A COMPUTATIONAL STUDY OF TEAM COLLABORATION AND PERFORMANCE

By

Goran Kuljanin

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ABSTRACT

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A common notion in definitions of teams emphasizes that teams consist of interacting individuals. Understanding how teammates collaborate to yield a team outcome presents a critical problem for teams. Utilizing team research in organizational and sports psychology, and the work by physicists modeling human dynamics, the present work develops a computational study to investigate how individuals in a team collaborate to yield team performance. Collaboration may depend on factors such as team member preferences to work together, what teammates work together, and how teammates define the rules of interaction. These elements combine to affect the extent to which teammates work on their own (i.e., act) or work together (i.e., interact). Some configurations of collaboration provide greater opportunities to utilize the individual competencies of teammates, whereas other configurations provide greater opportunities to utilize teamwork competencies. The present work provides a nuanced understanding of how team collaboration leads to team members utilizing their most effective skills to impact team performance.

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INTRODUCTION

The last two decades of increased global competition led organizations to utilize teams as fundamental structures to accomplish work tasks (Devine, Clayton, Philips, Dunford, & Melner, 1999; Kozlowski & Bell, 2003; LePine, Piccolo, Jackson, Mathieu, & Saul, 2008). Teams form and accomplish work at all levels of the organization from the manufacturing plant to top management teams (Barrick, Bradley, Kristof-Brown, & Colbert, 2007). Not only do organizations utilize singular teams to accomplish work tasks, but they also increasingly utilize multi-team (i.e., teams of teams) systems (Marks, DeChurch, Mathieu, Panzer, & Alonso, 2005). Additionally, in this age of rapidly advancing information and communication technology, teams no longer merely exist and work inside the confines of an organization, but also, exist and complete work in a virtual environment (Bell & Kozlowski, 2002; Lipnack & Stamps, 1999). Given the omnipresence of teams in organizational structures, the increasing flexibility of their use, and their importance to accomplishing organizational goals, the study of team effectiveness presumes a critical area of investigation for organizational scientists (Ilgen, Hollenbeck, Johnson, & Jundt, 2005).

Fortunately, organizational scholars act accordingly and accumulate much knowledge in terms of the inputs, mediators, moderators, and processes that affect team effectiveness. This research offers numerous studies of theorizing, investigating, and reporting relationships between team competencies and team effectiveness. Empirical and theoretical work focuses on the effects of composition of individual abilities, team member heterogeneity, and personality (e.g., Barrick, Stewart, Neubert, & Mount, 1998; Bell, 2007; Campion, Medsker, & Higgs, 1993; Edwards, Day, Arthur, & Bell, 2006), teamwork processes and emergent states (e.g., LePine et al., 2008; Marks et al., 2005; Salas, Cooke, & Gorman, 2010; Stout, Salas, & Fowlkes, 1997), and interdependencies related to team tasks, goals, and outcomes (e.g., Campion, Papper, & Medsker, 1996; Gully, Incalcaterra, Joshi, & Beaubien, 2002; Wageman, 1995) on team effectiveness. Although this work provides a foundational basis for understanding the impact of individual competencies on team effectiveness, a more complete understanding of team effectiveness necessitates an understanding of how teammates may collaborate to utilize their competencies to yield team performance (Kozlowski, Brown, Weissbein, Cannon-Bowers, & Salas, 2000).

The effective use of competencies forms a critical problem for teams (Steiner, 1972). Consider the commonly discussed phenomenon in organizational psychology that stipulates the whole may exceed the sum of its parts (e.g., Tziner & Eden, 1985). For teams this means that a particular team exceeds performance expectations based on composite team member skill levels. Explaining such unexpected performance gains, or for that matter, unexpected performance losses, lies in the effective or ineffective use of team member competencies (Kerr & Tindale, 2004). The dynamics of teammates utilizing their team member competencies results from team member collaboration. Yet, despite emphasis on teams consisting of interacting individuals (e.g., Kozlowski & Bell, 2003), a need exists for theoretical work to examine how individuals in a team combine efforts to yield team performance.

Understanding the nature of team collaboration informs on as to why teams may exceed or fall short of expectations. Team collaboration may depend on factors such as team member preferences to work together, the interconnectivity of teammates, and how teammates define the rules of interaction. These elements combine to affect the extent to which teammates work on their own (i.e., act) or work together (i.e., interact). In other words, some configurations of collaboration provide greater opportunities to utilize the individual competencies of teammates, whereas other configurations provide greater opportunities to utilize teamwork competencies. An adequate match between team competencies and collaboration must exist for teams to perform effectively. Without such a match, teams underachieve by not utilizing their competencies effectively. Teams that appropriately match their competencies with corresponding team collaboration succeed as opposed to those teams that do not. Thus, a formulated problem comes to the forefront that asks how teammates may collaborate to maximally utilize their competencies to yield effective team performance.

The solution to this problem comes from an understanding of the collaboration mechanisms by which competencies affect team effectiveness. Two areas of research provide a framework for a solution. The organizational science literature provides an understanding of the effects of competencies on team effectiveness, while the work of sports psychologists and physicists serves as a basis for developing an understanding of team collaboration dynamics. Given the complexities inherent in understanding the interactions of several factors on team performance, the approach taken in the present work develops mathematical and computational solutions to this problem. Similar to experimental and correlational studies, a computational study provides descriptions and prescriptions with regard to the relationships between variables. Yet, in addition to the capability of handling several factors with greater ease than experimental and correlational studies, perhaps the greatest advantage of a computational study stems from the insights garnered from an examination of process dynamics. Such an examination motivates the present work on team collaboration.

