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Step by step: Capturing the dynamics of work team process through relational event sequences

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Summary

The emergence of group constructs is an unfolding process, whereby actions and interactions coalesce into collective psychological states. Implicitly, there is a connection between these states and the underlying procession of events. The manner in which interactions follow one another over time describe a group's behavior, with different temporal patterns being indicative of different team characteristics. In this study, we explicitly connect event sequences to the process of emergence. We argue that the temporal relationship between events in a sequence will vary depending on the team's psychological outcome. Further, certain patterns of behavior will be repeated at different rates in teams with varying emergent states. To support this approach, we apply a statistical methodology—relational event modeling—for analyzing sequences of interactions that builds on the foundation of social network analysis. Using a dataset comprised of 55 work teams of military personnel engaged in a tactical scenario, we found that individuals who perceived team process (regarding coordination and information sharing) as having different qualities engaged in significantly different patterns of behavior. Our findings indicate that individuals who had a positive perception of process quality were more likely to initiate communication events in a reciprocal, transitive, and decentralized fashion.

KEYWORDS

relational events, social networks, team process, work teams

1 | INTRODUCTION

Since the introduction of the input–process–output (IPO) model of team functioning (McGrath, 1964), team process and team emergent states have been the subject of significant research in the field of organizational behavior. Team process can be viewed as the various cognitive, affective, communicative, and behavioral activities that enable and constrain team members to accomplish their tasks and goals (Cooke & Hilton, 2015, p. 62). To describe the nature or quality of process, much work has focused on the *emergent states* of work groups (Kozlowski & Klein, 2000). These constructs (e.g., mental models, transactive memory, climate, cohesion, conflict, and psychological safety) may range from the emotional state of the team, shared cognition, or perceptions of process quality and performance (e.g., LePine, Piccolo, Jackson, Mathieu, & Saul, 2008). As Kozlowski and Klein define it, "[a] phenomenon is emergent when it originates in the cognition, affect, behaviors, or other characteristics of individuals, is amplified by their interactions, and manifests as a higher-level, collective phenomenon" (p. 55; see also Cronin, Weingart, & Todorova, 2011). At its core, this view of emergence implies some degree of dynamism, where a series of actions, interactions, or events coalesce into an overarching state or property of the group. In other words, emergent states are *outcomes* that are shaped, leveraged, and aligned by team *processes* (see Kozlowski & Ilgen, 2006).

Inherent in this definition is the acknowledgement that events, as well as their sequence, timing, and pattern, can explain elements of a team's behavior that an aggregate emergent state cannot. For instance, to understand how collective identity emerges in teams, it would be more fruitful to analyze patterns of event-based processes such as interactions, rather than correlating collective identity with another emergent state such as team trust. This distinction is important because although the notion of emergence evokes a sense of time, teams research has primarily considered emergent phenomena to be static characteristics of the group, rather than a process that develops and forms over time (Kozlowski, 2015).

Methodological advances in team research have attempted to remedy such issues by incorporating the notion of process through analyzing temporal events. Recent studies have proposed using sequence methods for analyzing team trajectories (Herndon & Lewis, 2015) and determining behavioral propensities based on patterns of events (Leenders, Contractor, & DeChurch, 2015; Pilny, Schecter, Poole, & Contractor, 2016). Leenders et al. (2015) specifically delineate the advantages of using such an approach, arguing that methods built on bottom-up emergence eliminate many of the assumptions inherent in prior team research. Also in this vein, Morgeson, Mitchell, and Liu (2015) advance event-systems theory, arguing that there are both a multilevel relationship and a longitudinal relationship between events, behaviors, and organizational states. A common theme among these studies is an emphasis on the role of events in shaping both future events and higher order outcomes such as emergent states.

However, this theme is only really implied in the above-mentioned studies. Building on the growing literature connecting events and processes, we propose a process-oriented relational event-based framework for studying emergence and argue that analyzing interaction event patterns over time has both theoretical and computational advantages over prior methods (Kitts, 2014; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013). More specifically, the current research builds on past like-minded approaches to emergence by including a higher order outcome term in the model itself. That is, by including a higher order outcome as an interaction effect in the sequential model, the current study adds empirical evidence, beyond theoretical conjecture, that patterns of interaction do indeed matter in the development of emergent states.

When compared to approaches that emphasize the character or structure of team interaction, the relational event approach to team process poses a fundamentally different question in the study of team and group behavior. Whereas traditional methods of team research conceptualize process as a convergence of behaviors and actions on a set of emergent phenomenon (cf. Cronin et al., 2011), the relational event method views team process as evolutionary (Leenders et al., 2015). Put another way, process grows and evolves with each new action until it culminates in a final output. Indeed, whereas the relational event framework provides a methodology for studying sequences and interaction processes, its previous applications have been oriented towards modeling behavioral patterns (e.g., Liang, 2014), rather than higher order phenomena (cf. Butts, 2008; Lerner, Bussmann, Snijders, & Brandes, 2013; Marcum & Butts, 2015; Vu, Pattison, & Robins, 2015).

Some prior work has differentiated between relational state structures and event mechanisms. For example, Quintane and Carnabuci (2016) determine whether individuals in a position of brokerage actually engage in brokerage behaviors. And Pilny, Proulx, Dinh, and Bryan (2017) used relational event modeling to look at how phone call interactions were correlated to various types of relational state networks (e.g., friendship and social media). Here, the assumption was that some macrolevel variable shaped or influenced the interaction processes. The relational event model has also been used to describe team outcomes. Quintane, Pattison, Robins, and Mol (2013) contrast the short- and long-term behavioral patterns, specifically reciprocity and closure, in two project teams. Here, relational event patterns are used to characterize the two groups. However, the authors use qualitative evidence to suggest a cause for the differences, rather than some measurable outcome variable. In our modeling framework, we instead assume that the emergent state is a *covariate* with the generative mechanisms. With this assumption, we posit that patterns of events will influence future event occurrences at different rates depending on the state of the individual or team. As such, the relational event framework can serve as a computational tool for characterizing the behavioral processes associated with various emergent states.

The purpose of this study is to expand on prior work and explicitly connect event sequences to emergence in teams. We argue that a relational event research approach allows for the development of new theories, which are significantly more nuanced with regard to time, and provides a more direct treatment of the mechanisms, which drive emergence. Specifically, relational events themselves are treated as the microprocess mechanisms, which coalesce into macrolevel phenomena (Kozlowski et al., 2013). In this study, we apply our proposed framework to develop and test research questions regarding how individual perceptions of process quality emerge because of the underlying patterns of relational events. Using an experimental dataset of 55 four-person teams, we find that individuals who perceive their team as having high-quality process have significantly different patterns of interaction over time relative to those who perceive the team as having poor process quality.

1.1 | Events as a foundation for theory

For some time now, the field of organizational behavior has incorporated temporality into the study of teams, culminating in the study of team dynamics. For instance, expanding on the classic IPO framework, Marks, Mathieu, and Zaccaro (2001) proposed a recurring phase model of team process, arguing that teams pass through cycles or episodes while completing a task. As such, different processes are required during different phases. In a similar vein, Ilgen, Hollenbeck, Johnson, and Jundt (2005) introduced the input–mediator–output–input model to describe how teams function over time. The authors define the output–input component of the Finishing Stage, "where the team completes one episode in the developmental cycle and begins a new cycle" (Ilgen et al., p. 521). Implicit in this characterization of a team is the recognition that a group can evaluate its performance, revise its work processes, and/or react to environmental changes over time. Likewise, Pincus and Guastello (2005), borrowing from field theory, note that self-organizing dynamics in groups, such as patterned turn-taking, are the dominant forces responsible for emergent properties such as conflict and closeness. More generally, there is a fundamental recognition that teams change over time, and that the trajectory of the team is shaped by both internal and external forces (Arrow, 1997; McGrath & Argote, 2001). The key challenge however is not the recognition of time and temporality, but rather the study design, data collection, and methodology required to appropriately study team dynamics (Stewart, 2010).

Examining the prior literature, there are several ways in which team dynamics—both temporal and relational—have been treated theoretically and empirically. One approach is to treat time as an external influence on group processes. For example, members of a team may treat other members differently if they anticipate working together for a longer period, and managers may alter their decision making for short-duration tasks (Bakker, Boros, Kenis, & Oerlemans, 2013). Alternatively, teams may experience periods of flux in which members may join, leave, or change roles. During such periods, the sequencing and timing of team coordination actions will be disrupted (Summers, Humphrey, & Ferris, 2011). Another approach is to characterize work styles by their temporal patterning. Studies have shown that employees will vary in their pace of work and perceptions of urgency (Mohammed & Nadkarni, 2011), as well as how they allocate time to multiple teams or commitments (Cummings & Haas, 2012). Further, in a study of multiple global organizations, Maznevski and Chudoba (2000) found that successful virtual teams altered their communication behaviors over time, and settled into a rhythm of alternating face-to-face meetings and virtual interactions. Finally, an alternative approach to time is to observe a team at two or more points and identify the longitudinal changes in some aspect of the team. For instance, over time, a team may shift its communication structure to become more adaptable or efficient through increased hierarchy and centralization. These changes can subsequently impact the performance of the team (Hollenbeck, Ellis, Humphrey, Garza, & Ilgen, 2011; Moon et al., 2004). On the other hand, changes to an emergent property of the team may evolve jointly with the underlying team structure. For example, perceptions of team psychological safety have been shown to coevolve with team members' social network ties (Schulte, Cohen, & Klein, 2012).

