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ADDRESSING PERFORMANCE TENSIONS IN MULTITEAM SYSTEMS: BALANCING INFORMAL MECHANISMS OF COORDINATION WITHIN AND BETWEEN TEAMS

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Due to their distinctive features, multiteam systems (MTSs) face significant coordination challenges—both within component teams and across the larger system. Despite the benefits of informal mechanisms of coordination for knowledge-based work, there is considerable ambiguity regarding their effects in MTSs. To resolve this ambiguity, we build and test theory about how interpersonal interactions among MTS members serve as an informal coordination mechanism that facilitates team and system functioning. Integrating MTS research with insights from the team boundary spanning literature, we argue that the degree to which MTS members balance their interactions with members of their own component team (i.e., intrateam interactions) and with the members of other teams in the system (i.e., interteam interactions) shapes team- and system-level performance. The findings of a multimethod study of 44 MTSs composed of 295 teams and 930 members show that as interteam interactions exceed intrateam interactions, team conflict arises and detracts from component team performance. At the system level, a balance between intrateam and interteam interactions enhances system success. Our findings advance understanding of MTSs by highlighting how informal coordination mechanisms enable MTSs to overcome their coordination challenges and address the unique performance tension between component teams and the larger system.

As the industrial landscape shifted to an increasingly knowledge-driven economy, early commentators (e.g., Drucker, 1999) directed attention to the unique challenges faced by individual knowledge workers. Subsequent scholarship (e.g., Wuchty, Jones, & Uzzi, 2007) redirected attention to teams as the locus of knowledge work, arguing that individual workers alone lack the capacity needed to solve problems of increasing scope and complexity. Most recently, scholars (e.g., Edmondson & Harvey, 2018; Zaccaro, Dubrow, Torres, & Campbell, 2020) have highlighted the rising prominence of knowledge work in multiteam systems (MTSs), which refers to "two or more teams that interface directly and interdependently in response to environmental contingencies toward the accomplishment of collective goals" (Mathieu, Marks, & Zaccaro, 2001: 290). Similar to the shift from the individual to the team, the shift from the team to the MTS has occurred because the complexity of many modern problems exceeds the capabilities of any single team (Zaccaro et al., 2020).

As MTSs seek to address complex knowledge-based problems, theory and research have revealed

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that coordination, or "the process of interaction that integrates a collective set of interdependent tasks" (Okhuysen & Bechky, 2009: 463), is particularly important—but also especially difficult—for MTS functioning (e.g., Davison, Hollenbeck, Barnes, Sleesman, & Ilgen, 2012; de Vries, Hollenbeck, Davison, Walter, & van der Vegt, 2016; Rico, Hinsz, Davison, & Salas, 2018; Shuffler & Carter, 2018). Distributing tasks across teams offers the promise of specialized expertise or focused effort to solve distinct elements of a larger and more complex problem, but the overall benefit to the system can only be realized if members effectively coordinate both within and across team boundaries. Doing so is especially difficult for MTSs because structural and psychological barriers emerging from a division of labor, specialization of expertise, and unique priorities stymie the flow of information between teams (Heath & Staudenmayer, 2000). As a function of these barriers, scholars have highlighted interteam coordination, in particular, as a primary contributor to the success or failure of MTSs (e.g., DeChurch & Marks, 2006; Firth, Hollenbeck, Miles, Ilgen, & Barnes, 2015). Understanding how to facilitate interteam coordination without degrading intrateam coordination has been a central focus of MTS research (Rico et al., 2018; Zaccaro et al., 2020).

Theory (e.g., Katz & Kahn, 1978; Thompson, 1967) and research (e.g., Faraj & Sproull, 2000; Van de Ven, Delbecq, & Koenig, 1976) have highlighted that informal coordination mechanisms—entailing direct, mutual, and ad hoc interactions between people (Okhuysen & Bechky, 2009)—are useful for accomplishing collective knowledge-based work. Given that MTSs are frequently deployed to address such problems (Zaccaro et al., 2020), past theory and research on coordination has seemingly suggested that informal mechanisms would be especially helpful for enabling MTS effectiveness. Yet, the degree to which informal mechanisms are beneficial or detrimental for MTS effectiveness remains unclear, in part, because prior studies have largely focused on formal structural (e.g., de Vries et al., 2016), role-based (e.g., Davison et al., 2012), and centralized (e.g., Lanaj, Hollenbeck, Ilgen, Barnes, & Harmon, 2013) mechanisms of coordination (Mathieu, Luciano, & DeChurch, 2018). Moreover, the findings of the few quantitative studies that have measured informal coordination are ambiguous, leading to contradictory recommendations about whether or how MTS members should use informal mechanisms to facilitate coordination (e.g., Davison et al., 2012; Marks, DeChurch, Mathieu, Panzer, & Alonso, 2005; Mell, DeChurch, Contractor, & Leenders, 2020). Thus, while broader coordination theory and research have generally prescribed the use of informal mechanisms for knowledge-based work, there remains considerable inconsistency regarding the usefulness of these mechanisms for enabling coordination in MTSs.

The purpose of this paper is to build and test theory that resolves this ambiguity about how informal coordination mechanisms—specifically, direct interpersonal interactions among MTS members—influence the effectiveness of MTSs engaged in knowledge-based work. While prior MTS research on informal mechanisms has assessed their intrateam and interteam effects independently, MTSs face the unique challenge of simultaneously coordinating activities within and between component teams. To address this challenge and the associated ambiguity, we develop new insights into informal coordination in MTSs by integrating MTS scholarship with broader theory and research on activities commonly known as boundary spanning, which describes a "team's actions to establish linkages and manage interactions with parties in the external environment" (Marrone, 2010: 914). The MTS and boundary spanning literatures share a focus on how team members engage with those outside of team boundaries, which for MTS members involves interteam interactions. However, because they are interested in outcomes at different levels of analysis, with MTS researchers focused principally on the system level and boundary spanning researchers on the team level, the theoretical bases of these literatures emphasize different constellations of processes. We integrate these two perspectives to derive the insight that the degree of balance of MTS members' intrateam and interteam interactions shapes team processes—specifically, team conflict—and team- and system-level performance.

We test our theoretical model in a study of 44 multiteam systems, composed of 295 teams and 930 members, charged with completing a knowledge-based engineering task over 11 weeks. Our findings make three main contributions to the MTS literature. First, our focus on informal coordination extends past studies in the MTS literature, which have yielded ambiguous conclusions regarding informal mechanisms (Carter, Cullen-Lester, Jones, Gerbasi, Chrobot-Mason, & Nae, 2020; Luciano, DeChurch, & Mathieu, 2018; Rico et al., 2018; Zaccaro et al., 2020). Given the documented importance of within- and between-team coordination for MTS effectiveness (Zaccaro et al., 2020), paired with the documented value of informal mechanisms for other forms of complex knowledge-based work (e.g., Faraj & Sproull, 2000), resolving ambiguity regarding the role of informal coordination mechanisms advances MTS theory and offers guidance for practice. Our findings challenge the oft-stated view that MTSs are too large, complex, and distributed to benefit from informal coordination (e.g., Davison et al., 2012; Lanaj et al., 2013), calling attention to informal interactions as a facilitator of MTS effectiveness.

Second, by examining the balance of intrateam and interteam interactions, our research takes into account the unique performance tensions in MTSs to help resolve ambiguity in the findings of the few studies that have considered informal coordination in MTSs (e.g., Davison et al., 2012; Marks et al., 2005; Mell et al., 2020). Deriving new insights by integrating the MTS and boundary spanning literatures, our coincident consideration of intrateam and interteam interactions enriches prior MTS research, which has often treated within-team and between-team dynamics as separate, additive contributors to coordination. We also identify team conflict as a mechanism that channels the effects of an imbalance of intrateam and interteam interaction patterns to team effectiveness. Even as interteam interactions are necessary for system-level coordination, when not balanced by corresponding intrateam interactions, conflict emerges and hinders team performance. Our joint consideration of intrateam and interteam interactions—specifically, their balance at the team and system levels—thus advances understanding of the potential "countervailing or confluent consequences of coordination processes" in MTSs (Rico et al., 2018: 11), presenting implications for how to overcome the performance tensions that are inherent to MTSs (Luciano et al., 2018; Mathieu et al., 2018).

Complementing our theoretical contributions, attributes of our study help address limitations in the MTS literature that scholars have recently spotlighted (e.g., Shuffler & Carter, 2018; Zaccaro et al., 2020), although this is not the main contribution of the paper. Our study of MTSs completing a generative engineering task enriches the diversity of MTS research in terms of task type (i.e., structured vs. unstructured), interaction medium (i.e., computer mediated vs. face-to-face), and size (i.e., relatively small vs. large number of component teams). Additionally, we used wearable sensors to measure interpersonal interactions among MTS members—an approach that scholars have advocated for assessing coordination in MTSs in a fine-grained way (e.g., Luciano et al., 2018; Mathieu et al., 2018; Shuffler & Carter, 2018; Zaccaro et al., 2020). Wearable sensors enabled us not only to test our a priori hypotheses but also to examine post hoc how different foci and forms of interactions relate to MTS effectiveness. Together, these hypothesized and post hoc examinations suggest new directions for future research on coordination in MTSs.

THEORETICAL DEVELOPMENT

Coordination challenges are particularly acute within MTSs due to two of their distinctive characteristics. First, the goals of an MTS are hierarchical, with at least two levels. At the proximal level, each component team has its own specific goals; at the distal level, the system has a superordinate goal that requires input from the component teams (Mathieu et al., 2001). This goal hierarchy creates structural interdependencies among component teams (Zaccaro et al., 2020) and contributes to potential performance tensions between the local component teams and the global system as a whole (Shuffler & Carter, 2018). Second, MTS component teams are structurally differentiated, with particular goals, norms, and processes that reinforce distinctions between teams (Luciano et al., 2018). Together, these attributes can be barriers to simultaneously achieving coordination in the two areas where it is necessary (DeChurch & Marks, 2006). Intrateam coordination—the integration of activities among the members of the same component team—is needed for teams to realize their local, proximal goals. Interteam coordination—the integration of activities across teams within the system—is needed to achieve the global, distal objectives of the MTS as a whole.

In trying to understand how organizations integrate their activities, researchers have studied a wide range of coordination mechanisms (Okhuysen & Bechky, 2009), which are ways that people integrate their activities when engaged in interdependent work. Scholars have often made a basic distinction between coordination mechanisms that are formal and those that are informal (e.g., Faraj & Xiao, 2006; Van de Ven et al., 1976). Formal mechanisms are impersonal and top–down—leaders deploy them with little concern for the idiosyncratic attributes and characteristics of individual members (Van de Ven et al., 1976). Informal mechanisms, in contrast, are personal and emerge organically; they entail direct, mutual, and real-time adjustments between people to facilitate the integration of their work (Van de Ven et al., 1976). The most ubiquitous informal mechanism in organizations, and the focus of our research, is interpersonal interactions—the direct, bi-directional exchange of information between two people (Katz & Kahn, 1978). Time spent in interpersonal interactions enables individuals to mutually adjust their activities and better integrate their work. To capture this fundamental informal coordination mechanism, we focus our research specifically on the duration of MTS members' interactions with one another. As MTSs must realize coordination both within and between teams (Luciano et al., 2018), we consider two kinds of interactions: intrateam and interteam interactions. Intrateam interactions are encounters among the members of the same component team; interteam interactions are encounters among the members of different component teams within the same MTS.