The following section considers the theoretical foundation of the present work. In particular, this section includes a discussion of team research in organizational psychology and the work by sports psychologists and physicists on collaboration dynamics. A section on computational modeling follows that discusses this methodology's utility in understanding complex phenomena and dynamics. In turn, the section on model development discusses the integration of the theoretical foundation for the computational study of the present work. The Introduction concludes with a presentation of the principles pertinent to understanding team collaboration and performance.

Theoretical Foundation

A review of research on teams in organizational psychology provides a strong foundation on the relationships between competencies and team effectiveness. This research forms a large database of the impact of team composition, processes and emergent states, and interdependencies on team effectiveness. Most definitions of teams emphasize that teams consist of interacting individuals (e.g., Hollenbeck et al., 1995; Kozlowski & Bell, 2003; Stout et al., 1997). Although social and organizational psychology offers much knowledge with regard to various interdependencies of a team that may lead to interaction among team members (e.g., Shiflett, 1979; Steiner, 1972; Van de Ven, Delbecq, & Koenig, Jr., 1976), physicists studying human dynamics (e.g., Barabási, 2005) and sports psychologists investigating sports teams (e.g., Passos et al., 2011) provide additional insight especially with regard to team collaboration dynamics. The merging of these literatures provides the theoretical foundation to formulate a computational study of team collaboration dynamics, team member competencies, and team performance.

Team Research in Organizational Psychology

An input-process-output (I-P-O) model framework, and the recent proposal to modify it to input, mediator, output, input (IMOI), serve as the basis for organizing research on team performance in organizational psychology (Ilgen et al., 2005). Inputs pertain to team characteristics such as team size and attributes of teammates such as personality and cognitive ability; processes or mediators pertain to the products of teammates interacting such as teamwork, shared mental models, transactive memory systems, team cohesion, group efficacy, and communication; outputs pertain to the products of team behavior such as team performance, team satisfaction, and team turnover. For the most part, inputs provide the foundation for understanding the individual competencies of teammates, while processes provide the foundation for understanding teamwork competencies. Thus, an examination of the effects of team composition and teamwork processes on team effectiveness provides a basis for understanding the impact of individual and teamwork competencies on team effectiveness.

Team composition. A considerable amount of research in organizational psychology deals with the effects of team composition on team effectiveness (e.g., Barrick et al., 1998; Bell, 2007). Team composition research investigates the impact of individual attributes of teammates, a natural extension to the focus of organizational psychologists on the attributes of individuals and their effects on individual processes and outcomes, and the impact of team characteristics on team effectiveness. The most commonly studied characteristics of teams and teammates include team size, team member heterogeneity, personality, and cognitive ability (Kozlowski & Bell, 2003). A review of these research streams follows.

Team size. The research generated on the impact of team size on team effectiveness provides mixed results. On the one hand, larger teams may inhibit collaboration amongst team members (Gladstein, 1984; Latané, Williams, & Harkins, 1979; O'Reilly & Roberts, 1977) and potentially reduce involvement and participation (Sheppard, 1993; Wicker, Kirmeyer, Hanson, & Alexander, 1976), whereas on the other hand, larger teams may enhance performance by providing greater learning opportunities as result of greater diversity in idea generation of more team members (Dennis & Valacich, 1994; Gallupe, Bastianutti, & Cooper, 1991) and by offering greater opportunities for teammates to resolve each other's deficiencies (Hill, 1982). Adding to the ambiguities in the relationship between team size and team effectiveness, replicating team size effects may prove difficult as well. Campion et al. (1993) found a positive relationship between team size and team productivity in one study, but in a replication study, Campion et al. (1996) found a negative relationship using similar measures of team size and team productivity across the two studies. Thus, merely investigating team size may not prove informative in terms of impacting team performance.

Team member heterogeneity. Similar to the research results on the effects of team size on team effectiveness, research offers inconclusiveness as to the nature of the effects of team member heterogeneity on team effectiveness. On the one hand, diversity in terms of abilities and experiences offers an advantage when a team needs to handle a diverse set of tasks (Gladstein, 1984), while on the other hand, demographic diversity, including tenure, may introduce intragroup task and emotional conflict, and therefore, reduce performance (Pelled, Eisenhardt, & Xin, 1999). Again, Campion et al. (1996) could not replicate earlier findings of no effect of team member heterogeneity on team effectiveness by Campion et al. (1993), and instead, found a positive relationship. In addition to these mixed findings, meta-analytic results point to an absence of an effect between job-related diversity and performance (Webber & Donahue, 2001). Seemingly, then, team member heterogeneity matters most when it comes to considering team member abilities.

Personality and preference for teamwork. Research on team composition of personality focuses on the five-factor model of conscientiousness, agreeableness, extraversion, emotional stability, and openness to experience. These factors represent characteristic patterns of thinking, feeling, and acting that researchers hypothesize to impact team performance through processes such as how team members approach task completion or how team members interact with one another (Bell, 2007). For instance, conscientious team members engage in behaviors related to goal completion and problem solving (Stewart, Fulmer, & Barrick, 2005) and request help from teammates only when needed (Porter et al., 2003). Agreeable, extraverted, and emotionally stable team members may impact team performance through the quality of their interactions with other team members. For example, agreeable individuals wish to reduce within-group competition (Graziano, Hair, & Finch, 1997); extraverted individuals seek help from other team members when needed (Porter et al., 2003) and exhibit an attraction to a team (Kristof-Brown, Barrick, & Stevens, 2005); emotionally stable individuals foster an atmosphere that promotes cooperation (Reilly, Lynn, & Aronson, 2002). Individuals open to experience may prove beneficial in situations requiring adaptability (LePine, 2003). Although this suggests there exist several mechanisms through which personality factors may influence team performance, meta-analytic findings suggest small effects without a single sample-weighted correlation exceeding 0.10 (Bell, 2007).