However, many accounts of time and dynamics are still focused on groups as aggregate entities or networks as fixed relational states, which, even in multipanel forms, tell us little about the sequences of interaction that have led to those outcomes. Although states are certainly significant, it is also important to consider the role of events in organizational and team processes. The structurational theory of networks argues that networks are constituted through a recursive process in which members draw on their knowledge of social structures as they interact (e.g., a perceived relational state), dynamically producing the emergence of network states on the basis of their collective understanding of these structures while reproducing the social structures (Corman & Scott, 1994). That is, when teams interact in a series of dynamic communication interactions, they can draw upon a host of rules and resources (i.e., structures) created by the group (e.g., group identity, culture, and norms) and, thereby, recursively perpetuate or change such structures.

Our approach incorporates networks, time, and dynamics into team and organizational processes and views them not as relational states but instead as *relational events* (Butts, 2008). Relational events are episodic and happen at a specific moment of time (i.e., A sends a message to B at time T). Unlike relational states, they are well ordered, forming a relational event *history* (i.e., the full timing or stream of interactions over time). Thus, a relational event framework provides information on each individual unit of interaction, offering “the highest possible resolution to examine team processes” (Leenders et al., 2015, p. 14). In other words, the measurement of organizational and team process variables is conducted at *the same level* at which key processes are enacted.

In this way, the event framework can address many of the same questions as prior research, but in a more dynamic fashion. When we build theories of emergence, we focus on the sequence, rhythm, and timing of a team's process, rather than an overall description. An event-based process theory regarding emergence should explicitly connect an emergent phenomenon to the variable influence of certain generative mechanisms on the unfolding of the underlying process. As such, theories based on relational events will “clearly, concisely, and precisely specify process mechanisms” (Kozlowski, 2015, p. 291) by determining the exact pattern and timing in interaction sequences. The variations in how a process unfolds, and consequently the generative mechanisms driving the process, can therefore explain differences in the higher order phenomena.

1.2 | Event models as computational tools

To complement the proposed theoretical approach, appropriate computational modeling techniques are required to build and test theories. Several methods, particularly in the network sciences, are available for studying temporal relational data (e.g., Krivitsky & Handcock, 2014; Snijders, Bunt, & Steglich, 2010). Other approaches include examining node and edge trajectories (Hasan, 2012), predicting evolving measures of network centrality (e.g., Allatta & Singh, 2011; Srivastava, 2015), or simulating network dynamics through agent-based modeling (Frantz & Carley, 2009). However, these do not provide an explicit mathematical framework to deal with events as we have defined them. To remedy this issue, we look to sequence analysis.

Sequence analysis is a general category of methods for describing how social processes can be represented as series of events (Abbott, 1995). In a recent review, Herndon and Lewis (2015) demonstrated how sequence methods can be applied to team process dynamics, and argue that sequences can help shape research questions that involve time. There have also been advances in the use of sequences in social network analysis. These include regression models for a series of binary links (Almquist & Butts, 2014; Vu, Hunter, Smyth, & Asuncion, 2011; Zenk, Stadtfeld, & Windhager, 2010), models based on stochastic processes (Perry & Wolfe, 2013; Stadfeldt, 2012), and models based on event histories (Butts, 2008; De Nooy, 2011).

To accompany our event-based approach, we utilize the relational event framework (Brandes, Lerner, & Snijders, 2009; Butts, 2008), which is a statistical tool for determining the generative mechanisms that drive the occurrence of future events in a sequence. This modeling framework has gained traction as a tool to analyze group and team interaction processes (Leenders et al., 2015; Pilny et al., 2016; Quintane et al., 2013; Quintane & Carnabuci, 2016). The relational event model assumes that all events occur at a certain rate or frequency, and these rates are a function of the prior sequence as well as other exogenous factors. Thus, as patterns of action such as reciprocity or closure repeat themselves over time, subsequent events become more or less likely. The relational event model shares many of the modeling capabilities of exponential random graph models (see Lusher, Koskinen, & Robins, 2013), while incorporating elements of sequence analysis to leverage continuous event data.

2 | CASE STUDY: GENERATIVE DETERMINANTS OF PROCESS QUALITY

In the typical IPO paradigm of research on teams, the objective success or failure of a team can be predicted by the character and quality of the work processes. Indeed, a meta-analysis of the literature on team process indeed finds that subjective assessments of process quality positively predict group outcomes (LePine et al., 2008), and a similar finding was noted by Shuffler, Jiménez-Rodríguez, and Kramer's (2015) recent review of the multiteam system literature. As Marks et al. (2001) would conclude, process quality is an emergent state of the team not directly measurable through the independent actions of the members themselves. As such, the development of process quality as an emergent state is tied to the temporal pattern of observed team process, resembling something not very far from the basic tenets of social constructivism, that collective realities (e.g., process quality) are often the result of different patterns of human interaction (e.g., team process).

In this study, we focus on two subjective measures of effective process, (a) level of *coordination* and (b) efficiency in *sharing information*. We employ the definition of coordination provided by Marks et al. (2001), which states that coordination is "[o]rchestrating the sequence and timing of interdependent actions" (p. 363). Likewise, we simply define effective information sharing as the "degree to which team members share information with each other" (Johnson et al., 2006, p. 106). Both constructs together have been shown to predict the objective success of a team (e.g., see reviews by Hollingshead et al., 2005; Mesmer-Magnus & DeChurch, 2009; Okhuysen & Bechky, 2009). A high level of coordination indicates that actions were perceived as smoothly planned and creates conditions for orchestrated activity to exist for teams to perform collective goals (Okhuysen & Bechky, 2009). Likewise, a high level of information sharing indicates that the requisite knowledge was provided in a timely manner throughout the team's work cycle, "thereby enabling groups to reach higher quality solutions that could be reached by any one individual" (Mesmer-Magnus & DeChurch, 2009, p. 535).

To analyze how different patterns might influence coordination and information sharing, we focus on two elements of structure, (a) *centralization* and (b) *hierarchy*, which have been empirically tested in teams (e.g., Ahuja & Carley, 1998; Hollenbeck et al., 2011; Moon et al., 2004) and in systems of teams (Lanaj, Hollenbeck, Ilgen, Barnes, & Harmon, 2013). In prior studies, measures of structure were either static in nature or static for phases of a team's life cycle and changed at discrete time points. A dynamic version of these constructs would focus instead on whether the interactions that lead to centralization and hierarchy unfolded, and what their relative rates were.

Centralization is said to occur when a small few in the team or organization are responsible for most incoming and outgoing communication. The process that leads to centralization is commonly referred to as preferential attachment (Barabási & Albert, 1999) or the Matthew effect (Merton, 1968). In process terminology, such a rich-get-richer phenomenon exists because of the tendency for nodes to establish ties with nodes that are already popular. Thus, preferential attachment would predict that a sequence of communication events is likely to be exponentially influenced by the continuous buildup of past events by popular actors.

Centralization has had mixed theoretical and empirical relationships with team performance (see Bunderson, van der Vegt, Cantimur, & Rink, 2016, p. 1280). On the one hand, much of the collective action literature, along with other fields, has highlighted the positive benefits of network centralization (Marwell & Oliver, 1993). In this view, centralization is vital to ensuring coordination and information sharing because centralized members (i.e., the critical mass) can reach almost anybody in the network to mobilize for collective action and teamwork (see Marwell & Oliver, 1993, pp. 105–106). Castells (2009) calls this *network power*, and it is the type of power that comes with highly central actors being able to influence others in the network.

On the other hand, there exists some evidence to suggest that a decentralized network structure is more efficient with regard to coordination and information sharing. For one, there is the systems flexibility argument (Cox, 1994), which posits that the diversity of participation from all team members creates a team or organization that is more fluid and flexible in response to environmental and task changes. This advantage is a consequence of multiple members' perspectives being integrated, which might include better and/or more critical information. Likewise, centralized structures in which only a few members are receiving information may be too deterministic, reductionist, and bureaucratic (McChrystal, Silverman, Collins, & Fussell, 2015). For instance, Woolley, Chabris, Pentland, Hashmi, and Malone (2010) have also demonstrated the positive influence of decentralized turn-taking on the team performance across various tasks (see also Rulke & Galaskiewicz, 2000; Sparrowe, Liden, Wayne, & Kraimer, 2001).

For instance, in work teams, when members are primarily sending messages to one member in the group, there may be the impression that the team is functioning in a predictable and mechanistic way (Kilduff & Tsai, 2003, p. 32). This pattern may create perceptions that coordination and information sharing are too rigid and routine to be effective (e.g., why do I always have to run this through team member X?). On the other hand, some work team members may perceive centralization as conducive to effective leadership (Brands, Menges, & Kilduff, 2015), creating perceptions that the team can effectively coordinate tasks and share information through the creation of such centralized hubs (e.g., why does everything always have to be run by everybody?).

As this example implies, there is an underlying dynamic element to the emergence of perceived process quality. Emergent states, such as perceptions or feelings, develop over time. They grow and change both endogenously (e.g., they naturally get stronger with time) and exogenously (e.g., actions and experiences influence states). One type of exogenous influence is the set of interactions initiated and received by the focal individual. Indeed, relational events are expressions of the underlying tendencies governing communication (Poole, 2012) and should thus recursively shape and be shaped by individuals' psychological states. In the case of a centralized tendency, a person will increasingly display a propensity to communicate with one individual. Likewise, when an individual sends messages at a higher rate, they will occupy a more focal position in the group. This experiential structure will help to shape their view of the group. Thus, rather than take a static configural view of process, we emphasize the role of repetitive patterns of action in influencing perceived coordination and information sharing. Accordingly, we ask:

R1a: Do dynamic interactions that lead to centralization have a relationship with coordination?

