is to understand information routing. I chose betweenness centrality over Burt's network constraint (Burt, 2004) as a brokerage measure because network routing requires people to consider the paths traversed by messages, beyond their immediate egocentric network, to their final destination.

Control Variable: Gender

I collected data on the gender information of participants. Participants chose their gender identity out of three options: female, male, and other. Of 405, 57% are female, 42% are male, and 1% are other.

Analytic Approaches

I conducted analyses in three steps to address my two research questions. First, I analyzed SNREs for each of the five rounds. This analysis enabled me to address the patterns and prevalence of SNREs (RQ1a) and learning from them (RQ1b).

Second, to answer factors that impact an individual's error propensity (RQ2a) and learning (RQ2b), I used multilevel modeling of the changing trend for each individual (Singer & Willett, 2003). Specifically, this analysis estimated the intercept and slope in the SNRE within and between rounds. At Level 1, I examined the relationship between time and SNRE within each round for each individual. This generated the Level 1 parameters, an intercept and slope(s), which determines the shape of each individual's "true trajectory of change" (Dobrow Riza & Higgins, 2019; Lenzenweger et al., 2004) because the intercept parameter represents an individual's "true" (or baseline) value of routing error propensity at the beginning of the round. The slope parameter(s) represents an individual's true rate of change (presumably by learning) in the routing error over time.

$$SNRE_{ij} = \pi_{0i} + \pi_{1i}Time_{ij} + \epsilon_{ij} \tag{1}$$

where $SNRE_{ij}$ is an error rate of individual *i* at time *j*, $Time_{ij}$ is the time at which routing events *j* of individual *i* took place, π_{0i} is the intercept parameter representing error propensity of individual *i*, π_{1i} is the slope parameter indicating learning of individual *i*, and ϵ_{ij} is a Level 1 error term.

The Level 2 model tests how the intercept π_{0i} and slope π_{1i} from Level 1, estimated for each individual, is explained by between-subjects factors (*e.g.*, the positional and dispositional factors for Research Question 2), nesting rounds and groups. I conduct these analyses using the *lme4* package in R (Bates et al., 2015).

$$Error\ Propensity\ \pi_{0itk} = \beta_{0tk} + \beta_{1tk}Round_{itk} + \beta_{2-10}Factors + \xi_{itk} \tag{2}$$

The model specifies individual *i* nesting of rounds *t* and groups *k*. The model estimates *i*'s error propensity at time *t* as a function of factors such as popularity, brokerage, personality traits, abilities, gender, and an error term (ξ_{itk}). The same thing goes for *i*'s learning at time *t* as follows:

$$Learning\ \pi_{1itk} = \beta_{0tk} + \beta_{1tk}Round_{itk} + \beta_{2-10}Factors + \xi_{itk} \tag{3}$$

This model enabled me to estimate the relationship between learning from errors and positional and dispositional factors by fitting random intercepts and slopes.

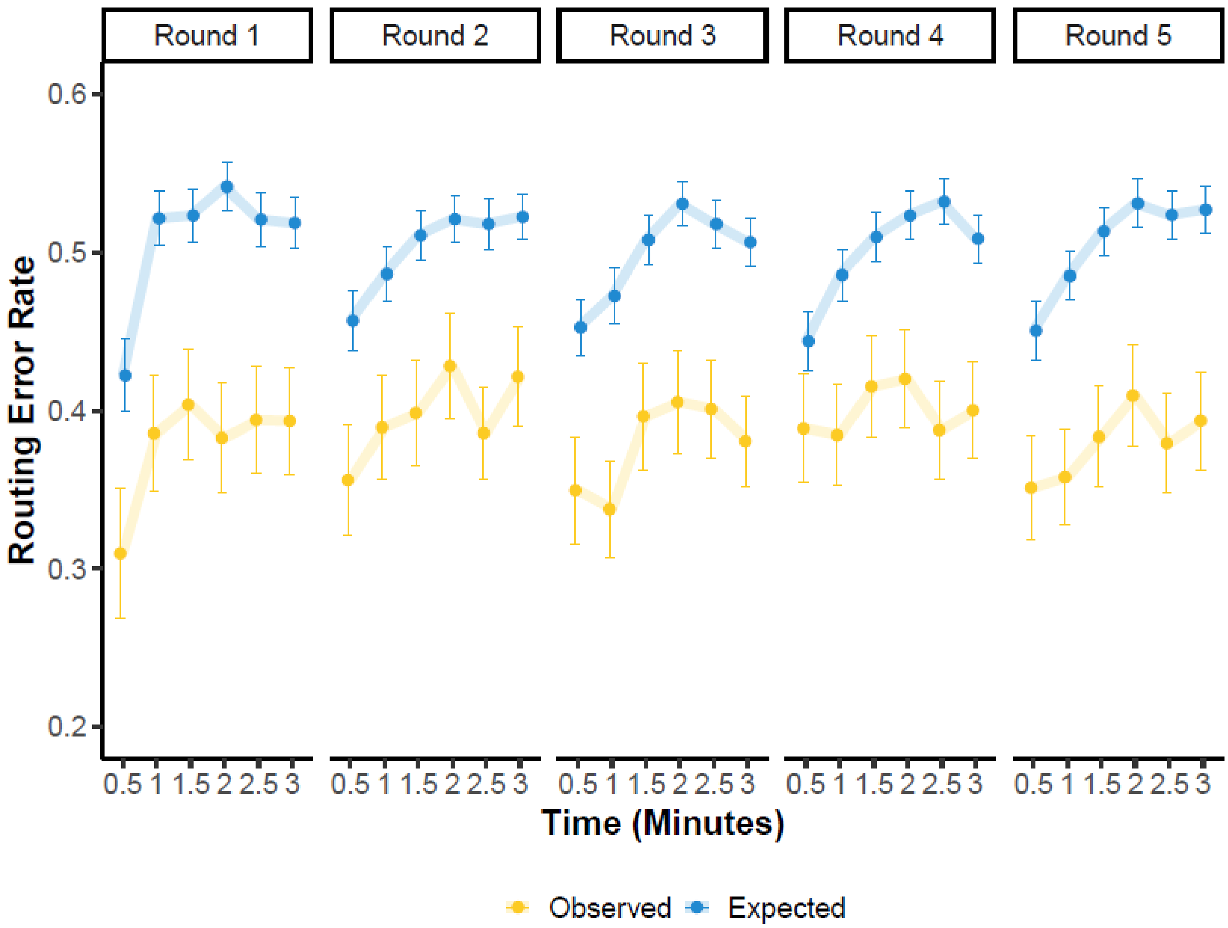
RESULTS

I began by examining the patterns of SNRE and learning from them. My results, reported here, provide evidence that people commit and actively learn from SNREs while engaging in a network routing task. Learning occurs when the individual makes more errors at the beginning of each round than at the end. Next, I test the effects of positional and dispositional factors on error propensity and learning. Finally, I present exploratory results based on the interaction effects between positional and dispositional factors.

Social Network Routing Errors and Learning from Them

I began by examining how often people committed SNREs (Figure 4-1). Figure 4-1 shows the observed and expected routing error rates. The expected routing error rate was computed by a null model of routing error rates using 1,000 randomly shuffled routing decisions for each individual. On average across rounds, people committed SNREs 37% of the time (SD = 33.7%). This is 13.7% lower than expected by chance (M = 50.7%, SD =16.9%), and the difference is statistically significant, $t(18953) = -41.18$, $p < .01$. The over-time trends shown in Figure 4-1 might suggest, counterintuitively, that SNRE rates generally increase as time passes in each round. The reason is that participants increased their routing activities as the round progresses. To control for this, I computed SNRE as a z-score as mentioned earlier in the Measures section.

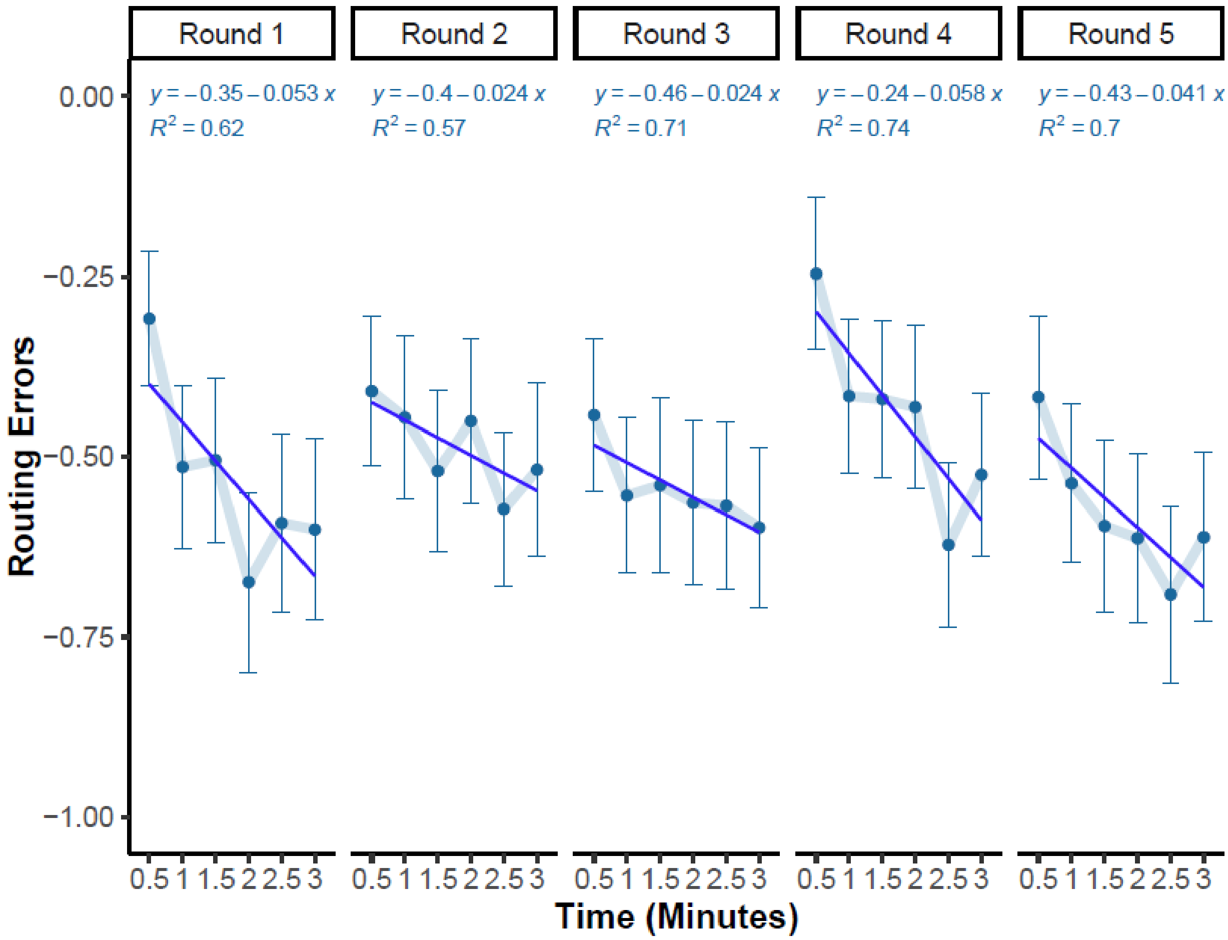
Figure 4-1. Comparison Between Observed and Expected Routing Error Rates



Note: Each point indicates the average value, and bars represent 95% confidence intervals.