As another general tendency besides personality, individuals may harbor a preference for teamwork as opposed to autonomous work (Wagner, 1995). Researchers suggest that those who prefer teamwork may sacrifice for the group and create an atmosphere of cooperation (Campion et al., 1993; Hackman & Oldham, 1980). Researchers make similar arguments for those individuals holding collectivist orientations (Bell, 2007). The willingness to sacrifice for the group and build a strong environment for cooperation and collaboration may ultimately lead to effective team performance (Jung & Sosik, 1999). Interestingly, meta-analytic results suggest greater importance of preference for teamwork and collectivism for team performance than personality with sample-weighted correlations of about 0.20 and 0.16, respectively (Bell, 2007).

Cognitive ability. The most studied relationship in organizational psychology finds strong effects of cognitive ability on individual performance for practically all types of jobs (Hunter, 1986; Hunter & Hunter, 1984; Schmidt, 2002; Schmidt, Hunter, & Pearlman, 1981). Researchers argue that since team output depends on individual contributions, then it follows that greater levels of cognitive ability among team members should lead to higher team performance (Barrick et al., 1998). In addition, if in fact cognitive ability relates to performance through knowledge acquisition (Ree, Carretta, & Teachout, 1995), then teams composed of high cognitive ability individuals may produce more accurate task mental models, and as a result, perform better than teams composed of low cognitive ability individuals (Edwards et al., 2006). Study results indicate that military crews with high cognitive ability soldiers perform best, and perhaps, even beyond expectations (Tziner & Eden, 1985), and as the most common measure of a team's cognitive ability, a team's mean cognitive ability correlates positively with both behavioral measures of team performance (e.g., Williams & Sternberg, 1988) and supervisor ratings of team performance (e.g., Stevens & Campion, 1994). Indeed, multiple meta-analyses indicate that generally one of the strongest relationships with team performance results from measures of team cognitive ability (e.g., Bell, 2007; Devine & Phillips, 2001; Stewart, 2006).

Teamwork processes and emergent states. The majority of the team composition literature concerns itself with the actions of individuals, whereas the literature on emergent states and team processes concerns itself with the products of interactions among team members (Marks, Mathieu, & Zaccaro, 2001). With respect to interactions among teammates, researchers investigate teamwork skills and processes, and how teamwork processes lead to emergent states pertaining to cognitive, affective, motivational, and behavioral constructs relevant to enhancing interactions. This section first reviews teamwork skills and processes, and then goes on to explore some of the most researched emergent states pertinent to team cognition, affect, motivation, and behavior.

Teamwork skills and processes. Researchers distinguish teamwork skills from task work skills. Task work skills pertain to the technical skills that allow individuals to complete the duties of their jobs, whereas teamwork skills pertain to those skills that empower individuals to work effectively with others to accomplish common goals (Kozlowski & Bell, 2003). In other words, researchers separate the knowledge, skills, and attitudes pertaining to teamwork competencies from those pertaining to individual competencies. With respect to teamwork competencies, knowledge competencies consist of the knowledge necessary to perform team tasks and understanding team member roles and responsibilities such as team mental models and transactive memory; skills competencies pertain to those skills necessary to undertake functions and actions such as adaptability, situational awareness, performance monitoring, leadership, and communication; attitude competencies consist of beliefs about performing team tasks such as collective efficacy, collective orientation, teamwork and cohesion (Stout et al., 1997). Research posits the trainability of teamwork skills, and the positive relationship between teamwork skills and team performance (Morgeson, Reider, & Campion, 2005; Stevens & Campion, 1994; Stout et al., 1997).

In order for teams to perform effectively, not only do individuals need teamwork skills, but they also need to adhere to appropriate team processes. Teamwork processes occur during two phases of team performance episodes: an action phase and a transition phase (Marks et al., 2001). The action phase consists of a period of time when teams coordinate and monitor activities relevant to accomplishing work tasks; the transition phase consists of a period of time when teams focus on mission analysis, planning, goal setting, and evaluation activities (Marks et al., 2005). These two processes cyclically trigger each other for the duration of team tasks such that well executed transition processes provide the foundation for action processes, which leads to enhanced team performance. This, of course, does not preclude that effective transition processes may also directly impact team performance. Additionally, team members manage interpersonal relations throughout action and transition processes through interpersonal processes such as conflict management, motivation and confidence building, and affect management (Marks et al., 2001). Meta-analytic findings indicate that most correlations corrected for measurement error among these various teamwork processes exceed 0.50, and a confirmatory factor analytic model with a second-order teamwork process latent variable subsuming the three teamwork (i.e., action, transition, and interpersonal) processes fit the meta-analytic data the best (LePine et al., 2008). Additionally, meta-analytic results suggest that the three teamwork processes correlate around 0.25 with team performance and around 0.35 with team member satisfaction, which indicates that the three teamwork processes correlate with team performance about as well as any team composition variable.