R1b: Do dynamic interactions that lead to centralization have a relationship with information sharing?

Although sometimes conflated with one another, hierarchy is distinct from network centralization. Hierarchy "appears as unreciprocated ties directed from each position to the position immediately 'above' it" and looks similar to "a chain of command in an organization" (Wasserman & Faust, 1994, p. 420). Bunderson et al. (2016) refer to this type of hierarchy as *acyclicity*. The authors argue that acyclicity is distinct from hierarchy as commonly perceived, often measured as steepness or centralization. Acyclicity refers to one-way flows of cascading relationships as often emphasized by network researchers (e.g., Everett & Krackhardt, 2012). Although Krackhardt (1994) provided explicit measures on the basis of graph theoretical configurations, there has been little theorizing on the processes that specifically lead otherwise free-to-organize actors to naturally create acyclical hierarchies. One theory that may hold some promise is Barker and Cheney's (1994) theory of concertive control, which explains how organizational members self-organize into hierarchical relationships on the basis of a process of *identification* with the values of management or society. In other words, if team members identify (consciously or not) with hierarchy as an effective functional mechanism to achieve goals (Hollingshead et al., 2005) or simply a pervasive institutional rule (Lovaglia, Mannix, Samuelson, Sell, & Wilson, 2005), then they will create relationships that resemble such structures. Another related concept is Haken's (1984) theory of synergetics, which has been used to describe how similar hierarchical command structures can be seemingly self, rather than top-down organized. Here, a driver–slave relationship can develop where once a hierarchical cascade develops; it acts a driver that influences bottom-level dynamics giving rise to the hierarchy (Guastello & Liebovitch, 2009). Alternatively, cascading flows can be driven by *functional interdependence*, meaning that teams are constituted by actors with different skills and roles, which create conditions for a division of labor. Such functional interdependence is common for influencing network interactions in multiteam systems (Poole & Contractor, 2011).

Like centralization, hierarchy has also had mixed results with team performance (see a review by Bunderson et al., 2016). Classic organizational theory has suggested that the main benefit of hierarchy is task efficiency, conflict reduction, and clear accountability (see Halevy, Chou, & Galinsky, 2011, for a more recent theoretical review). However, only a handful of studies have explicitly made the link between network hierarchy and team performance (e.g., Ahuja & Carley, 1998; Halevy, Chou, Galinsky, & Murnighan, 2012). For instance, when hierarchy is analyzed as acyclicity, Bunderson et al. (2016) found that it had a positive relationship with performance and reduction of conflict.

Contrastingly, the common criticism of hierarchy is that it can be overly oppressive (e.g., Max Weber's infamous *iron cage*) and not equipped to handle complex environmental changes due to their strict structure (Back, 1974). However, very little work has tested such a negative relationship between hierarchy (as acyclicity) and team performance. To the authors' knowledge, Cummings and Cross' (2003) study on the work on 182 work groups in a Fortune 500 telecommunications firm is the only one to demonstrate a negative relationship. They found that an acyclical hierarchical structure was negatively related to performance evaluations by senior-level managers and team members.

For instance, when work teams engage in interaction sequences that result in many local acyclic structures, they may be consistent with their expectations and norms about how teams are traditionally supposed to function as a hierarchy (Kilduff & Tsai, 2003, p. 39). When individuals' ontological securities are not challenged or violated, perceptions of coordination and information sharing may be higher because they do not disrupt these notions of a natural pecking order. On the other hand, norms regarding hierarchy are changing in the wake of issues such as workplace democracy and team management (Harrison & Freeman, 2004). When team members rarely reciprocate and have to go through an acyclic chain of command, they may perceive such structures as outdated, ineffective, and repressive, which may then negatively influence how they recall coordination and information during a task.

In these examples, as in the case of centralization, it is not an individual's position in a network that influences their perceptions but rather the pattern of interactions they are involved in over time. As a team member displays a greater tendency towards reciprocity, for example, they are engaging in less hierarchical behavior. Similarly, an individual may experience a hierarchical structure if they send and receive messages through a single channel, rather than with multiple others. Accordingly, the accumulation of relational events is representative of a team member's perceived position in the group, and subsequently should influence their perceptions of the group's process quality. As such, we ask:

R2a: Do dynamic interactions that lead to hierarchy have a relationship with coordination?

R2b: Do dynamic interactions that lead to hierarchy have a relationship with information sharing?

3 | METHODS

3.1 | Data

Data collection was performed during the Leader and Team Adaptability in Multi-National Coalitions project of the North Atlantic Treaty Organization (NATO) Allied Command Transformation Futures and Engagement Concept Development and Experimentation (TR-HFM-138, 2012). The original data collection was part of a study to understand how personality and cultural tendencies affect situational awareness, team interaction, and team performance. The deidentified dataset was made available for research purposes. To collect data, participants from several NATO countries took part in a simulated military-style strategy game. The game scenario and data logging/preprocessing software were developed for the Defense Modeling and Simulation Office.

3.1.1 | Participants

The NATO dataset included 55 four-person teams from the United States, Bulgaria, Norway, Sweden, and the Netherlands. The participants were all military officers. Most teams were comprised of participants from a single country, but a few teams possessed mixed nationality. Participants varied in age, rank, computer proficiency, English proficiency, and prior contact. Before participating in the game task, participants completed a training scenario on how to play the game. Each participant only played the game once.

3.1.2 | Task

The game activity was a four-person team scenario implemented in the Neverwinter Nights game engine using an experimental platform known as SABRE (Leung, Diller, & Ferguson, 2004). The teams were tasked to maximize goodwill points while searching a town for weapons caches, including both exterior and interior locations. Goodwill was gained by taking weapons caches into custody, but goodwill was lost by searching houses or containers and not finding weapons. The activity included a planning phase at headquarters and a mission execution phase in the town. The teams were given unlimited time to complete the planning phase of the mission, and 1 hr for mission execution.

During mission execution, by interacting with computer-controlled townspeople through dialog menus, participants could gather tips about possible cache locations to help focus their search efforts. The in-game gear included weapons sensors to screen houses and containers for weapons without entering to conduct a search; however, there were limited numbers of these sensors. During the game, participants could communicate with their teammates through text chat, forwarding/assigning tips, and leaving markers at locations. An undirected text chat could be received by zero to three teammates, depending on the in-game distance from the originator. A directed text chat was received by exactly one teammate, regardless of in-game distance. During mission execution, players could choose to split up to cover more ground, or stay close for easier communication.

The scenario was designed so that participants needed to coordinate and communicate to succeed. The town was large enough so that a brute force searching strategy would not be effective, requiring a combined use of tips from townspeople and weapons sensors. Townspeople with tips were widely distributed, so players had to seek them out. The tips often referenced locations far away from the informant, so it was not efficient for each player to follow up on all the tips he or she gathered. As weapons sensors were limited in number, the team had to share and prioritize.

3.1.3 | Data collection

The activity data were collected via automated server logging of participant actions and interactions during a multiplayer online team game. When all four members of the team shared the same nationality, they were collocated but visually isolated from each other using partitions and isolated from sound by wearing headsets. Multinational teams operated remotely. No verbal communication was allowed. Participants completed online pregame and postgame surveys, including familiarity with English, comfort with computers, prior experience working with other participants, demographic information, and subjective ratings of teammates and team dynamics. All instructions, surveys, and game interactions were in English.

3.2 | Measures

3.2.1 | Team constructs

Our two team-level constructs, team coordination and team information sharing, were measured on a 5-point Likert scale. To assess coordination, we asked the question "In your opinion, to what extent was the team's behavior coordinated?" with a response of 1 indicating *poorly coordinated* and 5 indicating *extremely well coordinated*. Across all participants, the average response was a 2.35 with a standard error of 1.19. To assess information sharing, we asked the question "In your opinion, to what extent did team members provide relevant information to another team member, in a proactive way, without that team member having to ask for it?" A response of 1 indicated *not at all* and 5 indicated *very frequently*. Across all participants, the average response was a 2.48 with a standard error of 1.18.

3.2.2 | Time-invariant controls

From our initial surveys, we collected a variety of demographic information, which we included in our models as controls. First, we asked participants to describe the extent of their prior experience with other members of the team. The responses were recorded on a Likert scale with a value of 1 indicating *no experience* to 7 *significant experience*. The mean response was 3.65 with a standard error of 2.17. Second, we asked participants to list their nationality. From the responses, we created a control of *same nationality*, which took a value of 1 if all participants shared the same nationality, and 0 otherwise. By design, this variable also encapsulates collocation. Out of 55 sessions, 44 were carried out by members of one nationality. Next, participants listed their age, which ranged from 19 to 57 years with a mean of 31.37 and standard error of 7.61. Finally, participants were asked to give their English proficiency, which we recorded on a Likert scale from 1 indicating *poor* to 5 indicating *excellent*, and their computer proficiency, which we recorded on a Likert scale from 1 indicating *poor* to 3 indicating *good*. The average scores in our sample were 3.73 and 2.37 with standard errors of 0.81 and 0.58, respectively. A summary of all time-invariant measures—the team construct response variables and our demographic controls—is given in Table 1.

