MULTITEAM SYSTEM INTERTEAM COMMUNICATION AND TASK-CRITICAL LEADERSHIP: THE MODERATING EFFECTS OF SYSTEM SIZE

by

CYNTHIA K. MAUPIN

(Under the Direction of Dorothy Carter)

ABSTRACT

Many complex challenges are beyond the scope of single teams, and instead, require coordination and collaboration across larger interdependent systems comprised of multiple 'component' teams. Referred to as *multiteam systems* by organizational scholars, these teams of teams offer a number of advantages, including increased resource capacity and structural flexibility. Yet, despite their advantages, multiteam system structures also present coordination challenges, such as overcoming functional divides, increased cognitive load, and performing in highly dynamic environments, which may lead to system failures. Multiteam system researchers have identified important interaction processes, including *interteam communication* (i.e., communication spanning component team boundaries) and *task-critical leadership* (i.e., influence that is exerted by leaders with relevant task expertise to coordinate multiteam system actions), which can help to enhance multiteam coordination and promote system success. Recent theoretical work asserts that multiteam system *size* (i.e., the number of teams involved in the system) may be a critical boundary condition that determines the patterns of interaction processes that are most effective. However, traditional research approaches that have examined short-term, stable multiteam systems have yet to investigate this question due to data collection constraints.

I build and test hypotheses to uncover the effects of interteam communication and task-critical leader influence under different task conditions that present different levels of system size. I test my hypotheses using data collected from a multinational military coalition training simulation which dynamically adapted its structure in response to disruptive events. Specifically, this system changed the number of teams that were required to resolve those events, thus altering system size in response to changing task demands. This approach enabled investigation into the moderating effects of system size on the relationship between interteam communication and task-critical leadership on multiteam system success. My results suggest that whereas tasks involving a larger number of teams require centralized leadership influence through task-critical leaders; tasks involving fewer teams can benefit from either interteam communication *or* task-critical leadership, but attempting to leverage both strategies is unnecessary. These findings determine important boundary conditions that enable researchers and managers alike to better align multiteam system interaction processes with system size to enable multiteam system success.

INDEX WORDS: Multiteam systems, interteam communication, task-critical leadership, multiteam system size

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LEADERSHIP: THE MODERATING EFFECTS OF SYSTEM SIZE

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DEDICATION

I dedicate this dissertation to my beloved grandparents: Henry and Betty Maupin, and Richard and Susie Risku. Although they did not get to see me finish this degree, I know they would be proud. Thank you all for sharing your love of education with me and inspiring me to be a ‘striver and achiever’.

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CHAPTER 1

INTRODUCTION

Many important and complex challenges in contexts such as military combat (e.g., Goodwin, Blacksmith, & Coats, 2018), disaster response (e.g., DeChurch et al., 2011), emergency care (e.g., Mathieu, Marks, & Zaccaro, 2001), and medicine (e.g., Taplin, Foster, & Shortell, 2013), are beyond the scope of single teams working in isolation and instead, require coordination and collaboration across larger interdependent systems comprised of multiple 'component' teams (Davison, Hollenbeck, Barnes, Sleesman, & Ilgen, 2012; Shuffler & Carter, 2018; Mathieu et al., 2001; Zaccaro, Marks, & DeChurch, 2012). Referred to as *multiteam systems* by organizational scholars, these teams of teams offer a number of advantages, such as more resource capacity than single teams and more structural flexibility than traditional organizations (Davison et al., 2012). However, despite their many advantages, multiteam system structures also present coordination challenges, such as overcoming functional divides between component teams, increased cognitive load while balancing both team-level and system-level goals simultaneously, and performing in highly dynamic environments (Mathieu et al., 2001; Luciano, DeChurch, & Mathieu, 2018).

To address challenges of multiteam system collaboration, a growing stream of research is seeking to better understand the factors that enable multiteam system success. Paralleling research on the effectiveness of stand-alone teams (e.g., Marks, Mathieu, & Zaccaro, 2001; McGrath, 1964; McIntyre & Salas, 1995), research on multiteam system functioning has sought to identify the patterns of *interaction processes* (i.e., behavioral interactions among members) that support system performance. This stream of research has identified two key categories of interaction processes in multiteam system contexts that are particularly relevant to performance: (1) *interteam communication* (i.e., communication spanning component team boundaries) and (2) *multiteam system leadership* (i.e., influence that is exerted to coordinate action in support of multiteam system goals; Shuffler, Jiménez-Rodríguez, & Kramer, 2015). Interteam communication can signal both information sharing and collective coordination across team boundaries, which are important for enabling multiteam systems to capitalize on expertise across teams (Waring, Alison, Shortland, & Humann, 2018). Meanwhile, multiteam system leadership can provide order across interteam boundaries and direct the system's coordination efforts to ensure that key functions are being fulfilled, especially when leadership is assumed by task-critical leaders who are pivotal to task demands (Aime, Humphrey, DeRue, & Paul, 2014).

For the most part, conclusions about interaction processes in multiteam systems are drawn from studies investigating systems that operate over a short duration of time and have stable configurations of teams and task demands. For example, laboratory studies of multiteam systems typically examine systems that interact together for less than one day's time, are composed of the same configuration of teams working together across all tasks, and are focused on achieving a single superordinate goal which remains consistent throughout the entirety of their interactions (e.g., Cuijpers, Uitdewilligen, & Guenter, 2016; DeChurch & Marks, 2006; Marks, DeChurch, Mathieu, Panzer, & Alonso, 2005; Murase, Carter, DeChurch, & Marks, 2014; Porck, Matta, Hollenbeck, Oh, Lanaj, & Lee, 2018). These studies have uncovered important insights, including the benefits of multiteam system identification for tempering between-team conflict (Cuijpers et al., 2016), the importance of leadership functions to improve multiteam system effectiveness (DeChurch & Marks, 2006), and how system-wide shared mental models benefit multiteam collaboration (Murase et al., 2014).

However, studies of multiteam systems with stable configurations of teams that operate in stable contexts also leave important theoretical questions about multiteam system functioning unanswered. For example, recent theoretical work asserts that multiteam system *size* (i.e., the number of teams involved in the system; Zaccaro et al., 2012) may be a critical boundary condition or moderating variable that determines the patterns of interaction processes that are most effective (Lanaj, Hollenbeck, Ilgen, Barnes, & Harmon, 2013; Mathieu, Luciano, & DeChurch, 2018). Prior paradigms for studying multiteam systems empirically—that held multiteam system configuration and task demands stable—are not feasible for addressing theoretical questions about the patterns of processes that benefit systems with different system sizes (i.e., small versus large numbers of teams).

The lack of understanding regarding the patterns of processes that benefit system performance under different levels of system size is unfortunate because prior theory suggests that small versus larger systems may need very different interaction patterns in order to succeed. For example, on the one hand, very large systems with many members and teams present extremely complex coordination demands. Given the added coordination challenges incumbent to larger systems, these systems may benefit substantially from centralizing communication through 'task-critical' leaders (Davison et al., 2012; Zaccaro & DeChurch, 2012). On the other hand, smaller systems comprised of fewer members and teams present less complex coordination demands (but are nonetheless 'multiteam systems'; Luciano et al., 2018) and may function more similarly to single stand-alone teams, which have been shown to benefit from higher levels of decentralization in communication (Marks, Sabella, Burke, & Zaccaro, 2002; Woolley, Chabris, Pentland, Hashmi, & Malone, 2010).

To resolve this gap in understanding, in this dissertation, I advance a novel case study approach that follows a single multiteam system over time as it encounters a variety of disruptive events that require different configurations of teams to be activated to address each event. I develop and test hypotheses regarding the degree to which interteam communication and task-critical leadership benefit system performance under varying levels of system size. In doing so, I contribute to theory and research on multiteam system functioning by addressing the practically-relevant question: *How should multiteam systems of different sizes structure their processes to achieve shared goals?*

Further, I investigate multiteam system processes quantitatively in a context that closely resembles many ‘real-world’ systems. Although laboratory studies of multiteam systems have tended to simulate systems with stable configurations and task demands, in reality, case studies suggest that systems often operate for much longer time periods and have more dynamic task demands and system configurations (e.g., DiazGranados, Dow, Perry, & Palesis, 2014; Larson, Nystad, & Taylor, 2014; Lee et al., 2016). For example, Lee and colleagues (2016) present a patient care multiteam system case study which took place over the course of several months that involved the activation and deactivation of various teams depending on the patient’s changing healthcare needs (i.e., task demands). In fact, a major strength of multiteam systems is their ability to flexibly aggregate and disaggregate in response to evolving task demands (Mathieu et al., 2001; Shuffler & Carter, 2018), yet this ability may be overlooked when researchers leverage more traditional empirical approaches.

I test my hypotheses using data collected from a multinational military coalition training simulation which took place over the course of two weeks. In this training simulation, a large-scale multiteam system comprised of teams with highly developed expertise coordinated with one another to achieve both team-level and system-level goals in the presence of more than one hundred disruptive events which triggered changes in task demands. I leverage digital traces of teamwork interactions (i.e., the communication records) to assess patterns of communication processes, leadership, and system-level recovery in response to disruptive events. Moreover, I employ a novel pattern recognition approach, *Hidden Markov Models* (Rabiner, 1989), to identify unobtrusively both action and recovery phases in the digital communication data (i.e., through distinguishing high-, low-, and baseline-activity states).

This research makes a number of theoretical and practical contributions to the study of multiteam systems. My work extends the theoretical literature by answering calls to investigate the potential moderating effects of system size on multiteam system interaction processes (Lanaj et al., 2013; Mathieu et al., 2018). In fact, I find evidence to support that the size of the system involved in responding to different tasks is an important boundary condition for the efficacy of both interteam communication and task-critical leadership. Whereas effective coordination across a larger number of component teams is enabled through centralizing communication through task-critical leaders, smaller numbers of component teams can leverage either interteam communication or task-critical leadership to enhance their coordination effectively. Moreover, these findings provide important practical advice for multiteam systems in real-world contexts. For systems that have few teams collaborating together to achieve a shared goal, enhancing interteam communication could be beneficial for enabling multiteam system performance. However, in highly complex systems with many teams interacting together, it is most beneficial if task-critical leaders are central in the flow of communication. These results can assist researchers and practitioners alike in understanding the important effects system size can have on multiteam system interaction processes and performance.

CHAPTER 2

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Today's organizations must address a variety of complex challenges in order to remain competitive in a dynamic and complex world (Bolman & Deal, 2017; Ferraro, Etzion, & Gehman, 2015; George, Howard-Grenville, Joshi, & Tihanyi, 2016; Li & Liu, 2014). To do so, many organizations have begun to rely heavily on flexible and collaborative team-based work structures that allow organizations to capitalize on diverse expertise and adapt to evolving task demands (Anderson & West, 1998; Devine, Clayton, Philips, Dunford, & Melner, 1999; Kozlowski & Bell, 2003; Lawler, Mohrman, & Ledford, 1995; Mathieu, Hollenbeck, van Knippenberg, & Ilgen, 2017). In fact, as important challenges are increasingly beyond the scope of any single individual or single team working in isolation, teams are often called upon to work in collaboration with other teams in larger, interdependent collectives—or *multiteam systems* (Mathieu et al., 2001)—that strive to achieve not only proximal team goals, but also to combine their efforts to address a more distal, shared superordinate goal (Zaccaro et al., 2012). The prevalence of multiteam systems in today's world has resulted in many investigations seeking to understand strategies for promoting multiteam system effectiveness (e.g., Asencio, Carter, DeChurch, Zaccaro, & Fiore, 2012; Davison et al., 2012; DeChurch & Marks, 2006; Lanaj et al., 2013; Marks et al., 2005; Murase et al., 2014; Shuffler et al., 2015; Shuffler, Rico, & Salas, 2014).

Defining Multiteam Systems

Multiteam systems are a distinct way of organizing that presents unique benefits and challenges that differ from other types of organizational units. As defined by Mathieu and colleagues (2001), multiteam systems consist of "two or more teams that interface directly and interdependently in response to environmental contingencies toward the accomplishment of collective goals. Multiteam system boundaries are defined by virtue of the fact that all teams within the system, while pursuing different proximal goals, share at least one common distal goal; and in doing so exhibit input, process and outcome interdependence with at least one other team in the system" (p. 290). Importantly, multiteam systems are unique in their needs and function differently from both "big teams" and "small organizations" (Lanaj et al., 2013; Shuffler & Carter, 2018), which means that although they share some common features with these other types of entities, they require separate forms of investigation.

Multiteam systems, although composed of multiple teams, are not just "big teams". Salas and colleagues (1992) defined *teams* as "a distinguishable set of two or more people who interact dynamically, interdependently, and adaptively toward a common and valued goal/objective/mission" (p. 4). Teams have their own unique norms, identities, and processes, which are distinct from other teams (Sundstrom, De Meuse, & Futrell, 1990). Whereas a team exhibits interdependence among individuals for the accomplishment of shared team-level goals, multiteam systems must balance the presence of both team-level goals and system-level goals, with interdependence occurring both within and between teams (DeChurch & Zaccaro, 2010). Accordingly, each component team that makes up a multiteam system can have its own unique norms, identities, and processes, which introduces additional potential barriers toward collaboration which do not exist within teams. Thus, not all insights gleaned from research on single teams are wholly applicable to multiteam system contexts (Shuffler & Carter, 2018).