Cognitive emergent states. Research on team cognition generally focuses on two constructs: team mental models and transactive memory (DeChurch & Mesmer-Magnus, 2010). The critical distinction between these two constructs centers on the extent to which team members hold common knowledge as opposed to distributed knowledge (Kozlowski & Ilgen, 2006). Team mental models reflect shared understanding and mental representation of knowledge among team members with respect to the important elements of a team's task (Klimoski & Mohammed, 1994; Stout, Cannon-Bowers, Salas, & Milanovich, 1999). Such a shared understanding and mental representation of knowledge may facilitate the coordination of actions among team members without the need for overt communication (Cannon-Bowers & Salas, 2001). Team transactive memory reflects the distributed knowledge of team members and the use of each other's expertise (DeChurch & Mesmer-Magnus, 2010). A team's transactive memory system, a far more extensive memory system than that of any individual, allows each team member to enhance their abilities by the effective use of their teammates' resources (Zhang, Hempel, Han, & Tjosvold, 2007). Both team mental models and transactive memory demonstrate positive relationships with team performance (Edwards et al., 2006; Stout et al., 1999; Zhang et al., 2007), and a meta-analysis combining the two cognitive emergent states and constructs estimates the sample-weighted correlation with team performance as 0.33 (DeChurch & Mesmer-Magnus, 2010).

Affective and motivational emergent states. Research on team affect and motivation focuses on four constructs: cohesion, collective mood, team efficacy, and conflict management (Kozlowski & Bell, 2003). Cohesion reflects synergistic interactions between team members (Barrick et al., 1998). Empirical research often measures cohesion in terms of three dimensions: attraction to members of a group, the activities of the group, and the prestige of the group (Beal, Cohen, Burke, & McLendon, 2003). Although initial meta-analytic work suggested that only task-based cohesion as relevant for team performance (Mullen & Cooper, 1994), a more recent meta-analysis that all three dimensions of cohesion may influence team performance with uncorrected correlations around 0.25 (Beal et al., 2003). Research on collective mood attempts to represent how the feelings and behaviors of individuals arise from group dynamics or investigate the means by which the emotions of team members combines to affect team outcomes (Kozlowski & Bell, 2003). Empirical research findings suggest an impact of group mood on group outcomes such as group absenteeism and prosocial behavior (Barsade, Ward, Turner, & Sonnenfeld, 2000; George, 1990). However, there lacks a thorough examination of the relative influence of the moods of individuals in a group in particular those at the minimum and maximum end of the spectrum as these individuals may garner great influence for group outcomes (Kozlowski & Bell, 2003). Team efficacy pertains to team members' collective perceptions of effectively executing relevant team tasks (Bandura, 1997; Gibson, 1999). Just as in research at the individual level, meta-analytic results suggest team efficacy as one of the most strongly correlated constructs with team performance (Gully et al., 2002). Conflict management reflects the manner in which team members proactively and reactively deal with group conflict, and beneficial conflict management involves cooperation, compromise, and respectfulness (LePine et al., 2008; Marks et al., 2001). Meta-analytic results indicate a positive correlation of 0.20 with team performance (LePine et al., 2008).

Behavioral emergent states. Research on team behavior focuses on three constructs: coordination, cooperation, and communication (Kozlowski & Bell, 2003). Coordination refers to the process of synchronizing team member contributions via information exchange and mutual adjustment of actions (Brannick, Roach, & Salas, 1993; LePine et al., 2008; Marks et al., 2001). The importance of coordination may particularly prove valuable in situations requiring numerous contributions from all team members or in situations requiring sequenced team member actions (Kozlowski & Bell, 2003). Meta-analytic results indicate a positive correlation of 0.24 with team performance (LePine et al., 2008). Cooperation refers to individuals willing to contribute to interdependent actions (Kozlowski & Bell, 2003). Empirical findings suggest a positive relationship between cooperation and team performance in terms of efficiency and effectiveness (Seers, Petty, & Cashman, 1995; Smith et al., 1994). Team efficiency, similar to the effects of team mental models, may result from cooperative teams needing less overt communication (Pinto & Pinto, 1990). Team communication refers to the nature by which teammates exchange task related information, and in general, establishing patterns of interaction (Barrick et al., 2007; Kozlowski & Bell, 2003). Generally, empirical findings suggest a weak positive relationship between team communication and team performance (Ancona & Caldwell, 1992; Campion et al., 1993; Smith et al., 1994; Waller, 1999).

Team interdependence. Team researchers suggest the most important contingent variables in team research pertain to team interdependencies as defined by team tasks, goals, and outcomes (Campion et al., 1993; Saavedra, Earley, & Van Dyne, 1993; Wageman, 1995). In general, research on team interdependence refers to the extent by which contextual features outside the control of individuals define a relationship between them as a collective whereby one individual's behavior may affect another's behavior and vice versa (Barrick et al., 2007). In other words, these contextual features may lead to interaction among team members. This section reviews the most studied team interdependencies.

Task interdependence. Task interdependence refers to the degree to which team tasks make team members depend on one another for their efforts, resources, and information (LePine et al., 2008; Wageman & Baker, 1997). Interdependence varies across teams as a result of increasing workflow from pooled to sequential to reciprocal to team (Gully et al., 2002; Van de Ven et al., 1976). Saavedra et al. (1993) defined these various forms of task interdependence. Under pooled interdependence each team member makes a contribution to team output without direct interaction with other team members. This typically occurs for tasks where each individual completes the whole task on their own. Thus, team performance depends solely on the individual abilities of team members. Steiner (1966) defines four single-resource models (i.e., additive, conjunctive, disjunctive, and discretionary tasks) that all fall under pooled task interdependence wherein team members possess a skill level to complete the whole task on their own. Task constraints, representing motivation and coordination losses, restrict the utility of each team member to use his skills to complete the task (Shiflett, 1979). All team members possess the same task constraint under additive tasks and differential constraints under conjunctive, disjunctive, and discretionary tasks. Under sequential interdependence one team member must act before another team member acts (Van de Ven et al., 1976). Typically this means that team members possess different roles, and thus, perform different parts of the whole task in a specified order. Thus, team performance depends on each team member correctly doing his part so that the next team member may complete the next aspect of the task. Reciprocal interdependence refers to temporally lagged two-way interactions wherein one team member's output serves as another team member's input and vice versa (Saavedra et al., 1993). Typically team members serve different roles and perform different parts of the task in a flexible manner. Sequential and reciprocal task interdependence represent Steiner's (1966) multiple-resource models wherein a particular team member performs only part of the total team task while other team members perform the remaining parts and possess potentially different skills or resources. For tasks requiring multiple-resources, optimal team performance requires a division of the total team task so that each sub-task suits the resources of different team members (Shiflett, 1979). Pooled, sequential, and reciprocal task interdependence all lead to team members dividing the set of tasks composing a team project among team members, and thus, leads to team members working independently to complete tasks. On the other hand, team task interdependence refers to team members not only coordinating the responsibilities of each team member but also at times jointly collaborating, or working together, to complete tasks composing a team project