3.2.3 | Generative communication mechanisms

Measures of generative process were performed by unitizing the server logs into communication events. Given the granular nature of the data, we choose to apply a relational event framework for our analysis (Pilny et al., 2016). Each relational event constitutes a timestamp, sender, and receiver of the message. We represent these components with a set of functions (Butts, 2008); for an event e, $s(e)$ is the sender, $r(e)$ is the receiver, and $\tau(e)$ is the time. For example, if we observe an event $e = \{Player\ A; Player\ B; 17:00\}$, then $s(e) = Player\ A$, $r(e) = Player\ B$, and $\tau(e) = 17:00$. The full sequence of these events is notated E. From these data, we can construct event sequences that represent various interaction patterns. To represent the accumulated weight of the interaction between two individuals, we apply the operationalization of Brandes et al. (2009):

$$\omega_t(i,j) = \sum_{e \in E} 1\{s(e) = i, r(e) = j, \tau(e) < t\} \exp\left(-\frac{\Delta t_e \log(2)}{T_{1/2}}\right)$$

Here, Δt_e is the time that passed between the current event and the event prior. The value $T_{1/2}$ is the half-life of an event. We apply a half-life to represent the notion of memory in the team (Leenders et al., 2015). As time passes, the effect of an interaction should fade

TABLE 1 Time-invariant variables

Variable	Description	Measurement
Psychological constructs		
Coordination	The degree to which an individual i views the team's actions as coordinated	$C(i) \in \{1, \ldots, 5\}$
Information sharing	The degree to which an individual i believes that information is shared effectively within the team	$I(i) \in \{1, \ldots, 5\}$
Controls		
Prior experience	The amount of familiarity an individual i has with the other members of the team	$x_{EX}(i) \in \{1, \ldots, 7\}$
Nationality	An indicator for whether the members of the team share the same nationality as i	$x_{NAT}(i) \in \{0, 1\}$
Age	The age of the participant i	$x_{AGE}(i) \geq 0$
English fluency	The participant i's comfort with reading and writing in the English language	$x_{ENG}(i) \in \{1, \ldots, 4\}$
Computer proficiency	The participant i's comfort with using a computer	$x_{COM}(i) \in \{1, \ldots, 3\}$

relative to more recent events. The shorter the half-life, the more quickly prior events are forgotten. Thus, the strength of the interaction from i to j at time t given by $\omega_t(i, j)$ is equivalent to the number of messages sent from i to j up to time t, weighted exponentially by how long ago they occurred.

Building on this weighting function, we can create statistics that reflect the frequency, timing, and pattern of past interactions. We specify five structural mechanisms, which we define in the proceeding section: inertia, reciprocity, triadic closure, activity rate, and preferential attachment. These five mechanisms conceptually map on to more static representations of centralization and hierarchy. Specifically, as a certain pattern repeats itself over time, the group will become more entrenched in the corresponding structural alignment. Whereas the mechanism inertia corresponds to a baseline tendency to interact, the mechanisms reciprocity and triadic closure are more closely related to hierarchy; the mechanisms activity rate and preferential attachment are related to centralization. In summary, hierarchical signatures are those which correspond to more or less cyclicality in the system; centralized signatures are those which correspond to more or less activity involving a select few "hubs" in the group. In Figure 1, we illustrate archetypical network structures characterized by centralization and hierarchy.

Inertia represents the tendency for an individual to send messages to a target whom they have frequently corresponded with in the past (Brandes et al., 2009). This measure is comparable to the persistence metric computed by Butts (2008), although that statistic does not explicitly include the timing of prior events. Reciprocity represents the tendency for individuals to reply more frequently to those who have sent the most messages to them in the past.

We operationalize triadic closure specifically as *transitive closure*, which is the tendency for an individual i to send a message to k with greater frequency if there is a third party j who often acts as a broker between the two (Brandes et al., 2009; Quintane et al., 2013). We compute transitive closure similarly to how Butts (2008) computes outbound two-paths. More generally, we sum the strength of *all possible third-party relationships*, assigning equal weight to each. Naturally, it is possible that many of these two-paths have zero weight; these will have no impact on the measure of transitive closure. This fact follows the approach of prior methods. Butts (2008) computes the transitivity measure by summing the minimum weights of every outbound two-path (i.e., if $i \rightarrow j$ has weight 1 and $j \rightarrow k$ has weight 0, the contribution of the $i \rightarrow j \rightarrow k$ path would be the minimum of 1 and 0, or 0). Accordingly, incomplete or empty paths are not considered. Quintane et al. (2013) sum the product of the weights along a path, scaled proportionate to the activity of the sender and receiver (i.e., $i \rightarrow j$ has weight 1 and $j \rightarrow k$ has weight 0, the contribution of the $i \rightarrow j \rightarrow k$ path would be 1 times 0, or 0). Again, incomplete or empty paths are not considered. Thus, there can be a high measure of triadic closure between two nodes if there is one strong third-party relationship, many weak third-party relationships, or some combination of the two. In our

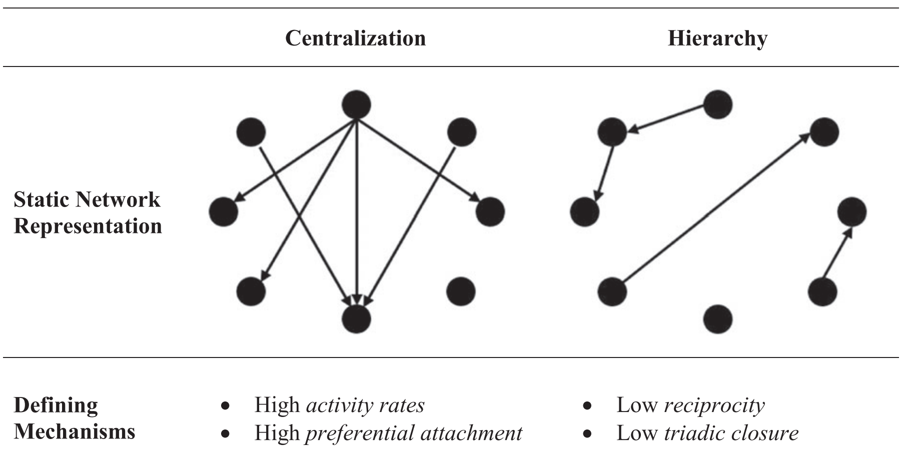


FIGURE 1 Centralized and hierarchical networks and corresponding mechanisms

analyses, we choose to follow the approach of Quintane et al. (2013) and use a multiplicative path weight, scaled by the overall volume along all paths. To illustrate this fact numerically (excluding scaling), consider the following example. If $\omega_t(i, j) = 3$, $\omega_t(j, k_1) = 1$, and $\omega_t(j, k_2) = 2$, then $x_{TC}(i, k_1, t) = 3 \times 1 = 3 < x_{TC}(i, k_2, t) = 3 \times 2 = 6$; in this case, the measure favors the dyad with the higher weight two-path. As another example, suppose $\omega_t(i, j_1) = 3$, $\omega_t(i, j_2) = 2$, $\omega_t(j_1, k_1) = 1$, $\omega_t(j_1, k_2) = 0$, $\omega_t(j_2, k_1) = 1$, and $\omega_t(j_2, k_2) = 1$. Then, $x_{TC}(i, k_1, t) = 3 \times 1 + 2 \times 1 = 5 > x_{TC}(i, k_2, t) = 3 \times 0 + 2 \times 1 = 3$; here, the measure is greater for the dyad having multiple two-paths with nonzero weight.

The activity rate of an individual is simply the volume of prior actions taken by that person, weighted by recency. As such, an individual's activity rate is a dynamic analog to out-degree and represents the tendency for an individual to actively become more or less central in the communication network. Finally, preferential attachment describes the tendency for messages to be sent to the most popular or central actors in the network (Barabási & Albert, 1999). We compute preferential attachment using the formula provided by Butts (2008). In Table 2, we summarize our generative measures and provide the formulae for computing them.

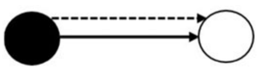
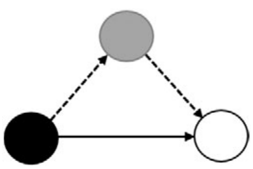
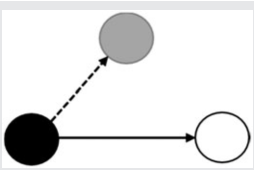
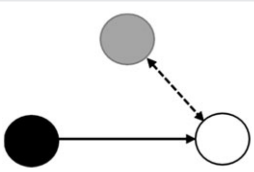
To capture the differences in behaviors between teams displaying high coordination versus low coordination—and high versus low information sharing—we introduce interaction terms to the relational event model. For each pattern, we include as a continuous moderator the measure of the team construct. The resulting models will thus depict the behavioral patterns associated with a certain level of the outcome measure. We differentiate our approach from a typical causal inference model; rather than predict the outcome as a function of some antecedents, we characterize an outcome by the underlying process associated with it. In this way, we avoid claiming that a pattern or measure is better or worse, or that a specific sequence leads to a specific result. Rather, we analyze the extent to which behavioral patterns differ across values of psychological states. In other words, we may test if an individual who views his or her team as highly coordinated has a greater tendency towards reciprocity than an individual who has a negative view of the team's coordination. A recent application of this modeling approach focuses on brokers in an organizational network and examines how brokers engage in different dynamic behavioral patterns (Quintane & Carnabuci, 2016).