Likewise, multiteam systems are not simply "small organizations." *Organizations* are defined as stable social units that are deliberately created with the explicit intention of continuously pursuing the accomplishment of a particular goal or purpose (Stinchcombe & March, 1965). In contrast, multiteam systems are highly flexible and adaptive with the ability for individuals or teams to join or leave the system at any time, pursuant to the achievement of the overarching goal of the system (Shuffler & Carter, 2018). For example, it is common for temporary multiteam systems to be created to address a societal problem and then disbanded once the problem has been addressed (e.g., Edmondson & Harvey, 2017; Uitdewilligen & Waller, 2011). Furthermore, although organizations can be composed of one or several multiteam systems who pursue both proximal team-level and more distal system-level goals, multiteam systems are not confined to functioning within organizational boundaries, and in fact, are often composed of teams from different organizations that come together to solve a larger problem (Zaccaro et al., 2012). This introduces ambiguity with regard to hierarchical structure and decision-making power, as components teams in multiteam systems frequently have no formal authority over one another (DeRue & Ashford, 2010), and instead must rely on informal influence to guide the activities of others within the system (Shuffler & Carter, 2018).

Although researchers seeking to understand effective multiteam system functioning might draw from some aspects of the teams and organizational literatures, multiteam systems have many unique demands which defy explanation from existing teams and organizational theories (Luciano et al., 2018). For example, multiteam systems with extremely effective within-team coordination may still fail due to a lack of between-team coordination (Firth, Hollenbeck, Miles, Ilgen, & Barnes, 2015). Due to their unique role within, and sometimes across, organizations, multiteam systems have different advantages and challenges to consider when investigating strategies to promote their success (Shuffler & Carter, 2018).

Advantages of Multiteam Systems

There are a number of benefits to deploying multiteam systems to tackle important missions. First, multiteam systems can be rapidly formed to address grand challenges that require diverse knowledge and perspectives in the form of highly specialized teams that come together in pursuit of a complex shared goal (Mathieu et al., 2017; Kozlowski & Ilgen, 2006). Due to their specialized structure, multiteam systems have the ability to multitask by assigning sub-goals to its specialized teams, which feed into the larger superordinate goal of the system (Marks et al., 2005). Furthermore, they have access to a variety of deep expertise which can span across boundaries and enhance innovative thinking and problem-solving (Carter, DeChurch, & Zaccaro, 2014). In fact, Shuffler and Carter (2018) identify *flexibility* and *specialization* as key aspects of multiteam systems which enable systems to both focus on specific sub-goals and 'act as one' as part of a highly coordinated system (Marks et al., 2005; Thompson, 1967).

Multiteam system flexibility means that component teams within the larger system can be added, removed, or adapted as needed to match expertise demands in order to achieve the superordinate goal (Shuffler & Carter, 2018). For example, in a healthcare context, an emergency response team may be a crucial aspect of the multiteam system when providing initial care and transporting a patient from the scene of an accident to the hospital; however, once that patient is under the hospital's direct care, they may no longer serve as a member of the system that is charged with caring for that patient and be removed from the patient's care. Likewise, as the patient's treatment progresses, the medical staff may choose to add a surgical team to the system in order to address a newly discovered heart condition. Flexibility with regard to which component teams are assigned particular tasks in the multiteam system and the ability to change structures to support the overarching superordinate goal is a key advantage of multiteam systems (Mathieu et al., 2001).

Multiteam system specialization of component teams enables these systems to leverage deep knowledge in unique functional areas to focus on specific aspects of a larger goal in order to maximize process gains (Shuffler & Carter, 2018). In particular, specialization allows multiteam systems to divide challenging and complex goals into more manageable sub-goals, which can then be assigned to component teams based on a match to their specific areas of expertise. Following on the previous example, the emergency response team might have a sub-goal unique to their team of “stabilizing the patient for transport to the hospital”; however, this team-level goal helps build the foundation for achieving the superordinate goal shared by the healthcare multiteam system of “saving the patient’s life”. This multilevel goal hierarchy composed of separate sub-goals that feed into the shared superordinate goal is an additional advantage unique to multiteam systems (Mathieu et al., 2001).

There are clear benefits to utilizing a multiteam system structure to tackle complex goals; however, the advantages that come with this unique way of organizing also come with additional challenges. Flexibility and specialization introduce another level of complexity that can also lead to system-wide failures (e.g., DeChurch et al., 2011; DeChurch & Mathieu, 2009; Goodwin, Essens, & Smith, 2012; Rico, Hinsz, Davison, & Salas, 2018). These challenges should also be considered when crafting the larger picture of effective multiteam system functioning.

Challenges of Multiteam Systems

Many systems are created to address grand challenges, yet systems frequently fail to capitalize on their potential. For instance, the Hurricane Katrina response effort is a notable example of multiteam system failure that researchers have examined to provide clues which might be able to enhance multiteam functioning. DeChurch & Mathieu (2009) leverage this example to show how challenges with the mismanagement of a large and highly complex multiteam system resulted in failure to achieve the superordinate goal of responding effectively to disaster relief efforts. In particular, teams from different backgrounds—including local, state, federal, military, governmental, and volunteer organizations—were required to share information and coordinate leadership across team boundaries, yet inefficiencies and distrust throughout the system resulted in a lack of action that directly impacted thousands of people (Clift, 2005).

In comparison to single teams, multiteam systems face additional coordination challenges, as their components teams must work together across team boundaries in order for the system to be successful (Mathieu et al., 2001). Therefore, teamwork and taskwork processes such as communication and coordination become increasingly difficult due to both the (generally) larger size of multiteam systems as well as the presence of differential team boundaries (Lanaj et al., 2013; Marks et al., 2005). Furthermore, interdependence exists both within teams and between teams, thus potentially disparate teams must be able to exchange resources, share information, reduce competition, and manage conflicts in order to achieve their goals (Mathieu et al., 2001; Zaccaro et al., 2012).

There are also additional relational challenges in multiteam system contexts. Members of a multiteam system have to navigate not only their relationships and interactions with members of their own team, but they also have to balance these with their relationships and interactions with members of other teams in the system (Rico et al., 2018). In fact, countervailing forces suggest interpersonal relationships differ across levels and can have differential impacts on the system (DeChurch & Zaccaro, 2013). For example, too much within-team cohesion relative to between-team cohesion can result in multiteam system coordination failures. Thus, multiteam systems have to carefully manage both within and between team relationships to ensure collective success of both teams and the system as a whole.

Members of multiteam systems also face additional cognitive demands as they pursue both proximal team-level and distal system-level goals. The multiteam system goal hierarchy is a central tenet of the original multiteam system framework (Mathieu et al., 2001), thus balancing and shifting goal priorities as needed requires individuals and teams within multiteam systems to have strong shared cognitive structures. As an illustration, Murase and colleagues (2014) demonstrate the importance of collective system-level cognition for synchronizing interactions across teams in multiteam systems. Maintaining awareness of who within the multiteam system has particular types of knowledge, skills, and expertise is critical for multiteam system success, but is cognitively taxing due to the sheer number of people and teams involved.

Multiteam systems are also unique in that, by definition, they require multilevel interdependence of inputs, processes, and/or outcomes (Mathieu et al., 2001). Component teams within a multiteam system are expected to pursue their own team-level goals while simultaneously contributing to a larger, system-level goal, which results in nested goal hierarchies. However, multiteam system researchers have often theorized under the assumption that the lower-level team goals are aligned with the higher-level superordinate goal (i.e., positive forms of interdependence; Deutsch, 1949), which may not always be the case (Zaccaro et al., 2012). In fact, goal discordancy when attempting to facilitate cross-team interdependence is an additional area in which differentiation can come into play within a system (Luciano et al., 2018).

Leadership is also more challenging for multiteam systems than it is for single teams (DeChurch & Marks, 2006). Leading within multiteam systems has garnered much scholarly interest due to the unique coordination challenges systems of teams can impose (e.g., Davison et al., 2012; DeChurch & Marks, 2006; Murase et al., 2014). Frequently, systems are composed of teams which function outside of a traditional organizational hierarchy, with component teams from different organizations who have no formal authority over one another (Zaccaro et al., 2012). Some systems have addressed this issue by designating a "leader" or "integration" team (e.g., Davison et al., 2012), whose role is to coordinate processes across the multiteam system in pursuit of the superordinate goal. However, many systems have no integration team, and thus must negotiate with one another by leveraging informal means of influence (Shuffler & Carter, 2018). Additionally, component team leaders may need to function as interteam boundary spanners to ensure actions within the team are aligned with the priorities of the system (Davison et al., 2012).

Each of these challenges are compounded when teams are highly differentiated from one another, meaning that they have separate team goals (e.g., Zaccaro et al., 2012), norms (e.g., Asencio et al., 2012), identities (e.g., Connaughton & Williams, 2012), areas of expertise (e.g., Mathieu et al., 2001), work processes (e.g., Marks et al., 2005), geographic locations (e.g., Luciano et al., 2018), and more. In fact, boundary enhancing forces that arise due to component team differentiation reinforce distinctions between component teams, enhancing their desire to coordinate primarily within their own team and not with other teams (e.g., Allport, 1954; Tajfel, 1982). Furthermore, Luciano and colleagues (2018) assert that differentiation can have a compilational effect, such that the presence of multiple forms of differentiation within one multiteam system increases the likelihood of boundary-enhancing forces. Thus, the unique structure inherent to multiteam systems contributes to opportunities for cross-boundary integration failures (Rico et al., 2018; Williams & Mahan, 2006).

An additional aspect that can impact multiteam system coordination is the dynamism of the environment in which it is embedded, which impacts the overall instability and variability of the system over time (Luciano et al., 2018). In particular, multiteam systems have been theorized to exist in highly dynamic environments with evolving task demands, fluid system structures, variable system membership, and frequently changing goal priorities (Luciano et al., 2018; Mathieu et al., 2001). Task demands might change due to either internal or external disturbances which force the system to shift its priorities and shift their attention to new tasks in response. Additionally, the structure of the system can change due to teams joining or leaving the system (i.e., changing total system membership) or by dynamically changing which teams must work together (i.e., changing which teams are activated to address a task), thus impacting interaction patterns across the system. Finally, shifting the attentional focus of the multiteam system and its teams toward different goals over time changes how the system coordinates depending on goal priorities. Each of these features of dynamic environments contributes to instability in the system, making it nearly impossible for multiteam systems to "plan ahead" for all possible scenarios, thus they must be able to dynamically adapt moment to moment.

Multiteam systems operate in highly dynamic—and frequently high-risk (e.g., military combat; Goodwin et al., 2018)—environments, with continuously evolving task demands (Mathieu et al., 2001). Indeed, the trigger for multiteam systems to change their task priorities often arises in the form of an 'event' (Morgeson, 2005), which requires systems to change its processes and behaviors to address new goals. Importantly, events can be either endogenous or exogenous to a system. *Endogenous events* are those that occur internally within the system. For example, an interpersonal conflict between members of two different teams may force the multiteam system to change how it organizes and collaborates in order to achieve system goals. On the contrary, *exogenous events* are those that stem from outside the system itself to impact system functioning. For example, a sudden shortage of supplies can crucially impact how the system redirects their efforts and prioritizes tasks in the pursuit of system-level success.

In my dissertation, I focus specifically on a class of exogenous events called *disruptive events*, defined as unexpected disturbances to usual group functioning (Morgeson, 2005). Investigating the impact of disruptive events on system-level functioning and success is critical for understanding how multiteam systems must adapt in highly dynamic environments. In particular, multiteam systems must change their interaction processes in order to better address and recover from disruptive events in order to promote multiteam system performance.

In order to help multiteam systems to succeed in dynamic environments, we need to understand the processes that support their performance. In particular, it is important to uncover how multiteam systems are able to recover effectively from disruptive events that trigger changes in task demands. In highly dynamic environments, events can vary widely in their characteristics (Morgeson, Mitchell, & Liu, 2015), and thus their ultimate impacts on system functioning. Indeed, Morgeson (2005) found that the more disruptive an event, the more extensive actions taken by self-managing teams had to be in response to those events. Thus, research is needed that investigates the processes that promote multiteam system recovery from disruptive events.

Interaction Process Patterns to Support Multiteam System Performance

We can draw directly from previous research on stable multiteam system environments to predict which interaction processes may be important for enabling multiteam system recovery in dynamic contexts. Previous empirical research has identified two key processes that may promote recovery from disruptive events: 1) *interteam communication*, and 2) *task-critical leadership influence* (Shuffler et al., 2015). Indeed, both of these interaction processes have been linked to enhanced multiteam system performance (e.g., Davison et al., 2012; DeChurch & Marks, 2006; Shuffler et al., 2015).

Communication has been demonstrated to be a critical teamwork process for enhancing performance, as evidenced by the vast literature examining communication patterns within and between teams (e.g., Allen, 1984; Ancona & Caldwell, 1992; De Vries, Van den Hooff, & de Ridder, 2006; Marks et al., 2001; Shaw, 1964; Tushman, 1979; Zenger & Lawrence, 1989). Communication serves as a conduit through which information is shared, directions are given, and coordination is enacted, thus it is critical for team and multiteam effectiveness. However, within multiteam system contexts, communication can occur either within teams, between teams, or through a combination of both, which might differentially impact system success.

Communication within teams has been shown to promote information sharing (e.g., Mesmer-Magnus & DeChurch, 2009) and collective coordination (e.g., Salas, Wilson, Murphy, King, & Salisbury, 2008) in pursuit of team goals. In multiteam system contexts, communication within teams takes on an important role to ensure teams are able to achieve their team-level goals, which frequently are required to also achieve more distal system-level goals (Mathieu et al., 2001). Yet, within-team communication occurs somewhat naturally, as individuals tend to have more similar expertise, norms, and shared proximal goals that benefit from individuals talking to members of their own teams (Tajfel, 1982). On the other hand, communication between teams is less natural for members of a multiteam system, yet it is highly critical for multiteam system goal attainment (Mathieu et al., 2001).