(Saavedra et al., 1993). Neither Steiner (1966) nor Shiflett (1979) discuss team task interdependence.

Goal interdependence. Goal interdependence refers to the interconnections among team members as a function of the type of goal (individual or team) that guides their performance (DeShon, Kozlowski, Schmidt, Milner, & Wiechmann, 2004; Gully et al., 2002). Individual goals may encourage strategies that merely focus on maximizing individual performance, whereas team goals may encourage more cooperative strategies to impact team performance (Gully et al., 2002; Saavedra et al., 1993). In other words, the type of goals set by or given to team members may influence how teammates allocate their time and effort toward achieving individual or team outcomes (Earley, Wojnaroski, & Prest, 1987). Although the link between goals and performance at the individual level offers a robust relationship, the effects of group goals on team performance does not (Kerr & Tindale, 2004). While some findings include that goal interdependence may affect group performance and task strategy (Saavedra et al., 1993), other findings suggest that the relationship depends on the nature of performance assessment (Campion et al., 1993; Campion et al., 1996). However, researchers suggest, just like at the individual level, that the relationship between team goals and team performance might function through mediators such as team efficacy (DeShon et al., 2004; Prussia & Kinicki, 1996) or a participative goal setting process (Latham, Winter, & Locke, 1994).

Outcome and feedback interdependence. Outcome and feedback interdependence refers to the interconnections among team members based on whether they receive individual or team feedback and outcomes (Gully et al., 2002; Saavedra et al., 1993). Giving interdependent rewards to teams indicates that the outcomes each team member receives depend significantly on the performance of the team as a whole, while independent rewards indicate that the outcomes for each team member largely depend on one's own performance (Wageman, 1995). Naturally, team feedback informs individuals how the team performed as a whole and may offer advice as to how team members may modify their actions to improve coordination, whereas individual feedback informs individuals how each team member performed (Saavedra et al., 1993). Individual rewards and feedback both point each team member's attention to individual behavior and efforts, and thus, may inhibit team performance through blocking, undermining, and hindering behaviors (Miller & Hamblin, 1963). Team rewards and feedback, on the other hand, draw attention to team behaviors, and thus, may influence team performance by motivating team members to cooperate and assist each other (Gully et al., 2002). Empirical findings indicate that group feedback and rewards impact team performance more than individual feedback and rewards (Campion et al., 1993; Campion et al., 1996; Wageman, 1995). Findings of a lack of an effect may result from a misalignment between goal and feedback interdependence. Teams may need to receive group goals and feedback for such factors to impact team performance (Saavedra et al., 1993).

Summary of team research in organizational psychology. Research on teams in organizational psychology informs on how the characteristics of individuals, teamwork processes, and the interdependencies of a team relate to team outcomes. Most importantly, the essence of effective team performance rests on the individual qualities of teammates and the nature of their interaction. Organizational psychology offers much knowledge in terms of the impact of individual qualities (e.g., preferences for teamwork, task work skills, teamwork skills) on team performance and informs on the products of (e.g., team efficacy) and potential reasons for (e.g., outcome interdependence) team interaction. Recent research in sports psychology and physicists investigating human dynamics offers insights on the nature and dynamics of team collaboration and its impact on team performance. A discussion of this work follows.

Research on Team Collaboration Dynamics

Although organizational psychology provides a strong foundation on the inputs, processes, and outputs of teams, there exists a lack of knowledge pertaining to a critical area of teams. The nature of collaboration among team members compromises the most fundamental aspect of teamwork (Hollenbeck et al., 1995; Salas et al., 2010; Stout et al., 1997). The most informative investigations of interaction dynamics in teams come from the recent analytical and qualitative work by sports psychologists on sports teams and physicists researching human dynamics. Typically, research into collaboration dynamics by sports psychologists utilizes case study methodology to focus on the collaborations of a particular sports team during a game (e.g., Passos et al., 2011), whereas work by physicists involves mathematics and simulations and focuses on the differences between the dynamics of individuals acting on their own to complete tasks as opposed to the dynamics of individuals interacting to complete tasks together (e.g., Oliveira & Vazquez, 2009). As a whole, an examination of these research areas provides a foundation for understanding team collaboration dynamics.