Figure 4-2 presents SNREs based on a z-score calculation. This routing error should be interpreted as an error rate that is higher or lower than would be expected or by random chance. The results show that each round has the same pattern where people committed more SNREs at the beginning than at the end. Also, I observe negative slopes within each round, which I interpret as evidence that supports learning from SNREs. Each regression fit line is negative and significant ($p < .05$).

Figure 4-2. SNRE and Learning Slope



Impacts of Positional and Dispositional Factors on Error Propensity and Learning

Tables 4-1 and 4-2 present the descriptive statistics and correlation results. As I would expect, SNRE and the "baseline" routing error propensities are positively correlated (the intercept, r = -0.86, $p < .05$), whereas SNREs and learning (the change) are negatively correlated (the slope, r = -0.39, $p < .05$). SNREs are negatively correlated with popularity (r = -0.24, $p <$ .05), suggesting that popular individuals make fewer errors. Social and cognitive ability are negatively associated with SNREs (r = -0.15, $p < .05$), indicating that those with high ability levels tend to commit fewer SNREs. Social and cognitive ability are also positively correlated with error propensity. Brokerage and error propensity are negatively correlated (r = -0.10, p < .05). I did not find significant bivariate associations between positional and dispositional variables and learning.

Table 4-1. Descriptive Statistics and Pearson's Correlations

	Variable	Mean	S.D.	1	2	3	4	5
1	SNREs	-0.44	0.61					
2	Error Propensity	-0.45	0.58	0.86*				
3	Learning	-0.08	0.22	-0.39*	-0.56*			
4	Popularity	0.55	0.36	-0.24*	-0.24*	0.05		
5	Brokerage	0.05	0.10	-0.08	-0.10*	0.01	-0.06	
6	Openness	0.59	0.16	0.03	-0.01	-0.06	-0.08	0.03
7	Conscientiousness	0.57	0.13	-0.01	0.01	0.06	-0.05	0.05
8	Extraversion	0.58	0.17	-0.01	-0.04	0.01	0.03	0.10*
9	Agreeableness	0.48	0.17	-0.04	-0.03	0.01	0.02	-0.08
10	Neuroticism	0.49	0.19	-0.05	-0.08	0.02	0.05	-0.02
11	Social Ability	0.69	0.14	-0.15*	-0.11*	-0.01	-0.05	0.00
12	Cognitive Ability	0.78	0.13	-0.15*	-0.13*	0.07	-0.04	-0.02
13	Gender	2.16	0.99	0.07	0.01	0.07	-0.28*	0.09

Note: * p < .05

Table 4-2. (Continued)

	Variable	6	7	8	9	10	11	12
7	Conscientiousness	0.14*						
8	Extraversion	0.21*	0.20*					
9	Agreeableness	-0.34*	-0.14*	-0.35*				
10	Neuroticism	-0.21*	0.00	-0.20*	0.45*			
11	Social Ability	0.02	0.07	0.09	-0.10*	-0.01		
12	Cognitive Ability	0.03	-0.17*	-0.01	0.03	-0.03	0.13*	
13	Gender	0.00	0.28*	-0.01	-0.04	0.02	0.17*	-0.19*

Note: * p < .05

In Table 4-3, I examine how positional and dispositional factors impact the error propensity of individuals. I progressively add parameters to each model. Model 1a is my baseline model that includes round and gender. The results show that neither round nor gender is statistically significant. Model 1b adds dispositional factors to the model. In this model, cognitive ability is negative and significant, indicating that those with high cognitive ability commit fewer SNREs than those with low cognitive ability (β = 0.50, p < .05).

Model 1c includes both positional and dispositional factors. The results show that popularity and brokerage are negatively related to error propensity. Popular individuals tend to commit fewer SNREs (β = -0.50, p < .01), as do those who occupy a brokerage position (β = -0.56, p < .05). I ran the Likelihood Ratio test to check whether the model fit increased compared to Model 1a (a more parsimonious model). Indeed, the test indicates that Model 1c, which includes positional factors, provides a better fit than Model 1b, which includes only dispositional factors (χ^2 = 40.72, p < .01).

Finally, in Model 1d, I explore the interaction effects of positional and dispositional factors on error propensity. While I examined all of the interaction combinations (see Appendix B), I report the best-fit model based on deviance for Model 1d, including interaction effects between popularity and neuroticism and between brokerage and openness. Figure 4-3 plots these interactions between network position and traits at 1 *SD* above and below the observed mean on the relevant trait variable. When interpreting Figure 4-3a and Figure 4-3b, it is important to note that a negative slope is favorable, as it indicates that the combination of personal and positional attributes results in a reduced propensity to make errors.

Examining Figure 4-3a (based on Model 1d) suggests the benefits of popularity to error propensity are greater for those who are low (rather high) in neuroticism. The relationship between popularity and errors is always negative; having many in-ties is associated with a reduced error propensity. However, the form of the interaction indicates that those who are low in neuroticism gain a greater advantage from their popular position in the network, relative to those higher in neuroticism.

Table 4-3. Multilevel Models for Error Propensity

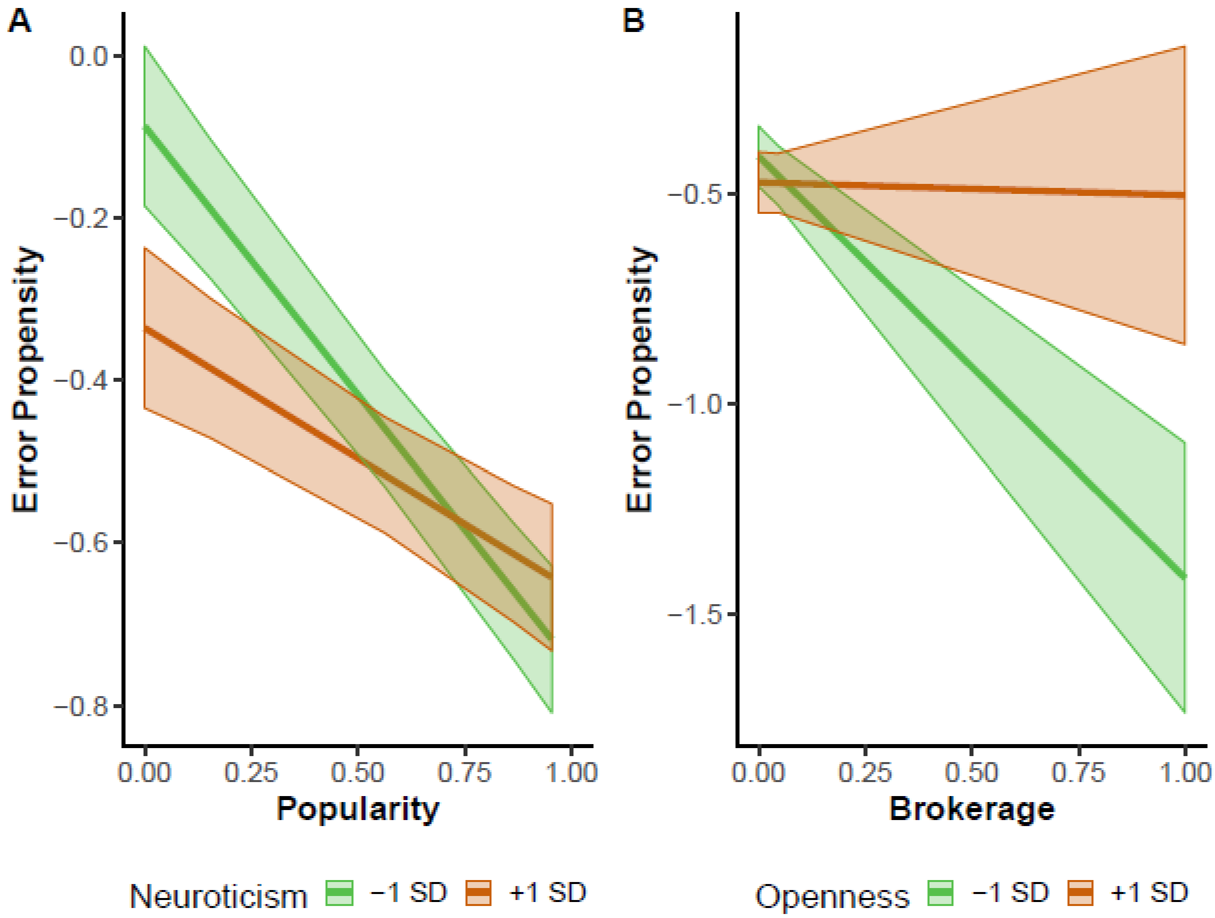
	Model 1a		Model 1b		Model 1c		Model 1d	
				Error Propensity				
Intercept	-0.37*	(0.07)	0.34	(0.28)	0.66*	(0.28)	0.92**	(0.29)
Round	-0.03	(0.03)	-0.03	(0.03)	-0.03	(0.03)	-0.03	(0.03)
Gender (Other)	0.50	(0.36)	0.49	(0.36)	0.53	(0.35)	0.58	(0.34)
Gender (Female)	-0.02	(0.06)	-0.03	(0.06)	-0.06	(0.06)	-0.05	(0.05)
Openness			-0.06	(0.16)	-0.05	(0.16)	-0.20	(0.17)
Conscientiousness			-0.09	(0.20)	-0.08	(0.19)	-0.06	(0.19)
Extraversion			-0.13	(0.16)	-0.05	(0.15)	-0.04	(0.15)
Agreeableness			0.13	(0.18)	0.08	(0.17)	0.09	(0.17)
Neuroticism			-0.18	(0.14)	-0.18	(0.14)	-0.67**	(0.25)
Social Ability			-0.17	(0.18)	-0.17	(0.18)	-0.19	(0.17)
Cognitive Ability			-0.50*	(0.20)	-0.56**	(0.19)	-0.53**	(0.19)
Popularity					-0.50**	(0.11)	-0.94**	(0.21)
Brokerage					-0.56*	(0.26)	-2.32**	(0.89)
Popularity× Neuroticism							0.92*	(0.37)
Brokerage× Openness							3.06*	(1.50)
AIC	6296.21		6311.08		6290.10		6282.62	
BIC	6358.74		6413.40		6403.78		6407.68	
Log Likelihood	-3137.11		-3137.54		-3125.05		-3119.31	
Deviance	6260.50		6249.10		6219.80**		6210.13**	
Num Observation	2024		2024		2024		2024	
Num Individuals	405		405		405		405	
Num Groups	23		23		23		23	