The amount of communication between teams within the multiteam system needs to be sufficiently high in order to promote coordinated action across team boundaries to address highly disruptive events (Davison et al., 2012). This is particularly important, as interteam communication has been demonstrated to be a primary precursor to effective multiteam system coordination (DeChurch & Marks, 2006). Without communication across team boundaries, teams with relevant expertise are unable to coordinate with other teams to concurrently solve problems, which can hinder the functioning of the entire system (Zaccaro et al., 2012). Indeed, research on information sharing within teams demonstrates that people tend to more naturally share common information as opposed to unique information (Stasser & Titus, 1985), and prefer to share within groups as opposed to between groups (Allport, 1954; Tajfel, 1982), all of which can hinder team performance. Thus, multiteam systems who promote interteam communication processes facilitate coordinated action across the system, which can enable the system to have the information necessary to appropriately address and recover from disruptive events. Accordingly, I assert:

Hypothesis 1: Amount of interteam communication is positively associated with multiteam system performance (i.e., speed of recovery) after a disruptive event.

Additionally, leadership is important for multiteam system success. Functional leadership theory asserts that the leader’s job is “to do, or get done, whatever is not being adequately handled for group needs" (McGrath, 1962, p. 5), which suggests leadership improves multiteam system performance by shaping effective interaction processes among teams within the system. In fact, Marks and colleagues (2005) suggest a major role of multiteam system leaders is to balance the management of within-team teamwork with between-team teamwork in response to task and performance environment demands. Whereas within-team leadership is focused on enabling teams to coordinate their internal processes to achieve team-level goals, between-team leadership must coordinate the actions across multiple teams to ensure the system combines team efforts to achieve system-level goals (DeChurch & Marks, 2006).

There are many categories of people who might exert leadership influence within a multiteam system. For instance, formal team leaders might exert within-team leadership to direct teamwork processes within their teams (e.g., Zaccaro, Rittman, & Marks, 2001). Additionally, a formal leadership or 'integration team' might be responsible for coordinating between-team processes and directing efforts across the system (e.g., Davison et al., 2012). There might also be individuals who exert leadership influence informally to direct the actions of others based on their social relationships (e.g., Balkundi & Kilduff, 2006). For example, even in groups with a formally appointed leader, there can be individuals who perform leadership behaviors, thus exerting influence as informal leaders (Judge, Bono, Ilies, & Gerhardt, 2002). Multiteam systems might also have individuals who, without formal roles, exercise leadership behaviors on behalf of the system (Shuffler & Carter, 2018). In fact, multiteam systems often require multiple leaders sharing leadership collectively in order to effectively direct the efforts of the system as a whole (Carter & DeChurch, 2014).

An understudied aspect of multiteam system leadership is the importance of matching leadership needs to task demands, which are frequently changing in multiteam system contexts

(Luciano et al., 2018). In dynamic environments and in response to a highly challenging events, leadership influence needs to be granted to people within the system who have the requisite skill sets to address those challenges. Indeed, research has shown that teams perform at their best when they grant leadership to those whose skills and expertise match the task at hand (Aime et al., 2014). If leadership in a multiteam system is not appropriately aligned with task demands, the leadership might become inefficient and impede effective coordination efforts. Furthermore, if the ‘wrong’ people who do not have relevant skills or expertise try to exert influence which distracts the system from completing its tasks, this can hurt the system as a whole. Thus, an important method for ensuring the ‘right’ people are leading the system is by matching leadership needs to task demands.

Granting leadership influence can manifest in a variety of ways (DeRue & Ashford, 2010); however, one particularly effective method for permitting someone to exercise leadership is through allowing them to direct communication within a system (Shuffler et al., 2015). Indeed, prior research demonstrates the importance of centralizing activity through leaders, as decentralized structures in multiteam systems can lead to excessive risk-taking and coordination failures (Lanaj et al., 2013). On the other hand, the centralization of leadership has been shown to positively benefit group performance (e.g., Mukherjee, 2016). Taken together, enabling task-critical leaders (i.e., leaders whose teams have relevant expertise to resolve the task at hand) to be highly central in communication processes for multiteam systems in dynamic environments would be beneficial as a strategy by which systems can promote recovery from changing task demands. Therefore, I assert:

Hypothesis 2: Centralizing communication through task critical leaders is positively associated with multiteam system performance (i.e., speed of recovery) after a disruptive event.

The Moderating Effect of System Size

One response that happens when a system encounters disruptive events is that the set of teams that are needed to address the event might change. For example, Lee and colleagues (2016) described a patient care multiteam system that operated over the course of several months to coordinate a patient's cancer care. Although the bigger picture goal was to treat the patient's new cancer diagnosis, the system operated in a highly dynamic environment that presented new, and often disruptive, task demands. For example, unanticipated treatment interactions between chemotherapy drugs and the patient's diabetes medicine required prompt action on behalf of the component teams and redirection of the patient's primary care plan. Importantly, the evolving task demands presented by the operating environment required systems of varying sizes to work together. For instance, at the beginning of the patient's diagnosis, the oncology and surgical teams needed to work together; but when coordinating actual treatment of the cancer, a larger system was activated to also include the gastroenterology, chemotherapy, and administrative services teams. Thus, this system dynamically activated different teams and shifted the size of the system that was responsible for achieving different task goals over time.

Although previous empirical studies have yet to investigate the impact of changing system size, multiteam system theory suggests that the size of the system that addresses a disruptive event may be an important boundary condition for many critical interaction processes (e.g., Lanaj et al., 2013; Mathieu et al., 2018). Every additional team that is involved in coordinating together increases the inherent complexity of the system, as the number of potential relationships and interactions increases exponentially (Mathieu et al., 2018). Larger systems experience many benefits, such as access to a wider range of expertise, more people to whom tasks can be designated, and the ability to shift work dynamically over time as needed (Mathieu et al., 2001). However, larger systems also have some drawbacks, including introducing the ability for teams to create counterproductive alliances which may impede coordination, additional individuals and teams that must be coordinated, potential diffusion of responsibility and social loafing, and higher opportunities for conflict as team identities become more salient and system identities become less salient (e.g., Cronin & Weingart, 2007; Hinsz & Betts, 2012; Mathieu et al., 2018).

The size of the system likely impacts how the system enacts various team processes, including communication. In particular, interteam communication is critical for systems to achieve collective coordination across team boundaries (Davison et al., 2012), but how communication is focused (i.e., within or between teams) in a system may change depending on how many teams are involved in coordination behaviors. When a system is very large, there should be increased amounts of communication across team boundaries, as the sheer number of teams involved and the amount of communication required in order to get all teams onto the same page is far greater than for smaller systems (Lanaj et al., 2013). If a large system has very little interteam communication, teams within that system are probably not coordinating their behaviors together, and instead, are attempting to function more independently which can hurt system-level effectiveness.

Following this logic, I propose that interteam communication is more important for system-level success when the size of the system is larger rather than smaller. Particularly when a system is responding to disruptive events that trigger changes in task demands, more interteam communication indicates an "all hands on deck" response in order to enhance coordination across even more individuals and teams to address the event. However, less complex events which require few teams to coordinate likely require less interteam communication in order to enhance multiteam system recovery, as there are fewer individuals and teams involved that must exchange information and coordinate their actions. This is expected, as fewer teams likely require less frequent and less complicated interactions with one another in order to ensure their actions are synchronized appropriately (e.g., Davison et al., 2012). Thus, I hypothesize:

Hypothesis 3a: The benefits of interteam communication for system performance depend on the size of the system such that interteam communication has the strongest positive effects on multiteam system performance (i.e., speed of recovery) in larger (as opposed to smaller) systems.

Likewise, system size is a potential moderator of the effectiveness of task-critical leadership influence on multiteam system performance (e.g., Mathieu et al., 2018). Small systems with few teams can handle coordination efforts that are decentralized (e.g., Mehra, Smith, Dixon, & Robertson, 2006), as the smaller number of individuals and teams involved allows for decentralized activities across team boundaries to be effectively managed without as much effort. However, larger systems require centralization of interaction processes or the system can become overwhelming and chaotic, leading to negative multiteam system outcomes (e.g., Lanaj et al., 2013). Thus, larger systems likely benefit from centralizing their communication processes in order to maintain efficiency in their coordination activities throughout the system.

In particular, task-critical leaders are ideal for being the conduit through which communication is centralized in large systems, as they have the expertise to determine which messages and discussion topics are critical (or superfluous) to task demands, and thus, they can more easily control information to ensure the system is focusing on aspects that are important for achieving system success (e.g., Aime et al., 2014). Furthermore, centralization of communication through of task-critical leaders is particularly important in highly dynamic contexts, where task demands are constantly evolving (Luciano et al., 2018). Task demands triggered by disruptive events require prompt attention and execution of directives in order to be resolved quickly. Thus, when a multiteam system activates many teams to respond to a disruptive event, the system may benefit from centralizing communication through task-critical leaders to streamline the system's response and improve the speed with which the task can be resolved (e.g., Davison et a., 2012). On the contrary, having too many individuals within a system focused on trying to coordinate efforts across the system (i.e., through decentralized communication) can distract individuals who are critical for other specialized tasks from achieving goals for which their attention is better suited. In sum, task-critical leadership is likely more necessary when addressing disruptive events which require coordination across larger numbers of activated teams in order to enable the system to perform effectively. Accordingly, I hypothesize:

Hypothesis 3b: The benefits of centralizing communication through task-critical leaders depend on the size of the system such that task-critical leadership has the strongest positive effects on multiteam system performance (i.e., speed of recovery) in larger (as opposed to smaller) systems.

It remains an open question whether interteam communication is always beneficial for multiteam systems, or whether it can be harmful if that communication is not centralized through task-critical leaders, as suggested by some in the multiteam system literature (e.g., Davison et al., 2012). Uncontrolled interteam communication may become chaotic and distract the system from achieving its goals (Williams & Mahan, 2006). Moreover, assertions by research on standalone teams (e.g., Marks et al., 2002) suggest interteam communication alone is sufficient for enabling multiteam system performance, and thus task-critical leader influence is unnecessary to promote multiteam system performance. In fact, centralizing communication through task-critical leaders may lead to bottlenecks in communication which slow down effective collaboration processes (de Toni & Nonino, 2010). Thus, theoretical assertions conflict in their recommendations regarding which interaction process is more critical for multiteam system performance.

I suggest a potential solution to these conflicting assertions is that interteam communication and task-critical leadership exist along a continuum, such that systems that are smaller can benefit from either of these interaction processes. Relying only on task-critical leaders to direct communication or leaving communication completely decentralized between teams could each independently be sufficient for enabling cross-team coordination. However, at larger system sizes, both interteam communication and task-critical leadership are necessary to effectively coordinate in response to disruptive events. Events requiring more teams are likely far more critical for goal attainment, and so lots of interteam communication needs to be directed through task-critical leaders to ensure the system remains focused on achieving its goals. These conjectures are exploratory, thus I propose two research questions:

Research Question 1: When multiteam system sizes are smaller, do the positive effects of interteam communication depend on whether communication is centralized through task critical leaders?

Research Question 2: When multiteam system sizes are larger, do the positive effects of interteam communication depend on whether communication is centralized through task critical leaders?

CHAPTER 3

METHOD

Participants

The goal of this dissertation is to examine how multiteam systems alter their interaction processes in response to disruptive events which trigger changes in task demands. I tested my hypotheses and research questions using data collected from a multinational military coalition training simulation, which involved 93 participants (both active duty and retired Soldiers and officers), across 20 teams, divided into 3 larger organizing cells (see Figure 1 for an illustration). The three cells were: the Division, consisting of 48 participants; Brigade Combat Team 1, consisting of 21 participants; and Brigade Combat Team 2, consisting of 24 participants. The Division was the highest hierarchical level of this coalition, and the two Brigade Combat Teams were on the same hierarchical level below that of the Division. Brigade Combat Team 2 was composed of military personnel of a different nationality than the Division and Brigade Combat Team 1, in part to assess how well Brigade Combat Team 2 would be incorporated into the existing hierarchical structure set forth by the Division and Brigade Combat Team 1. The Command Team of each cell was the leadership team tasked with making decisions on behalf of the coalition. The system of teams was assembled to respond to and solve realistic cross-functional problems that occur in combat contexts. The simulation context was particularly useful for testing my hypotheses due to the long-term nature of their interactions and the external validity of the exercise. Participants were performing their genuine military roles during the simulation. Due to the sensitive nature of this training exercise, and to maintain operational security for the individuals involved in this training simulation, traditional demographic data were not collected. However, demographic information regarding military rank and tenure are summarized in Table 1.

Procedure

The multinational coalition training simulation was created in order to evaluate command and control interoperability between multiple nations and organizational units in a collaborative combat simulation exercise. The two nations represented in this exercise frequently integrated their units into their coalition partner's operations, thus this exercise provided a valuable opportunity to observe and understand the effectiveness of this integration in a high-fidelity context. Extensive cooperation and coordination were required for this coalition to address and resolve disruptive events, which were generated to simulate a combat context within this exercise.

Training Simulation. The simulation was created with realistic disruptive events based on real-world situations in a controlled off-site location. Due to the size and scope of the training exercise, the coalition operated in a simulated, virtual environment. Participants were seated in a myriad of control rooms with a computer workstation, which they used to send and receive information to communicate with fellow participants. Notably, this environment mimicked the typical setting for these organizational units during real world operations. Moreover, the computer interface relayed information and triggered events intended to impact the coalition's decisions about deploying and coordinating several thousand simulated ground troops in a virtual world.