Sports psychology. The past three decades of popular professional team sports (e.g., baseball, football, basketball, hockey, soccer) generated much quantitative analysis from fans, bloggers, journalists, coaches, general managers, and academics on the value and effectiveness of individual players (Lewis, 2003; Moskowitz & Wertheim, 2011; Nevill, Atkinson, & Hughes, 2008; Winston, 2009). Although this analytical work sheds much light on the ineffectiveness, in terms of valuing the work of a player, of typical statistical information tracked by professional sports leagues (e.g., Major League Baseball, National Basketball Association), it generally lacks any theorizing or investigating into one of the most important aspects of team sports, collaboration among team members. In other words, such analytical work generally implicitly considers that team performance merely stems only from the skills of individuals composing a team and not also from the complexities inherent in the interactions amongst teammates. Only the recent work by academic sports psychologists begins to explore the nature of collaboration in teams and the relative effectiveness of various forms of collaboration (e.g., Passos et al., 2011). Interestingly, these empirical case studies utilize the team literature in organizational psychology and the work of physicists investigating human dynamics as the foundation for their work. At the same time, though, this work provides an intricate and unique look into the collaboration dynamics of teams. This section reviews this recent work into team collaboration networks and dyadic communication modes.

Team collaboration networks. Definitions of teams share the notion that teams consist of interacting individuals that depend on each other to achieve common goals (e.g., Hollenbeck et al., 1995). Not only must individuals in teams undertake their own roles and responsibilities, but they also may need to work with each other to accomplish team tasks. Thus, understanding the interaction structure of teams formulates an important area of study. Recent case study analyses of sports teams by sports psychologists demonstrates that teams shape their interdependence with various interaction structures (e.g., Bourbousson, Poizat, Saury, & Seve, 2010) and that these various interaction structures offer differing levels of team effectiveness (e.g., Passos et al., 2011).

In particular, Bourbousson et al. (2010) undertook a descriptive, qualitative study of a youth basketball team that utilized the same five-man line-up for the entire first quarter (i.e., ten minutes) of an international basketball game. They found four typical forms of collaboration networks during these ten minutes of play, each with its own set of variants. The first form of collaboration networks involved a subset (e.g., two or three) of players from the team that interacted with each other, while the other subset of players remained isolated from teammates during the length of the team's possession of the ball. This type of collaboration network occurred the most frequently around 50% of the total number of specific team collaboration networks. Whereas the first type of collaboration network involved dyadic interactions among team members that did not link the whole team, the second type of collaboration network involved dyadic interactions that did link the whole team. However, even in this type of collaboration network, no single team member took into account the activity of all other team members. Each team member only took into account the activity of typically one other player in a manner that stringed the whole team together through unidirectional linkages. This type of collaboration network occurred the second most frequently around 42% among the specific team collaboration networks. The third type of collaboration network involved all players in dyadic interactions with one or two teammates, creating not isolated individuals as in the first type of coordination network, but instead, creating an isolated dyad and triad. The fourth type of collaboration network involved the teammates acting completely individually and not taking into account the activity of any other teammate. These various types of team collaboration networks offer the perspective that teams engage in different levels of interconnectivity that may differentially impact team performance depending on the skills of the team.

Passos et al. (2011) set out to test the impact of interconnectivity of teammates on team performance while observing a water polo match between two teams. The winning team displayed a higher number of interactions among team members and a higher probability of players interacting in subsequent units of attack. In other words, the winning team possessed a greater level of interconnectivity among its players and a more even distribution of interaction among team members. The losing team displayed a lower probability of interaction amongst team members suggesting their play relied on individual efforts, whereas the higher frequency and probability of interaction among team members of the winning team suggests their play relied on collective efforts. However, team collaboration networks that utilize individual efforts may not necessarily lead to poor team performance as long as the skills of particular individuals provide an advantage to the team. The central take away point, then, pertains to the idea that different team collaboration networks lead to different patterns of action and interaction in a team. Whether or not a particular team collaboration network leads to effective team performance depends on the level of task work and teamwork skills of teammates.

Dyadic communication and collaboration modes. In order for team members to combine their efforts, they may engage in several forms of team communication. These various forms of team communication may provide benefits in terms of achieving coordination and costs in terms of time and cognitive resources (Eccles & Tenenbaum, 2004). In particular, Bourbousson et al. (2010) observed two forms of dyadic collaboration modes in their study of a youth basketball team that appeared via various forms of communication. The first form of collaboration mode they labeled mutual dyadic collaboration, which pertains to communication between team members when each member of the pair took account of the other teammate. This type of dyadic collaboration mode came in the form of explicit, verbal or nonverbal (e.g., hand clapping, making a pass) communication; and in familiar situations, practiced in training sessions where team members knew to take account of other teammates. The second form of collaboration mode they labeled unidirectional dyadic collaboration, which pertains to an interaction where one player took account of a teammate but the teammate did not reciprocate.

This type of collaboration mode occurred predominantly, around 87% of all direct dyadic collaboration. Seemingly, mutual dyadic collaboration may require more time and cognitive resources to execute among team members as opposed to unidirectional dyadic collaboration where only one team member takes account of the activity of the other teammate. Thus, unsurprisingly perhaps, unidirectional dyadic collaboration occurred with much greater frequency in this study. However, the greater frequency of the unidirectional dyadic collaboration mode may particularly result from the specific competitive contest of a basketball game wherein an opponent attempts to force efficient decisions. Teams operating under a less overtly competitive environment may utilize the mutual form of dyadic collaboration with greater frequency. In such situations, mutual dyadic collaboration may lead to greater levels of collective efficacy, which, in turn, may positively impact team performance (Fiore & Salas, 2006).