3.3 | Modeling

3.3.1 | Fitting relational event models

In a relational event model, the dependent variable is an interaction event between members of the group. The goal of this statistical tool is to determine what factors most accurately predict this event's occurrence, given the characteristics of the sender, characteristics of the receiver, the timing of the event, and the pattern of interactions that have already transpired. Following this logic, at any given time, there is a rate or frequency with which a specific event is expected to occur. The more likely an event, the larger the rate and vice versa. Butts (2008) thus proposes the following function to describe the rate of event $e = \{i, j, t\}$:

TABLE 2 Time-varying generative mechanisms

Variable	Visualization	Probabilistic interpretation	Formula
Inertia		As *i* sends more messages to *j*, *i* becomes more/less likely to send messages to *j* in the future	$x_I(i,j,t) = \frac{\omega_t(i,j)}{\sum_k \omega_t(i,k)}$
Reciprocity		As *j* sends more messages to *i*, *i* becomes more/less likely to send messages to *j* in the future	$x_R(i,j,t) = \frac{\omega_t(j,i)}{\sum_k \omega_t(k,i)}$
Triadic closure		As *i* sends more messages to *k* who subsequently sends messages to *j*, *i* becomes more/less likely to send messages directly to *j* in the future	$x_{TC}(i,j,t) = \frac{\sum_{k \neq i \neq j} \omega_t(i,k)\omega_t(k,j)}{\sum_v \sum_{k \neq i \neq v} \omega_t(i,k)\omega_t(k,v)}$
Activity		As *i* sends more messages overall, *i* becomes more/less likely to send messages to *j* in the future	$x_A(i,j,t) = \frac{\sum_k \omega_t(i,k)}{\sum_v \sum_k \omega_t(v,k)}$
Preferential attachment		As *j* both sends and receives more messages overall, *i* becomes more/less likely to send messages to *j* in the future	$x_{PA}(i,j,t) = \frac{\sum_k (\omega_t(j,k) + \omega_t(k,j))}{\sum_v \sum_k (\omega_t(v,k) + \omega_t(k,v))}$

Note. A solid line indicates the proposed future event. A dashed line indicates a prior relationship. Arrow indicates directionality. The black node is the focal node, the white node is the receiver, and the gray node is an arbitrary third party. All equations use the weight formula defined in the text.

$$\lambda_{ij}(t;\theta) = \exp\left(\sum_{p=1}^{P} \theta_p x_p(i,j,t)\right)$$

Here, x_p is a statistic that determines the rate of the event. The value θ_p is an intensity parameter controlling the magnitude of x_p's effect on the rate. The statistics used to construct the rate are our time-invariant controls (see Table 1) and our generative mechanisms (see Table 2). As a simple example, if θ_{AGE} is positive, then the older someone is, the greater their rate of sending messages. In this way, the relational event model has a similar interpretation to a conditional multinomial logistic regression model.

To fully incorporate the effects of sequence and timing into our model, we can express the full probability of the event sequence E using the rate function we defined. For a set of events, we follow prior work (Brandes et al., 2009; Butts, 2008; Marcum & Butts, 2015; Stadtfeld, 2012) in defining the full likelihood, as follows:

$$f(E\theta) = \prod_{e\in E}\left(\lambda_{s(e),r(e)}(\tau(e);\theta)\times \exp\left(-\Delta t_e \sum_{a\in\mathcal{A}_{\tau(e)}} \lambda_{s(a),r(a)}(\tau(a);\theta)\right)\right)$$

We may interpret the above formula as the probably of the specific event e occurring, multiplied by the probability that in the timespan Δt_e, none of the other potential events $a\in\mathcal{A}_{\tau(e)}$ did occur. The set $\mathcal{A}_t$, known as a risk set (Butts, 2008), is a list of the events that are possible at time t. This set may be all the dyads (i.e., all pairs of nodes in the network), or some subset. For example, Quintane, Conaldi, Tonellato, and Lomi (2014) consider bipartite relational event models; in that instance, the risk set excludes all events in which the sender and receiver belong to the same group. The risk set may also change over time as nodes enter or leave the network. For our case study, we consider all pairs as possible relational events, excluding self-loops. Thus, there are 12 potential events at any point in time. Because each event in the sequence is conditionally independent given the prior history, we may take the product of these probabilities. This formulation and interpretation follow directly from the statistical techniques of survival modeling (Cox, 1972) and event-history modeling (Blossfeld & Rohwer, 1995).

Our modeling of event patterns explicitly deals with time in two ways. First, by using the half-life weighting scheme, events that occur more recently are more impactful than are those that occurred further in the past. This approach carries over into the computation of our sufficient statistics, which are derived from the interaction weights. For instance, consider the value of inertia. If individual i is considering sending a message to j or k, and i has sent five messages to each in the past, then the inertia value will be greater for whichever target i has *more recently sent* the messages. Second, the full likelihood function considers the time between events, Δt_e. In this way, the sufficient statistics are mapping not just to the likelihood of a pair but also to how long the interval is between events. As such, a positive parameter value θ indicates that larger values of the corresponding statistic will lead to a more rapid pace of events.

Finally, because we have multiple event sequences generated by the 55 experiments, we need to apply a hierarchical modeling scheme to account for the differences between teams. To account for this, we apply the hierarchical relational event modeling approach (DuBois, Butts, McFarland, & Smyth, 2013). This methodology uses principles of hierarchical linear modeling applied to social network analysis (Sweet, Thomas, & Junker, 2013). An alternative approach would be to conduct a meta-analysis of the parameters corresponding to each generative mechanism (Snijders & Baerveldt, 2003), which would yield analogous results given the same modeling assumptions. We assume a fixed-effects model, in which there is one upper-level distribution of parameters θ, which fit each of our event sequences. This assumption is based on our inclusion of multiple individual-level controls, which account for many of the explicit variations between teams. We do note that it is possible to include higher order terms to reflect differences among teams, but for this study, we do not consider these.

We fit the model to our observed data using maximum likelihood estimation (MLE). The result of this modeling approach is a set of parameters $\theta^* = \mathrm{argmax} f(E^{(1)}, \ldots, E^{(55)} \mid \theta)$, which describe the direction and magnitude of the effect that each variable has on the likelihood of an interaction event. The statistical significance of the parameters can be determined using their standard error, which is computed using the inverse Hessian matrix at the final MLE solution.

3.3.2 | Goodness of fit

We assess the goodness of fit for each model by computing the log likelihood, Akaike information criterion (AIC), and Bayesian information criterion score at the final solution. When comparing two solutions, a larger log likelihood for one parameter vector indicates that the data are given a higher likelihood of occurring given that set of parameters—that is, the parameters are a better fit. The AIC score is a similar measure, although lower values are preferred. The Bayesian information criterion is an alternative to the AIC, which penalizes a model for having too many terms. As such, it is a more conservative measure for determining whether an additional statistic adds value. To assess the goodness of fit for our models, we first find the parameters for a relational event model with only control terms. Then, we add each generative mechanism individually and finally add all five. For each combination, we may compute all three measures of fit to determine which model is best.

4 | RESULTS

We analyzed a total of 35,829 events across 220 people organized into 55 groups of four (660 possible dyads). In Table 3, we present summary statistics and intercorrelations between the time-invariant study variables including coordination, information sharing, and demographic metrics. Perceived coordination and information sharing have a relatively strong positive correlation. There is also a significant correlation between prior experience and being from the same nationality, essentially indicating that countrymen are more likely to have worked together. It is also worth noting that younger individuals are more likely to report higher fluency in English and computer proficiency, and that these skills are positively correlated. Interestingly, we observe that there is not a significant correlation between prior experience and the two measures of process quality; in other words, having worked together previously does not positively bias perceived coordination or information sharing.

We conducted our relational event analysis in two steps: first, we computed a model with only control variables and then added each of

TABLE 3 Summary statistics and intercorrelations among psychological variables and time-invariant controls

Variable	Mean	*SE*	1	2	3	4	5	6
1. Coordination	2.35	1.18						
2. Information sharing	2.48	1.19	0.37					
3. Prior experience	3.65	2.17	0.04	0.04				
4. Nationality	0.80	0.16	−0.04	0.03	0.45			
5. Age	31.37	7.61	−0.16	−0.19	−0.19	−0.07		
6. English fluency	3.73	0.81	0.04	0.06	−0.24	−0.06	−0.09	
7. Computer proficiency	2.37	0.58	0.14	0.13	−0.18	−0.03	−0.16	0.38

Note. Values computed across 220 individuals. Pearson correlations with $|\rho| > 0.13$ are significant at the $p < .05$ level.

the five generative mechanisms individually and as a group to determine if additional variance was explained by the dynamic variables; second, we fit full models with interaction variables representing individual-level measures of coordination and information sharing.

Model selection

For the first step of our analysis, we fit multiple models to determine which combination of variables best reflected the patterns in the data. The results of this procedure are presented in Table 4.

Our baseline model contained each of the demographic control variables. We then added each generative mechanism and then ran a full model with every variable included. From Table 4, we observe that each generative mechanism improved the model quality significantly when added independently, justifying our inclusion of these variables. Further, the full model—controls plus all five generative mechanisms—was the most preferred overall model. Essentially, the most variance in the sequence data is explained by a model containing both controls and generative mechanisms.

Analysis of interactions

In the second phase of our analysis, we ran relational event models, which included the interactions between the perceived team constructs and the generative mechanisms. In Table 5, we present the parameter estimates for the control model (Model 0), the full model (Model 1), and the interaction models (Models 2 and 3).

TABLE 4 Summary of model fits

Model variables	Parameters	Log likelihood	AIC	BIC
Control	6	−207,780	415,570	415,620
Control + Inertia	7	−192,420	384,850	384,900
Control + Reciprocity	7	−203,440	406,890	406,940
Control + TC	7	−196,090	392,200	392,260
Control + Activity	7	−201,090	402,190	402,250
Control + PA	7	−197,840	395,690	395,750
Full model	11	−187,790	375,600	375,690

Note. We report the log likelihood, AIC, and BIC scores for each model. A larger log likelihood, smaller AIC, and smaller BIC indicate better goodness of fit. The control model includes all time-invariant survey variables. We include each relational event statistic individually. Note that TC = triadic closure and PA = preferential attachment. The difference in log likelihood between each model is significant at the $p < .001$ significance level by applying the likelihood ratio test. The full model includes all five statistics. This final model is the best fit to the dataset by all three measures. AIC = Akaike information criterion; BIC = Bayesian information criterion.