Timeline. The simulation took place across two weeks (Monday-Thurs, 8 days in total) and lasted for approximately 6-8 hours at a time. Prior to the simulation, all participants received training to familiarize themselves with their roles, responsibilities, and the relevant technology that would be used during the training simulation.

Goal Structures. The shared superordinate goal of the simulation exercise had two main components: (1) to cooperate in order to disrupt the operations of a local terrorist group that was working to portray the local (virtual) government as illegitimate, and (2) to ensure that an upcoming (virtual) election was able to take place without undue influence or interruption. Thus, the coalition had to address numerous shorter-term goals to overcome disruptive events in order to achieve the shared goal of the simulation. To achieve these shorter-term goals, both intra- and inter-team coordination were required, including across functional and national boundaries. Team-level goals were matched to team functional expertise, which are summarized in Table 2. Team size ranged from 2 to 9 individuals. Data were collected continuously throughout this exercise, including communication data in the form of more than 10,000 emails (collected in real-time) and military subject matter expert (SME) data describing the nature of the disruptive events (events determined and categorized prior to the training simulation).

Multiteam System Recovery Time following Disruptive Events (Dependent Variable).

During the simulation, members of the coalition encountered 144 disruptive events (on average, 14 events/day) which were triggered in order to test the coalition's adaptive responses. Successful functioning for the multiteam system was assessed in the form of the system's ability to *recover* (i.e., return to previous levels of functioning) after addressing a disruptive event and return to baseline levels of communication.

In order to distinguish between different levels of activity and to reliably define a baseline state from the observed communication patterns in the email data, I employed an activity state identification approach called *Hidden Markov Modeling* (HMM; Rabiner, 1989).

This approach has been widely used in other scientific disciplines to extract patterns within sequences of observations from time series data (Ghahramani, 2001), and is an especially useful tool for identifying different levels of activity within the time series communication data from this training simulation.

Hidden Markov Models are used for identifying differential underlying distributions in time series data that come about due to unobserved Markov processes (Rabiner, 1989). HMMs assume the probability distribution of each observation in time series data depends on an unobserved (or 'hidden') state of a Markov chain; thus, each observation in time series data may belong to one of several potential states, which are identified during model estimation (Zucchini, MacDonald, & Langrock, 2016). Because the email communication data for this exercise contained many time points where no activity was detected (i.e., there were many minutes in the simulation in which no emails were sent, see Figure 2), I leveraged a special class of HMMs called "zero-inflated hidden Markov models", which were specifically designed to handle count data which include a disproportionate number of zeros (Wang & Alba, 2006). This specification allows for zeroes to be fit as either "sampling zeroes" (i.e., those generated from an underlying Poisson process) or "structural zeroes" (i.e., those that do not operate as part of any process), thus improving model estimation and fit (Olteanu & Ridgway, 2012).

First, I converted the times series data from individual sequences of emails to counts of the number of emails that occurred per minute (i.e., the lowest level of time granularity) in the simulation (N = 3179 total minutes; M = 2.85 emails per minute, SD = 8.32 emails per minute). Next, I began the HMM process by testing an initial model (i.e., a 2-state model) by specifying the number of potential hidden states in the provided email count data, which returned the optimal state classifications for each minute within the simulation, the state transition probability matrix, and model fit statistics. I repeated this process in order to compare additional models with an increasing number of states (i.e., one additional possible state for each new model test) until a model sufficiently fit the observed data.

As seen in Table 3, model comparison indicated the 6-state model as the best fit to the data due to the overall reduction in both AIC and BIC (Zucchini et al., 2016). This model sorted each minute of the simulation exercise into one of six states based upon the patterns of communication which indicated the underlying distribution (i.e., state) to which each minute belonged. As seen by examining each state's descriptive statistics in Table 4, the model extracted a "baseline activity state" characterized by an absence of communication (i.e., state 5), "low-activity states" characterized by small amounts of communication (i.e., states 1 and 2), and "high activity states" characterized by large amounts of communication (i.e., states 3, 4, and 6). See Figure 3 for an exemplar of the communication patterns which are sorted into each type of state.

Based upon the state classifications for each minute within the simulation, I defined *multiteam system recovery time* as the amount of time that elapsed between the origin time of a disruptive event and the return to a "baseline" activity state after one or more high activity states. The system recovered from some events very quickly (i.e., as low as 8 minutes) and from other events very slowly (i.e., as high as 317 minutes) when addressing disruptive events (M = 71.99 minutes, SD = 82.72 minutes). Table 5 summarizes additional descriptive statistics (e.g., minimum, maximum, and mean values, standard deviations, and correlations with other study variables) for the multiteam system recovery time variable.

Disruptive Event Characteristics

The 144 disruptive events varied with regard to their *complexity* (i.e., number of teams involved) and *immediacy* (i.e., how quickly the event required attention). Additionally, the operating context at the moment of each event varied with regard to the number of *other ongoing events,* the degree to which the system had encountered *similar* events at previous points in time, and the degree to which the system had progressed through the simulation (i.e., *minutes of simulation progress*). The following sections define these event characteristics and describe how they were operationalized in this research.

System Size (H3a, H3b, RQ1, RQ2). Military subject matter experts (SMEs) determined *a priori* which teams were required to address each type of event in the simulation (based on expertise and chain of command), which created differential numbers of teams that responded to each disruptive event, thus dynamically changing the size of the system. Less complex events (e.g., resupplying ammunitions to a unit in the field) required only a few teams to address the event (i.e., as few as 4 teams); however, more complex events (e.g., a mass casualty event from a suicide bomb attack) required coordination across a large number of teams (i.e., as many as 15 teams) to address the event (M = 8.88 teams, SD = 3.02 teams). Thus, system size was operationalized as the number of teams required to address the event during the simulation.

Disruptive event immediacy (control). Military SMEs determined the *immediacy* of each disruptive event based on how quickly coordinated action was needed on behalf of the coalition to address and contain the event. Different levels of immediacy were based on varying levels of mission-relevance, as defined by real-world operations in combat contexts, such that less mission-critical events were categorized as lower in immediacy and more mission-critical events were categorized as higher in immediacy (i.e., 1= low, 2= medium, 3= high, 4= critical; M = 1.80, SD = 1.00).

Number of ongoing events (control). I operationalized the number of ongoing events as the number of events that overlapped within the hour after the focal event's origin time. For example, an ongoing event score of “4” meant that four other events were either ongoing or began during the hour after which the focal event was triggered. This variable captured the extent to which multiteam system effectiveness was a function of the total number of events that they system had to address while responding to each new disruptive event. Some disruptive events occurred in isolation (i.e., as few as 0 ongoing events) and other events overlapped with many other events (i.e., as many as 14 events; $M = 5.33$ events, $SD = 3.31$ events).

Number of similar prior events (control). I operationalized this variable as the number of similar types of events the multiteam system had already experienced prior to the origin time of the focal event. For example, if the focal event was a “mass casualty situation”, the prior events variable would reflect the number of times the system had handled mass casualty situations previously during the simulation exercise (i.e., a score of “3” meant the system had already experienced three mass casualty situations earlier in the simulation). This variable accounted for the possibility that the multiteam system functioned more efficiently in response to disruptive events with which it was more familiar, as opposed to events which were more unique or novel and required finding new ways of coordinating. For the very first occurrence of a particular kind of event, the prior event score was a “0” as they system had addressed zero events of that type previously, but events at which the system had more practice were higher scores (i.e., as many as 21 similar prior events; $M = 5.20$, $SD = 5.46$).

Minutes of simulation progress (control). Minutes of simulation progress was operationalized as a measure of how many minutes had passed from the beginning of the simulation up to the origin time of the disruptive event. The first event was triggered after 142 minutes into the simulation, and the last event was triggered 3,025 minutes into the simulation.

Multiteam System Response Patterns Following Disruptive Events

The military coalition also differed in the manner in which it responded to various disruptive events throughout the simulation: these responses varied in terms of where system communication was focused (i.e., *interteam communication*, *task-critical leader influence*, and *intrateam communication*), and when the system altered its communication activity levels (i.e., *time to initial response*). The following sections define these event characteristics and describe how they were operationalized in this research.

Interteam communication (H1, H3a, RQ1, RQ2). Interteam communication was operationalized as the total volume of incoming and outgoing communication occurring between teams following a disruptive event. More specifically, this variable was calculated as a count of the number of emails that occurred between individuals who were members of different teams in the hour following the origin time of a disruptive event (i.e., the exact time the disruptive event was triggered). The amount of interteam communication ranged from 15 emails to 747 emails (M = 132.83 emails, SD = 121.66 emails).

Task-critical leader influence (H2, H3b, RQ1, RQ2). Each disruptive event had designated teams that were supposed to be those addressing a particular event due to their expertise. I identified task-critical leaders for each event as the formal leaders of the teams who were responsible for addressing the specific type of event (e.g., the intelligence team leader is a task-critical leader for a disruptive event regarding an intelligence leak to enemy forces). I operationalized task-critical leader influence as the extent to which task-critical leaders were central in communication following each disruptive event. More specifically, this variable was the proportion of total emails that were sent to or received by the individuals who were categorized as task-critical leaders in the hour following the origin time of the event. Task-critical leader influence was a proportion of the total emails which ranged from low levels (i.e., 0.01 or 1% of the total emails) to high levels (i.e., 0.84 or 84% of the total emails) to address disruptive events in this simulation (*M* = 0.30 or 30%, *SD* = 0.19 or 19%).

Intrateam communication (control). I operationalized intrateam communication as the total amount of emails exchanged between members of the same team during the hour after a disruptive event was triggered. Some disruptive events had lower levels of intrateam communication (i.e., 7 emails) and other events had higher levels of intrateam communication (i.e., 347 emails) following the disruptive event (*M* = 63.60, *SD* = 45.71).

Time to initial response (control). The origin time for the event (i.e., the exact time when the event was triggered) was logged digitally via the simulation interface; however, due to the additional ongoing duties system members were required to address throughout the simulation, the time when the system began coordinating to respond to the event was often delayed. I operationalized *time to initial response* as the amount of time that elapsed (in minutes) between the origin time of the disruptive event and the onset of coordination behaviors after the event was triggered.

In order to determine when coordination behaviors commenced, I employed Hidden Markov Modeling (HMM; Rabiner, 1989) to identify the emergence of high-activity states from the observed communication data. Notably, I chose the presence of high-activity states (as opposed to low-activity states) as a more conservative indicator of system-level coordination behaviors, as low-activity states could also represent usual system functioning and not necessarily coordinated response to a disruptive event. Leveraging the information from these extracted states, I calculated the time that elapsed between a disruptive event's origin time and the first appearance of a high activity state after the event was triggered. Thus, the number for each event's *time to initial response* was the number of minutes after the event's origin that passed before the system exhibited a high activity state, which represented the system's coordinative behaviors. The quickest response time was within "1" minute of the event being triggered, and the longest response time was "44" minutes after the event was triggered (*M* = 8.94 minutes, *SD* =8.94).

Analytic Approach

The general multiple moderation approach used to test this dissertation's hypotheses and research questions was modeled off of established best practices for multiple moderated regression (Cohen & Cohen, 1983). However, due to the unique distribution of my outcome measure, I tested my hypotheses via hierarchical Poisson regression modeling (Christiansen & Morris, 1997). The outcome measure for my hypotheses (i.e., *multiteam system recovery time*) was a count variable, which followed a Poisson distribution as opposed to a normal distribution (i.e., a primary assumption of traditional regression models; Myers & Myers, 1990); thus, Poisson-based regression was the most appropriate way to test my hypotheses. Mirroring the practice for normally-distributed regression analyses, all predictors in my dissertation were centered before being entered into the Poisson regression models to aid in interpretation of effects (Dalal & Zickar, 2012). I tested my hypotheses in a series of hierarchical Poisson regression models regressing multiteam system recovery time on the hypothesized antecedents and a set of controls.

Although the same general practices for model comparison are consistent for comparing model fit between normally-distributed multiple regression and Poisson multiple regression models, the appropriate model fit statistics differ (Christiansen & Morris, 1997; Cohen & Cohen, 1983; McFadden, 1973). Rather than examining the more traditional R^2 statistic from a normally distributed regression to determine variance explained by each model, the Poisson regression model relies on McFadden's *Pseudo-*R^2, which examines the percentage of reduction in model deviance between a null (intercept) model and the current model. The difference in deviance forms a χ^2 distribution with degrees of freedom equal to the number of added parameters, which is comparable to an F-test in Ordinary Least Squares (OLS) models (McFadden, 1973). A significant increase in *Pseudo-*R^2 (i.e., Δ*Pseudo-*R^2) in subsequent models indicates improvement in model fit. I also employed a comparison of Akaike Information Criterion (*AIC*) statistics, which can be interpreted such that lower *AIC*s indicate better model fit. Thus, I conducted my model comparisons as part of the hierarchical Poisson regression modeling by comparing *AIC*, *Pseudo-*R^2, and Δ*Pseudo-*R^2 to determine which model best fits the data during my hypothesis testing.

CHAPTER 4

RESULTS

All data included in my measures and hypothesis tests are at the event-level (N = 144 disruptive events). Descriptive statistics for my study variables—including minimum values, maximum values, means, standard deviations, and correlations—are summarized in Table 5. Study variable correlations indicated potential initial support for some of my hypotheses: task-critical leader influence had a strong positive association with event complexity (r = 0.55, p < .01), which might indicate initial support for the multiplicative effects of both event characteristics and interaction processes proposed in H3b, RQ1, and RQ2.