Due to the size and complexity of MTSs, scholars have extolled the benefits of formal coordination mechanisms (DeChurch & Marks, 2006; Lanaj et al., 2013). Indeed, a review of the MTS literature reveals that the vast majority of published studies—particularly those using quantitative methods—have documented the value of various formal mechanisms for enabling system-level effectiveness. For example, MTS researchers have found that coordination can be enhanced through the use of a well-defined, hierarchical structure that features a higher-order "integration team" (Davison et al., 2012; de Vries et al., 2016). Researchers have also found performance benefits from centralized a priori planning (Lanaj et al., 2013) and pre-task formal frame of reference training (Firth et al., 2015). Overall, existing research has clearly demonstrated the value of formal mechanisms for MTS coordination and system effectiveness.

The picture is far less clear regarding the effects of informal coordination mechanisms on MTS functioning. On the one hand, with few exceptions—like Mell et al.'s (2020) study of information sharing—research has rarely directly studied the interpersonal interactions that are an informal means of coordinating activities. Rather than assessing interpersonal interactions, past studies that have forwarded conclusions about informal coordination have drawn inferences from, for example, synchronous activity (e.g., Davison et al., 2012) or from the effects of a multifaceted set of action processes (e.g., Marks et al., 2005). On the other hand, papers that have alluded to informal mechanisms in MTSs—particularly with respect to interteam coordination—have presented ambiguous empirical findings (e.g., Davison et al., 2012; Mell et al., 2020), and the resulting interpretations have suggested rather broad pessimism (Rico, Hinsz, Burke, & Salas, 2017). Davison et al. (2012: 809), for example, argued that "direct mutual adjustment among all members in the collective ... is actually detrimental to performance in multiteam systems"—a view echoed by Lanaj et al. (2013: 737), who asserted that "multiteam systems are too large to support mutual adjustment among all team members."

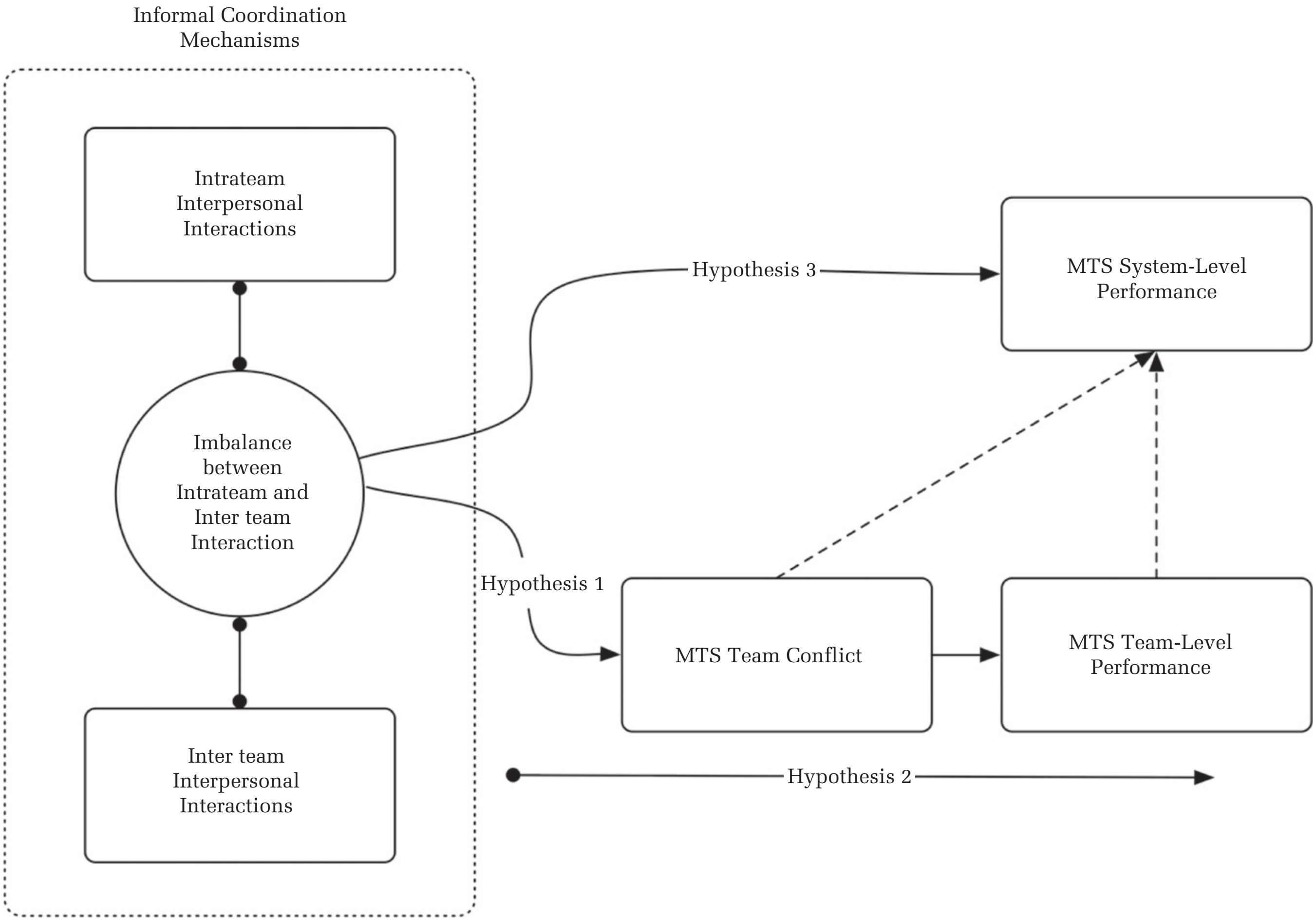
The dearth of research on informal mechanisms in the MTS literature and the relatively pessimistic view of their system-level effects is perplexing given broader theory and research on coordination in knowledge-based work (e.g., Faraj & Xiao, 2006; Heath & Staudenmayer, 2000; Van de Ven et al., 1976). Outside the MTS literature, informal mechanisms have been viewed as essential for enabling coordination for information-intensive collective tasks—tasks for which "coordination is less dependent on structural arrangements and more contingent on knowledge integration" (Faraj & Xiao, 2006: 1155). This body of broader theory and research suggests that informal mechanisms should be especially valuable for work that is complex, uncertain, and interdependent (Choi, 2002), like the knowledge-based problems that MTSs often address.

To begin to resolve equivocality regarding informal coordination in MTSs, we propose a conceptual model—depicted in Figure 1—that delineates how interpersonal interactions among members influence MTS processes and outcomes. Integrating prior findings from the MTS literature with insights from the team boundary spanning literature (e.g., Choi, 2002), our core assertion is that how individuals balance their interpersonal interactions—between the members of their own component team and the members of other teams in the system—shapes whether informal interactions help or hinder the effectiveness of the team and system.

Informal Coordination Mechanisms and Component Team Effectiveness

For an MTS to achieve its global system-level objectives, the component teams within it must first achieve their local team-level objectives. How informal mechanisms influence the internal functioning of component teams—a topic studied extensively in broader research on teams—has been of lesser concern in the MTS literature. Instead, and reflecting the unique characteristics of MTSs, scholars have foremost sought to understand how to enable the between-team coordination needed to achieve

FIGURE 1
Model of Hypothesized Relationships



system-level outcomes (Carter et al., 2020; Zaccaro et al., 2020). To formulate predictions about how informal interactions shape component team processes and outcomes in MTSs, we derive insights from theory and research on team boundary spanning (Ancona, 1990; Marrone, 2010). From a boundary spanning perspective, interteam interactions in an MTS are one—but certainly not the only—form of boundary spanning behavior (Marrone, 2010). Although centered on traditional, standalone teams, the boundary spanning literature provides complementary insights that aid in developing predictions about how interpersonal interactions influence component teams in MTSs. Whereas the focus of MTS research on interteam interactions has been system-level outcomes, the focus of boundary spanning research on interteam interactions has been team-level effectiveness (Marrone, 2010).

The team boundary spanning literature has put forward a nuanced view of the effects of interteam interpersonal interactions (Choi, 2002; Marrone, 2010). When team members venture beyond the boundaries of their own team, they are able to secure resources, gain support, and—importantly for the context of MTSs—align their activities with other organizational units (Ancona, 1990; Ancona & Caldwell, 1992; Marrone, Tesluk, & Carson, 2007). However, it takes time and effort to seek out, engage with, and procure resources from external teams, and it requires internal coordination to implement or use those resources (Marrone et al., 2007). For these reasons, when not balanced with corresponding internal coordination efforts, extensive boundary spanning behavior can breed divergence in team members' conceptualizations of their tasks and spark disagreements about how best to accomplish their team's objectives (Choi, 2002; Faraj & Yan, 2009; Marrone, 2010). These symptoms are indicative of intrateam conflict—unpleasant disagreements among team members regarding their work (Jehn & Bendersky, 2003)—which may serve as an important intermediary mechanism for understanding how informal mechanisms relate to component team effectiveness in MTSs (Lanaj, Foulk, & Hollenbeck, 2018). Although conflict can be sparked by a range of issues—elements of a task, aspects of work processes, or relationships among members, for example (Jehn, Northcraft, & Neale, 1999)—it is often experienced in a diffuse way, with one form spilling over to others (de Wit, Greer, & Jehn, 2012). For this reason, although task-based disagreements can sometimes facilitate knowledge-based work, conflict often undermines team effectiveness because it disrupts the collective information processing (De Dreu & Weingart, 2003) that MTS members need to integrate knowledge gained through their interteam interactions.

To redress potential disruption, boundary spanning theorists have advocated that team members balance external and internal activities (Choi, 2002; Marrone, 2010). As they increase their boundary spanning, team members should engage in a corresponding amount of internal interaction because effective boundary spanning "requires the transmission of resulting external information and knowledge back into the team itself" (Marrone, 2010: 930). When team members engage with one another internally, they can share new information acquired externally and resolve potentially discrepant understandings of their task (Choi, 2002; Faraj & Yan, 2009; Keller, 2001). In this regard, a balanced configuration creates synergies between intra- and interteam informal coordination efforts (Choi, 2002). The idea that external and internal activities work in concert to influence team effectiveness has received support in boundary spanning research on team coordination (Faraj & Yan, 2009), learning (Bresman, 2010; Cummings & Haas, 2012; Wong, 2004), and communication (Keller, 2001).

This core idea from the team boundary spanning literature—that balance between external and internal activities is needed to leverage knowledge from outside the team and avoid disruptive conflict—serves as a grounding principle for our hypotheses about how intrateam and interteam interactions influence component team processes and outcomes in MTSs. Within the unique context of MTSs, external activities are not just beneficial, but essential (DeChurch & Marks, 2006). The necessity of interteam interactions does not, however, obviate their potential costs in terms of intrateam conflict if not appropriately balanced with intrateam interactions. Following boundary spanning theory, an excessive external focus relative to internal interactions can increase role overload and undermine team viability—two states that may breed conflict among team members (Bresman, 2010; Bron, Endedijk, van Veelen, & Veldkamp, 2018; Marrone et al., 2007; Wong, 2004). From a boundary spanning perspective, this type of incongruence reflects an "underbounded" configuration, referring to many external interactions without the capacity to sufficiently coordinate team members to use the requisite knowledge and skills and achieve their own local goals (Ancona & Caldwell, 1992). Thus, although theory has suggested that informal mechanisms are valuable for coordination in knowledge work, the key insight from the boundary spanning literature has been that a team must strike "a balance between internal and external activities" (Choi, 2002: 187). When interteam interactions exceed intrateam interactions, MTS component teams are likely to become embroiled in conflict.

Hypothesis 1. Imbalance between intrateam and interteam interactions is positively related to team conflict, such that team conflict is higher as interteam interactions exceed intrateam interactions.