Note: * $p < .05$; ** $p < .01$. Unstandardized exponentiated coefficients are presented with standard errors in parentheses.

I observed a significant interaction between brokerage and openness. Figure 4-3b shows the benefits of brokerage to error propensity are greater for those low (rather than high) in openness. In fact, examining Figure 4-3b shows the relationship between brokerage and errors is negative only for those low on trait openness (less than 1 *SD* below the mean). For those with 1 *SD* above the mean on trait openness, the relationship between brokerage and errors is near zero.

Brokers high on the openness personality dimension exhibit the same error rate propensity as non-brokers with high openness. The Likelihood Ratio test indicates that Model 1d, with the interaction effects, increases the model fit compared to Model 1c (χ^2 = 9.66, p < .01).

Figure 4-3. Interaction Effects on Error Propensity. (a) The interaction effect of popularity with neuroticism. (b) The interaction effect of brokerage with openness



Next, I examine how positional and dispositional factors affect learning (Table 4-4). Here again, I incrementally add different sets of parameters to subsequent models for comparison. Model 2a is my baseline model for learning. In the model, neither round nor gender is statistically significant.

Model 2b adds dispositional factors to the baseline model. The results of the model show that cognitive ability is positively related to learning (β = 0.18, $p < .05$), meaning that those with high cognitive ability are *less* likely to learn from SNREs than those with low cognitive ability.

Model 2c examines the effect of positional factors on learning. In the model, neither popularity nor brokerage is statistically significant. However, cognitive ability remains positive and significant (β = 0.19, $p < .05$).

Finally, I explore the interaction effects of positional and dispositional factors on learning. Model 2d presents the results of the interaction effects. Whereas I explore all the combinations (see Table B-3 and B-4 in Appendix B), I report the best-fit model here. The Likelihood Ratio test also indicates that Model 2d with the interaction effects increases the model fit compared to Model 2b (χ^2 =19.31, p = .05). In Model 2d, the interaction effect of popularity and openness is positive and significant (β = 0.50, $p < .05$). Moreover, the interaction effect of brokerage and social ability is negative and significant (β = -1.89, $p < .05$). To interpret these results, I created graphic representations (Figures 4-4a and 4-4b).

Figure 4-4 plots these interactions between network position and traits at 1 *SD* above and below the observed mean on the relevant trait variable. As with Figure 4-3, I interpret the negative slope in Figure 4-4 as favorable. A negative slope indicates that individuals with higher popularity or brokerage positions show a reduction in the number of errors they make. Conversely, a positive slope indicates that individuals are making more errors over time as a unit of popularity or brokerage increases.

Table 4-4. Multilevel Models for Learning

	Model 2a		Model 2b		Model 2c		Model 2d	
				Learning				
Intercept	-0.11*	(0.04)	-0.26*	(0.13)	-0.28*	(0.13)	-0.20	(0.15)
Round	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)
Gender (Other)	0.02	(0.16)	0.01	(0.16)	0.00	(0.16)	0.02	(0.16)
Gender (Female)	0.03	(0.02)	0.03	(0.02)	0.04	(0.03)	0.04	(0.03)
Openness			-0.07	(0.07)	-0.07	(0.07)	-0.31**	(0.12)
Conscientiousness			0.14	(0.09)	0.14	(0.09)	0.11	(0.09)
Extraversion			-0.01	(0.07)	-0.02	(0.07)	-0.01	(0.07)
Agreeableness			-0.02	(0.08)	-0.02	(0.08)	-0.02	(0.08)
Neuroticism			0.03	(0.06)	0.02	(0.06)	0.03	(0.06)
Social Ability			-0.04	(0.08)	-0.04	(0.08)	0.04	(0.09)
Cognitive Ability			0.18*	(0.09)	0.19*	(0.09)	0.20*	(0.09)
Popularity					0.04	(0.04)	-0.25	(0.12)
Brokerage					0.03	(0.11)	1.31*	(0.62)
Popularity× Openness							0.50*	(0.20)
Brokerage× Social Ability							-1.89*	(0.91)
AIC	3146.31		3176.97		3186.85		3179.63	
BIC	3208.84		3279.29		3300.54		3304.69	
Log Likelihood	-1562.16		-1570.49		-1573.42		-1567.82	
Deviance	3102.90		3096.00		3094.70		3083.60*	
Num Observation	2024		2024		2024		2024	
Num Individuals	405		405		405		405	
Num Groups	23		23		23		23	

Note: * $p < .05$; ** $p < .01$. Unstandardized exponentiated coefficients are presented with standard errors in parentheses.

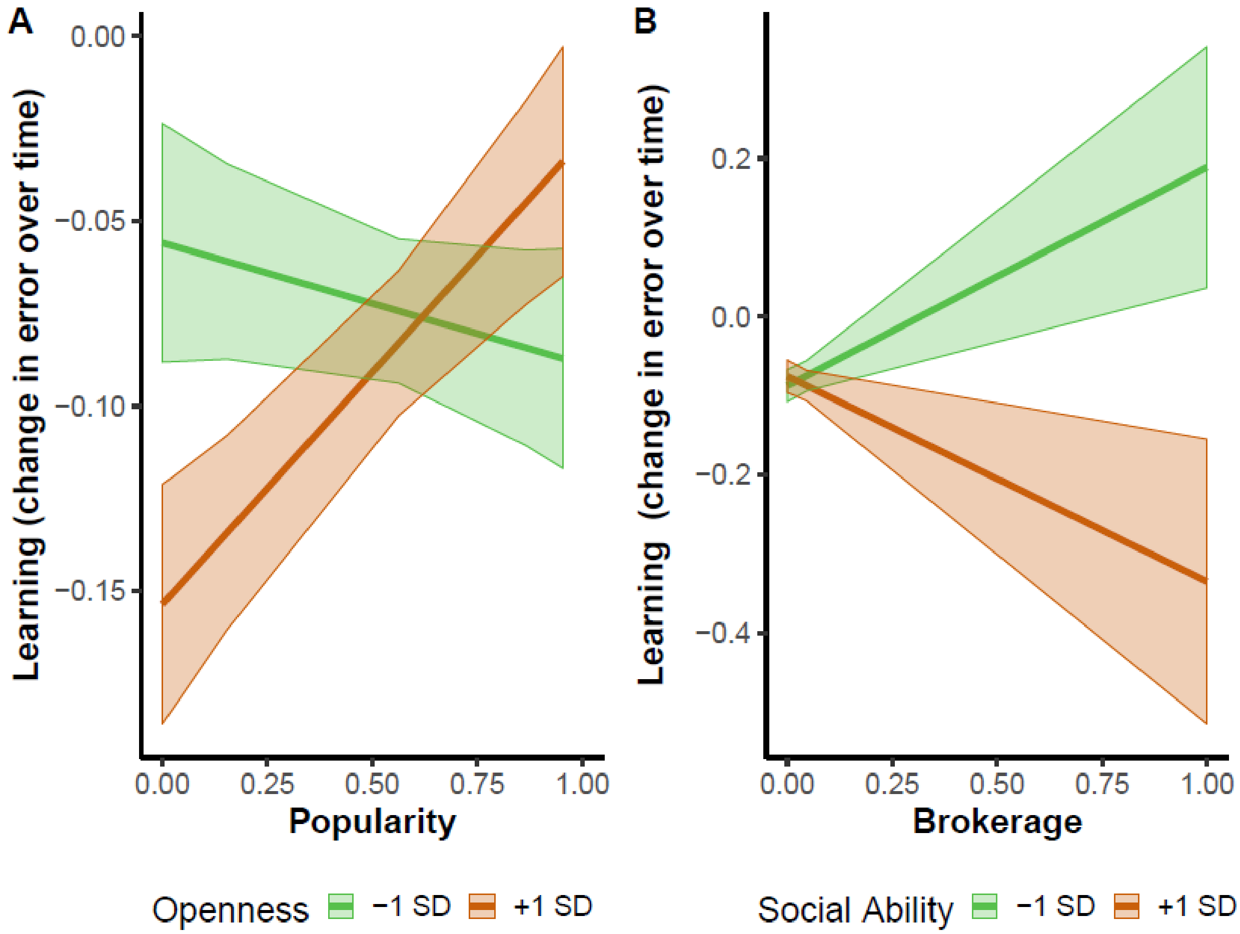
Examining Figure 4-4a shows the interaction effect of popularity and openness on learning. Examining the relationship between popularity and learning for those with 1 *SD* above and below the mean scores on openness shows that, for those who are not popular in the network, those with high levels of openness show greater learning than those with lower levels of openness. However, as popularity increases, greater learning is shown by those who are low (rather than high) on openness.