We first observe the overall patterns in the data, as given by the generative mechanism parameters in Model 1. There is a positive tendency towards inertia ($\theta = 0.73, p < .001$), reciprocity ($\theta = 0.08, p < .001$), and triadic closure ($\theta = 0.11, p < .001$). Essentially, participants tend to send messages to those whom they have sent and received messages with frequently in the past. Further, they were likely to send messages to targets with whom they had frequently communicated via intermediaries in the past. We also note that there is a tendency away from sender activity ($\theta = -0.21, p < .001$), and preferential attachment ($\theta = -0.42, p < .001$). This result implies that the communication processes are relatively decentralized overall, without any one individual dominating the discourse.

Next, we consider Models 2 and 3, which include the effects of perceived coordination and information sharing, respectively. We find that when an individual perceives the group to be more coordinated, they have a greater tendency towards inertia ($\theta = 0.09, p < .001$), and triadic closure ($\theta = 0.02, p < .001$), and tend to avoid becoming more central over time ($\theta = -0.04, p < .001$). Similarly, we find that when an individual perceives the group share information effectively, they have a greater tendency towards inertia ($\theta = 0.06, p < .001$), reciprocity ($\theta = 0.01, p < .001$), and triadic closure ($\theta = 0.01, p < .001$), whereas they tend to be less likely to become more central ($\theta = -0.03, p < .001$) and avoid preferential attachment ($\theta = -0.08, p < .05$). One explanation for this behavior is a greater sense of efficiency; the individual's communication patterns are repetitive, and the participant engages in both frequent direct contact and communication through third parties. Further, this individual is less likely to seek out the most central individual or become more central themselves, suggesting they prefer a more decentralized communication structure.

To illustrate these interaction effects, we plot the marginal log likelihood of an event on the basis of the level of each generative mechanism, holding the others constant. The marginal likelihood of an event given a level of statistic p, holding all else constant, is equal to

$$P_p(e = \{i, j, t\}; \theta) = \frac{1}{1 + \exp(-(\theta_p \bar{x}_p + \theta_{p+5} \bar{x}_p C(i)))}.$$

Here, $\bar{x}_p$ is a constant level of the statistic p; we set this measure to the mean value of the generative mechanism, plus or minus the standard error. We then compute this marginal likelihood across possible values of $C(i)$. For coordination, these plots are in Figure 2. We follow

TABLE 5 Relational event model parameter estimates

Variable	Model 0	Model 1	Model 2	Model 3
Controls				
Rate	−4.53 (0.04)***	−5.96 (0.04)***	−5.96 (0.04)***	−6.35 (0.06)***
Prior experience	0.13 (0.01)***	0.17 (0.01)***	0.13 (0.01)***	0.16 (0.01)***
Same nationality	0.01 (0.02)***	−0.18 (0.02)***	−0.13 (0.02)***	−0.16 (0.02)***
Age	−2.85 (0.08)***	0.79 (0.08)***	0.60 (0.08)***	0.83 (0.08)***
English fluency	0.63 (0.03)***	0.15 (0.03)***	0.22 (0.03)***	0.25 (0.03)***
Computer proficiency	−0.11 (0.03)***	−0.16 (0.03)***	−0.32 (0.03)***	−0.33 (0.03)***
Structural variables				
Inertia		0.73 (0.01)***	0.44 (0.02)***	0.50 (0.02)***
Reciprocity		0.08 (0.00)***	0.05 (0.01)***	0.02 (0.02)***
TC		0.11 (0.00)***	0.04 (0.01)***	0.08 (0.01)***
Activity		−0.21 (0.00)***	−0.06 (0.01)***	−0.09 (0.01)***
PA		−0.42 (0.03)***	−0.26 (0.08)***	−0.08 (0.08)*
Coordination effects				
$C(i)$			0.02 (0.01)**	
$C(i)$ × Inertia			0.09 (0.00)***	
$C(i)$ × Reciprocity			0.01 (0.00)***	
$C(i)$ × TC			0.02 (0.00)***	
$C(i)$ × Activity			−0.04 (0.00)***	
$C(i)$ × PA			−0.03 (0.02)***	
Information-sharing effects				
$I(i)$				0.11 (0.01)***
$I(i)$ × Inertia				0.06 (0.01)***
$I(i)$ × Reciprocity				0.01 (0.01)***
$I(i)$ × TC				0.01 (0.00)***
$I(i)$ × Activity				−0.03 (0.00)***
$I(i)$ × PA				−0.08 (0.02)***
Log likelihood	−207,780	−187,790	−187,320	−187,340
AIC	415,570	375,600	374,680	374,720
BIC	415,620	375,690	374,820	374,860

Note. Models fit to 35,829 events across 55 teams of 4. Results of relational event models for the control variables (Model 0), control variables plus structural variables (full model/Model 1), and full models plus interaction terms (Models 2 and 3). Values are parameter estimates, with standard errors in parentheses. Goodness of fit is assessed by log likelihood, AIC, and BIC. AIC = Akaike information criterion; BIC = Bayesian information criterion; PA = preferential attachment; TC = triadic closure.

*$p < .05$. **$p < .01$. ***$p < .001$.

the same procedure for information-sharing values $I(i)$ and illustrate those results in Figure 3.

Our graphical analysis supports the numerical results. As an individual increasingly perceives the team to be performing well—that is, they are more coordinated or share information better—they are more likely to be motivated by inertia, reciprocity, and triadic closure. Additionally, they are much less likely to send a message on the basis of their prior activity or preferential attachment to a teammate. The similar patterns exhibited are likely due to the strong correlation between the two measures of team performance.

When considered together, the empirical evidence suggests a link between positive perceptions of team coordination and information sharing and decentralized, nonhierarchical behaviors. To be more specific, individuals who perceive greater process quality have a lower activity rate and tend to avoid preferential attachment. Thus, it is unlikely that these participants will dominate the discourse by sending out a large number of messages. They will also more evenly distribute their communication among their team members, rather than focus all of their attention on one central person. Individuals who perceive high process quality also tend to be highly reciprocal in communication, which implies that they are engaging in discussion with other members of the team, rather than taking or receiving orders. Further, these participants have a tendency towards transitivity, indicating that they are more likely to engage someone directly if they have previously utilized an intermediary.

In sum, individuals who perceive greater coordination and information sharing engage in more open and democratic patterns of

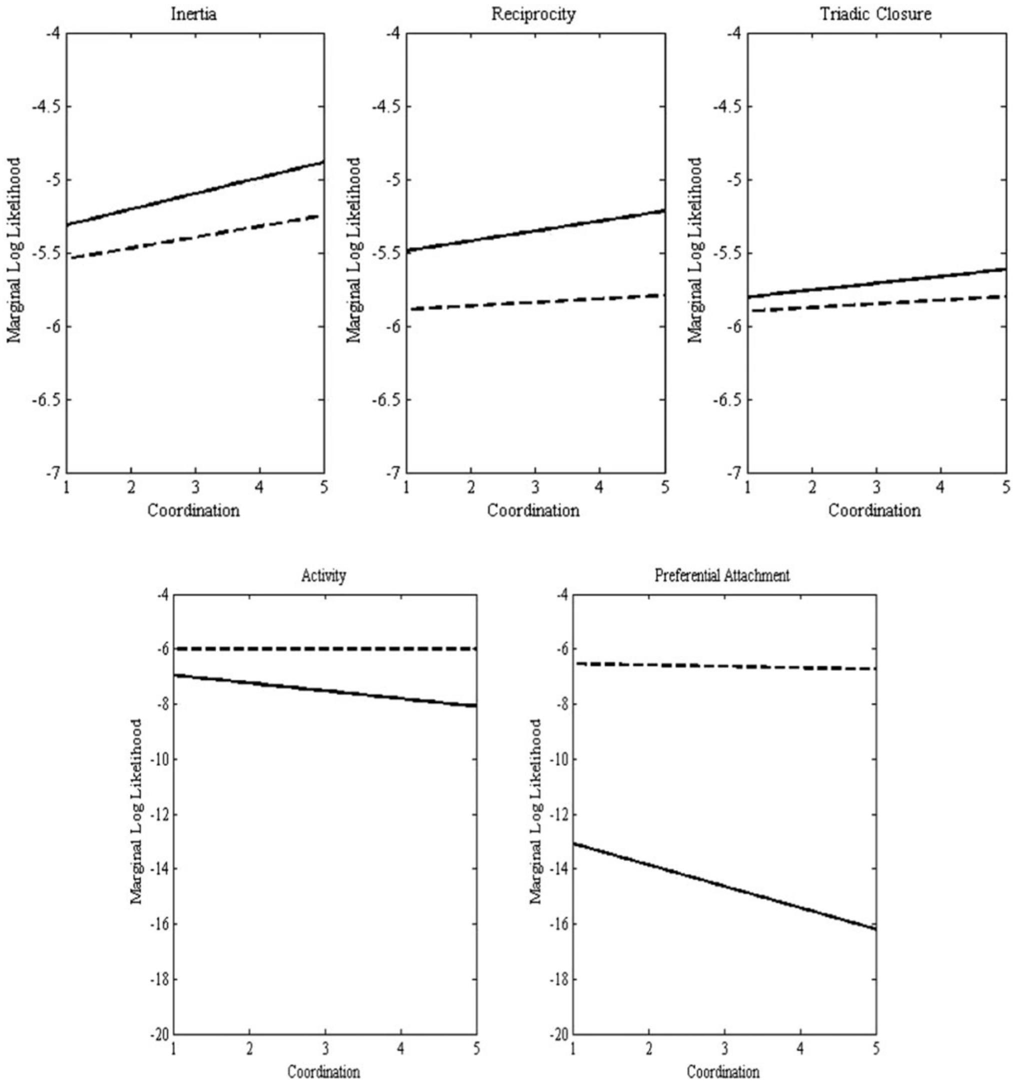


FIGURE 2 Interaction effects between coordination and generative mechanisms. *Notes*. The horizontal axis is the coordination score provided by the focal individual. The vertical axis is the log likelihood of an individual sending an event, based solely on the value of the generative mechanism. The solid line represents the above-average case (e.g., high inertia), and the dashed line represents the below-average case. For each variable, we hold the other four generative mechanisms constant at their average value

communication. Indeed, as we argued previously, centralization and hierarchy may lead to a rigid structure, which is unable to adapt, and may negatively influence members' perceptions of team effectiveness. Further, although centralized and hierarchical networks can be advantageous for straightforward tasks, these advantages are mitigated by the open-ended nature of our task (search for clues in a large environment). Our findings lend empirical evidence to the notion that for more complex tasks that may change over time, open and collaborative communication patterns are beneficial.