Extending this hypothesis, we propose that an imbalance in intrateam and interteam interactions has implications—indirectly through team conflict—for component team performance. There is robust evidence that conflict—especially disagreements about how to allocate resources and disputes that are emotionally charged—is detrimental for team performance. Meta-analyses have documented that although disagreements about ideas may be helpful under some circumstances, team conflict generally is negatively related to team performance (De Dreu & Weingart, 2003; de Wit et al., 2012). Moreover, even helpful disagreements often spill over into destructive forms of conflict (e.g., Simons & Peterson, 2000).

For MTS component teams—entities that already face the challenge of allocating scarce resources—time spent resolving discrepant understandings of who is responsible for what or how the team will complete its work is time taken away from advancing toward their local objectives. Related research on boundary spanning similarly implicates team conflict as a mechanism that transmits the effects of an imbalance between external and internal activities to team performance (Choi, 2002). Bresman

(2010: 82), for instance, suggested that an imbalance leads team members to view external activities as a "waste of time," reflecting conflict over the allocation of resources. Wong (2004: 647) argued that an imbalance will "increase cognitive variation in members' beliefs about their task and how things are done," implicitly implicating conflict as an important mechanism (Hinsz & Betts, 2012). Bron et al. (2018: 454) further noted that teams that have a high external focus and low internal focus will struggle "to come to within-team consensus and reach decisions"—a situation emblematic of team conflict.

Hypothesis 2. Imbalance between intrateam and interteam interactions is indirectly negatively related to team performance through team conflict.

Informal Coordination Mechanisms and System-Level Effectiveness

Although component team effectiveness is a necessary building block for MTS effectiveness, team effectiveness alone is insufficient (Marks et al., 2005). The teams within an MTS must also coordinate their activities to realize effective system-level performance (Luciano et al., 2018). MTS scholars have noted that performance-enabling mechanisms at one level—such as effective within-team coordination—may have performance-inhibiting effects at the other level (DeChurch & Zaccaro, 2010; Shuffler, Jiménez-Rodríguez, & Kramer, 2015). Given these countervailing effects, "MTSs must be aware of team and MTS functioning at the same time to balance needs" (Shuffler & Carter, 2018: 393).

Boundary spanning across the system can help achieve this simultaneous awareness of the team and system. Extending the notion of boundary spanning to higher forms, Marrone (2010) discussed network boundary spanning across mutually interdependent teams, such as those that compose an MTS. Intraorganizational boundary spanning (e.g., Rosenkopf & Nerkar, 2001; Zhao & Anand, 2013) is a means for the exchange and integration of knowledge within a broader system. Decentralized interactions between units in an organization can serve as a "collective bridge" that enables knowledge transfer (Zhao & Anand, 2013). Organizational units must balance their focus, spanning their boundaries to obtain external knowledge and engaging in internal activities to integrate it. As Choi (2002: 189) asserted, "internal and external activities may maintain synergistic relationships through mutual reinforcement."

Balancing external and internal processes to coordinate information is thus likely paramount for MTS functioning. Interpersonal interactions may be important for coordinating laterally within and between teams but may have opposing effects unless sufficient attention is placed on each (Rico et al., 2018). Disproportionately engaging in intrateam interactions may enable component teams to perform at a high level independently but could contribute to a breakdown in between-team coordination. On the other hand, favoring interteam interactions over intrateam interactions may impede system-level coordination because component teams will struggle to integrate necessary changes into their internal work (Rico et al., 2017). MTSs must have interteam interactions to adjust at linkage points (Mell et al., 2020) and corresponding intrateam interactions to integrate these adjustments locally (Choi, 2002; Marrone, 2010).

Members of an MTS may be particularly at risk of becoming imbalanced in their intrateam and interteam interactions. A primary reason that MTSs fail to achieve their system-level objectives is insufficient coordination between teams (Mathieu et al., 2018; Rico et al., 2017). That is, an imbalance—in either direction—is likely problematic for an MTS (Mathieu et al., 2018). Providing some peripheral support for these ideas, Firth et al. (2015) found in a study of a formal training program that the effectiveness of between-team coordination in an MTS depends on how well component teams coordinated their internal activities. Similarly, MTS researchers studying identification have found that an overemphasis on either the component team or the system can undermine system-level performance (Porck, Matta, Hollenbeck, Oh, Lanaj, & Lee, 2019). These findings lend credence to the idea that balance between intrateam and interteam interpersonal interactions serves as an informal coordination mechanism that can enable system-level success in an MTS.

Hypothesis 3. Controlling for component team conflict and performance, imbalance between intrateam and interteam interactions is negatively related to system performance.

METHOD

Research Setting

We tested our hypotheses in a multisource and multimethod study of MTSs that were formed as part of the laboratory component of a required undergraduate engineering course at a university on the East Coast of the United States. Students worked together in an MTS to design and build a Rube Goldberg machine—a complex, over-engineered device that completes a trivial or mundane task. The building block of a Rube Goldberg machine is the transfer of energy across events. For example, a marble rolls into and knocks over a sequence of dominos, triggering the release of a helium balloon to lift a switch that turns on a light. Within each laboratory section, students were first organized into component teams, and each team was charged with the goal of constructing a Rube Goldberg machine comprising at least six prescribed energy transfer events. Each component team's Rube Goldberg machine was itself one part of a larger Rube Goldberg machine assembled by connecting all machines designed by the teams within that section. Teams were assigned an order and had to link their team's machine with adjacent teams' machines to create a larger, system-level Rube Goldberg machine. Thus, within each section, the teams needed to work together interdependently as an MTS to ensure the smooth transfer of energy between machines and through the system to complete the final goal. Throughout the 11-week course, each team had a separate physical workstation in the same classroom where, for roughly two hours per week, members worked on their component Rube Goldberg machine. Members were not restricted to only their workstation, though; they could move freely throughout the classroom to visit other teams' workstations to discuss and coordinate transfers of energy between machines within the larger system.

This task exemplifies the challenges faced by MTSs engaged in knowledge work, particularly in terms of structural differentiation and hierarchical goals. As the sample machine layout depicted in Figure 2A shows, students formed a sequentially interdependent MTS (Rico et al., 2018), with reciprocal interactions between adjacent teams. Moreover, these teams had to complete a knowledge-based task involving complex (multiple and varied energy transfer events), specialized (each team developed their own unique machine), and interdependent (linkage between adjacent teams) requirements (Zaccaro et al., 2020). Each component team was free to work in idiosyncratic ways, resulting in variant norms and routines across teams that needed coordination and integration to yield a system-level work product. In addition, a goal hierarchy existed; each component team needed to build its own machine but also coordinate with other teams to achieve the superordinate goal of building a system-level machine. Reinforcing the goal hierarchy, students' performance in the course was both a function of the performance of their component team's machine and the performance of their section's integrated machine.

Sample and Data Sources

We collected data from 44 MTSs, which were composed of 295 teams and 930 members. Teams comprised either three or four members ($M = 3.15$, $SD = 0.46$), and the MTSs consisted of between four and eight teams ($M = 6.70$, $SD = 1.11$). Participants were, on average, 19 years old ($SD = 1.68$). The sample was predominantly male (76%) and represented a range of ethnicities (59% White, 25% Asian, 6% Hispanic or Latino, 5% multiethnic, 4% Black or African American, and 1% Native Hawaiian or Pacific Islander).

To guard against single-source and single-method limitations (e.g., Podsakoff, MacKenzie, Lee, & Podsakoff, 2003), we collected data in three ways. First, we used self-report surveys to collect background information during Week 1 and to assess team conflict during Week 8. At each time, participants received an email inviting them to complete a web-based survey. We received 913 completed responses to the first survey (98% overall response rate, 100% median team-level response rate) and 827 responses to the second survey (89% overall response rate, 100% median team-level response rate). Second, we used wearable sensors to measure how often participants interacted with one another. In total, 912 participants (98% overall participation rate, 100% median team-level participation rate) wore a sensor during Weeks 5, 6, and 7. Third, we used trained observers to assess the performance of the Rube Goldberg machines, which were evaluated at the team and system levels in Week 11. Figure 2B visually arrays these data collection sources and timings. The findings that we report in this paper were part of a larger data collection designed for pedagogical purposes and to provide individual feedback to students. One other paper (Graham, Mawritz, Dust, Greenbaum, & Ziegert, 2019) has also used one variable (individual dominance orientation) from this same data collection effort. Some participants from the data collection effort were participants in a different study six months later; Graham et al. (2019) used data on students' individual dominance orientation as a baseline assessment. Although there was a minor overlap in participants, there are no overlaps

FIGURE 2
Empirical Method
A: Sample Layout of MTS Rube Goldberg Machine

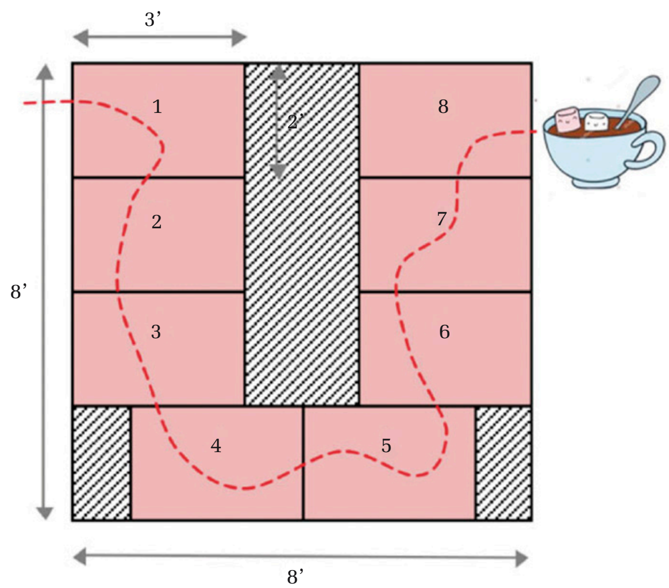
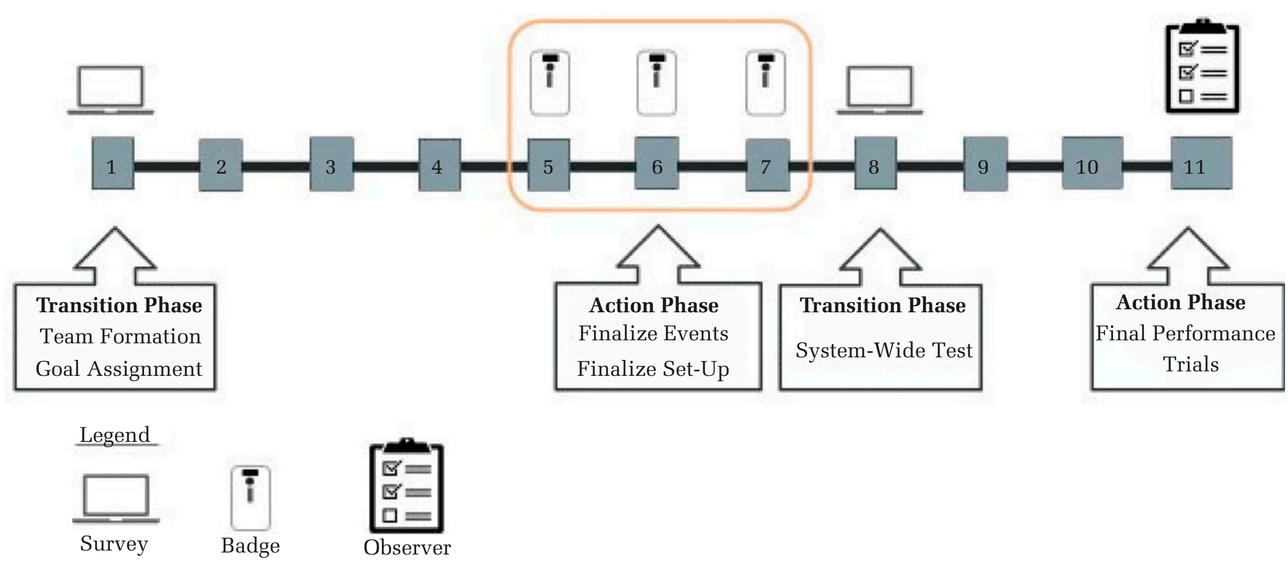


FIGURE 2
B: Project Timeline (in Weeks) and Data Sources



Notes: Each component team built their local machine within a 3 foot × 2 foot area at their own separate workstation and then subsequently connected it to adjacent teams’ machines to create the overall system based on the pattern above (the particular method and location of connection between adjacent teams was determined based on mutual discussion and coordination among adjacent teams). The final energy output of transferring sugar to a cup of coffee was completed by the last team in the system.

in the variables used in this paper and those used in Graham et al. (2019).