Tests of Hypotheses: MTS Interaction Processes' Impact on MTS Recovery

I tested my hypotheses and research questions in a series of hierarchical Poisson regression models (see Table 6). This series of models tested whether certain interaction processes (i.e., *interteam communication* and *task-critical leader influence*) enhanced the ability of the multiteam system to recover more quickly from disruptive events with varying degrees of complexity. Model 1 consisted of regressing *multiteam system recovery time* on control variables (i.e., *number of ongoing events*, *number of similar prior events*, *time to initial response*, *event immediacy*, *minutes of simulation progress*, *and intrateam communication*) to establish a comparative model. Model 2 tested the main effects for my proposed interaction processes by adding *interteam communication* (H1) and *task-critical leader influence* (H2) to the model with controls.

Model 3 tested the interaction effects between event characteristics (i.e., *system size*) and interaction processes (i.e., *interteam communication* and *task-critical leader influence*). To test this third model, I first multiplied the vectors for *intrateam communication* and *task-critical leader influence* by *system size* to create two interaction terms: "interteam communication x system size" and "task-critical leader influence x system size", respectively. Next, I added the main effect predictor for *system size* and the interaction effects for both "interteam communication x system size" (H3a) and "task-critical leader influence x system size" (H3b) to Model 3, and regressed *multiteam system recovery time* onto all of these controls, predictors, and interaction terms.

Finally, in Model 4, I tested Research Questions 1 and 2 to determine whether the two interaction processes had a multiplicative effect for enhancing *multiteam system recovery time* when employed together for different levels of event characteristics (i.e., *system size*). Before testing this model, I created an additional 2-way interaction between the interaction processes by multiplying them together to create a term for "intrateam communication x task-critical leader influence" to be used as a lower-order term in the full 3-way interaction model. Lastly, I created the 3-way interaction term for "interteam communication x task-critical leader influence x system size." Thus, Model 4 regressed *multiteam system recovery time* onto control variables, main effect variables, three lower-order 2-way interactions, and finally the 3-way interaction, which was the model term of interest.

My first set of hypotheses predicted that the main effects for the interaction processes of *interteam communication* (H1) and *task-critical leader influence* (H2) would be negatively associated with *multiteam system recovery time*, such that leveraging these communication strategies following a disruptive event would enable the system to recover more quickly. I tested these hypotheses with a series of hierarchical Poisson regression models beginning with Model 1, which regressed *multiteam system recovery time* on relevant control variables (i.e., *number of ongoing events*, *number of similar prior events*, *time to initial response*, *event immediacy*, *minutes of simulation progress*, and *intrateam communication*; see Table 6). Model 2 tested the main effects hypothesized for *intrateam communication* (H1) and *task-critical leader influence* (H2) by adding these predictors to the model with the controls. Demonstrating support for H1, interteam communication was negatively associated with multiteam system recovery time (B = -0.03, p < .10), such that more interteam communication yielded a quicker system response time. Additionally, H2 was supported, as task-critical leader influence was negatively associated with multiteam system recovery time (B = -0.08, p < .01), such that high proportions of task-critical leader influence following a disruptive event enabled the system to recover more quickly.

My next set of hypotheses tested the interaction effects of *system size* and the interaction processes of *interteam communication* (H3a) and *task-critical leader influence* (H3b) with regard to their impact on *multiteam system recovery time*. First, I created the relevant interaction terms for "interteam communication x system size" and "task-critical leader influence x system size", and then I added those to the previous model with relevant main effects and controls. Thus, for Model 3, I regressed multiteam system recovery time onto the controls, main effects, and interaction effects to test Hypotheses 3a and 3b (see Table 6).

In contrast to expectations for Hypothesis 3a, Model 3 indicated that there was a significant interaction effect between interteam communication and system size (B = 0.05, p < .01), yet this effect was in the opposite direction of what I hypothesized. As depicted in Figure 4, there was a negative association between interteam communication and multiteam system recovery time under different system sizes, such that when events required a smaller system size, interteam communication enhanced multiteam system recovery. However, when disruptive events required a larger system size, interteam communication was positively associated with multiteam system recovery time, such that events requiring a larger system size with higher amounts of interteam communication was detrimental and led to longer system recovery times. Thus, there were differential effects for the effectiveness of the interteam communication interaction processes depending on disruptive event characteristics, but Hypothesis 3a was not supported in the hypothesized direction.

In support of Hypothesis 3b, Model 3 indicated that there was also a significant interaction effect between task-critical leader influence and system size (B = -0.02, $p < .01$). As shown in Figure 5, there was a positive association between task-critical leader influence and multiteam system recovery time for differential system sizes, such that when events required smaller system sizes, task-critical leadership influence led to longer system recovery times. However, for events requiring larger system sizes, task-critical leadership influence enabled the multiteam system to recover more quickly. Therefore, there were also differential effects for the effectiveness of task-critical leader influence depending on the size of the system tasked with responding to the disruptive event at hand, and Hypothesis 3b was supported in the hypothesized direction.

Lastly, I tested Research Questions 1 and 2, which considered which strategy (i.e., *interteam communication* and/or *task-critical leader influence*) was most effective under differing system sizes for benefitting multiteam system recovery time. In order to test this research question, I created a 3-way interaction term for “interteam communication x task-critical leader influence x system size” and an additional 2-way interaction for “interteam communication x task-critical leader influence” as a lower-order effect for the model. When multiteam system recovery time was regressed onto the 3-way interaction, the result was significant (*B* = -0.07, $p < .01$), which was further inspected via Figure 6 by focusing on the 3-way interaction for smaller systems (i.e., RQ1) and Figure 7 by focusing on the 3-way interaction for large systems (i.e., RQ2; full 3-way interaction depicted in Figure 8).

As depicted in Figure 6, for events requiring smaller system sizes, there was a positive association between interteam communication and multiteam system recovery time when the system also leveraged task-critical leader influence, meaning that task critical leader influence was a beneficial interaction process with low amounts of interteam communication. Additionally, there was a negative association between interteam communication and multiteam system recovery when there were low levels of task-critical leader influence, meaning having high interteam communication was an effective strategy for recovering more quickly from disruptive events when the system did not also rely on task-critical leader influence. Taken together, for smaller system sizes, leveraging *either* interteam communication *or* task-critical leader influence following disruptive events was effective for reducing the amount of time it took the multiteam system to recover, but leveraging either both of these processes or neither of these processes increased the time it took for the system to recover.

As shown in Figure 7, for events requiring larger system sizes, there was a positive association between interteam communication and multiteam system recovery when task-critical leader influence was low, meaning that interteam communication was a poor communication strategy for larger systems when task-critical leaders were also not involved in communicating after the disruptive event. However, for larger systems, having high task-critical leader influence led to shorter recovery times regardless of whether there were low or high levels of interteam communication. Additionally, as shown in Figure 8 depicting the entire 3-way interaction illustration, the system recovered most quickly when addressing events requiring larger systems with high levels of task-critical leader influence. In summary, for events requiring smaller systems, the system could have chosen either interteam communication or task-critical leader influence in order to recover more quickly (but not both), whereas for larger systems, it was especially important for the task-critical leaders to be able to direct the actions of the system following a disruptive event in order to enable the system to recover quickly.

CHAPTER 5

DISCUSSION AND CONCLUSIONS

Organizations rely on multiteam systems in order to address increasingly challenging tasks (Mathieu et al., 2001). Multiteam systems have the capability to flexibly adapt to situational needs by combining insights across teams with varied areas of expertise, adding or removing additional teams as necessary, and shifting coordination behaviors to match situational demands (Zaccaro et al., 2012). Extant research on multiteam systems in stable environments has identified two key processes—interteam communication and task-critical leadership influence—which can enhance multiteam system performance (Shuffler et al., 2015). Yet the predominant practice of investigating these two interaction processes in stable, short-term multiteam systems has left important theoretical questions unanswered, particularly with regard to whether that are boundary conditions under which these processes are more or less effective. Researchers have posited that the size of the system that must coordinate together to address a particular task may be an important boundary condition or moderating influence on multiteam system interaction processes (Lanaj et al., 2013; Mathieu et al., 2018).

This dissertation addresses this need by investigating the moderating effects of system size on the effectiveness of multiteam system interaction processes in response to frequently changing task demands triggered by disruptive events. Data from a multinational military coalition training exercise suggest that interteam communication and task-critical leader influence are both effective for enabling multiteam systems to recover more quickly from disruptive events, but have differential impacts depending upon the size of the system that is required to respond to those events. More specifically, multiteam system recovery time is quicker for smaller systems when systems increase interteam communication or rely on task-critical leadership, but notably, leveraging both interaction processes simultaneously leads to longer system recovery times.

Additionally, I found that systems recover from events requiring larger systems more quickly when primarily relying on the influence of task-critical leaders, but high levels of interteam communication without task critical-leaders can have a chaotic and detrimental effect on system recovery when many teams must coordinate to respond to an event. These findings support the notion that the role of system size must be carefully considered when promoting interaction processes in multiteam systems, and in fact, that processes previously deemed beneficial in studies of static multiteam systems (i.e., interteam communication) can actually have detrimental impacts on system performance when many teams must coordinate together to address a challenging task.

Contributions to Theory and Research

This dissertation makes four main contributions to the multiteam system research literature. First, I answer calls to examine the moderating impact of system size on multiteam system interaction processes and performance (Lanaj et al., 2013; Mathieu et al., 2018). In the first empirical test of multiteam system size as a boundary condition, I find that system size critically alters the positive impacts of both interteam communication and task-critical leadership on multiteam system effectiveness. In fact, these findings suggest that multiteam systems may need to intentionally change the interaction processes they employ depending on how many teams are required to coordinate to address a task. Notably, I find interteam communication can hurt multiteam system recovery from disruptive events when many teams are involved in a task, which contradicts the generally positive impacts of interteam communication in previous studies which hold system size constant (e.g., Healey, Hodgkinson, & Teo, 2009). Moreover, task-critical leadership tends to have positive impacts regardless of system size, reaffirming the importance of leadership across team boundaries (e.g., DeChurch & Marks, 2006). Thus, the moderating role of system size critically expands scholarly understanding about the effectiveness of interteam communication and task-critical leadership influence for enabling multiteam system success in dynamic environments.

Second, I resolve a long-standing debate between the teams and multiteam system literatures regarding recommendations for effective interaction processes in groups. Whereas evidence from the teams literature asserts that decentralized communication is beneficial for team success (e.g., Marks et al., 2002; Woolley et al., 2010), evidence from the multiteam systems literature finds centralized communication structures to be more beneficial for multiteam system success (e.g., Davison et al., 2012; Lanaj et al., 2013), thus introducing conflicting advice for teams that function within multiteam systems. Findings from this study propose a potential solution to these conflicting findings, such that the larger the number of people and teams that must coordinate together to address a task, the more beneficial centralized communication structures become for enhancing system success, especially when communication is focused through task-critical leaders. Although it has been theorized that system size may be the critical factor impacting these conflicting recommendations (Lanaj et al., 2013), this study is the first to disentangle these effects conclusively.

Third, I advance a new paradigm for studying multiteam system functioning that lays the foundation for future investigations of complex phenomena. Due to the challenges of collecting multiteam system data generally (i.e., a large number of participants, highly complex interactions, etc.; Davison et al., 2012), many empirical studies employ a between-system approach which examines many small systems performing the same tasks over time (e.g., Marks et al., 2005), yet these investigations frequently have to simplify multiteam system functioning to make comparison across systems. To investigate more complex phenomena, such as differential system sizes, the total sample size to compose enough separate multiteam systems of varying sizes would be extremely large, which is likely unfeasible. However, I overcome this challenge in this dissertation by employing an in-depth quantitative case-study approach to examine a single multiteam system longitudinally as it dynamically changes its structure in response to disruptive events. Whereas a between-system approach would require more than twenty systems per size condition and many size conditions, this event-based approach enables inferences to be made by comparing the same system's responses to a variety of events with different characteristics in a highly realistic environment. This novel paradigm for studying multiteam systems enables researchers to ask and examine theoretical questions which have yet to be explored due to data collection constraints, promoting a more robust multiteam system literature.

Fourth, this dissertation employs a unique statistical approach to unobtrusively identify activity levels from digital communication data. Hidden Markov Models (Rabiner, 1989) are frequently leveraged in other scientific domains including natural language processing (e.g., Kupiec, 1992), temporal learning (e.g., Nguyen, Phung, Venkatesh, & Bui, 2005), and bioinformatics (e.g., Krogh, Larsson, von Heijne, & Sonnhammer, 2001), but this statistical approach has yet to be embraced by the organizational sciences. As organizational researchers continue to dive into the world of digital trace data in order to unobtrusively address their research suppositions, HMMs offer a robust approach for detecting unobserved patterns in time series data that might be otherwise overlooked (Zucchini et al., 2016). The current work demonstrates one method through which meaningful information about behavioral patterns can be extracted to inform important research questions in dynamic contexts, where traditional measurement techniques may not be suitable.

Contributions to Practice

Although the contributions of this dissertation are primarily conceptual, this research also suggests several contributions to managerial practice. First, this study provides several notable recommendations for members within and leaders of multiteam systems in real-world organizations. I find that encouraging interteam communication can be beneficial when tasks are not very complex and involve few teams; however, increasing interteam communication is not beneficial for all collaboration contexts. In fact, interteam communication was consistently negatively related to faster multiteam system recovery time when tasks involved cooperation between many teams in the system, suggesting managers may need to be cautious about promoting excessive amounts of interteam communication in highly complex contexts.