5 | DISCUSSION

A key tenet of this study is to explore the methodological and theoretical implications of using temporal, process-oriented methods to study emergence in organizations. Whereas prior methods attempt to establish a causal link between characteristics and outcomes, in this research, we consider the entire process of interaction. Consequently, we directly utilize microprocesses that serve as the foundation for emergence (Kozlowski, 2015; Kozlowski et al., 2013). Under the lens of relational events, lower level interactions are no longer viewed as elements of a broader phenomenon, but rather as realizations of process itself (Van de Ven & Poole, 2005). Specifically, each interaction is driven by the situational context, the attributes of the individuals, and the preceding events (Leenders et al., 2015). In our study, we examine the behavioral propensities that drive an individual to communicate; is it familiarity with the target, or a sense of reciprocity? More generally, this methodology can answer nuanced questions about the development of shared norms and practices. For instance, do individuals tend to request information from physically proximal teammates or perhaps teammates more like themselves? By asking these fundamental questions, we no longer focus on how actions form broader phenomenon but rather focus on how action itself evolves. This approach brings to light the concept of quality tendencies or propensities. In other words, are specific actions indicative of a high-functioning team, given the context for the event itself?

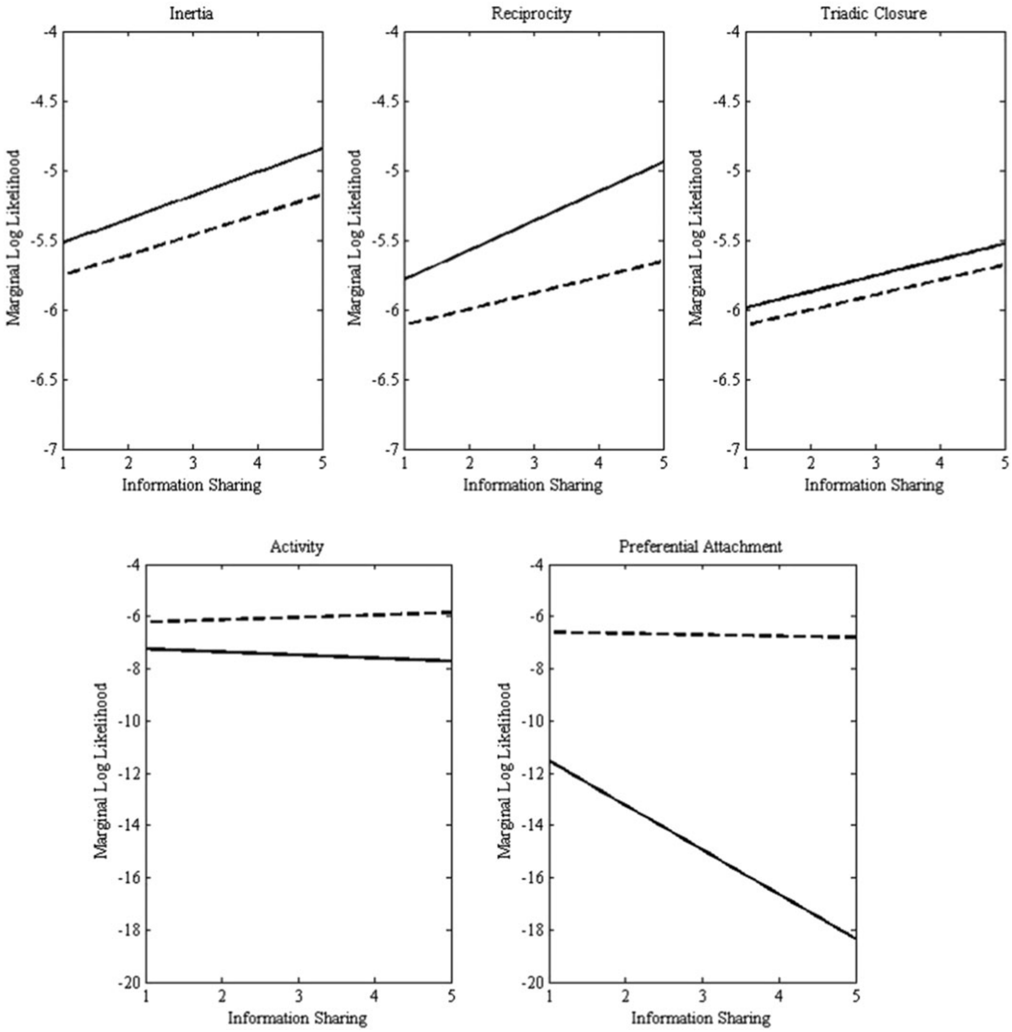


FIGURE 3 Interaction effects between information sharing and generative mechanisms. *Notes*. The horizontal axis is the information-sharing score provided by the focal individual. The vertical axis is the log likelihood of an individual sending an event, based solely on the value of the generative mechanism. The solid line represents the above-average case (e.g., high inertia), and the dashed line represents the below-average case. For each variable, we hold the other four generative mechanisms constant at their average value

5.1 | Assessing process quality with the relational event framework

In this study, we demonstrated how the relational event framework could be applied to build and test theory about teams and organizations. We proposed two sets of research questions focused on how temporal patterns of relational events were associated with common indicators of process quality, coordination, and information sharing (LePine et al., 2008). Research Question 1 asked about the relationship between network centralization and coordination (R1a) and information sharing (R1b). A centralized team structure involves a focal individual or individuals who are primarily responsible for coordinating the group's efforts, while also contributing disproportionately to the norms and practices of the system. Whereas teams with a centralized structure tend to be more efficient, decentralized organizational units are often more adaptable to adverse conditions (Hollenbeck et al., 2002; Hollenbeck et al., 2011). We assessed the degree of centralization by determining how individuals exerted disproportionate influence on the group dynamically, by both sending and receiving messages at rates beyond that of the other members. The measure *activity* captured the propensity for an individual to send messages, given their prior volume of messages sent. The measure *preferential attachment* captured the propensity for an individual to receive messages, on the basis of their prior interactions.

We determined the relationship between perceived process quality and behavior by analyzing the interactions between the reported measures and the realized actions. In other words, we assessed how likely an individual was to engage in communication patterns associated with centralization, on the basis of their perceptions of team coordination (R1a) and information sharing (R1b). We found that those who view the team as being well coordinated have a stronger negative propensity towards activity and preferential attachment than have those who do not. Similarly, those who perceive the team to be effective at sharing information also have a negative propensity towards centralized behavior. Essentially, someone who believes the team is functioning well is also less likely to increase their volume of messages over time and is less likely to send messages to the most central individual. This finding suggests that the more individuals act in a decentralized or democratic manner, the more likely they are to perceive the team as having quality work process. Conversely, if an individual dominates the conversation or feels that all their messages are routed to a focal person, they are more likely to have a negative view of the group.

Research Question 2 asked about the relationship between network hierarchy and coordination (R2a) and information sharing (R2b). Following Bunderson et al. (2016), we defined hierarchy as a network topology of acyclical cascading flows that often indicate a division of labor. This in contrast to hierarchy as power imbalance or ideology as often indicated by critical organizational studies or hierarchy as steepness or centralization. The three network processes associated with hierarchy were (a) inertia, (b) reciprocity, and (c) triadic closure. Our measure of *inertia* captured the propensity for an individual to send messages to those whom they have sent the most messages to prior. Conversely, *reciprocity* encapsulated the tendency for an individual to respond to an increasing volume of received messages. Finally, *triadic closure* captured the propensity for individuals to directly communicate with others rather than through an intermediary. As defined, a strong tendency towards inertia and triadic closure would indicate a calcification of directed acyclical relationships, whereas a tendency towards reciprocity would indicate more mutual relationships and a less hierarchical structure.

To assess the relationship between our dynamic mechanisms and measures of coordination and information sharing, we again examined the interaction between individual-level perceptions and the levels of each propensity. Our results partially supported Bunderson and colleagues on the functional benefits of acyclical hierarchy, because we found that individuals tended to report higher levels of coordination and information sharing when they created communication patterns defined by higher inertia and higher transitivity, but also higher reciprocity. Indeed, these results suggest that individual perceptions of process quality are positively associated with strong, mutual relationships among team members. Moreover, those who viewed the team as being well coordinated and effective at information sharing were more likely to directly communicate with other members, rather than through a third party.