Figure 4-4b displays the pattern of the interaction between brokerage, social ability, and learning from network errors. Examining the relationship between brokerage and learning for those with 1 *SD* above and below the mean scores on social ability shows that brokerage only results in learning (a reduction in errors over time) for those who are also high on social ability. For those low on social ability and *not* occupying brokerage positions in the network, there is little if any difference in learning (*i.e.*, no difference in the change in errors over time). In contrast, there is *negative* learning (indicated by positive value on learning in Figure 4-4b) for those who do. That is, if those who are low on social ability *do* occupy brokerage positions, they tend to commit more errors over time. Taken together, the results reported in Figures 4-4a and 4-4b indicate that, while positional factors do not have a direct impact on learning, they do moderate the impact of dispositional factors on learning.

DISCUSSION

Organizational networks can be designed to efficiently and effectively enable information flows, yet leveraging those networks requires that individuals learn who is connected to whom. Existing work on errors has tended to focus on the individual, the team, or the system. This study expands the focus to explore relational dyadic-level errors that occur within social networks. Whether formal or informal, networks determine the flow of information within and across organizations. When individuals fail to correctly intuit the social connections around them, they can send information to the wrong people, overload communication channels, increase message distortion, and ultimately impede important decisions that hinge on timely access to information. To better understand the errors involved in leveraging networks, I introduced the concept of a *social network routing error* (SNRE) and studied 23 pre-existing group networks as they engaged in five rounds of a network routing task. This provided insight into the prevalence of SNREs, learning from SNREs, and the dispositional and positional factors associated with each.

Figure 4-4. Interaction Effects on Learning (change in error over time). (a) The interaction effect of popularity with openness. (b) the interaction effect of brokerage with social ability



How Prevalent Are SNRE and Learning?

My first research question had two parts: How often do individuals commit social network routing errors (RQ1a), and to what extent do individuals learn from their social network routing errors over time (RQ1b)? My findings suggest SNREs occur even among existing networks. Across all individuals, rounds, and groups, the prevalence of SNREs was 37%. Though fewer than what would be expected by chance, this error rate is appreciably higher than zero, indicating that, even in groups with existing social networks, errors can happen. Whereas errors were prevalent in each of five rounds, people also generally learned from these errors. The error rate was lower at the end than at the beginning of each round. Network learning occurs through trial and error as individuals make routing choices, and the result of those choices comes to pass.

These findings are consistent with a social network study estimating that, around 50% of the time, people fail to use the shortest path in their network based on survey data (Killworth et al., 2006). This suggests that information often goes through longer paths, which increases the chance of it either becoming distorted along the way (Huber, 1982; Miller, 1972) or not reaching the intended destination in time if at all (Milgram, 1967). My results also add to the literature by finding that people indeed learned from SNREs when they repeatedly engage in this type of task.

Who Commits SNREs and Who Learns From SNREs?

My second question probed what types of people make more errors, why, who learns from errors better than others, and why. Which positional and dispositional factors explain who is more likely to commit social network routing errors? (RQ2a) And related to this, which positional and dispositional factors explain who is more likely to learn from social network routing errors (RQ2b)? Individuals high in cognitive ability make fewer errors, but when they do make errors, they are less likely to learn from them than individuals lower in cognitive ability. Social ability is not related to error propensity or learning from errors, nor is personality. However, social ability and personality interact with network position to jointly affect error propensity and learning. Before considering these interactions, I turn to positional factors.

My findings show that, in addition to characterizing who individuals are, it is also important to determine where they are in the network. Where individuals were located within the network was directly related to their propensity to make routing errors. Being popular (having many others who chose you as a contact) or being a broker (connecting others who were not connected to each other) both resulted in making fewer routing errors. These findings support recent empirical confirmation that knowledge acquisition and provision are the highest when employees are popular, motivated, and highly capable of knowledge sharing (Reinholt et al., 2011). These findings suggest an additional benefit of network position is the reduced propensity to make mistakes with the integration of personal characteristics. The advantage of popularity may stem from observability; these individuals have a greater chance to perceive their neighbors' neighbors easily (Friedkin, 1983), and so personal characteristics might impact the observability, which in turn affects their routing ability. Interestingly, their location did not directly influence their ability to learn from errors. Instead, location in the network interacts with personal characteristics in shaping learning.

Indeed, with both errors and learning, I found person-by-position interactions. With personality traits, I found interactions involving emotional stability and openness. Individuals who are more popular in the network benefit more from their position if they are high (rather than low) on emotional stability. Openness played a role in errors and learning. Interestingly, the trait was disadvantageous to errors and learning. A brokerage position only afforded a reduction in error propensity for individuals who were low on openness to experience. In other words, I found openness to impede the ability to capitalize on brokerage for error reduction. Popular members who were also low on openness were able to learn from errors; for those high in openness, learning decreased as popularity increased. I also found that brokerage only increased learning for those high in social ability, yet decreased for those low on social ability.

Based on my definition of SNRE, all of these factors make sense. With respect to dispositional factors, as expected, cognitive ability is negatively correlated with an individual's error propensity, suggesting that the process of complex information plays a key role in making fewer errors. In contrast, cognitive ability has an unexpectedly negative impact on learning from SNREs. This finding is not straightforward. My interpretation is that, in combining the early finding in the error propensity model, individuals with high cognitive ability commit fewer errors in the first place than low ones, and that amount compensates for an error rate at the end of each round. In other words, they make very few errors on average and thus may not have much room to improve.

Contributions

In answering these questions, this study makes three contributions to the literature on errors in organizations. The first contribution is to explore errors that occur within social networks. Along with the introduction of the notion of SNRE, I also shift focus from the individual-team-system levels characteristic in error research (Lei et al., 2016) to explore errors occurring at the dyadic level. This level of analysis illustrates how individuals acting within a social system make errors and learn from those errors. SNRE is a type of dyadic error and has been understudied in the error literature (Sieweke & Zhao, 2015).

Moreover, I approached SNREs from a temporal perspective. My analysis incorporates time into errors and learning. I found that people generally learned from SNREs, as evidenced by the observation that they committed more SNREs at the beginning of each round than at the end of the round. This trend repeated each of the five rounds in my study. Moreover, this temporal dynamic sheds new light on how people learn from errors in a networked team environment. In other words, the rewiring of network connectivity requires members of a network to reconfigure who is connected to whom. Specifically given that Lei, Naveh, and Novikov (2016) called for studies leveraging a temporal and dynamic design, my study demonstrates how a simulated study enables researchers to better understand an emerging error pattern over time. Hence, my findings advance the current understanding of emerging error patterns.

My second contribution is to develop quantitative metrics needed to measure SNREs and learning from SNREs. I measured SNREs by combining an empirical behavioral task result with a null model. My results show that individuals make errors at a lower rate (37%) than expected by random chance (50.7%). To this date, my measurement is an important contribution to social network research since none of the existing social network research uses a behavioral measure to capture SNREs. Social network literature has long been aware that people are prone to make errors when they perceive their social network (Brands, 2013; Casciaro, 1998; Krackhardt, 1987), and my findings suggest that people are also ineffective at using their social network. Furthermore, these findings are consistent with a TMS study of team members' errors in transactive memory behaviors (expertise directory, information allocation, and retrieval coordination) (Pearsall et al., 2008). Since the errors in transactive memory behaviors were aggregated at the team level in their study, my work expands to a more precise measure of errors in transactive memory behaviors at the dyadic level.

My third contribution is to identify positional and dispositional factors that explain an individual's propensity for making SNREs and subsequently learning from them. I explored the interaction effects of positional and dispositional factors. Current error research remains unclear in terms of how these antecedents can have an impact on errors and learning (Lei et al., 2016). My findings advance this direction of work by providing nuanced evidence that supports the complex interplay between individual traits and learning environments (Gully et al., 2002; Naveh et al., 2015). I found that the interplay between positional and dispositional factors impacts learning from SNREs. Highly open individuals learn more than those low on openness if they are not popular in the network. However, for popular individuals, the effect of openness reverses, and those low in openness are at an advantage. Similarly, if brokers have high social ability, they are more likely to learn from SNREs, whereas if they possess low social ability, their learning is hampered. My findings are novel because I explore the interplay between an individual's network position and disposition. Given that people increasingly work in complex team environments, these findings suggest that SNREs can stem from a *mismatch* between members' position and disposition.

Practical Implications

This study has practical implications for error management training. I used a technological platform, 6 Degrees of Separation (6-DoS), to leverage my data collection for this study. Based on my own experiences, as well as those of my colleagues, I believe that this kind of technological platform helps members of a network recognize the value of network awareness ("who knows whom") and, by engaging in multiple rounds, see how the network awareness "muscle" can be exercised through training. Clearly, there is the potential for organizations to incorporate information routing activities such as these as part of their training efforts to mitigate communication errors and the risks of communication breakdowns.

A further implication is the heightened importance of understanding SNREs in technologically augmented work environments. Since automated technological assistance is becoming increasingly prevalent, some might argue that people no longer need to develop accurate perceptions of who knows who in the network. However, drawing from the literature on automation bias and TMS, I argue that, because of the integration of automated systems with our human systems, SNRE management is becoming even more important. For example, people tend to overestimate the reliability of automated systems without taking into account other factors, yet underestimate the automated systems when the systems present contradictory information to their own beliefs (*i.e.*, automation bias) (Mosier et al., 1998; Skitka et al., 2000). To overcome this automation bias, it is necessary for individuals to develop an awareness of when the automated assistant is not to be relied upon. For instance, pilots using flight simulators for their training need to develop an awareness of when they should *not* rely on automated systems. Additionally, a recent study found that information dashboards have a negative effect on the development of TMS within a team (Gupta & Woolley, 2018). Thus, I argue that exercising the awareness muscles of "who knows whom" is ever more essential to manage errors in teamwork.