Human dynamics. Physicists parlay the success of statistical models explaining the laws of nature in physics and attempt to model phenomena in fields as diverse as biology, medicine, information technology, and computer science (Castellano, Fortunato, & Loreto, 2009). Recently, physicists also take interest in studying the dynamics of human behavior and interacting individuals. Much of this research focuses on the large-scale regularities commonly observed in complex systems composed of interacting elements (e.g., humans, cells, particles, chemicals; Vicsek, 2004). Some of the large-scale regularities observed as a result of social interactions include opinions, culture, and language (Albert & Barabási, 2002). Yet, inherently, these social regularities derive from the dynamics of individual actions. Thus, a focus of study for physicists pertains to the modeling of individual activities such as e-mailing, movie watching, instant messaging, web browsing, and downloading (Han, Zhou, & Wang, 2008; Salganik &

Watts, 2009). In addition to examining the dynamics of individual activities, physicists also focus on the dynamics of dyadic interactions (e.g., Oliveira & Vazquez, 2009). Similar to the work done by sports psychologists, part of examining interactions involves an understanding of the effects of team collaboration networks and dyadic modes of collaboration. This section reviews the empirical, mathematical, and simulated work by physicists to examine the underlying dynamics of human behavior and interactions.

Modeling the dynamics of human behavior. As their motivation that many social, technological, and economic phenomena result from individual human actions, physicists preoccupied themselves with modeling the waiting time dynamics of human action (Gabrielli & Caldarelli, 2007; Han et al., 2008; Barabási, 2005). The measure of waiting time refers to the amount of passed time between two events. As an example using human behavior, the waiting time may refer to the inter event times between doing various activities such as sending e-mails, playing sports, or engaging in financial transactions. An important issue at hand dealt with the nature of the waiting time statistical distribution of human activity. In particular, physicists observed that inter-event times may not follow Poisson processes, which imply that an event takes place with a given probability p and long delays between events virtually do not exist. Instead, human behavior often displays a burst of rapidly occurring activity followed by long periods of inactivity and power law distributions may best approximate such heavy-tailed processes (Castellano et al., 2009).

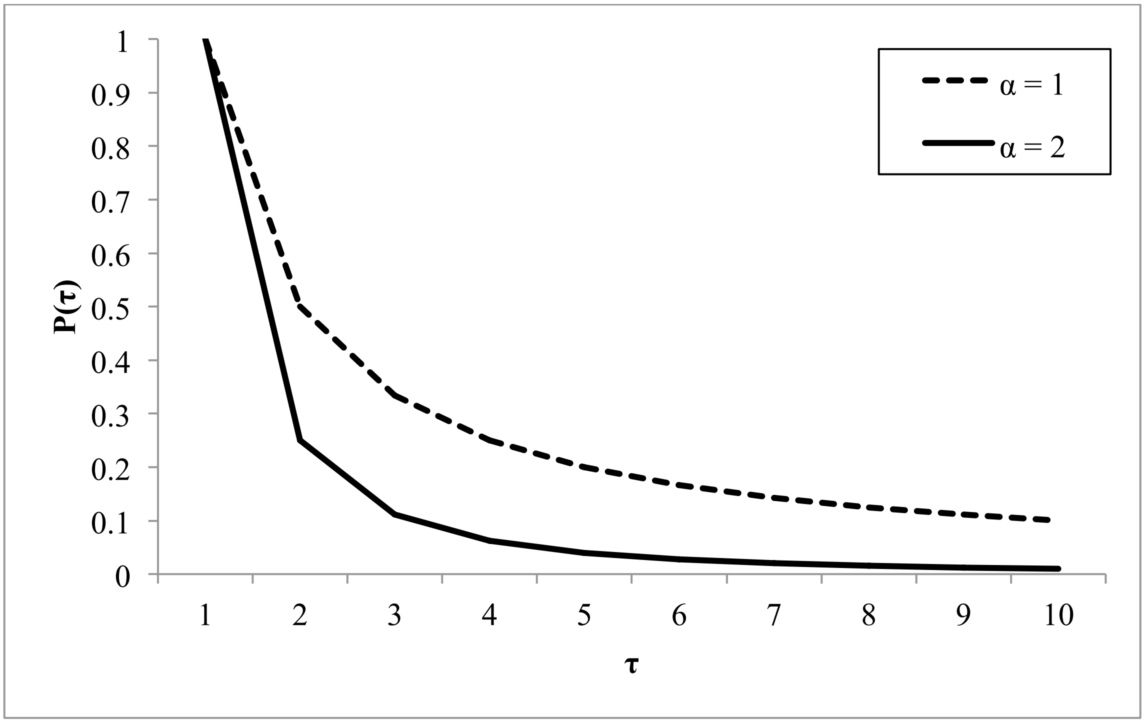
Poisson distributions decrease exponentially, forcing consecutive events to follow each other at regular time intervals, whereas heavy-tailed distribution decay slowly allowing long periods of inactivity that separate periods of intensive activity. Barabási (2005) proposed a queuing model to explain the origin of a heavy-tailed distribution of waiting times for human behavior. He argues that most human initiated events require an individual to prioritize various activities such as playing sports, making a phone call, or working. An agent with *L* tasks assigns a priority *x* to each task, which offers the agent the opportunity to compare the urgency or importance of tasks. Upon completing a task, a new task may enter the task queue. Barabási (2005) asks the question how long does a given task wait before its execution by the agent. The agent may execute the tasks in several ways each of which affect the nature of the waiting time distributions of the tasks. As a simple rule, the agent may utilize the first-in-first-out protocol wherein the agent executes tasks in the order that they appeared on the task queue. In this case, the waiting time of a given task on the queue depends entirely on the cumulative time required to perform all of the tasks before it in the queue. This leads to most tasks experiencing similar waiting times and waiting time distributions with exponential tails. An alternative mode of execution of tasks involves the agent randomly selecting tasks and executing them without regard to task priorities. This random selection also leads to most tasks experiencing similar waiting times over a large number of selections. Yet, another form of executing tasks involves the agent executing the task with the highest priority. This offers a contrasting waiting time distribution to the first two modes of execution. In this form of execution, the agent executes high-priority tasks soon after their addition to the task queue, whereas low-priority tasks wait until the execution of all higher priority tasks. This mode of execution produces heavy-tailed waiting time distributions often observed in human activity. Thus, the queuing model offers a way of capturing the dynamics of human behavior.