A key insight of our analysis is the relationship between behavioral patterns and individual perceptions. Rather than treating a perceived state as an outcome of an accumulation of actions (Cronin et al., 2011), we instead claim that there is a continual feedback loop between the emergent construct and the sequence of interactions (Morgeson & Hofmann, 1999). Using the relational event framework, we can develop temporal mechanisms that capture interaction sequences, and investigate their relationships with emergence. One such notable mechanism is inertia—or persistence as Butts (2008) terms it—because it is a sequence that is specifically tailored for a dynamic relational event framework. That is, without time, there is no useful way to measure inertia in a relational state framework. Indeed, every other structure measured in the current study can at least be approximated in a relational state framework using exponential random graph models (see Lusher et al., 2013). Inertia, therefore, deserves more theoretical treatment in the organizational and team literature. For instance, inertia is not far removed from larger sociological notions theorized to reduce uncertainty and entropy in teams and organizations. Several concepts from habitus (Bourdieu, 1990), ontological security (Giddens, 1984), and institutional theory (DiMaggio & Powell, 1983) all theorize on why actors create different patterns of inertia, repetition, and consistency. Likewise, Kim, Oh, and Swaminathan (2006) articulate the idea of *network inertia*, referring to the tendency of organizations to renew ties to other organizations. Like the current study, such inertia was positive, being viewed as network management that can "generate synergies for the participating organizations" (Kim et al., 2006, p. 705). The current study supports a similar idea because it showed how inertia may create normative structures that induce positive perceptions of coordination and information sharing.

5.2 | Theoretical implications

The results of the research suggest the promise of a more processual, sequential, and microdynamic perspective regarding networks and organizational behavior (e.g., Ahuja, Soda, & Zaheer, 2012). Indeed, an event-based framework has also been suggested in the communication (Hewes & Poole, 2012), group (Kitts, 2014), and management (Van de Ven & Poole, 1995, 2005) literature, with interactions framed as an unfolding series of events. After all, communication is inherently a process defined by a complex series of events (Poole, 2012). The current study focuses on relational events. A consequence of such an approach is a theoretical shift because understanding relational events "requires a theoretical framework and analytic foundation that incorporates the distinctive properties of such micro-behaviors" (Butts & Marcum, 2017, p. 52–53). That is, research may have to transition from graph theory (i.e., the relational state approach) to *process* theory (see Mohr, 1982; Van de Ven & Poole, 2005).

Put succinctly, process theory attempts to understand a series of events and the mechanisms that link them together. As Poole (2012) notes, three elements are generally ideal for sufficient process theories:

> *(a) a description and explanation of the overall pattern that characterizes the series (e.g., "the process follows four stages, A, B, C, and D, because these stages are logically required to get from the beginning of the process to the end"); (b) a more microlevel account of how one event leads to and influences subsequent event in the series; and (c) an explanation of how event transitions are related to the overall pattern. (p. 381)*

Process theory is well suited for relational events because it challenges the researcher to theorize at the microlevel why one relational event leads to the next, accounting for the larger pattern of interactions (Quintane et al., 2013). Some recent studies have incorporated events into the study of team dynamics. These include studying emailing patterns in work teams (Zenk, Stadtfeld, & Windhager, 2010), contributions to open source software (Quintane et al., 2014), and brokerage strategies (Quintane & Carnabuci, 2016; Spiro, Acton, & Butts, 2013). What distinguishes our approach is an emphasis on connecting event sequences to emergent properties of the team, whereas the previously mentioned studies identify aspects of a process that are predictive of future components of the process.

As the current study demonstrates, in terms of the study of emergence states, a framework grounded in process theory focuses on the complex dynamics that give rise to emergent states. For instance, consider a recent study of Google teams and the finding that psychological safety is a key emergent state that plays a big factor in discriminating between high- and low-performing teams (Rozovsky, 2015). A process theory of psychological safety would focus less on why psychological safety helps teams perform better and more on the dynamics that make psychological safety possible in the first place (i.e., the antecedents, rather than outcomes). For example, the process of *reciprocal disclosure* seems like an obvious starting point to theorize on the drivers of psychological safety. That is, when certain members self-disclose on various aspects (e.g., fears, values, goals, and secrets), if other team members do not reciprocate in the next series of communication sequences, a hypothesis could be formed that in such dynamic structures, psychological safety might be less likely to emerge. Indeed, a variety of emergent states have been shown to influence team performance (Kozlowski & Ilgen, 2006).

Theorizing on the different content, patterns, and styles of different relational events can serve as a promising process-oriented approach to the study of organizational behavior. In particular, the current results suggest that it may be time to go beyond asking *if* there is a relationship between centralization, hierarchy, and emergent states, to *what* direction(s) future theory and research might actually hypothesize. In other words, a more formal theory could explicitly develop propositions as to why low levels of hierarchy and centralization are related to perceptions of process quality. If the results replicate on a different sample, then we could be more confident on understanding the complicated nature of sequences of interaction.

5.3 | Practical implications

An important facet of the relational event framework is the ability to identify behaviors that are differentially associated with emergent outcomes. Consequently, some event sequences will be beneficial for team functioning, whereas others may hamper performance. For example, in our study, we demonstrated that frequent reciprocal behavior was associated with greater perceived process quality, whereas a stronger tendency towards preferential attachment has a negative effect. However, structures may vary in effectiveness over time depending on the task at hand (Hollenbeck et al., 2011). Therefore, we posit that there is a balance to be struck between encouraging certain activities while discouraging others to optimize the efficiency of a team. Further, such an intervention must be motivated by the relative priority of various team objectives, which may change on the basis of the work phase of the group (Marks et al., 2001).

As such, this begs the question of "what types of interventions can shape and leverage dynamic relational event patterns?" or in other words, how can leaders manage emergent phenomena (e.g., Guastello, 2002)? In the current case, the intervention must be a dynamic process as well (i.e., requisite variety), rather than placing subjects in a fixed network structure. A useful starting point would be to create interventions that manipulate *interaction norms*, creating structures that normalize when, to whom, and what to communicate is appropriate in teams. For example, Postmes, Spears, and Cihangir (2001) manipulated norms by creating dynamic pretask exercises. One team received a *consensus* norm condition, where the pretask involved a more artistic and casual undertaking (e.g., collaborating on making a poster). The other half received a *critical* norm condition, where the pretask involved a more deliberative and contentious assignment (e.g., articulating a response to an unfavorable policy). As such, in a more critical norm condition, teams may be more likely to "speak up" and create decentralized relational event patterns because critical engagement is encouraged and may be perceived of as a norm of team communication. Interventions such as these may serve as a fruitful starting point for practical implications regarding the relationship between relational events and emergent phenomena.

5.4 | Limitations

Although our study makes several contributions to research on organizational dynamics, there are a few limitations that must be acknowledged. First, the participants are trained military officers from various NATO countries. On the one hand, this fact makes their reactions to the game scenario more realistic, relative to how an actual team would function in that situation. On the other hand, their behaviors are at least in part shaped by their training and by norms of military communication, which may reduce the variability in interaction patterns. However, our methodology does find that there are distinct behavioral trends across teams, which suggests that this limitation is at least partially mitigated.

A second limitation concerns the length and nature of the task performed. Although the planning stage was not limited in duration, actual gameplay unfolded over only 1 hr, which is to a certain extent an artifact of a laboratory environment. This relatively brief length of time ensures that participants were not interrupted by outside distractions, nor were they able to develop characteristics of more mature teams. Thus, although we can compare across experimental units, it may be difficult to generalize to teams working over a longer timespan. We also acknowledge that the task performed was specifically concerned with information search and problem solving and did not incorporate many of the task types described in McGrath's (1984) circumplex model. Consequently, our findings may not extend to teams engaging in tasks such as creative idea generation or conflict resolution.

Another limitation stems from the lack of context given to each interaction. Our focus has been on the sequence and timing of person-to-person interactions, without accounting for what was said in the messages themselves. Future research could use a categorization schema such as Bales (1950, 1999) to delineate different types of interactions. Alternatively, it could be fruitful to classify messages per the team process taxonomy proposed by Marks et al. (2001). Further, participants communicated in a purely digital fashion, which may have limited the possible modes of conveying emotion and meaning (Short, Williams, & Christie, 1976). Although our content-free approach did indeed delineate between teams with various outcomes, incorporating semantic and nonverbal information could produce further interesting results.

Finally, although our measurement of interaction was dynamic, our two measures of emergent states (coordination and information sharing) were static. It may be the case that there is a more complicated reciprocal and dynamic relationship between the two. However, beyond multiple survey panels, there remains difficulty at capturing the emergence of attitudes in real time. Nevertheless, in the current study, we would expect the team-relevant emergent states to develop at the end of the mission, when the survey was administered. Future research might take advantage of more psychological ways to measure emergent states (e.g., electroencephalography) to correlate dual dynamic measurements of interaction and states.

6 | CONCLUSIONS

The emergence of group constructs is a temporal process, yet current theories and methodologies in organizational behavior research often do not fully incorporate time. To more accurately characterize teamwork dynamics, a process-oriented paradigm is necessary. Following the recent calls for more nuanced theories and methodologies in organizational behavior research, this study proposes a framework for studying organizational behavior that is built on the foundation of microlevel events. We operationalize work behaviors as sequences of interactions, and use relational event modeling to determine the propensities of each normative pattern. Our findings from a set of 55 team experiments suggest that various rates of interaction sequences are associated with different outcomes, even though static descriptions were not. This study advances organizational behavior research by both developing a new theoretical approach and demonstrating the efficacy of an associated statistical methodology.

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