Measures

Interpersonal interactions. We operationalized interpersonal interactions as the amount of time that individuals spent in relative physical proximity to one another, as assessed by using wearable Bluetooth sensors. Proximity is a medium through which coordination-focused interactions often occur in organizations (Okhuysen & Bechky, 2009). Undergirding this idea is the premise that if two people are physically close to one another, they are likely to be engaged in an interpersonal interaction with one another (Bernstein & Turban, 2018; Ingram & Morris, 2007; Müller, Meneses, Humbert, & Guenther, 2020). Substantiating this premise, research has repeatedly found that proximity is a valid measure of interpersonal interaction and collaboration in field-based settings (e.g., Chaffin et al., 2017; Kraut, Egido, & Galegher, 2014; Matusik, Heidl, Hollenbeck, Yu, Lee, & Howe, 2019; Müller et al., 2020; Parrino, 2015). Of particular relevance for our measurement approach, researchers have used wearable Bluetooth sensors and examined the relation between their measurement of physical proximity and self-report survey measures of interpersonal interactions (e.g., advice giving or receiving and friendship), finding support for convergent validity (Matusik et al., 2019; Müller et al., 2020).

Nonetheless, because proximity assessed using Bluetooth sensors does not consider people's orientation toward one another (e.g., whether they are face-to-face or back-to-back), we recognize that it is possible for two people to be physically close but not engaged in an interpersonal interaction. It is also possible for two people to be physically distant and engaged in an interaction through technology (e.g., texting, phone calls, or web conferencing). Each of these possibilities, as sources of measurement error, would reduce the statistical power and result in more conservative tests of our hypotheses (Schwab, 1980). Given Matusik et al.'s (2019) and Müller et al.'s (2020) guidance on understanding contextual nuances that might influence the validity of proximity-based measures from Bluetooth sensors, we observed all 44 MTSs in our study for at least two hours during Weeks 1–3 of the project. In these observations, we sought to scrutinize the use of physical proximity as a reasonable indicator of work-related interpersonal interactions within the specific context of our research. Our observations indicated that proximity did indeed correspond with meaningful interactions in this context. When participants varied their physical location—either moving toward teammates at their workstation or toward members of other teams—it was because they sought to examine or inquire about others' work. Participants in our context did not rely upon digital means to interact—their colocation in the same classroom each week rendered in-person interactions the easiest means of communicating with each other.

We assessed interpersonal interactions during Weeks 5, 6, and 7. We chose these weeks because they comprised the action phase when teams were responsible for building their component machines and designing mechanisms for transferring energy between teams. Given prior theory and research regarding the benefits and costs of informal coordination (e.g., Kanfer & Kerry, 2012; Mathieu et al., 2018), it is during this phase when we expected the relations that we hypothesized to be most salient (Rico et al., 2017). Further, boundary spanning activities were most likely to occur and have the greatest impact during this MTS action phase (Choi, 2002; DeChurch & Marks, 2006; DeChurch, Burke, Shuffler, Lyons, Doty, & Salas, 2011). This action phase—before the MTSs in our study shifted in Week 8 to an outcome phase to start system-wide testing of the machines (Marks, Mathieu, & Zaccaro, 2001; Rico et al., 2017)—thus constituted the right time for assessing informal interactions (Mitchell & James, 2001).

We recorded physical closeness using wearable multisensor devices (i.e., Kim, McFee, Olguin, Waber, & Pentland, 2012). Following recent validation studies (Chaffin et al., 2017; Matusik et al., 2019; Müller et al., 2020), we used the raw Bluetooth signal strength values recorded by the sensors to assess the time that members spent interacting with one another. Bluetooth devices regularly scan the environment (e.g., every 25 seconds) to determine whether other devices are available for connection. When one device detects a second device, it records the strength of the connection between the two devices, called the RSSI value, at that moment. Although signal strength can be influenced by other factors (e.g., walls made of different materials), validation studies have found that variations in RSSI values correspond to variations in the proximity of two Bluetooth devices; the higher an RSSI value, the closer in physical space the two devices are likely to be (Matusik et al., 2019; Müller et al., 2020).

To measure intrateam and interteam interactions, we aggregated the markers of physically proximal interactions between two people to the team level. For intrateam interactions, we calculated the number of dyadic interactions detected by the sensors among members within the same component team. The devices' regular and periodic scans for other devices indicated the amount of time that the members of a given team were engaged with others in their own team. To measure interteam interactions, we calculated the number of dyadic interactions that the sensors detected between the members of one component team and the members of other teams in the MTS. This indicated the time the members of one team were engaged in interpersonal interactions with others who were outside their team. To test our system-level hypothesis, we used the system-level mean (i.e., across teams) of these team-level measures. Appendix A details the steps we took to measure interpersonal interactions using the raw values obtained from the sensors. Appendix B reports the results of sensitivity analyses, which examine and support the robustness of our findings to operationalizing interactions using different signal strength values when processing the raw Bluetooth detection information.

Team conflict. During Week 8, participants completed Jehn and Mannix's (2001) 9-item measure of team conflict using a 7-point scale ranging from 1 (*never*) to 7 (*all the time*). A sample item is "How often are there disagreements about who should do what in your work group?"[1] We measured conflict in Week 8 because this is when team members had worked through the goal-striving process and action phase that theory has suggested engender conflict (Marks et al., 2001; Rico et al., 2017). This is also the time when conflict may be particularly detrimental to team effectiveness (Jehn & Mannix, 2001). The measure instructed members to rate conflict behaviors in the team agnostic of a specific timeframe to allow for members to reflect back over the entirety of the preceding action phase. We found high team-level interitem reliability ($\alpha = 0.94$) and justification for aggregation to the team level [median $r_{wg(j)} = 0.91$; ICC(1) = 0.21, $p < 0.01$; ICC(2) = 0.43] (Bliese, 2000). The relatively low ICC(2) was due to the small size of the component teams, consisting of three to four members (Bliese, 2000).

Team performance. Instructors informed teams in the first week of the course that team performance would be assessed as the percentage of successful energy transfers across the events within their Rube Goldberg machine. A transfer was considered successful when energy passed seamlessly from one event to the next within the same team's Rube Goldberg machine without any manual intervention by team members. Trained observers measured component teams' performance across five trial runs of the machines conducted in Week 11. We calculated team performance as the total percentage of successful within-team energy transfers across the five performance trials. Component team performance ranged from 16.67% to 100%.

System performance. Trained observers measured system performance as the rate of successful energy transfers between component teams' machines in the system. Between-team energy transfers represented the successful execution of the MTS's tasks between adjacent teams in the sequentially interdependent MTS (Rico et al., 2018). To successfully transfer energy from one team to the next, adjacent teams had to determine the precise location in three-dimensional space (i.e., length, width, and height) of where the transfer would occur and the means of the transfer (e.g., a marble rolling down a ramp from one team to another). This measure of system performance also included the final event of transferring sugar to a cup of coffee. As with team performance, we calculated system performance across the five performance trials conducted in Week 11; its range was 73.33% to 100%.

Controls. We used a theoretically driven approach to select controls for inclusion in our models (Becker, Atinc, Breaugh, Carlson, Edwards, & Spector, 2016). In predicting team conflict and team performance, we controlled for team familiarity (i.e., the degree to which team members knew one another at the start of the project) and team size (i.e., the number of people on the team roster). We controlled for team familiarity because teams with familiar members may experience less conflict and perform at a higher level than teams with unfamiliar members (e.g., Huckman, Staats, & Upton, 2009). We assessed familiarity using a round robin survey item during Week 1 (i.e., "I know this team member well" using a 7-point

[1] This measure comprises three items each for task, process, and relationship conflict. Like other field studies of conflict (e.g., Bunderson, van der Vegt, Cantimur, & Rink, 2016; O'Neill, McLarnon, Hoffart, Woodley, & Allen, 2018), we found high, positive correlations among these three forms of conflict (mean correlation = 0.70). Although confirmatory factor analyses showed that a three-factor model was better than a one-factor model ($\Delta\chi^2 = 569.22$, $p < 0.01$), our results were substantively the same across the three different forms of conflict. To present our results parsimoniously, we report results for the single overall measure of team conflict.

agreement scale) and used the mean across these dyadic ratings to operationalize team-level familiarity as an additive construct (Chan, 1998). We controlled for team size because larger teams possess more resources than smaller teams and, as a result, might be better equipped to perform at a high level by design (e.g., Thomas & Fink, 1963). In predicting system-level performance, we controlled for the number of teams in the MTS, as larger systems introduce the potential for greater complexity (Shuffler & Carter, 2018). We also controlled for average team familiarity, team performance, and team conflict when predicting system-level performance. We controlled for these variables to focus specifically on system performance over and above team-level dynamics.[2]

Analyses

Central to our model is the idea that the benefits of informal coordination mechanisms are a function of how well MTS members balance their intrateam and interteam interactions. That is, the balance of interactions, irrespective of the amount of interactions, shapes team conflict, team effectiveness, and system effectiveness. To test this idea, we used polynomial regression with response surface analysis (Barranti, Carlson, & Côté, 2017; Edwards, 1994; Edwards & Parry, 1993). Whereas traditional approaches—such as using a difference score or creating a product term between two variables—are conceptually intuitive, these approaches are limited in two important ways (Edwards, 1994, 1995, 2001; Edwards & Parry, 1993). First, interpreting statistical tests of balance effects using these simpler approaches rests upon assumptions about the form of the relation among the variables that could lead to erroneous interpretations (Edwards, 2001). Second, in contrast to the coarse view of balance effects afforded by simpler approaches, polynomial regression and response surface analysis afford the ability to examine the specific form of balance effects on a criterion variable (Edwards & Parry, 1993). Response surface analysis involves plotting and testing the parameters from a polynomial regression model to determine the shape of the relationship between the congruence and incongruence of two variables and an outcome. This is important because our first hypothesis specified that excessive interteam interactions relative to intrateam interactions enhance conflict.

We tested our hypotheses using a subsample of the 295 teams comprising the 44 multiteam systems. Wearable device hardware or system failures, similar to those documented by other researchers (e.g., Chaffin et al., 2017; Matusik et al., 2019), necessitated excluding 22 teams for which we lacked data on interpersonal interactions. We also excluded 5 teams that were outliers in measures of interpersonal interactions (i.e., greater than three standard deviations above the mean). We excluded these teams because we suspected invalid measurement of interactions; specifically, the sensor data from these teams suggest that participants removed their devices and placed them in a common physical location (Müller et al., 2020). Including these five teams in our hypothesis tests does not change the magnitude or significance of the focal parameters for testing our hypotheses. More broadly, the 27 teams that we excluded did not differ significantly from the remaining 268 teams with respect to team size, familiarity, conflict, or performance.

Our hypotheses consider relationships at two levels of analysis—the team level and the system level. Because teams are nested within systems, the team-level observations of any given system are nonindependent, which violates the assumption of independence that underlies the calculation of standard errors in ordinary least squares regression. To address this in our analyses predicting team conflict and team performance, we used clustered standard errors to adjust for potential inflation due to nonindependence (McNeish, Stapleton, & Silverman, 2017).