Second, these results demonstrate that task-critical leader influence has consistently beneficial impacts for highly complex tasks involving many teams working together. Therefore, this study reiterates the importance of centralizing communication through relevant leaders when many teams are required to coordinate with one another to address changing task demands in a highly dynamic environment. Thus, the ultimate takeaway for managers is that the interaction and communication processes that multiteam systems employ to address tasks are dependent, in part, on the characteristics of the task itself. In particular, the size of the system responding to the task should be carefully considered before recommending changes to communication and leadership patterns, as ‘more’ is not always better.

Limitations and Opportunities for Future Research

My research lays the foundation for several exciting future research directions that can contribute greatly to the multiteam system literature. By identifying both interteam communication and task-critical leadership as interaction processes that are differentially effective depending upon the size of the multiteam system, I present evidence that system size is an important boundary condition for multiteam system interaction processes. However, interteam communication and task-critical leader influence are hardly the only processes that might be impacted by system size; thus, future research should propose and evaluate other potential processes (e.g., planning, system monitoring, task prioritization; Marks et al., 2001) to determine whether system size differentially impacts their effectiveness for promoting multiteam system success.

Further, although the current study has many strengths, there are a number of limitations which future research might address. First, although the digital communication data examined in this study were rich in communication patterns regarding senders, receivers, and timestamps for communication exchanges, the content of these communications were not available. Thus, inferences about coordination behaviors relied on hidden state profiles extracted by inductive data analysis techniques (i.e., Hidden Markov Models; Rabiner, 1989). In future studies, access to the content of electronic communications would enable researchers to determine far richer conclusions about coordination behaviors, such as precisely how events disruptive events were being discussed, who is exercising formal and/or informal influence to direct behaviors within the system, and how other members of the system respond to those directions.

Second, while this study context is highly generalizable for multiteam systems in highly dynamic environments, systems that experience changing task demands in less volatile environments (e.g., product development or scientific collaboration multiteam systems) might see differential impacts when employing the focal interaction processes examined in this study. For example, in less volatile contexts, interteam communication might be especially critical for highly complex disruptive events in order to maintain creative freedom when proposing solutions, as opposed to limiting the free flow of ideas by centralizing communication through formal leaders. Accordingly, future research should examine the impact of differing system size and complexity in less dynamic environments to uncover which communication patterns have more universal impacts based on changes in system complexity, and which may be context-specific to dynamic environments where task complexity may also have been associated with task importance.

Finally, the approach leveraged in this dissertation was to take a deep dive into the ways one multiteam system changed its processes and structure to dynamically respond to disruptive events over time; however, additional important insights might be gained from combining both a within-system and between-system approach to better understand multiteam system interaction patterns under differing size and complexity conditions. Although the data collection requirements for a combined within- and between- system approach would be quite intensive, the ability to leverage both of these approaches simultaneously would provide a robust corpus of data from which the effects of individual multiteam systems could be disentangled.

Conclusion

Multiteam systems dynamically change their interaction processes and system-level structures in response to frequently changing task demands, yet little is known about how patterns of interaction processes must shift when different sets of teams are activated. In this dissertation, I examined how interteam communication and task-critical leadership impacted multiteam system recovery under differing levels of system size in response to disruptive events. My results suggest that whereas tasks involving a larger number of teams require centralized leadership influence through task-critical leaders; tasks involving fewer teams can benefit from either interteam communication *or* task-critical leadership, but attempting to leverage both strategies is unnecessary. This dissertation sets the stage for a body of research which examines how different multiteam system structures create boundary conditions for the effectiveness of various multiteam interaction processes, which are critical to consider when informing the science and practice of multiteam systems.

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Table 1

Descriptive Statistics for Participants in Multinational Military Coalition

	Mean	**Median**	**Min**	**Max**	**SD**	
Tenure (years in military)	13.53	12.00	0.50	37.50	7.99	
	O-2	**O-3**	**O-4**	**O-5**	**O-6**	
Officer Rank	1, 1.25%	15, 18.75%	22, 27.50%	19, 23.75%	1, 1.25%	
					Total # Officers	58
	E-2	**E-3**	**E-4**	**E-5**	**E-6**	**E-7**
Enlisted Rank	2, 2.50%	2, 2.50%	4, 5.00%	4, 5.00%	5, 6.25%	1, 1.25%
					Total # Enlisted	18

Note. Responding to descriptive data was optional, thus information regarding tenure and rank was restricted to reporting by 76 individuals.

Table 2

Functions for each Organizing Cell and Team in the Coalition

Unit	Function
Cell 1: Division	
Command	Plans, provides direction, and executes decisions on behalf of the cell.
Special	Coordinates activities and systems to support communications and information management.
Intel	Facilitate understanding of the enemy, terrain, and civil considerations.
Sustain	Provide support to prolong endurance including tasks associated with logistics, personnel services, and health support.
Maneuver	Coordinate activities to move forces to achieve a position of advantage in relation to the enemy.
Signal	Responsible for all tactical communications assets on behalf of the cell.
Fires	Provide both lethal and non-lethal artillery in support of operational objectives.
LNO	Serves as the liaison across unit boundaries to coordinate the movement of information.
Protection	Preserves the force, including protecting personnel, physical assets, and information.
Cell 2: BCT 1	
Command	Plans, provides direction, and executes decisions on behalf of the cell.
Fires	Provide both lethal and non-lethal artillery in support of operational objectives.
LNO	Serves as the liaison across unit boundaries to coordinate the movement of information.
Maneuver	Coordinate activities to move forces to achieve a position of advantage in relation to the enemy.
Intel	Facilitate understanding of the enemy, terrain, and civil considerations.
Cell 3: BCT 2	
Command	Plans, provides direction, and executes decisions on behalf of the cell.
Intel	Facilitate understanding of the enemy, terrain, and civil considerations.
Maneuver	Coordinate activities to move forces to achieve a position of advantage in relation to the enemy.
Fires	Provide both lethal and non-lethal artillery in support of operational objectives.
LNO	Serves as the liaison across unit boundaries to coordinate the movement of information.
Special	Coordinates activities and systems to support communications and information management.

Table 3

Zero-Inflated Hidden Markov Model Comparison Results

Model	*AIC*	*BIC*	*ΔAIC*	*ΔBIC*	*ΔTotal Fit*
1. 2-States	14472	14509	--	--	--
2. 3-States	12365	12438	-2107	-2071	-4178
3. 4-States	11839	11960	-526	-478	-1004
4. 5-States	11659	11841	-180	-119	-299
5. 6-States	**11619**	**11873**	**-40**	**+32**	**-8**
6. 7-States	11723	12063	+104	+190	+294

Note. State extraction from 3,180 minutes of activity. Model selection made based on maximum reduction in both AIC and BIC, as represented by total change (i.e., best practices by Zucchini et al., 2016). Best model fit indicated in bold.

Table 4

Descriptive Statistics for Hidden States in Zero-Inflated Hidden Markov Model

State	*Activity*	*Min*	*Max*	*Mean*	*SD*	*Frequency*	*% of Minutes*
1	Low	0	6	1.74	1.12	148	4.66
2	Low	0	4	0.95	1.22	1661	52.25
3	High	4	15	7.87	2.67	381	11.98
4	High	12	41	21.75	7.07	103	3.24
5	Baseline	0	0	0.00	0.00	859	27.02
6	High	42	155	73.74	23.78	27	0.85

Note. Numbers are counts of emails per minute during the simulation exercise. Activity levels were determined by examination of the overall trends in each state's descriptive statistics.

Table 5

Descriptive Statistics for Study Variables

Variable	*Min*	*Max*	*M*	*SD*	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. MTS Recovery Time	8.00	317.00	71.99	82.72	--								
2. System Size	4.00	15.00	8.88	3.02	-0.21*	--							
3. Interteam Communication	15.00	747.00	132.83	121.66	-0.08	0.08	--						
4. Task-Critical Leader Influence	0.01	0.84	0.30	0.19	-0.09	0.55**	-0.07	--					
5. Intrateam Communication	7.00	347.00	63.60	45.71	-0.02	0.08	0.74**	0.14+	--				
6. Number of Ongoing Events	0.00	14.00	5.33	3.31	0.17*	0.02	-0.08	0.20*	0.09	--			
7. Number of Prior Similar Events	0.00	21.00	5.20	5.46	0.02	-0.34**	0.04	-0.10	0.00	-0.01	--		
8. Time to Initial Response	1.00	44.00	8.94	10.51	0.21*	-0.20*	-0.38**	-0.22**	-0.47**	-0.19*	-0.04	--	
9. Event Immediacy	1.00	4.00	1.80	1.00	-0.22**	0.51**	0.16+	0.20*	0.07	-0.02	-0.28**	-0.23**	--
10. Minutes of Simulation Progress	142.00	3025.00	1519.37	865.44	-0.04	-0.03	0.13	0.07	0.04	-0.07	0.66**	-0.04	-0.12

Note. $N = 144$ disruptive events. Minimum values, maximum values, mean values, standard deviations, and correlations for study measures. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 6

Tests of Hypotheses and Research Questions: Multiteam System Recovery Time Regressed on Interaction Processes

Variables	Model 1 *B*	*SE*	Model 2 *B*	*SE*	Model 3 *B*	*SE*	Model 4 *B*	*SE*
Controls								
Number of Ongoing Events	0.22**	0.01	0.24**	0.01	0.22**	0.01	0.22**	0.01
Number of Similar Prior Events	0.02	0.01	-0.00	0.01	-0.04*	0.01	-0.04**	0.01
Time to Initial Response	0.25**	0.01	0.24**	0.01	0.22**	0.01	0.22**	0.01
Event Immediacy	-0.22**	0.01	-0.20**	0.01	-0.15**	0.01	-0.16**	0.01
Minutes of Simulation Progress	-0.07**	0.01	-0.05**	0.01	-0.03*	0.01	-0.02	0.01
Intrateam Communication	0.09**	0.01	0.12**	0.02	0.10**	0.02	0.12**	0.02
Predictors								
Interteam Communication (H1)			-0.03+	0.02	-0.01	0.02	0.03**	0.02
Task-Critical Leader Influence (H2)			-0.08**	0.01	0.00	0.01	0.01**	0.01
System Size					-0.16**	0.02	-0.14**	0.02
Interactions								
Interteam Comm. x System Size (H3a)					0.05**	0.01	-0.01	0.02
TC Leader Influence x System Size (H3b)					-0.02*	0.01	-0.02	0.01
Interteam Comm. x TC Leader Influence							0.06**	0.02
Interteam x TC Lead x System Size (RQs)							-0.07**	0.02
AIC	9950		9904		9802		9738	
Pseudo-R^2	0.14**		0.14**		0.15**		0.16**	
ΔPseudo-R^2			0.00		0.01**		0.01**	

Note. N = 144 disruptive events; TC = Task-Critical; Estimates are unstandardized Poisson regression coefficients. Hypothesized effects are in bold. Significance tests for *Pseudo-R^2* based on the χ^2 distribution.
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

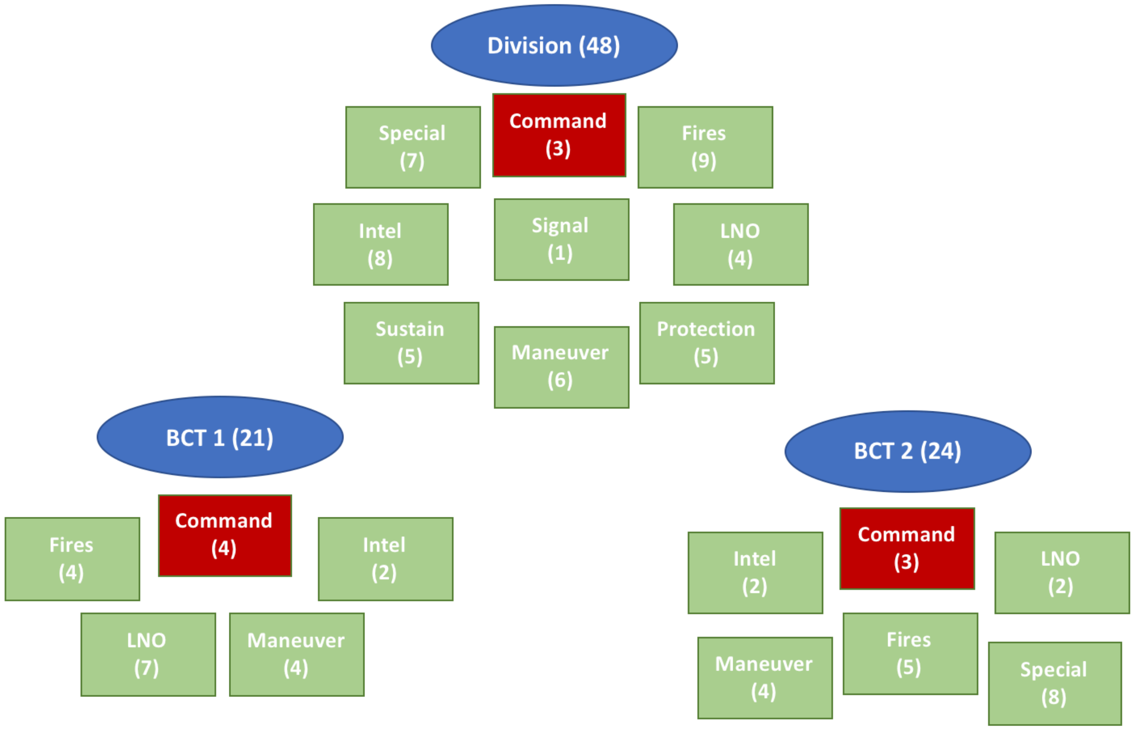

Figure 1. *Depiction of Multiteam System Structure of the Multinational Military Coalition*

Note. Each Cell is labeled in blue, each Command Team for the Cells is labeled in red, and the functional teams within each Cell are labeled in green, with the number of total members for each cell or team included in parentheses.