Limitations and Future Directions

This study has some important limitations. First, the generalizability of findings is limited by the fact that I recruited networks sampled from student organizations. Students may have an easier or harder time completing a network routing task than more seasoned employees in organizations. On the one hand, most of my participants grew up using social media and digital platforms, so they may be better at completing such tasks. Yet they may also be less familiar with one another than employees who work together over years or decades, meaning the latter may be better positioned to anticipate communication channels. Likewise, the current sample may find it easier or harder than more seasoned employees to learn from errors and to accurately detect changes in a rewired network. This cautions against interpreting errors and learning rates as a representative, but rather as illustrative of the phenomenon. I was interested in a relatively fundamental psychological process of making sense of people's connections, and this renders the current sample reasonable for this purpose. A critical selection factor was membership in an existing organizational group whose members were aware of most others. An advantage of the current approach is that I could study SNREs in 23 relatively similar networks performing the same task under the same performance constraints.

The second limitation is the lack of a formal reporting structure alongside my informally determined communication channels. Most organizations specify some degree of formal structure in reporting relationships to maintain continuity and efficiency. Hierarchy, for example, plays a major role in the routing processes (Singh et al., 2010). Informal channels certainly emerge, and some formal channels are followed more than others; nonetheless, in this study, there was only an informal network. An important avenue for future research is to explore SNREs in a context in which both formal and informal networks exist.

The third limitation of this study is the focus on the measure of the shortest path. As discussed in my introduction to social network routing errors, several scholars (Fleming et al., 2007; Hansen, 1999, 2002; Huber, 1982; Miller, 1972; Singh et al., 2010; Uzzi et al., 2007) have found theoretical and empirical value in defining errors as departures from the "shortest path." However, one can—and should—consider a variety of alternative dimensions to gauge departures from error in information routing. These include aspects such as reaching all the recipients, following proper channels, and including feedback loops to confirm the accuracy of information flow. For instance, to develop a collective mind (Weick & Roberts, 1993), every person in the network needs to be connected and aware of the information. However, if senders and recipients always use the shortest path, by implication, it bypasses other members. As a result, the use of the shortest path might hamper the achievement of the collective mind. Additionally, using computer simulations, Lazer and Friedman (2007) demonstrated that the small world consisting of many short paths diffuses information more quickly, but this property of quick information diffusion actually drowns out superior solutions that emerge more slowly. Thus, the shortest-path information exchange generates the highest short-term performance but a weaker long-term performance. Given that my findings were based on a routing task in which participants were given one clear criterion (shortest path) for error-free performance, I caution against a premature generalization to routing scenarios in which routing errors are defined by different and/or multiple criteria.

This study also suggests four directions for future research. First, this study focused only on the antecedents of SNREs. An important next step is to understand the consequences of SNREs, especially at the collective level for the entire network. Future work is needed to explore the effects of SNREs and learning on team mental models, transactive memory, and collective performance.

Second, future research should consider the role of task complexity and network structure in SNRE. Classic network experiments found that centralized networks allowed participants to solve simple tasks more quickly than decentralized ones, yet the centralized networks resulted in slower work and more errors when it came to solving complex tasks (Bavelas, 1950; Leavitt, 1951). The impact of task complexity on the prevalence of SNREs and on individuals' ability to learn from those errors remains an open question.

Third, future research is also needed to examine how dyadic and situational factors explain SNREs. Dyadic relations, such as familiarity, trust, and authority, play a key role in whether people route information to certain receivers. Borgatti and Cross (2003) found that people tend to reach out to those with whom they are familiar. Moreover, people change their actions, depending on their environment. Error literature suggests that, when people are in a psychologically safe team, they are more likely to report errors and learn from errors over time (Edmondson, 1999; Goodman et al., 2011). I would expect that, since an SNRE is a dyadic error, situational factors such as psychological safety can also be important factors to explain SNREs.

Finally, it is important to address message modification and misinterpretation in information routing. As demonstrated by Brashears and Gladstone (2016), people correct and amplify errors created in the process of message routing, but they still convey the essence of the original messages to their indirectly connected recipients. Although I acknowledge this crucial part of information routing, my focus here is on how effectively people route their messages within their network. Future research should investigate how SNREs impact message transfer accuracy.

Conclusion

Our ability to route queries and information without errors determines group and organizational effectiveness. This study has demonstrated that the ability to engage in network routing is, as we may expect, error-prone and varies from person to person based on their abilities, personality traits, and location within the network. These discoveries highlight that both positional and dispositional characteristics play a significant role in committing and learning from network routing errors. I hope that, by elaborating on the concept of social network routing errors, I spark future research on the widely prevalent and under-researched phenomena of network routing errors. Whereas prior work focuses on either the individual or the collective, my focus on the dyads through which individual actions and reactions create system states is a promising new line of inquiry in organizational errors.

CHAPTER 5. CONCLUSIONS

In this dissertation, I have introduced a conceptual framework to advance our understanding of the error phenomena in communication networks, focusing specifically on with whom people choose to share information. Based on the conceptual model, the two empirical studies unpack the origins of cognitive and action errors in group communication networks. The results of my experiments highlight the importance of specific dispositional and positional factors for cognitive and action network errors, as well as the interplay between these factors. Additionally, they show that group members reduce cognitive and action errors by learning through simulated network routing tasks. With these studies, this dissertation specifically contributes to the theories on social networks and organizational errors by exploring cognitive and action network errors in information sharing. Next, I will summarize the main findings of the conceptual and empirical studies, then discuss theoretical contributions and future directions.

SUMMARY OF FINDINGS

In Chapter 2, I addressed which factors impact cognitive and action network errors in information-sharing processes within communication networks and how these errors result in information-sharing failures. To answer these research questions, I developed a conceptual framework of network and processing errors in communication networks based on an integrative review of multiple perspectives. I argued that information sharing processes are prone to errors that include an unintentional misunderstanding of the content between a source and an intended recipient (*i.e.*, processing errors) and an unintentional transfer of information to unintended recipients (*i.e.*, network errors). These errors can sometimes lead groups and organizations to unintended consequences, such as miscommunication, information loss, and information leakage. I use this overarching framework to better situate my specific contributions in this dissertation. Specifically, I focus on with whom to share, rather than what to share, since relatively little is known about how errors of with whom to share (*i.e.*, cognitive and action network errors) are related to communication failures. I articulate a theoretical framework on how dispositional, positional, and situational factors impact cognitive and action network errors. Using this framework, Chapters 3 and 4 empirically tested how specific dispositional and positional factors affect cognitive and action network errors.

Chapter 3 dealt with the question of why and how individuals make cognitive network errors in the presence of formal and informal structures of communication networks. To address this question, I posited a theory of relational schemas on how formal and informal structures in communication networks explain why members *mis*perceive and miss the existence of communication links in their networks. By comparing the actual and perceived networks, my results showed that members tend to overestimate the presence of communication links between members associated with one another in formal groups, as well as in informal structures based on reciprocity (a pair being connected to each other) and two-path (a friend of a friend). Group members also underestimate the presence of links between people in different formal groups and people who are not part of a closed triad (friends of friends). These results suggest a clear trade-off between accurate perceptions and errors of omission or commission in using relational schemas for perceptions of communication networks. These findings provide insights into how members' perceptions of "who knows whom" hinder their ability to share information effectively.

Finally, Chapter 4 focused on why and how individuals commit action network errors and learn from them in information sharing via communication networks. Using a network routing experiment with 23 groups comprising a total of 405 participants, I investigated the origins of social network routing errors (SNREs) and how people learn from them. My results showed that, across all individuals, rounds, and groups, the prevalence of SNRE was 37%. I also found that individuals high in cognitive ability make fewer errors, but when they do make errors, they are less likely to learn from them than individuals lower in cognitive ability. Social ability was not related to error propensity (*i.e.*, an SNRE rate per person) or learning from errors, nor was personality. Additionally, being popular (being chosen by many others as a contact) or being a broker (being connected to others who are not connected to each other) both result in fewer routing errors. Finally, my analysis showed that individuals' errors and their ability to learn from errors are explained by dispositional factors, positional factors, and the interplay between these factors. Popular individuals who are also low on openness tend to learn from errors; for those high in openness, learning decreases as popularity increases. My results showed that brokerage only increases learning for those high in social ability and decreases for those low on social ability. Overall, these findings suggest that SNREs can stem from the interplay between members' position and disposition.

CONTRIBUTIONS

The conceptual framework and empirical findings make contributions to the study of social networks, organizational errors, transactive memory systems, and information and communication technology.

First, I have developed a theoretical framework of errors in communication networks by leveraging theories on organizational errors and social networks. This framework is valuable because the literature on organizational errors and social networks has paid little attention to information-sharing problems due to network errors. Specifically, the distinction between processing and network errors is key to understanding information-sharing problems such as miscommunication, information leakage, and information loss. In addition, following Frese and Keith (2015), the framework differentiates the role of cognitive and action errors pertaining to "with whom to share information." Although prior work identifies the importance of human cognition (Huber, 1982), it has not fully appreciated the antecedents and consequences of cognition on information sharing. That being said, this contribution is particularly relevant to information systems and organizational design since the prior literature has only looked at the role of formal structure in solving information-sharing problems (Clement & Puranam, 2018). That is, they underscore the importance of building the *right* formal structure that helps members share information smoothly but do not integrate how people actually try to share information beyond the formal structure. Often, members in organizations share information through informal channels (Cross & Parker, 2004), which may influence individuals' perceptions of "who communicates with whom." I argue that these perceptions could result in information loss (*i.e.*, critical information never reaching the intended recipient) even though formal or informal channels exist. Thus, my framework illustrates how to incorporate human cognition and interactions alongside formal structure into information architecture and systems.