RESULTS

Tables 1 and 2 provide descriptive statistics for and intercorrelations among study variables at the team level and the system level, respectively.

Hypothesis 1 predicted that an imbalance between intrateam and interteam interpersonal interactions relates to component team conflict. Specifically, we argued that an excess of interteam interactions, relative to intrateam interactions, increases team conflict. Models 3 and 4 of Table 3 provide the results of the polynomial regression analyses used to test Hypothesis 1. Model 3 includes controls for team size and team familiarity; Model 4 shows the robustness of the results when excluding these controls. Following Barranti et al. (2017), we calculated four simple slope parameters (a1, a2, a3, and a4) that

[2] In subsequent sensitivity analyses, we also examined additional controls of the number of people in each MTS and the performance of the lowest performing team. The significance and approximate magnitude of the focal parameter estimates for our hypothesis tests were equivalent.

TABLE 1
Descriptive Statistics and Correlations Among Team-Level Variables

	M	SD	1	2	3	4	5
1. Team size	3.17	0.44					
2. Team familiarity	3.89	1.04	−0.11				
3. Intrateam interactions	0.92	0.44	−0.11	0.06			
4. Interteam interactions	0.12	0.08	−0.10	−0.04	0.30		
5. Team conflict	2.23	0.81	0.00	0.00	−0.14	0.02	
6. Team performance	0.89	0.10	0.06	−0.03	−0.03	0.01	−0.17

Notes: Entries are bivariate correlations. $n = 268$ teams nested within 44 systems. $p < 0.05$ (two-tailed) for correlations greater than $|0.12|$ in magnitude.

together reflect the shape of the three-dimensional response surface plot depicted in Figure 3A. Although all four parameters must be interpreted together, of particular relevance for testing Hypothesis 1 is the a3 parameter, which reflects the slope of the line of incongruence. As Model 3 and Figure 3A show, this parameter was significant and negative (a3 $= -0.32$, $p < 0.01$) supporting Hypothesis 1, indicating that team conflict increases when members spend more time engaged in interteam interactions than intrateam interactions.

Hypothesis 2 predicted that the imbalance effect of intrateam and interteam interactions indirectly relates to team performance through team conflict. Table 4 provides the results of regression analyses predicting component team performance. As shown in Model 5 of Table 4, there was a significant negative relation between team conflict and team performance ($B = -0.02$, $p < 0.01$). However, there were no significant effects of interpersonal interactions on team performance. This suggests that the relationship between interpersonal interactions and team performance is indirect, passing through team conflict. To test this indirect effect, we used a block variable approach with bootstrapped standard errors in which we created weighted linear composites of the five polynomial estimates on team conflict and performance (Edwards & Cable, 2009). We then estimated a path model and computed the indirect effect of the block variables on team performance through team conflict. Supporting Hypothesis 2, we found that the indirect effect of imbalance of intrateam and interteam interactions on team performance, through team conflict, was significant ($B = -0.02$, $SE = 0.01$, $p < 0.05$, $\beta = -0.04$).

At the system level, Hypothesis 3 predicted that—above and beyond component team conflict and performance—imbalance between intrateam and interteam interactions is negatively related to system performance. Table 5 presents the results of regression analyses predicting system-level performance. As seen in Model 3 of Table 5 and depicted in Figure 3B, the relationship between interpersonal interactions and system performance was curvilinear. Directly relevant to testing Hypothesis 3, based on the significant downward curvature along the line of incongruence, we found that system performance was higher when team members balanced their engagement in interpersonal interactions with the members of their own component team and the members of other component teams in the MTS (a4 $= -0.07$, $p < 0.05$). As members disproportionally engaged in intrateam or interteam interactions, resulting in an imbalance, system performance declined. Therefore, Hypothesis 3 was supported.

Post Hoc Examinations: Leveraging the Granularity of Data from Wearable Sensors

Following Hollenbeck and Wright (2017), who encouraged researchers to report the findings of post hoc analyses, we sought to extend the findings

TABLE 2
Descriptive Statistics and Correlations Among System-Level Variables

	M	SD	1	2	3	4	5	6
1. MTS size	6.66	1.12						
2. Team familiarity	3.85	0.55	−0.04					
3. Team conflict	2.22	0.35	0.05	−0.05				
4. Team performance	0.90	0.05	−0.21	−0.03	−0.36			
5. Intrateam interactions	0.93	0.25	0.09	0.17	−0.11	−0.02		
6. Interteam interactions	0.12	0.08	−0.03	−0.15	0.00	0.00	0.54	
7. System performance	0.90	0.10	0.12	−0.33	−0.13	0.15	0.10	0.20

Notes: Entries are bivariate correlations. $n = 44$ systems. $p < 0.05$ (two-tailed) for correlations greater than $|0.30|$ in magnitude.

TABLE 3
Results of Team-Level Analyses Predicting Team Conflict

	Model 1		Model 2			Model 3			Model 4		
	B	*SE*	*B*	*SE*		*B*	*SE*		*B*	*SE*	
Intercept	2.228	(0.06)	2.407	(0.14)		2.298	(0.08)		2.298	(0.08)	
Team size	−0.003	(0.11)	−0.020	(0.11)		−0.022	(0.12)				
Team familiarity	−0.001	(0.04)	0.008	(0.04)		0.000	(0.04)				
Intrateam interactions			−0.290	(0.14)	*	−0.142	(0.06)	*	−0.141	(0.06)	*
Interteam interactions			0.738	(0.76)		0.174	(0.07)	*	0.175	(0.07)	*
Intrateam interactions^2						0.030	(0.04)		0.030	(0.04)	
Intrateam × Interteam interactions						0.010	(0.05)		0.009	(0.05)	
Interteam interactions^2						−0.103	(0.05)	*	−0.103	(0.05)	*
Response Surface Parameters											
a1						0.032	(0.09)		0.034	(0.09)	
a2						−0.063	(0.06)		−0.063	(0.06)	
a3						−0.316	(0.08)	**	−0.316	(0.08)	**
a4						−0.083	(0.10)		−0.082	(0.10)	
Overall Model											
F	0.000		1.310			1.919		†	2.699		*
R^2	0.000		0.020			0.049			0.049		

Notes: n = 268 teams nested in 44 systems. Entries are unstandardized parameter estimates, with clustered standard errors in parentheses. Tests are two-tailed.
† $p < 0.10$
* $p < 0.05$
** $p < 0.01$

reported above by leveraging the granularity of our sensor data to gain further insights into informal coordination in MTSs. As an overarching structure for this effort, we drew from Mathieu et al. (2018), who organized research on coordination in MTSs by considering functions, foci, forms, and phases. Our hypotheses considered how interpersonal interactions are an informal coordination mechanism in MTSs—that is, we examined the function of interpersonal interactions. Informed by our results, we developed post hoc predictions and conducted analyses examining how differing foci of interactions (i.e., the specific targets of informal coordination) and differing forms of interactions (i.e., the structure of who is interacting with whom) relate to MTS effectiveness. While these analyses allow for a richer examination of informal coordination with foci and forms complementing functions, the sensor data, which we collected during a single period of the project, did not permit examining the phases component of Mathieu et al.'s (2018) framework.

Examining different coordination foci. Mathieu et al. (2018) referred to the different targets of coordination efforts in an MTS as foci. Our hypotheses differentiated between two broad foci—intrateam interactions and interteam interactions. However, the sequential nature of the project completed by the MTSs in our study may have rendered some interteam interactions more important for MTS effectiveness than others. As Figure 2A depicts, teams that are adjacent to one another in the MTSs that we studied (e.g., Team 3 with adjacent Teams 2 and 4) must directly integrate their machines for the system to function. Building from Rico et al.'s (2018) framework and our findings on the function of interpersonal interactions, we might expect that informal interactions between adjacent teams are more important than interactions between nonadjacent teams (e.g., Team 3 with nonadjacent Team 5). Rico et al. (2018) highlighted the need for explicit coordination processes, such as direct communication and interactions, for how work activities between teams "fit together" (Rico et al., 2018: 337), which may be especially valuable for adjacent teams due to sequential interdependence. We therefore suggest that interpersonal interactions are particularly beneficial to team and MTS success when the interteam foci are adjacent teams compared to nonadjacent teams.

To examine whether the imbalance effects that we hypothesized differ depending on whether teams are proximal in the flow of work, we assessed how much members interacted with the members of adjacent versus nonadjacent teams. Using sensor data, we calculated adjacent and nonadjacent interteam

FIGURE 3
Response Surface Plots
A: Response Surface Plot Predicting Team Conflict
B: Response Surface Plot Predicting System Performance

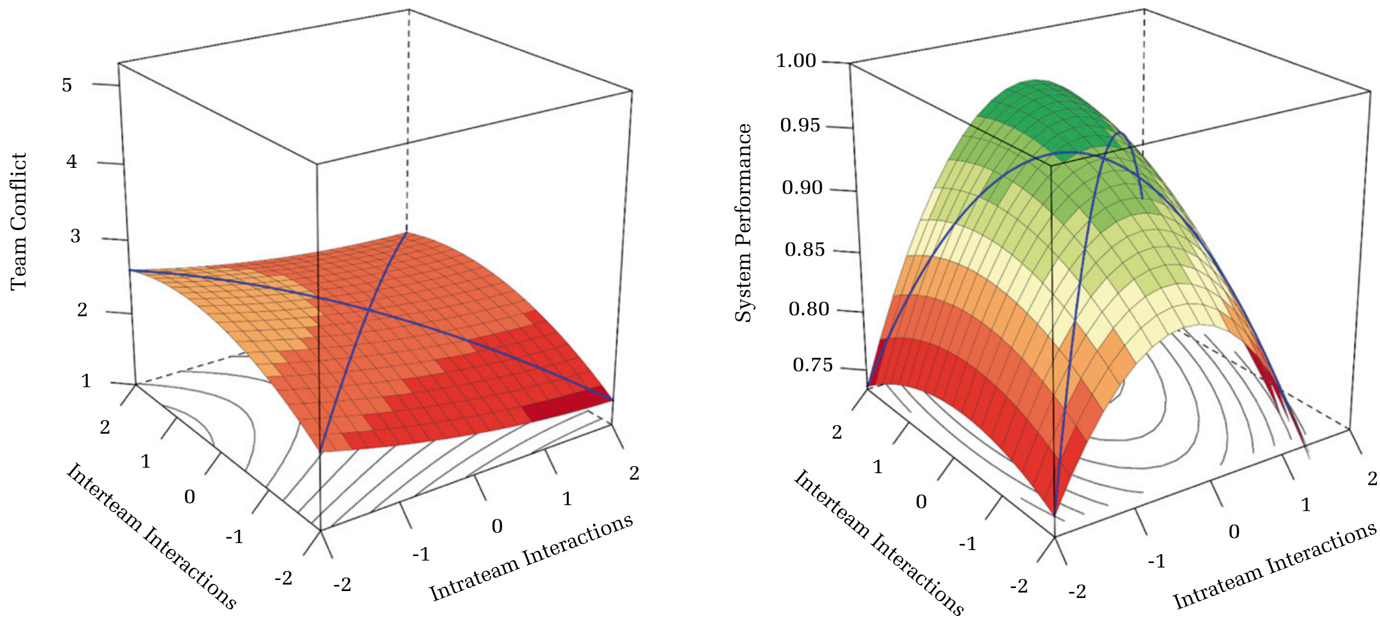


TABLE 4
Results of Team-Level Analyses Predicting Team Performance

	Model 1		Model 2		Model 3		Model 4		Model 5	
	B	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Intercept	0.892	(0.01)	0.895	(0.01)	0.886	(0.01)	0.886	(0.01)	0.935	(0.02)
Team size	0.013	(0.01)	0.013	(0.01)	0.012	(0.01)			0.011	(0.01)
Team familiarity	−0.002	(0.01)	−0.002	(0.01)	−0.001	(0.01)			−0.001	(0.01)
Intrateam interactions			−0.006	(0.02)	−0.003	(0.01)	−0.003	(0.01)	−0.006	(0.01)
Interteam interactions			0.027	(0.09)	−0.005	(0.01)	−0.005	(0.01)	−0.001	(0.01)
Intrateam interactions^2					0.000	(0.00)	0.000	(0.00)	0.001	(0.00)
Intrateam × Interteam interactions					0.005	(0.01)	0.005	(0.01)	0.005	(0.01)
Interteam interactions^2					0.004	(0.00)	0.004	(0.00)	0.002	(0.00)
Team conflict									−0.021	(0.01) **
Response Surface Parameters										
a1					−0.008	(0.01)	−0.009	(0.01)	−0.007	(0.01)
a2					0.010	(0.01)	0.010	(0.01)	0.008	(0.01)
a3					0.002	(0.02)	0.002	(0.02)	−0.005	(0.02)
a4					0.000	(0.01)	−0.001	(0.01)	−0.002	(0.01)
Overall Model										
F	0.630		0.34		0.446		0.478		1.289	
R^2	0.000		0.000		0.012		0.009		0.039	