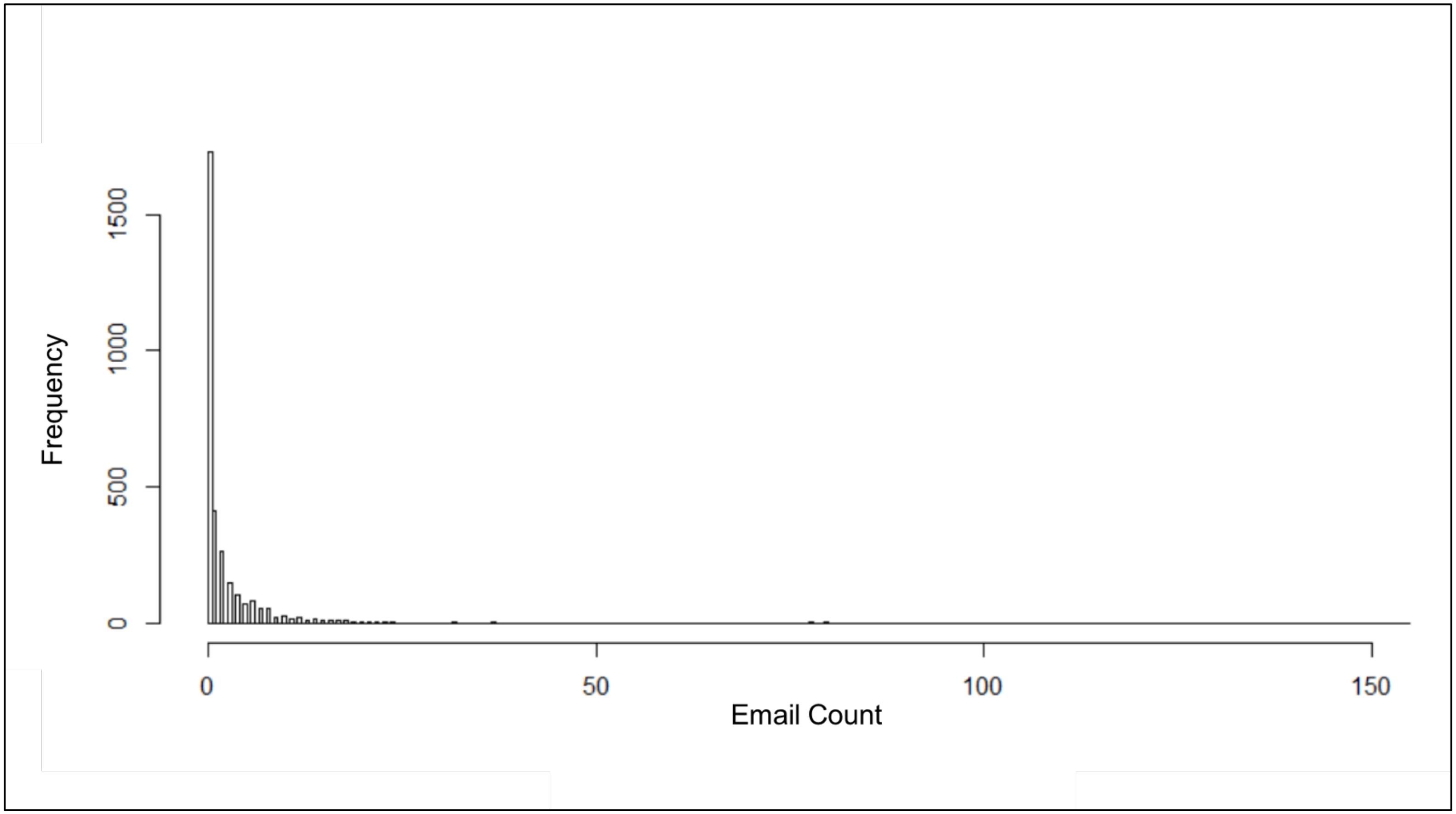

Figure 2. *Histogram for Frequency of Email Counts Per Minute*

Note. Email counts were number of emails per minute in the simulation. Distribution is zero-inflated Poisson distribution.

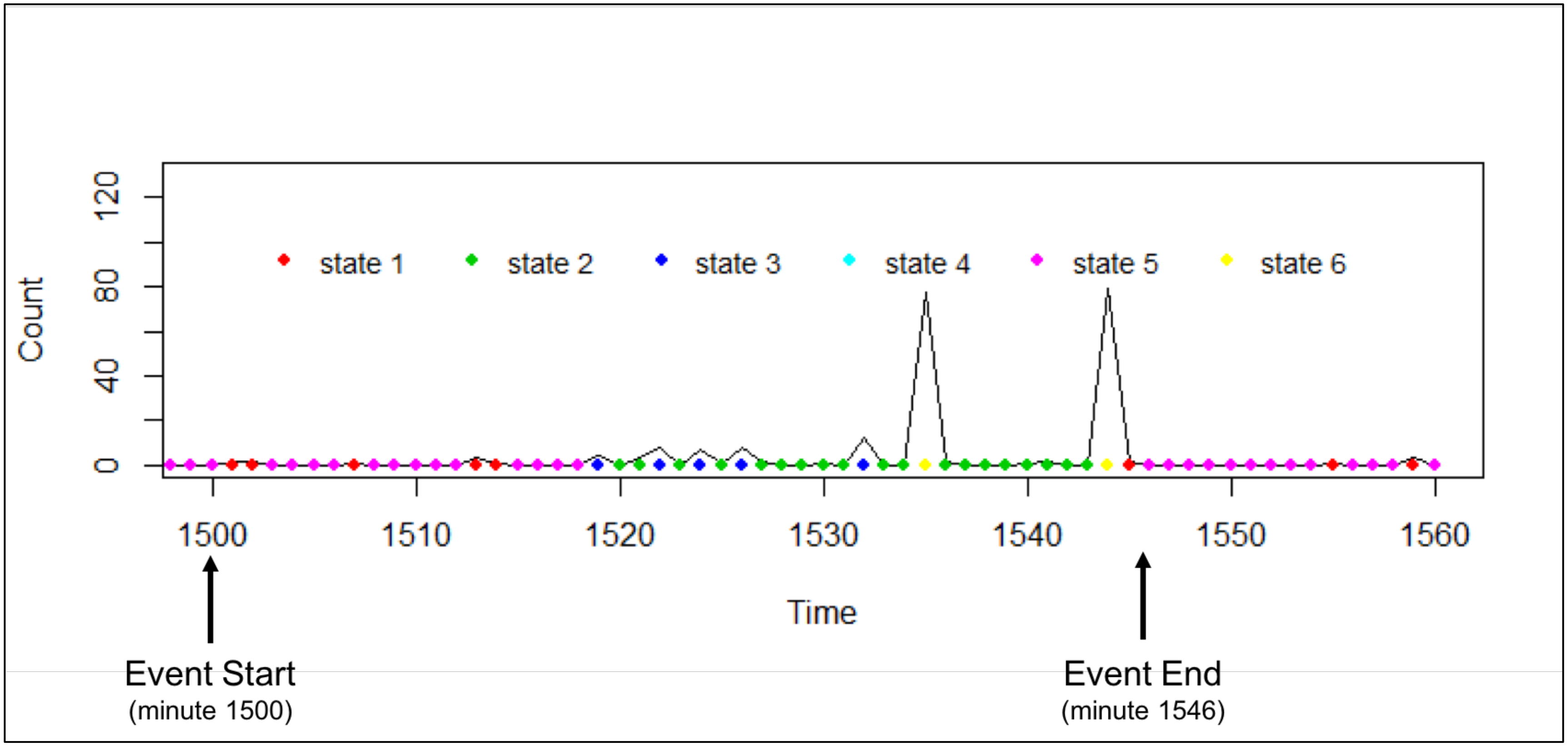

Figure 3. *Depiction of State Classifications from 6-State Zero-Inflated Hidden Markov Model*

Note. Time is in minutes. Count is the number of emails that occurred per minute of the simulation. An event was triggered at minute 1500; the system recovered at minute 1546; recovery time for the event was 46 minutes. States 1 & 2 = "low-activity states"; State 5 = "baseline state"; States 3, 4, & 6 = "high-activity states" (see Table 4 for additional descriptive information for each state).

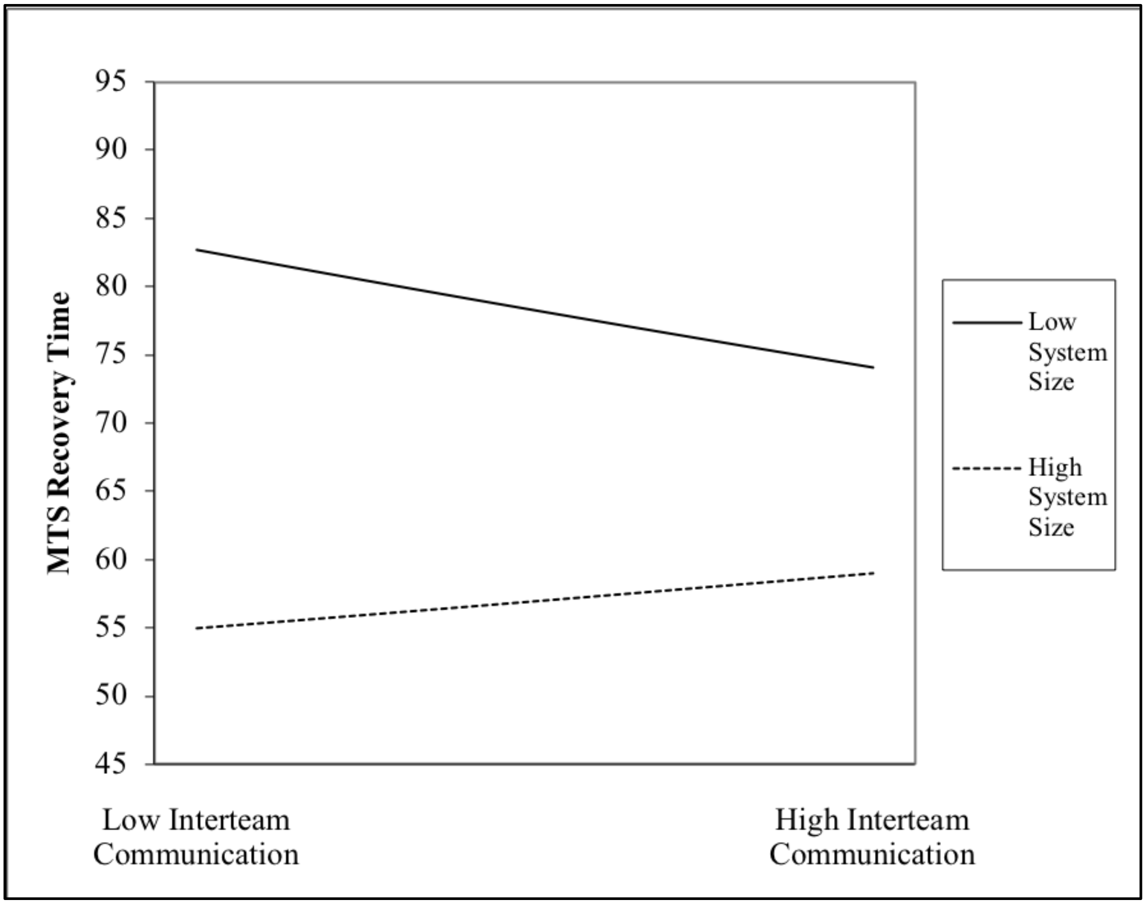

Figure 4. *H3a: Multiteam System Recovery Time and the Interaction between Interteam Communication and System Size*

Note. N = 144 events.