Second, my framework and findings also provide new insights for advancing our understanding of how observed and perceived networks are similar or different (*i.e.*, the perceptual gap). This is a longstanding question in social and communication networks (Brands, 2013; Killworth & Bernard, 1976; Krackhardt, 1987). Research suggests that there are two views of this question: Although the actual network structure is based on what individuals perceive in the network, it is based on a combination of how they act and what they perceive (Corman & Scott, 1994). Recent research proposes integrated models for observed and perceived networks. For example, Smith, Menon, and Thompson (2012) developed a framework in which individuals activated a specific set of their contacts depending on the situation. Their work underscores the importance of distinguishing between cognitive and action network errors. In line with their work, my framework and empirical results show that people use relational schemas to figure out their social environment while also learning from the trials and errors of their network action. Thus, they support a dynamic approach to explaining why a perceptual gap exists between observed and perceived networks.

Third, my dissertation demonstrates that group members make errors in two dimensions (*i.e.*, cognition and action) using novel laboratory experiments. One dimension of error comes from human heuristics (Tversky & Kahneman, 1974). Mainly, I expand on the literature regarding relational schemas—pre-existing expectations about social relations (Baldwin, 1992). My study finds that the same relational schemas provide reasonable sensemaking aids to perceive the structure of communication networks, yet simultaneously lead people to make certain types of errors. Specifically, this trade-off plays a vital role in transactive memory systems (TMS) because members need to mitigate the number of errors in "who knows whom" and "who knows what" to implement effective TMS (Ellis, 2006; Pearsall et al., 2008). TMS assumes that specialists as team members can leverage others' expertise through coordination and collaboration, based on their accurate metaknowledge of "who knows whom" and "who knows what" (Ren & Argote, 2011). The findings of network *cognitive* errors suggest the underlying mechanisms of "ambient awareness," in which members develop metaknowledge of TMS (Leonardi, 2015, 2018). Although it is crucial to make an effort to avoid errors in the first place, it is unavoidable to make errors in teams and organizations. Therefore, members should be aware of which types of errors (*i.e.*, errors of omission or commission) they need to prioritize in advance, because they cannot reduce them simultaneously.

The other dimension of error is *action*-based (Frese & Keith, 2015). In Chapter 4, I investigated an understudied type of error—social network routing errors (SNREs)—and demonstrated that SNRE is a common error (committed 37% of the time) yet less prevalent than simulated random decisions (modeled at 50.4% of the time) in my experimental data. Yet, my participants with high cognitive ability reduced their number of errors within each round, thereby learning from this type of error. These findings will help organizations and their members diagnose information-sharing problems. These also have important implications as to how members of a team overcome errors in coordination through information sharing. Combining the two dimensions of errors (*i.e.*, cognitive errors and action network errors), this dissertation has provided powerful and novel insight into the origins of network errors.

Next, the findings of my dissertation complemented the work that differentiates between topological and navigational views of complex social networks (*i.e.*, the knowing-doing gap) in two ways. First, my findings support the argument by Goel and his colleagues (2009) that the structural possibility to convey information from senders to the intended recipient through a short chain of intermediaries (*i.e.*, a topological view) does not guarantee that senders can navigate the short chain of intermediaries themselves (*i.e.*, navigational view). In short, knowing is not enough. Network navigation is similar to reading a map in cities. While some individuals use a map to navigate a city effectively, others cannot translate a map into where they are; thus, they often have difficulty navigating despite having a map. My findings reflect this phenomenon in social and communication networks. Second, I conducted network routing tasks in unique settings, unlike existing small-world experiments (see Schnettler, 2009a for a review). In other words, my experiment used pre-existing, midsize groups (15- to 26-person groups) to measure both the network navigation and topology of information routing together. This setting allowed me to capture whether participants could use the shortest path toward the intended recipient through a chain of intermediaries. Consequently, my findings demonstrated that people could, but their disposition (*e.g.*, cognitive ability) and network position (*e.g.*, popularity) impacted their capability to effectively navigate the network.

With relation to the role of cognition in network navigation, my dissertation also extends knowledge transfer literature, especially for a friction-based view of network research proposed by Ghosh and Rosenkopf (2015) that accounts for why information and knowledge are not transmitted through an inter-organizational network despite the existence of ties between organizations. While they stated that this view can be applied to interpersonal settings, its investigation at the interpersonal level is limited (*e.g.*, Tortoriello et al., 2014). More importantly, they do not incorporate the role of cognition as part of friction. As I empirically demonstrated in this dissertation, a perceptual gap between perceived and observed networks is a significant obstacle since information does not transfer as much as we anticipate. Thus, this perceptual gap is an essential additional mechanism to explain friction. My extension helps clarify the applicability of a friction-based view to interpersonal contexts and information sharing.

FUTURE DIRECTIONS

Even though my dissertation examined the origins of information-sharing errors using novel, simulated experiments, it has limitations that invite new avenues for future work. In this section, I discuss these limitations in relation to future opportunities.

First, my conceptualization of network and processing errors is context-dependent. As discussed in a dilemma among consequences, the errors and consequences of information sharing can be positive or negative, depending on the context. For example, while information loss is not ideal for everyday situations, it is a goal for some situations, such as intelligence agencies intervening in terrorism. Both intelligence agencies and terrorists use encoded messages that are difficult to decipher, meaning that processing errors are expected. They also try to increase network errors by manipulating and attacking communication networks.

Moreover, the assumptions of errors vary in different contexts. In particular, organizational politics—defined as “the exercise or use of power” (Pfeffer, 1993, p. 14)—make it difficult for individuals to act rationally. Put simply, politics distort the content of information and change the course of sharing it, regardless of intent. The reason for this type of political action is that power comes from control over and extensive access to accurate information in organizations. Consequently, desired behavior or standards can be different from written rules or procedures, or members of a particular organization may exercise standard procedures that are considered errors in other contexts. Organizational politics also might change information-sharing outcomes to prevent and manage errors in organizational communication networks.

Besides, classifying errors requires standards or desired behavior. In the case of action network errors, although the notion of the shortest path as a standard is legitimate (*e.g.*, Killworth et al., 2006; Singh et al., 2010), it is not always applicable to some organizational contexts in which the primary goal is to deliver messages to the intended recipients—irrespective of whether it is via the shortest path. For example, Erickson and Kringas (1975) studied how residents in Ottawa, Canada reached out to their political representatives and found that some participants did not use shortcuts to contact their representatives, instead of using more formal ways to reach out to them. This illustrates that we cannot apply the same criterion to classify network errors. Thus, we need to consider contexts before classifying network errors.

Second, although my conceptual framework signals the consequences of cognitive and action errors, my empirical investigations did not explore it. Instead, my empirical studies focused on the antecedents of cognitive and action network errors. Particularly, it is vital to investigate how error management (*e.g.*, training and psychological safety) can work to mitigate the impact of network errors on information-sharing outcomes. Thus, future research should empirically examine how cognitive and action errors affect communication consequences.

Additionally, while this dissertation focuses on cognitive and action network errors, integrating them with processing errors remains a vital research area. How do complexity and novelty of information content relate to processing errors? Although my experiments did not consider content mutation because participants passed a message without any content, prior research has shown that information content itself can also impact individual decisions (Hansen, 1999, 2002). For example, whereas simple information can go through weak ties, complex information requires strong ties to transfer because it includes tacit knowledge that requires the recipient to have the knowledge to comprehend. This assumption of complex knowledge can change a sender's choice of whom to share with. Furthermore, novel types of information flow through organizational networks since digital communication through social media has been rapidly expanding in organizations in recent years. This type of communication enables people to exchange not only texts but also images and short video and audio clips. As Brashears and Gradstone (2016) pointed out, future research should therefore explore non-textual communication (*e.g.*, images and videos). For instance, research on contagion investigates internet visual memes and how memes are mutated through a social media network (*e.g.*, Facebook) (Cheng et al., 2016). Although meme mutation is intentional and thus not an error, the technique of identifying memes can be applied to error research.

We also have very little knowledge of how processing and network errors are interrelated. In other words, processing and network errors coevolve when they coincide. For instance, telephone games are often used to demonstrate processing errors (Brashears & Gladstone, 2016; Moussaïd et al., 2015). A recent study by Ribeiro, Glogorić, and West (2019) examines how medical research abstracts mutate through pre-determined chains and finds that processing errors are more likely to be generated in low-quality summarization through a few steps of contacts and key messages (*e.g.*, conclusion). In these telephone games, there are chains but not networks, meaning that participants pass messages to predetermined contacts. What will happen if we conduct a telephone game in which people choose recipients, rather than communicating with predetermined ones? This question is crucial to address in future work since "with whom to share" can impact "what to share." Thus, investigating the coevolution process between processing and network errors will be a fruitful direction for future research.

To improve the generalizability of the findings, as the next step, it is necessary to conduct field research by collecting and analyzing real-world organizational data. Both of my empirical studies were based on simulated laboratory experiments. As a result, the findings of these studies have limitations of generalizability. Prior research on organizational errors shows that organizational setups (*e.g.*, hierarchy, organizational rules, routines, and monetary incentives) matter. Thus, future research should explore how these organizational components play a role in the relationship between cognitive and action network errors in real organizational settings.

Finally, cognitive and action errors can also be applicable to the current infodemic issues unfolding on social media. Infodemic refers to an epidemic of false information (Gallotti et al., 2020). It is a serious issue because people have difficulty gathering accurate information due to misinformation, disinformation, and malinformation on social media (*e.g.*, Facebook and Twitter). Particularly, misinformation comes from erroneous propagation, unlike disinformation (*i.e.*, false information that is knowingly disseminated) and malinformation (*i.e.*, harmful information that is deliberately created and distributed) (Wardle & Derakhshan, 2018). In other words, the phenomenon of misinformation is a combination of miscommunication and information leakage. Although this dissertation focuses on team and organizational phenomena, I argue that the proposed framework can be applicable to misinformation on social media. Thus, future research should expand the framework to this type of societal level phenomenon.