Notes: n = 268 teams nested in 44 systems. Entries are unstandardized parameter estimates, with clustered standard errors in parentheses. Tests are two-tailed.
† $p < 0.10$
* $p < 0.05$
** $p < 0.01$

interactions by aggregating dyadic interactions among MTS members according to the same approach previously described for interteam interactions. We demarcated whether a given interaction comprised the members of teams that were next to one another in the MTS (i.e., adjacent interteam interactions) versus teams that were separated by at least one other team (i.e., nonadjacent interteam interactions). Using this distinction, we re-ran Model 3 from Table 3, predicting team conflict separately for adjacent and nonadjacent interteam interactions. Similar to our a priori findings, we observed an imbalance effect for nonadjacent interteam interactions (a3 = -0.34, $SE = 0.08$, $p < 0.01$). As imbalance increased, with interteam interactions with nonadjacent teams exceeding intrateam interactions, team conflict increased. The imbalance effect was negative but nonsignificant, however, for interactions with adjacent teams (a3 = -0.12, $SE = 0.10$, $p > 0.10$). Conflict did not significantly rise as interteam interactions with adjacent teams exceeded intrateam interactions. At the system level, we re-ran Model 3 from Table 5, predicting system performance separately for adjacent and nonadjacent interactions. Like the team level, the imbalance effect differed for these two types of interteam interactions. The imbalance of nonadjacent interteam and intrateam interactions was significant and negatively related to system performance (a4 = -0.06, $SE = 0.03$, $p < 0.05$). The effect was not significant, however, for adjacent interteam interactions (a4 = -0.06, $SE = 0.05$, $p > 0.10$). Taken together, these post hoc findings suggest that it is important for researchers to consider the specific foci of informal coordination. The detrimental effects of imbalance that we reported in our hypothesis tests are especially pronounced when the interpersonal interteam interactions are with nonadjacent teams with which the focal team does not directly integrate in the system.

Examining different coordination forms. Mathieu et al. (2018: 338) used the term "form" to describe "the structure (e.g., boundary spanners, members, centralized, decentralized) of who in the MTS enacts the coordination functions." In our hypotheses, we considered interteam interactions agnostic to whether they were broadly distributed across team members—such that all members engaged in similar amounts of interactions with those outside the team—or concentrated in a single member. Although some MTS research has suggested that interteam interactions are best accomplished by a formally designated liaison (e.g., Davison et al., 2012), other MTS findings have

TABLE 5
Results of Regression Analyses Predicting System Performance

	Model 1			Model 2			Model 3			Model 4		
	B	***SE***		***B***	***SE***		***B***	***SE***		***B***	***SE***	
Intercept	0.896	(0.01)		0.854	(0.06)		0.938	(0.02)		0.922	(0.02)	
System size	0.012	(0.01)		0.012	(0.01)		0.013	(0.01)				
Team familiarity	−0.057	(0.03)	*	−0.056	(0.03)	†	−0.078	(0.02)	**			
Team performance	0.267	(0.34)		0.278	(0.35)		0.316	(0.30)				
Team conflict	−0.030	(0.04)		−0.027	(0.04)		−0.056	(0.04)				
Intrateam interactions				0.025	(0.07)		−0.004	(0.01)		−0.009	(0.02)	
Interteam interactions				0.159	(0.23)		0.025	(0.02)		0.031	(0.02)	
Intrateam interactions^2							−0.043	(0.01)	**	−0.025	(0.02)	†
Intrateam × Interteam interactions							0.014	(0.02)		0.009	(0.02)	
Interteam interactions^2							−0.008	(0.01)		−0.006	(0.01)	
Response Surface Parameters												
a1							0.022	(0.02)		0.023	(0.02)	
a2							−0.036	(0.02)	†	−0.022	(0.02)	
a3							−0.029	(0.03)		−0.040	(0.03)	
a4							−0.065	(0.03)	*	−0.041	(0.03)	
Overall Model												
F	1.820			1.410			2.078		†	0.911		
R^2	0.160			0.190			0.355			0.107		

Notes: $n = 44$ systems. Entries are unstandardized parameter estimates, with standard errors in parentheses. Tests are two-tailed.
† $p < 0.10$
* $p < 0.05$
** $p < 0.01$

indicated that teams may benefit from having several members engage in these activities (e.g., DeChurch & Marks, 2006; Mell et al., 2020). This ambiguity is further reflected in the boundary spanning literature in which the question of whether external interactions are "best reserved for only a single team member or leader" remains unresolved (Marrone, 2010: 931).

Given these differing possibilities, we leveraged our sensor data to examine coordination forms as the concentration of interteam interactions in a component team—the degree to which a team channeled interteam interactions through a subset of team members—might influence the functional value of informal interactions. To do so, for each MTS member, we first pooled the dyadic interteam interactions of that individual to create a measure of how much they interacted with the members of other teams. Then, we calculated the coefficient of variation for each team—a metric that captures concentration in terms of how much more a person engages in interteam interactions compared to the other members of their team (Harrison & Klein, 2007).

To examine the effect of the form of informal coordination, we replaced the general measure of interteam interactions with this measure of concentration and re-ran Model 2 from Table 3 to predict team conflict. Consistent with our earlier results, which did not consider concentration, we found that intrateam interactions were significantly negatively related to team conflict ($B = -0.26$, $SE = 0.11$, $p < 0.05$). Although the coefficient was negative, concentration of interteam interactions was not significantly related to team conflict ($B = -0.10$, $SE = 0.18$, $p > 0.10$). Also at the team level, we re-ran Model 2 from Table 4, predicting team performance by replacing interteam interactions with concentration. There was a positive relationship between concentration of interteam interactions and team performance ($B = 0.04$, $SE = 0.02$, $p = 0.05$). Teams where interteam interactions were more concentrated in a single member, as opposed to more equally distributed across members, performed better. These findings suggest that the form of coordination does not influence team conflict; however, concentrating boundary spanning efforts could have direct benefits for the performance of teams embedded within an MTS. Extending these analyses, we considered how the average concentration of component teams might influence system-level performance by re-running Model 2 of Table 5 but substituting the interteam interactions measure with the system-level mean of concentration of interteam interactions. The general tendency for teams to concentrate their interteam interactions was not related to system-level performance ($B = -0.07$, $SE = 0.05$, $p > 0.10$), controlling for component team performance. Finally, to examine the robustness of the results of our a priori hypothesis to concentration, we included this concentration measure as a control variable in our prior analyses. The hypothesis test results were robust to the inclusion of concentration in the models. These post hoc analyses with regard to the form of informal coordination suggest that concentrating interteam interactions within a subset of team members may have benefits for team performance that are not transmitted through team conflict. Moreover, these benefits do not seem to come at the cost of system performance.

DISCUSSION

Because of their unique properties—including hierarchically nested goals and structural differentiation—MTSs face unique coordination challenges (DeChurch & Marks, 2006; Zaccaro et al., 2020). Findings from our study resolve conceptual and empirical ambiguities regarding how informal mechanisms enable or inhibit coordination and thus influence MTS team and system effectiveness. Our conceptual model and empirical findings reveal that interpersonal interactions between the members of different component teams must be accompanied by a balanced amount of internally focused interactions among members of the same team for an MTS to benefit from informal interactions. This has implications for MTS theory and practice.

Theoretical Contributions and Implications for Future Research

Our research suggests that the pessimistic views about informal mechanisms in past MTS scholarship (e.g., Lanaj et al., 2013), compounded by ambiguous past empirical findings (e.g., Davison et al., 2012; Mell et al., 2020), may have undersold the potential utility for informal coordination to help MTS members overcome their unique challenges. Past empirical research on MTSs, which has considered the use of informal mechanisms within and between teams as independent factors, has indicated that informal coordination can be both detrimental (Davison et al., 2012) as well as beneficial (Mell et al., 2020) to MTS functioning. By integrating insights from the boundary spanning literature, we proposed that it is necessary to consider informal mechanisms within and between teams in concert, rather than as independent factors. The core insight that emerges from our research is that balance—manifested in the correspondence of intrateam and interteam interactions—serves a beneficial coordination function that enables effectiveness at both the team and system levels in MTSs.

At the team level, balanced interactions reduce the occurrence of team conflict, which, we find, undermines component team performance. Conflict is most likely to emerge and detract from performance when a component team engages in interteam interactions that exceed intrateam interactions. Our conceptual model and findings also indicate that balanced interpersonal interactions serve a valuable coordination function at the system level. MTS effectiveness is highest when interteam interactions, which our theory suggests help to integrate activities across teams, are accompanied by corresponding and similar levels of intrateam interactions, which we argue enable team members to adjust their local activities in response to external information. Although these ideas align with past boundary spanning theory (e.g., Choi, 2002), we did not directly measure system-level knowledge transfer mechanisms. As such, future research is needed to document precisely how informal interactions shape the flow of information between and within teams in MTSs.

Our findings regarding balance reinforce the need to jointly consider effects at the team and system levels to more fully understand how to navigate inherent coordination challenges within MTSs. The idea of a "performance tension" in MTSs—a tension between component teams and the overarching system—is a common thread running throughout the MTS literature (e.g., Luciano et al., 2018). Yet, only a handful of MTS studies have separately conceptualized and tested performance effects at the team and system levels of analysis (e.g., DeChurch & Marks, 2006; Mell et al., 2020). Building from the boundary spanning literature and the need for balance, our findings indicate that MTS members can neither maximize within-team coordination or between-team coordination to realize their objectives. Instead, the side-by-side comparison of effects at the team and system levels in Figure 3 illustrates the need for balanced interpersonal interactions in MTSs. Teams in the region of Figure 3A that overly emphasize interteam interactions have elevated levels of team conflict, which is related to lower levels of team performance. However, acting to minimize component team conflict by focusing entirely on intrateam interactions is not the answer within the unique context of MTSs. As Figure 3B illustrates, there are major consequences for system-level performance when teams engage in an incongruent pattern of informal interpersonal interactions. Instead, to address the tension for simultaneously achieving team-level and system-level performance, MTS members should seek balance to integrate interteam interactions with corresponding intrateam interactions.