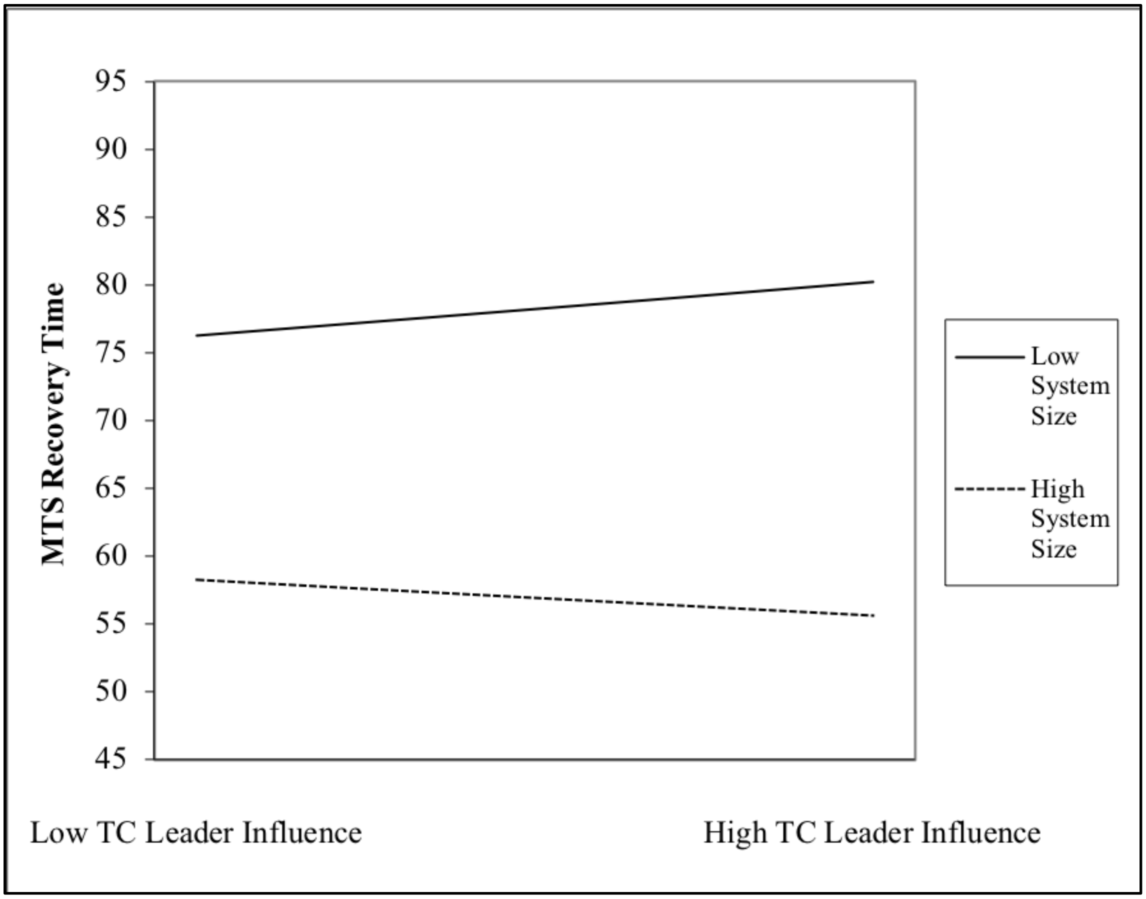

Figure 5. *H3b: Multiteam System Recovery Time and the Interaction between Task-Critical Leader Influence and System Size*

Note. N = 144 events.

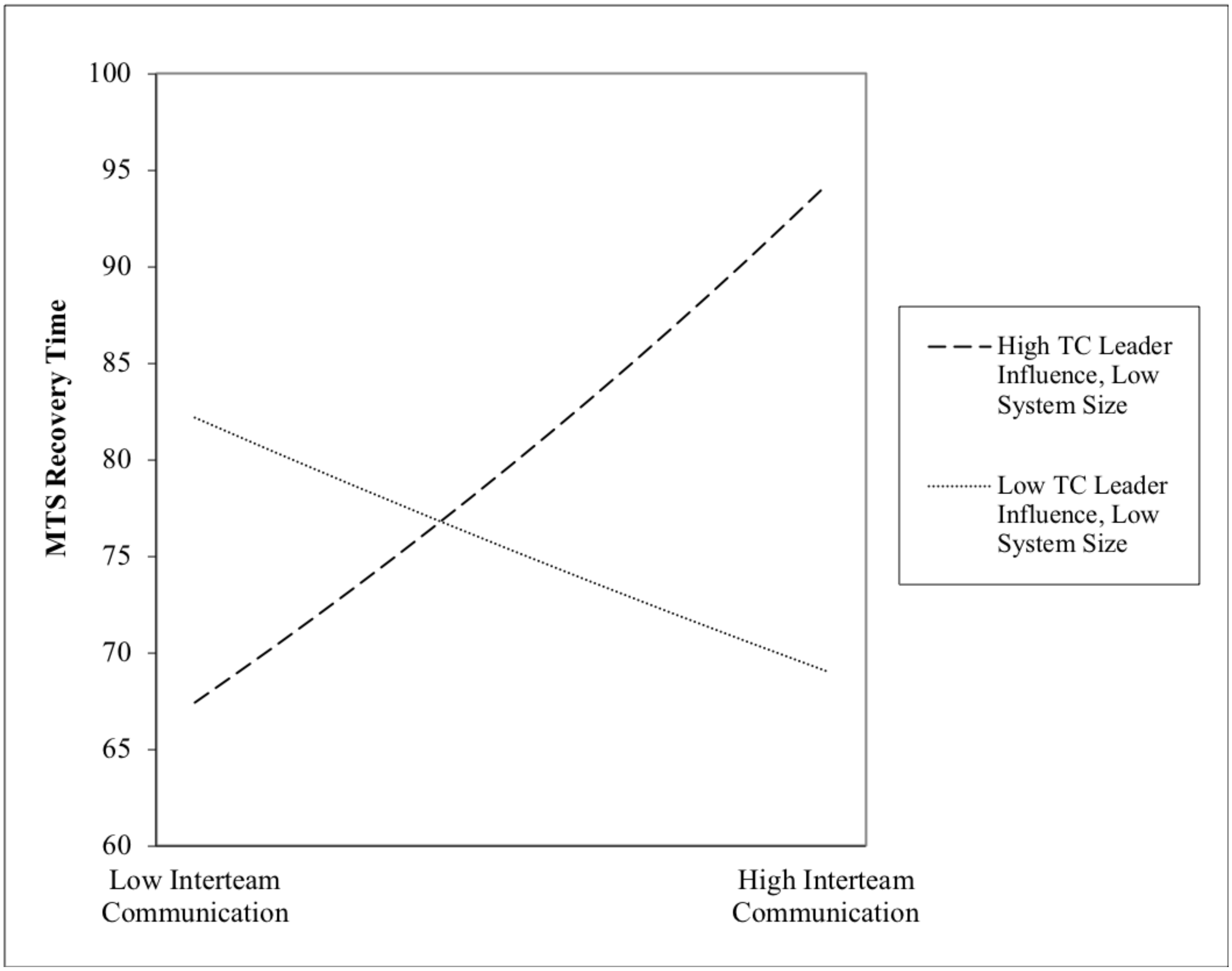

Figure 6. *RQ1: Three-way Interaction for Smaller System Sizes with Interteam Communication and Task-Critical Leader Influence*

Note. N = 144 events.

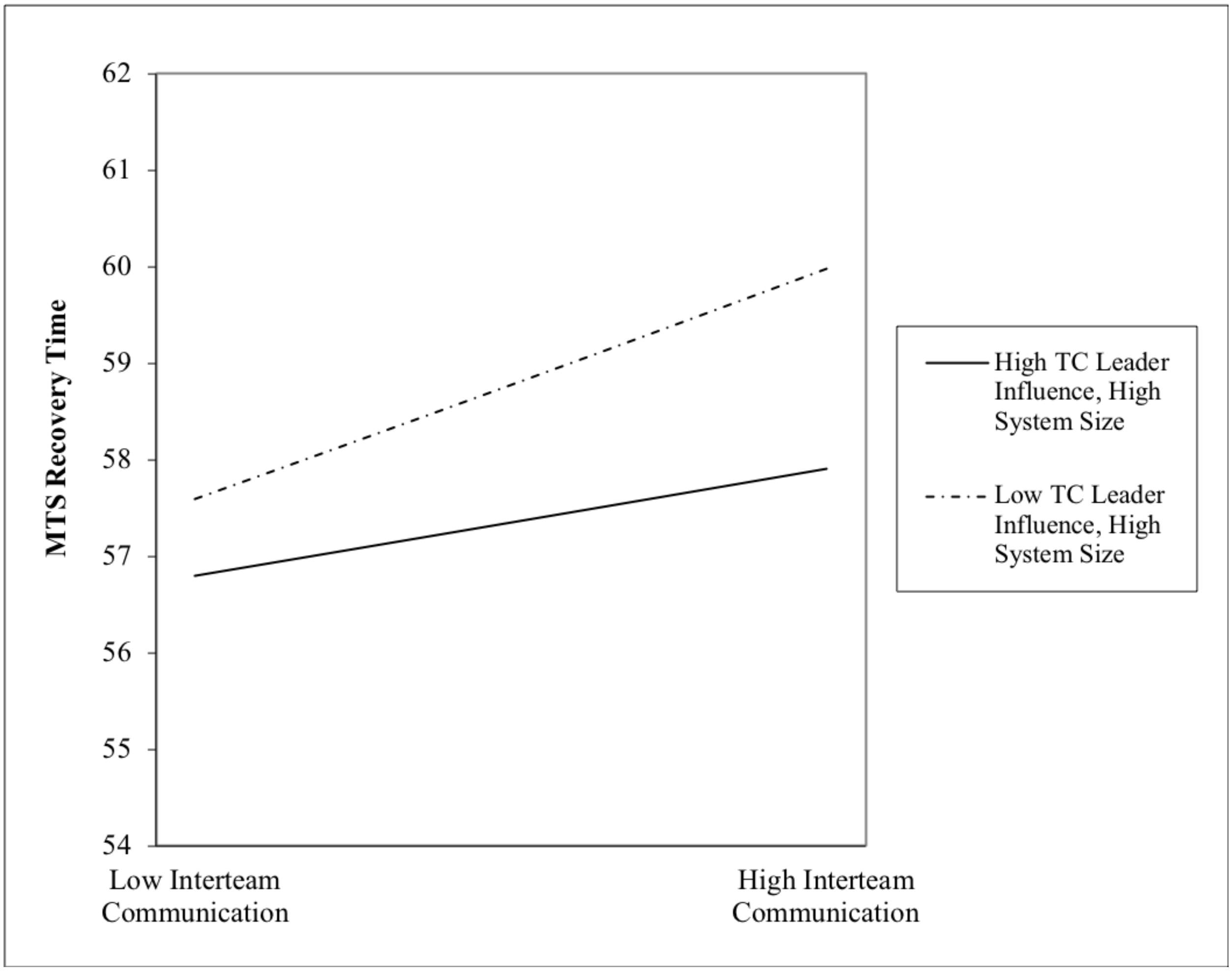

Figure 7. *RQ2: Three-way Interaction for Larger System Sizes with Interteam Communication and Task-Critical Leader Influence*

Note. N = 144 events.

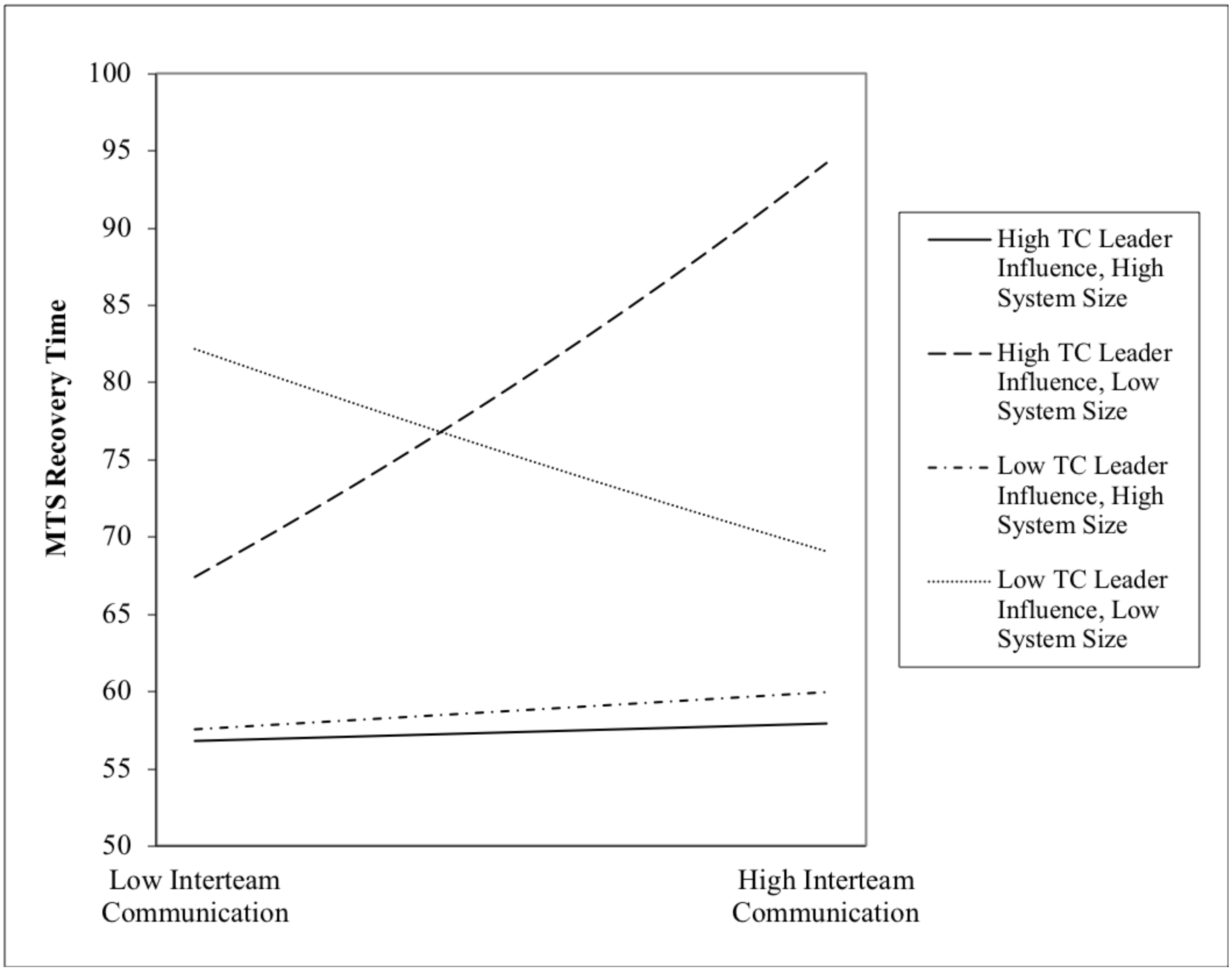

Figure 8. *RQ1 & RQ2: Full Three-way Interaction between Interteam Communication, Task-Critical Leader Influence, and System Size*

Note. N = 144 events.