CLOSING REMARKS

This dissertation sets out to examine the origins of cognitive and action errors in communication networks by integrating two primary perspectives—organizational errors and social networks. With the proposed conceptual framework and empirical investigations, I have identified how and why dispositional and positional factors impact cognitive and action network errors. Based on 23, 12-person multiteam systems, I found that positional factors of formal and informal roles are instrumental in cognitive errors, such as errors of omission and commission. Specifically, group members tend to overestimate the presence of communication links between members associated with one another in formal groups, as well as in informal structures based on reciprocity (a pair being connected to each other) and two-path (a friend of a friend). Group members also underestimate the presence of links between people in different formal groups and people who are not part of a closed triad (friends of friends). Experiment results from a network routing task also show that both dispositional and positional factors impact SNREs, and the interplay between them predicts learning from SNRE. For example, individuals who are high in cognitive ability (a dispositional factor) and popularity or brokerage (both positional factors) commit fewer SNREs. Additionally, as an illustration of an interplay between factors, I found that brokerage increases learning from SNREs among those high in social ability but decreases learning from SNREs for those low on social ability. Hence, the findings of these studies shed new light on how members of a group perceive and navigate their networks.

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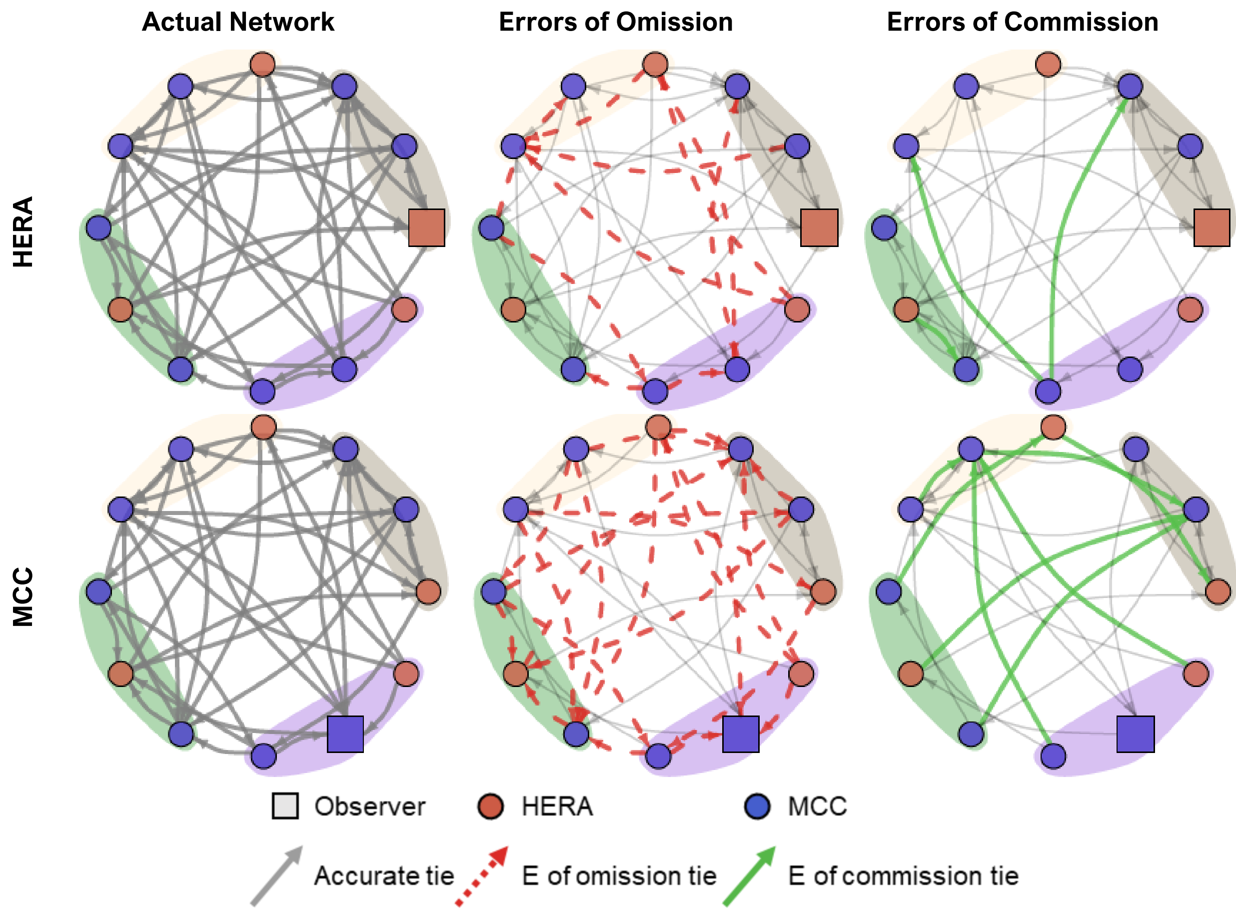
APPENDIX A

Figure A-1. Session 1's Actual Network, and Errors of Omission and Commission in Perceived Network



Note: Actual ties are gray, ties that are accurately perceived are black and thin, omission errors are red, and commission errors are green. Colored clusters indicate functional units. The colored nodes correspond to HERA (brown) and MCC (blue), respectively. The square node in each network indicates the respondent of the perceived network.

APPENDIX B

Table B-1. Interaction Effects of Popularity with Dispositional Factors on Error Propensity

	Model B1a		Model B1b		Model B1c		Model B1d		Model B1e		Model B1f		Model B1g	
	Error Propensity													
Intercept	0.47	(0.31)	0.51	(0.33)	0.48	(0.30)	0.80*	(0.30)	0.85*	(0.29)	0.32	(0.33)	0.36	(0.33)
Round	-0.03	(0.03)	-0.03	(0.03)	-0.03	(0.03)	-0.03	(0.03)	-0.03	(0.03)	-0.03	(0.03)	-0.03	(0.03)
Gender (Other)	0.51	(0.35)	0.53	(0.35)	0.52	(0.35)	0.54	(0.35)	0.57	(0.34)	0.55	(0.35)	0.52	(0.35)
Gender (Female)	-0.06	(0.06)	-0.06	(0.06)	-0.06	(0.06)	-0.06	(0.06)	-0.06	(0.06)	-0.06	(0.06)	-0.06	(0.06)
Openness	0.27	(0.26)	-0.03	(0.16)	-0.04	(0.16)	-0.06	(0.16)	-0.04	(0.16)	-0.06	(0.16)	-0.05	(0.16)
Conscientiousness	-0.05	(0.19)	0.15	(0.35)	-0.03	(0.19)	-0.06	(0.19)	-0.03	(0.19)	-0.08	(0.19)	-0.10	(0.19)
Extraversion	-0.05	(0.15)	-0.05	(0.15)	0.22	(0.27)	-0.05	(0.15)	-0.04	(0.15)	-0.06	(0.15)	-0.08	(0.15)
Agreeableness	0.09	(0.17)	0.10	(0.17)	0.10	(0.17)	-0.23	(0.28)	0.09	(0.17)	0.08	(0.17)	0.06	(0.17)
Neuroticism	-0.19	(0.14)	-0.18	(0.14)	-0.19	(0.14)	-0.19	(0.14)	-0.71	(0.25)	-0.17	(0.14)	-0.18	(0.14)
Social Ability	-0.19	(0.18)	-0.18	(0.18)	-0.17	(0.18)	-0.17	(0.18)	-0.18	(0.17)	0.33	(0.33)	-0.17	(0.18)
Cognitive Ability	-0.57*	(0.19)	-0.56*	(0.19)	-0.58*	(0.20)	-0.54*	(0.20)	-0.53*	(0.19)	-0.57*	(0.19)	-0.12	(0.32)
Popularity	-0.13	(0.27)	-0.29	(0.32)	-0.19	(0.27)	-0.80*	(0.24)	-0.97*	(0.21)	0.15	(0.38)	0.26	(0.45)
Brokerage	-0.59*	(0.26)	-0.56*	(0.26)	-0.57*	(0.26)	-0.58*	(0.26)	-0.57*	(0.26)	-0.55*	(0.26)	-0.54*	(0.26)
Popularity*Openness	-0.66	(0.43)												
Popularity*Conscientiousness			-0.37	(0.53)										
Popularity*Extraversion					-0.54	(0.43)								
Popularity*Agreeableness							0.61	(0.42)						
Popularity*Neuroticism									0.96*	(0.38)				
Popularity*Social Ability											-0.94	(0.52)		
Popularity*Cognitive Ability													-0.97	(0.56)
AIC	6289.64		6292.24		6291.54		6289.93		6286.95		6289.54		6288.44	
BIC	6409.01		6411.61		6410.91		6409.30		6406.32		6408.91		6407.81	
Log Likelihood	-3123.82		-3125.12		-3124.77		-3123.97		-3122.48		-3123.77		-3123.22	
Num Observation	2024		2024		2024		2024		2024		2024		2024	
Num Individuals	405		405		405		405		405		405		405	
Num Groups	23		23		25		23		23		23		23	

Note: * $p < .05$. Unstandardized exponentiated coefficients are presented with standard errors in parentheses.