The findings of our post hoc analyses, however, suggested that this interplay between the team and the system, and their underlying mechanisms, may be even more nuanced than we initially proposed. Rather than treating other component teams as a singular and undifferentiated external focus of coordination efforts, we found that that it is useful to differentiate the foci of interaction patterns and coordination efforts between external teams based on the level of direct interdependence. These findings could also point to the potential value of both formal and informal coordination mechanisms for MTSs—at the very least for the kind of sequential MTSs that we studied. Formal coordination mechanisms, such as planning or training, could focus MTS members' informal coordination efforts specifically on those linked teams (i.e., teams adjacent in the workflow) with whom mutual adjustments are most likely to be needed for system-level success. Recognizing that our findings regarding adjacent and nonadjacent teams were post hoc, further research is needed to better understand this distinction.

To be clear, although we find that informal mechanisms serve an important coordination function in MTSs, our work does not call into question the value of formal mechanisms or test the relative benefits of informal versus formal mechanisms for enabling coordination in MTSs. Indeed, several prior MTS studies have directly tested and found positive effects of a range of formal mechanisms for enabling coordination (Zaccaro et al., 2020). The purpose of our research was to resolve ambiguity about whether informal mechanisms could also serve a valuable coordination function within MTSs, as identified by both classic coordination theorists (e.g., Van de Ven et al., 1976) and scholars who have studied knowledge-based teams (e.g., Faraj & Sproull, 2000). Considering our findings alongside research that has examined formal mechanisms, though, highlights a particularly promising direction for future MTS research: studying the intersection of formal and informal mechanisms of coordination. Because formal and informal mechanisms are not mutually exclusive (Katz & Kahn, 1978; March & Simon, 1958), they could function together in additive, synergistic, or even incompatible ways. For example, it is possible that informal interactions enable a well-defined structure and role system to adapt to unexpected events or cope with a transient workforce. Research on organizations that face related coordination challenges hints at the value of adopting semi-structured mechanisms—ones that are neither exclusively formal nor exclusively informal (e.g., Bechky, 2006; Bechky & Okhuysen, 2011; Bierly & Spender, 1995; Brown & Eisenhardt, 1997). Considering our post hoc findings on coordination forms and the potential value for component teams, but not systems, of concentrating informal interactions, such semi-structured approaches may provide agility that helps MTSs respond to coordination challenges. It is also possible, however, that an excessive reliance on informal interactions could dilute the efficiency and clarity of formal design and planning, contributing to breakdowns. Future research is needed to answer these questions.

Finally, while our findings highlight the importance of balance, we did observe some indication that it may also be important to consider the absolute level of members' interactions with one another. In particular, the a2 parameter in Model 3 of Table 5, which indicates how the effect of balance changes across different levels of corresponding intrateam and interteam interactions, approached significance for system performance. As depicted in Figure 3B, this inverted-U shaped relationship suggests that, when balanced, increasing levels of intra and interteam interactions are valuable for system performance until an inflection point is reached whereby additional interactions begin to detract from system performance. Examining the volume of informal interactions could thus be a useful avenue for future MTS research.

Practical Implications

Our findings have actionable implications for organizations, given the nature of interdependence within and across teams in MTSs. Although the variance in performance across MTSs may be small, as was the case in our study, errors committed by any one component team can ripple throughout and undermine the entire system. A failure of one team can cause the entire system to fail given the interdependent nature of MTSs (Zaccaro et al., 2020). Moreover, the costs of coordination breakdowns in MTSs can be extraordinary. NASA, for example, suffered hundreds of millions of dollars in losses due to coordination breakdowns in an MTS working on the Mars Climate Orbiter (Shuffler & Carter, 2018). Our results speak to the benefits of effectively balancing intrateam and interteam interactions to achieve coordination and avoid such costly errors, especially in MTSs focused on knowledge work. The operationalization of performance in our study—the reliability of a machine—closely parallels the kinds of metrics that many knowledge-based MTSs (e.g., software development, mechanical engineering, etc.) rely on to assess the quality of their work. Conversely, the inverse of this measure—the error or defect rate of a machine—has implications for the avoidable costs that organizations seek to minimize as defects compound across levels (Lei, Naveh, & Novikov, 2016). One error within or between teams can ripple through and destabilize the overall MTS.

Our results suggest that the benefits of effectively balancing informal interactions could be substantial given the downstream impact of focusing too much on either intrateam or interteam interactions. For each additional point of team conflict, the error rate for the component teams' machines increases by approximately 2%. At the system level, imbalanced systems can have error rates approximately twice as high in comparisons to systems that balance intra and interteam interpersonal interactions. This difference is practically meaningful as even a 2% reduction in a product's defect rate is consequential for a modern knowledge-based MTS (Goodman, Ramanujam, Carroll, Edmondson, Hofmann, & Sutcliffe, 2011). Thus, although the variance explained in our analyses may seem relatively small, our findings regarding the need for MTS members to balance their interactions still offer consequential managerial insights.

Given this importance of balance for MTS functioning and performance, our findings indicate that MTS coordination efforts are aided when leaders and members consciously manage interpersonal interactions with regard to whom they interact with and how much time they devote internally and externally. While interteam interactions are necessary for coordinating across teams, team members need to ensure that these external interactions are coupled with at least a similar level of intrateam interactions to integrate new information within a team. Our post hoc analyses further suggest that members should focus these external interactions with members of those teams they integrate directly with in the system. In addition, teams but not systems may benefit from concentrating these boundary spanning efforts in a subset of team members. Social network analysis is one practical tool that may aid

MTS managers in monitoring and altering informal interactions within and between teams so that they are kept in balance (e.g., Leonardi & Contractor, 2018). Tools for tracking employee interactions through email, chat, and asynchronous messages could be specifically deployed to help MTS members maintain an appropriate balance in their informal interactions.

Limitations

Our work has limitations due to the research context and sample. Given the nature of sequential MTSs, the workflow is from one team to another in a linear fashion; however, the interactions between adjacent teams are also reciprocal in that adjacent teams need to coordinate between each other for successful handoffs and transfers (Rico et al., 2018). As such, our results are generally limited to this type of MTS structure, and more research is needed to determine how they generalize to other types of structures such as intensive forms of interdependence (Rico et al., 2018). Further, we examined a sample of students studying to become engineers in a U.S. university, which may limit the generalizability of our findings to organizations as well as cross-cultural contexts. However, this sample allowed multiple forms of measurement (sensors, surveys, and observations) across multiple time points and also provided a standardized task across multiple MTSs that enhanced internal validity (DeChurch & Marks, 2006). These benefits have similarly been noted in prior MTS research using targeted samples, such as Air Force trainees completing a simulation (e.g., Davison et al., 2012) or undergraduate students completing a simulation (Porck et al., 2019). Further, the sample enabled us to examine the implications of interpersonal interactions within larger MTSs than prior studies, which have tended to focus on smaller systems of two or three component teams. While our sample contains a comparatively larger number of teams per system (nearly seven teams on average) relative to prior quantitative research, the system-level sample size of 44 limits statistical power in our statistical analyses. Finally, the task structure enabled us to model interdependencies characteristic of MTSs, including a goal hierarchy and structural differentiation. Nonetheless, the generalizability of this task is unclear. Future research should examine informal coordination in other cultural contexts, organizational contexts, and in larger samples to better understand their role in MTSs.

While we believe sensors are an advantageous way of assessing interpersonal interactions, there are several potential limitations with this approach. In particular, we operationalized interaction as a quantity of time spent in close physical proximity. However, we could not assess the quality of the interactions among MTS members, nor were we able to measure the content of team members' interactions. Supplementing a quantity-based approach with a quality and content focus would further elucidate the nature of interactions in MTSs, such as valuable learning functions within and between teams. Further, while we assessed interactions during a key action phase of the MTS lifecycle that is especially relevant for external interactions and team processes (DeChurch & Marks, 2006), it would also be useful to examine interactions during transition phases. We were unable to do so because of incomplete sensor data over this time, but a fuller examination across the lifecycle of an MTS would enhance understanding of coordination phases (Mathieu et al., 2018). This issue of timing also relates to our measurement of conflict after the action phase and sensor measurement of interactions. It is possible that there are recursive relations between conflict and interpersonal interactions, such that conflicts arising from an initial imbalance in intrateam and interteam interactions spurs a change in members' interaction patterns. In this regard, in spite of assessing constructs at multiple time points, we were unable to establish causality given our methodology. Research is needed, perhaps leveraging computational modeling or experimental designs, to examine how cycles of informal coordination emerge in MTSs across time and their causal effects on conflict and performance.

Our hypothesis regarding system-level performance presumed that knowledge exchange is a mechanism stemming from congruence in intrateam and interteam interactions. While we did not directly measure this system-level mechanism, Argote and Ingram (2000) noted that interactions among members are a potent mechanism for transferring knowledge. A more in-depth examination of knowledge sharing, acquisition, and assimilation processes within MTSs is needed, especially at the system level. Future research should examine system-level mediating mechanisms, such as knowledge transfer and interteam conflict, to attempt to mirror our findings at the team level. Future research could also examine the connections among these interactions and knowledge transfer to learning and performance within the MTS context.

CONCLUSION

Our study highlights the role of informal coordination mechanisms for overcoming performance tensions in MTSs. For knowledge-based MTSs, balanced informal interpersonal interactions—when intrateam interactions correspond to interteam interactions—provide an informal coordination mechanism. When interactions are unbalanced, they engender conflict that threatens team and ultimately MTS performance. Our findings invite renewed attention to the potential role of informal mechanisms for enabling coordination within the context of MTSs.

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APPENDIX A
PROCEDURE FOR PROCESSING BLUETOOTH SIGNAL DETECTION DATA

Overview of Measurement Procedure

The wearable multisensor devices (i.e., Kim et al., 2012) we utilized have been used in other studies of teams (e.g., Bernstein & Turban, 2018; Parker, Cardenas, Dorr, & Hackett, 2018). The devices comprise infrared sensors, microphones, an accelerometer, and Bluetooth technology and were accompanied by proprietary software used to process sensor output (Kim et al., 2012). Although recent papers have raised important questions about the quality of some of the measures derived from these sensors (e.g., Chaffin et al., 2017, Kayhan, Chen, French, Allen, Salomon, & Watkins, 2018),

TABLE A1

a_team_id	a_indiv_id	b_team_id	b_indiv_id	detection_time	rssi	t_91	t_90	t_89	t_88	t_87	t_86	t_85	t_84
1	1	1	2	2019-01-01 10:00:05	−72	1	1	1	1	1	1	1	1
1	1	1	2	2019-01-02 10:00:30	−73	1	1	1	1	1	1	1	1
1	1	1	2	2019-01-03 10:00:55	−72	1	1	1	1	1	1	1	1
1	1	1	3	2019-01-03 10:15:25	−79	1	1	1	1	1	1	1	1
1	1	1	3	2019-01-03 10:15:50	−78	1	1	1	1	1	1	1	1
1	1	1	4	2019-01-03 10:15:25	−76	1	1	1	1	1	1	1	1
1	1	1	4	2019-01-03 10:15:50	−75	1	1	1	1	1	1	1	1
1	1	1	4	2019-01-03 10:16:15	−76	1	1	1	1	1	1	1	1
1	1	1	4	2019-01-03 10:16:40	−77	1	1	1	1	1	1	1	1
1	1	1	4	2019-01-03 10:17:05	−78	1	1	1	1	1	1	1	1
1	1	2	5	2019-01-03 10:27:05	−87	1	1	1	1	1	0	0	0
1	1	2	7	2019-01-03 10:27:05	−77	1	1	1	1	1	1	1	1
1	1	2	8	2019-01-03 10:27:05	−71	1	1	1	1	1	1	1	1
1	2	1	3	2019-01-01 10:00:05	−79	1	1	1	1	1	1	1	1
1	2	1	3	2019-01-02 10:00:30	−82	1	1	1	1	1	1	1	1
1	2	1	3	2019-01-03 10:00:55	−83	1	1	1	1	1	1	1	1
1	2	1	3	2019-01-04 10:01:20	−86	1	1	1	1	1	1	0	0
1	2	1	3	2019-01-05 10:01:45	−88	1	1	1	1	0	0	0	0
1	2	2	8	2019-01-03 10:15:50	−74	1	1	1	1	1	1	1	1
1	2	2	8	2019-01-03 10:15:25	−72	1	1	1	1	1	1	1	1
1	3	1	4	2019-01-03 10:16:15	−70	1	1	1	1	1	1	1	1
1	3	1	4	2019-01-03 10:16:40	−70	1	1	1	1	1	1	1	1
1	3	2	7	2019-01-03 10:17:05	−87	1	1	1	1	1	0	0	0
1	3	2	7	2019-01-04 10:17:25	−89	1	1	1	0	0	0	0	0
1	3	2	7	2019-01-05 10:17:45	−90	1	1	0	0	0	0	0	0

validation efforts have also suggested that the Bluetooth sensors in the devices can yield a valid measure of physical proximity if researchers use the raw signal information that the sensors record, rather than derivative metrics output by the software (Chaffin et al., 2017; Matusik et al., 2019; Müller et al., 2020).

We took several steps to reduce the likelihood of systematically biased measures of interpersonal interactions in MTSs. First, to guard against the potential for individual devices to systematically vary in their sensitivity to physical proximity (i.e., Chaffin et al., 2017), we randomly assigned devices to individual participants on a week-by-week basis. Second, we retrieved and used the raw Bluetooth detection data, which records any instance when two Bluetooth sensors detect one another and establish a connection. The strength of the signal serves as the key indicator of physical proximity and was the basis of our operationalization of interpersonal interactions (Chaffin et al., 2017; Matusik et al., 2019; Müller et al., 2020). Third, we adopted a threshold-based approach for determining whether a Bluetooth signal detection event constituted an interpersonal interaction. Consistent with Matusik et al. (2019), we considered a range of signal strength values (i.e., −91 to −69) as potential thresholds for determining whether a given detection event constituted an interaction. We report results using a threshold value of −80—the value at the midpoint of the signal strength range that we considered. Appendix B provides the results of sensitivity analyses used to assess the degree to which our findings were dependent on a particular threshold value. The results of these analyses build confidence in the robustness of our findings to a particular threshold.

Sample Dataset Excerpt Used in Example Below

Using the example in Table A1, we explain below the process that we used to calculate intrateam and interteam interactions.

Step 1: Retrieve Bluetooth Signal Data

We retrieved and used the raw Bluetooth detection data. This raw dataset records any instance when two Bluetooth sensors detect one another and establish a connection. Because the Bluetooth device conducts a scan for other devices once every 25 seconds, the count of signal detection events provides an indication of the amount of time that two badges are proximal to one another. For any signal detection event, the raw dataset includes an indication of which two badges detected one another, a timestamp to indicate when the detection occurred, and an indicator of the signal strength (i.e., RSSI value) for the

TABLE A2

a_team_id	a_indiv_id	b_team_id	b_indiv_id	t_91	t_90	t_89	t_88	t_87	t_86	t_85	t_84	Min
1	1	1	2	3	3	3	3	3	3	3	3	15
1	1	1	3	2	2	2	2	2	2	2	2	20
1	1	1	4	5	5	5	5	5	5	5	5	20
1	1	2	5	1	1	1	1	1	0	0	0	17
1	1	2	7	1	1	1	1	1	1	1	1	9
1	1	2	8	1	1	1	1	1	1	1	1	12
1	2	1	3	5	5	5	5	4	4	3	3	13
1	2	2	8	2	2	2	2	2	2	2	2	12
1	3	1	4	2	2	2	2	2	2	2	2	20
1	3	2	7	3	3	2	1	1	0	0	0	9

detection. The strength of the signal provides the indicator of physical proximity that we used to operationalize interpersonal interactions.

Step 2a: Mark Bluetooth Signal Detection Events as Interactions Using a Given RSSI Threshold

We adopted a threshold-based approach for determining whether a Bluetooth signal detection event constituted an interpersonal interaction. Although Matusik et al. (2019: 383) generally advised against using a threshold-based approach, they also commented that "perhaps there are research contexts in which thresholding makes practical and/or theoretical sense." A threshold-based approach is appropriate in our study because the MTSs that we studied worked collocated in a confined classroom space and because our interest was in assessing aggregate team- and system-level interpersonal interactions. Following Matusik et al.'s (2019) and Müller et al.'s (2020) recommendations, we considered a range of signal strength values (i.e., −91 to −69) as potential thresholds for determining whether a given detection event constituted an interaction and adopted a threshold value of –80 (midpoint of the signal strength range) for our analyses. Columns *t_91* through *t_84* provide a sample of marking a given Bluetooth signal detection event as an interaction at different thresholds. As can be seen in the sample dataset, when the absolute value of RSSI is less than or equal to a given threshold, the corresponding *t_#* variable is coded as 1; otherwise, it is coded as 0. In our analyses, we considered a range of RSSI values between −91 and −69 (inclusive).

Step 2b: Sum the Number of Marked Interactions for Each Dyad Across Time and Calculate the Number of Joint Active Minutes

The purpose of this step is to create a dyad-level measure of how often two individuals were engaged in an interpersonal interaction (as classified by a given RSSI threshold). Given the reality that participants wore their sensors for varying amounts of time (e.g., due to equipment failures, late arrivals, and early departures), we scaled the volume of marked interactions by the amount of time a given dyad wore an active sensor concurrently. We first summed the interactions within a given dyad across multiple time points. Doing so reduces the sample dataset to that shown in Table A2.

In addition to summing across the dyadic interactions, there is also now a variable (*Min*) to indicate the number of simultaneously recording minutes for the pair's sensors. That is, *Min* gives the number of minutes time that a's and b's sensors were simultaneously in operation. This information is gleaned from the output provided by each badge.

Step 3a: Compute Team-Level Intrateam Interactions

The purpose of Step 3 is to aggregate the dyad-level data to the team level. We first did so for intrateam interactions—interactions between individuals who belong to the same component team. For a given team, we thus summed the interactions that took place between individuals with the same team

TABLE A3

team_id	t_91	t_90	t_89	t_88	t_87	t_86	t_85	t_84	Min
1	17	17	17	17	16	16	15	15	88
2	…								

TABLE A4

team_id	t_91	t_90	t_89	t_88	t_87	t_86	t_85	t_84	Min
1	8	8	7	6	6	4	4	4	59
2	…								

identifier. Further, we summed to the team level the total number of minutes for these same dyadic observations. Note that the sample interaction Table A3 does not contain Team 2's intrateam interaction data. Were the sample to be extended, Team 2 would similarly have values for intrateam interactions.

Our measure of team-level intrateam interactions is a given threshold variable (i.e., *t_##*) divided by *Min*.

Step 3b: Compute Team-Level Interteam Interactions

Next, we computed team-level interteam interactions—interactions between individuals who belong to different component teams. For a given team, we thus summed the interactions that took place between individuals of the focal team with someone with a different team identifier. Again, we summed to the team level the total number of minutes for these same dyadic observations. We have again excluded Team 2's data, which are only partially represented in the sample dataset in Table A4. Were the sample to be extended, Team 2 would similarly have values for interteam interactions.

Our measure of team-level interteam interactions is a given threshold variable (i.e., *t_##*) divided by *min.*

Step 4: Aggregate to the System Level

To compute system-level intrateam and interteam interactions, we calculated the system-level mean (i.e., across teams) of the variables created in Steps 3a and 3b.

APPENDIX B
RESULTS OF ANALYSES EXAMINING SENSITIVITY OF RESULTS TO DIFFERENT RSSI THRESHOLD VALUES

The following tables provide the results of analyses conducted to examine the sensitivity of our results to different RSSI threshold values. Müller

TABLE B1
Examining the Robustness of Table 3 Model 3 Predicting Team Conflict

Variable	Mean	*SD*	Median	Min.	Max.
Intercept	2.305	0.025	2.298	2.251	2.341
Team size	−0.016	0.010	−0.019	−0.031	−0.001
Team familiarity	−0.003	0.003	−0.002	−0.011	0.000
Intrateam interactions	−0.134	0.018	−0.141	−0.159	−0.105
Interteam interactions	0.164	0.012	0.168	0.145	0.181
Intrateam interactions^2	0.011	0.021	0.022	−0.026	0.033
Intrateam × Interteam interactions	0.006	0.010	0.008	−0.010	0.020
Interteam interactions^2	−0.090	0.013	−0.092	−0.106	−0.052
a1	0.030	0.010	0.034	0.007	0.041
a2	−0.073	0.021	−0.065	−0.108	−0.030
a3	**−0.299**	**0.029**	**−0.315**	**−0.338**	**−0.250**
a4	−0.084	0.036	−0.083	−0.129	−0.011

TABLE B2
Examining the Robustness of Table 4 Model 5 Predicting Team Performance

Variable	Mean	*SD*	Median	Min.	Max.
Intercept	0.936	0.004	0.935	0.930	0.942
Team size	0.011	0.001	0.011	0.009	0.012
Team familiarity	−0.001	0.000	−0.001	−0.002	−0.001
Intrateam interactions	−0.008	0.004	−0.006	−0.018	−0.004
Interteam interactions	−0.002	0.006	−0.001	−0.011	0.008
Intrateam interactions^2	0.000	0.002	0.000	−0.003	0.005
Intrateam × Interteam interactions	0.006	0.004	0.005	0.002	0.014
Interteam interactions^2	0.002	0.004	0.002	−0.004	0.009
Team conflict	**−0.021**	**0.001**	**−0.021**	**−0.023**	**−0.020**
a1	−0.009	0.003	−0.008	−0.016	−0.005
a2	0.009	0.002	0.008	0.007	0.013
a3	−0.006	0.010	−0.005	−0.026	0.006
a4	−0.004	0.007	−0.002	−0.017	0.005

TABLE B3
Examining the Robustness of Table 5 Model 3 Predicting System Performance

Variable	Mean	*SD*	Median	Min.	Max.
Intercept	0.934	0.003	0.936	0.928	0.938
System size	0.011	0.002	0.012	0.007	0.014
Team familiarity	−0.074	0.007	−0.078	−0.082	−0.063
Team performance	0.308	0.037	0.317	0.249	0.364
Team conflict	−0.052	0.007	−0.056	−0.060	−0.040
Intrateam interactions	0.001	0.007	−0.002	−0.005	0.025
Interteam interactions	0.022	0.004	0.022	0.017	0.028
Intrateam interactions^2	−0.040	0.003	−0.040	−0.051	−0.038
Intrateam × Interteam interactions	0.018	0.008	0.014	0.008	0.033
Interteam interactions^2	−0.009	0.002	−0.009	−0.012	−0.006
a1	0.023	0.008	0.022	0.013	0.041
a2	−0.031	0.007	−0.035	−0.039	−0.021
a3	−0.021	0.008	−0.024	−0.029	0.008
a4	**–0.068**	**0.011**	**–0.065**	**–0.091**	**–0.054**

et al. (2020) demonstrated that while higher RSSI values typically indicate devices being closer together, there are a variety of factors that can impact them (cubicle walls, clothing over the sensor, etc.). Given these factors, RSSI values should be interpreted in terms of closer proximity or greater distance, rather than as precise measures of distance (Müller et al., 2020). We therefore examined a range of RSSI values to examine the sensitivity of the findings. Each table represents a single regression model, linked to our primary Results section. We considered a total of 23 threshold values, ranging from −91 to −69 (inclusive). Thus, each summary statistic in Tables B1, B2, and B3 is based on a distribution of 23 parameter estimates extracted from separate models run at these threshold values. The table summarizes the distribution of *t*-values for each variable (i.e., parameter estimate divided by its standard error) in the model across multiple RSSI threshold values. Focal variables highlighted in our results section are in bold font.