Table B-2. Interaction Effects of Brokerage with Dispositional Factors on Error Propensity

	Model B2a		Model B2b		Model B2c		Model B2d		Model B2e		Model B2f		Model B2g	
							Error Propensity							
Intercept	0.70*	(0.28)	0.67*	(0.28)	0.77*	(0.28)	0.58*	(0.28)	0.61*	(0.28)	0.73*	(0.29)	0.55	(0.30)
Round	-0.03	(0.03)	-0.03	(0.03)	-0.03	(0.03)	-0.03	(0.03)	-0.03	(0.03)	-0.03	(0.03)	-0.03	(0.03)
Gender (Other)	0.53	(0.35)	0.54	(0.35)	0.54	(0.34)	0.54	(0.35)	0.54	(0.35)	0.53	(0.35)	0.53	(0.35)
Gender (Female)	-0.05	(0.06)	-0.05	(0.06)	-0.05	(0.06)	-0.06	(0.06)	-0.06	(0.06)	-0.06	(0.06)	-0.05	(0.06)
Openness	-0.20	(0.17)	-0.03	(0.16)	-0.06	(0.16)	-0.07	(0.16)	-0.06	(0.16)	-0.05	(0.16)	-0.04	(0.16)
Conscientiousness	-0.07	(0.19)	-0.17	(0.21)	-0.07	(0.19)	-0.07	(0.19)	-0.07	(0.19)	-0.07	(0.19)	-0.06	(0.19)
Extraversion	-0.06	(0.15)	-0.05	(0.15)	-0.24	(0.17)	-0.07	(0.15)	-0.05	(0.15)	-0.07	(0.15)	-0.06	(0.15)
Agreeableness	0.09	(0.17)	0.09	(0.17)	0.10	(0.17)	0.23	(0.19)	0.10	(0.17)	0.08	(0.17)	0.10	(0.17)
Neuroticism	-0.16	(0.14)	-0.17	(0.14)	-0.20	(0.14)	-0.18	(0.14)	-0.10	(0.15)	-0.17	(0.14)	-0.18	(0.14)
Social Ability	-0.18	(0.18)	-0.17	(0.18)	-0.19	(0.18)	-0.18	(0.18)	-0.18	(0.18)	-0.26	(0.19)	-0.17	(0.18)
Cognitive Ability	-0.54*	(0.19)	-0.54*	(0.19)	-0.57*	(0.19)	-0.55*	(0.19)	-0.57*	(0.19)	-0.58*	(0.20)	-0.47*	(0.23)
Popularity	-0.49*	(0.11)	-0.50*	(0.11)	-0.49*	(0.11)	-0.49*	(0.11)	-0.51*	(0.11)	-0.50*	(0.11)	-0.50*	(0.11)
Brokerage	-2.39*	(0.92)	-2.20	(1.39)	-3.28*	(1.10)	1.25	(0.94)	0.45	(0.79)	-2.06	(1.36)	0.42	(1.48)
Brokerage*Openness	3.20*	(1.55)												
Brokerage*Conscientiousness			2.70	(2.25)										
Brokerage*Extraversion					4.25*	(1.67)								
Brokerage*Agreeableness							-3.97*	(1.97)						
Brokerage*Neuroticism									-1.89	(1.39)				
Brokerage*Social Ability											2.24	(2.00)		
Brokerage*Cognitive Ability													-1.27	(1.89)
AIC	6285.13		6288.39		6282.81		6284.88		6288.95		6287.62		6289.74	
BIC	6404.50		6407.76		6402.18		6404.25		6408.32		6406.99		6409.11	
Log Likelihood	-3121.56		-3123.20		-3120.40		-3121.44		-3123.48		-3122.81		-3123.87	
Num Observation	2024		2024		2024		2024		2024		2024		2024	
Num Individuals	405		405		405		405		405		405		405	
Num Groups	23		23		23		23		23		23		23	

Note: * $p < .05$. Unstandardized exponentiated coefficients are presented with standard errors in parentheses.

Table B-3. Interaction Effects of Popularity with Dispositional Factors on Learning

	Model B3a		Model B3b		Model B3c		Model B3d		Model B3e		Model B3f		Model B3g	
							Learning							
Intercept	-0.14	(0.14)	-0.29	(0.15)	-0.22	(0.14)	-0.36	(0.14)	-0.37	(0.14)	-0.23	(0.15)	-0.24	(0.15)
Round	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)
Gender (Other)	0.02	(0.16)	0.01	(0.16)	0.01	(0.16)	0.00	(0.16)	-0.01	(0.16)	0.00	(0.16)	0.00	(0.16)
Gender (Female)	0.04	(0.02)	0.04	(0.02)	0.04	(0.03)	0.04	(0.02)	0.04	(0.02)	0.04	(0.02)	0.04	(0.02)
Openness	-0.31*	(0.12)	-0.07	(0.07)	-0.07	(0.07)	-0.06	(0.07)	-0.07	(0.07)	-0.07	(0.07)	-0.07	(0.07)
Conscientiousness	0.12	(0.09)	0.16	(0.16)	0.13	(0.09)	0.13	(0.09)	0.13	(0.09)	0.14	(0.09)	0.14	(0.09)
Extraversion	-0.02	(0.07)	-0.02	(0.07)	-0.13	(0.12)	-0.02	(0.07)	-0.03	(0.07)	-0.02	(0.07)	-0.01	(0.07)
Agreeableness	-0.02	(0.08)	-0.01	(0.08)	-0.02	(0.08)	0.15	(0.13)	-0.01	(0.08)	-0.01	(0.08)	-0.01	(0.08)
Neuroticism	0.04	(0.06)	0.02	(0.06)	0.03	(0.06)	0.03	(0.06)	0.24*	(0.11)	0.02	(0.06)	0.02	(0.06)
Social Ability	-0.03	(0.08)	-0.04	(0.08)	-0.04	(0.08)	-0.04	(0.08)	-0.04	(0.08)	-0.12	(0.15)	-0.04	(0.08)
Cognitive Ability	0.19*	(0.09)	0.19*	(0.09)	0.20*	(0.09)	0.18*	(0.09)	0.18*	(0.09)	0.19*	(0.09)	0.13	(0.15)
Popularity	-0.25*	(0.12)	0.07	(0.14)	-0.09	(0.12)	0.20*	(0.10)	0.24*	(0.09)	-0.05	(0.17)	-0.06	(0.20)
Brokerage	0.05	(0.11)	0.03	(0.11)	0.04	(0.11)	0.04	(0.11)	0.04	(0.11)	0.03	(0.11)	0.03	(0.11)
Popularity*Openness	0.51*	(0.20)												
Popularity*Conscientiousness			-0.04	(0.24)										
Popularity*Extraversion					0.23	(0.19)								
Popularity*Agreeableness							-0.33	(0.19)						
Popularity*Neuroticism									-0.40*	(0.17)				
Popularity*Social Ability											0.14	(0.24)		
Popularity*Cognitive Ability													0.13	(0.25)
AIC	3183.56		3189.84		3188.96		3187.46		3185.18		3189.54		3189.50	
BIC	3302.93		3309.21		3308.33		3306.83		3304.55		3308.91		3308.87	
Log Likelihood	-1570.78		-1573.92		-1573.48		-1572.73		-1571.59		-1573.77		-1573.75	
Num Observation	2024		2024		2024		2024		2024		2024		2024	
Num Individuals	405		405		405		405		405		405		405	
Num Groups	23		23		23		23		23		23		23	

Note: * *p* < .05. Unstandardized exponentiated coefficients are presented with standard errors in parentheses.

Table B-4. Interaction Effects of Brokerage with Dispositional Factors on Learning

	Model B4a		Model B4b		Model B4c		Model B4d		Model B4e		Model B4f		Model B4g	
							Learning							
Intercept	-0.28*	(0.13)	-0.27*	(0.13)	-0.29*	(0.13)	-0.29*	(0.13)	-0.27*	(0.13)	-0.35*	(0.13)	-0.30*	(0.14)
Round	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)
Gender (Other)	0.00	(0.16)	0.01	(0.16)	0.00	(0.16)	0.01	(0.16)	0.00	(0.16)	0.00	(0.16)	0.01	(0.16)
Gender (Female)	0.04	(0.03)	0.04	(0.03)	0.04	(0.02)	0.04	(0.02)	0.04	(0.02)	0.04	(0.02)	0.04	(0.03)
Openness	-0.06	(0.08)	-0.07	(0.07)	-0.07	(0.07)	-0.07	(0.07)	-0.06	(0.07)	-0.07	(0.07)	-0.07	(0.07)
Conscientiousness	0.14	(0.09)	0.12	(0.10)	0.14	(0.09)	0.14	(0.09)	0.14	(0.09)	0.13	(0.09)	0.14	(0.09)
Extraversion	-0.02	(0.07)	-0.02	(0.07)	-0.01	(0.08)	-0.02	(0.07)	-0.02	(0.07)	-0.01	(0.07)	-0.02	(0.07)
Agreeableness	-0.02	(0.08)	-0.01	(0.08)	-0.02	(0.08)	0.00	(0.08)	-0.02	(0.08)	-0.01	(0.08)	-0.01	(0.08)
Neuroticism	0.02	(0.06)	0.02	(0.06)	0.03	(0.06)	0.02	(0.06)	-0.01	(0.07)	0.02	(0.06)	0.02	(0.06)
Social Ability	-0.04	(0.08)	-0.04	(0.08)	-0.04	(0.08)	-0.04	(0.08)	-0.04	(0.08)	0.03	(0.09)	-0.04	(0.08)
Cognitive Ability	0.19*	(0.09)	0.19*	(0.09)	0.19*	(0.09)	0.19*	(0.09)	0.19*	(0.09)	0.20*	(0.09)	0.21*	(0.11)
Popularity	0.04	(0.04)	0.04	(0.04)	0.04	(0.04)	0.04	(0.04)	0.04	(0.04)	0.04	(0.04)	0.04	(0.04)
Brokerage	0.13	(0.42)	-0.32	(0.63)	0.18	(0.50)	0.19	(0.42)	-0.51	(0.36)	1.34*	(0.62)	0.32	(0.67)
Brokerage*Openness	-0.17	(0.71)												
Brokerage*Conscientiousness			0.58	(1.02)										
Brokerage*Extraversion					-0.24	(0.76)								
Brokerage*Agreeableness							-0.36	(0.89)						
Brokerage*Neuroticism									1.01	(0.63)				
Brokerage*Social Ability											-1.96*	(0.91)		
Brokerage*Cognitive Ability													-0.38	(0.86)
AIC	3187.64		3186.64		3187.46		3187.07		3185.39		3182.58		3187.13	
BIC	3307.01		3306.02		3306.83		3306.45		3304.76		3301.95		3306.50	
Log Likelihood	-1572.82		-1572.32		-1572.73		-1572.54		-1571.70		-1570.29		-1572.57	
Num Observation	2024		2024		2024		2024		2024		2024		2024	
Num Individuals	405		405		405		405		405		405		405	
Num Groups	23		23		23		23		23		23		23	

Note: * $p < .05$. Unstandardized exponentiated coefficients are presented with standard errors in parentheses.