Dynamics of action and interaction. The investigation of human dynamics suggests a power law waiting time (τ) distribution of the form $P(\tau) \sim 1/\tau^{\alpha}$ with α greater than or equal to one (Castellano et al., 2009). The exponent, α, reflects different power law distributions. A larger exponent produces distributions that decay more rapidly, whereas exponents approaching one produce more heavy-tailed distributions. Figure 1 displays two power-law distributions where the power-law exponent, α, equals one or two. Physicists concern themselves with identifying universality classes that inform them on qualitative differences between processes. When it comes to identifying the universality classes of individual human activity such as e-mails and regular mail communications, empirical results suggest two universality classes, $\alpha = 1$ and $\alpha = 1.5$, respectively (Barabási, 2005; Oliveira & Barabási, 2005). However, universality classes may not only differ by the type of individual activity, but they may also differ as a result of human interaction.

Oliveira and Vazquez (2009) built on the queuing model of Barabási (2005) to investigate the impact of interactions on human dynamics. They developed a computational model that incorporated the possibility of two agents interacting with each other as they complete tasks either on their own or together. In their model, each agent possesses a priority list containing two tasks, an interacting task and an aggregate non-interacting task. From their perspective, the interacting task represents a common activity such as meeting each other, requiring the simultaneous execution of the task by both agents. The aggregate non-interacting task represents a meta-activity accounting for all other tasks the agents execute which do not require an interaction between the two of them. In the testing of their model, each agent assigns a random initial priority to the interacting and non-interacting tasks from a probability density distribution. At each step of the simulation, both agents select the task with the highest priority on their list. If both agents select the interacting task, then they execute it. Otherwise, each agent executes the non-interacting task. For these parameter specifications, the authors found that the interacting task exhibited power law tail with exponent $\alpha = 2$. When the number of

Figure 1

Two theoretical power-law distributions.



non-interacting tasks increases in the queue of either agent, then the interacting task exhibits a power tail exponent between $\alpha = 1$ and $\alpha = 1.5$ with α approaching one in the limit as the total number of tasks increases. Given that the exponent differs as a function of the queue lengths, the authors conclude that their model with two interacting agents does not exhibit universal behavior. These results suggest that the dynamics of interaction differ from that of individual activity. In particular, the resulting dynamics from models that incorporate interacting agents depend on system parameters.

Network topology and interaction rules. Given that interaction dynamics differ from the dynamics of individual activity, and the effect of system parameters such as queue length on interaction dynamics, the next natural question to ask deals with the effects of various network topologies of larger groups of interacting agents and their modes of interaction (Min, Goh, & Kim, 2009). The model by Oliveira and Vazquez (2009) investigated a particular type of mode of interaction. In their model, the non-interacting task served as the default task for execution for both agents at each time step of the simulation. Indeed, the two agents only executed the interacting task when the interacting task possessed the highest priority level for both agents. Other modes of interaction may generate different interaction dynamics. In addition, examining larger groups of interacting agents offers more possibilities for exploring the impact of various network topologies.

Min et al. (2009) further developed the work of Oliveira and Vazquez (2009) by examining the impact on individual action and dyadic interaction of different modes of interaction and network topologies. In particular, they studied the effects of network size, topology, and interaction protocol. Network size ranged from three to twenty agents. In terms of network topology, they studied the star graph where only a single agent may interact with every other agent and the fully connected graph where each agent may interact with all other agents. The considered interaction protocols included the AND protocol utilized by Oliveira and Vazquez (2009) and the OR protocol where two particular agents complete an interacting task as long as the interacting task possesses the highest priority for one of the agents. The task queue for each agent consists of one non-interacting individual task and a specified number of interacting tasks equivalent to the total number of possible interactions for that agent in a particular network topology. For example, in a five agent star graph, the task queue for the star node consists of one non-interacting task and four interacting tasks (i.e., the interacting tasks with the four leaf nodes), whereas the task queue for the four leaf nodes consists of one non-interacting task and one interacting task (i.e., the interacting task with the star node). The results indicate that all three factors affect the power law exponent to an extent. For example, in the OR interaction protocol, the power law exponent differs not only from the AND interaction protocol but also depends on the network topology. Additionally, the power law exponent for a particular agent depends on the agent's position within the network (e.g., star node as opposed to leaf node). These results, as a whole, reflect the idea that different collaboration modes and networks may differentially handle priority conflicts among agents.

Summary of research on team interaction dynamics. Research by sports psychologists and physicists informs on the differences between various team collaboration networks and modes. These collaboration networks and modes capture various forms of team interaction that may differentially impact team performance. This research complements the work in organizational psychology on team composition, teamwork processes, and team interdependence. Integrating the two areas of research should provide the most complete understanding of team effectiveness. In particular, such integration offers insights into the interactive effects of individual qualities and team collaboration on team performance. Integrating the work by organizational psychologists on individual qualities and the work by sports psychologists and physicists on interaction dynamics necessitates a method to consider numerous conditions and the ability to investigate complex dynamics. A discussion of such a method follows.

Computational Modeling

Researchers in organizational psychology increasingly recognize computational modeling as a method for scientific investigations (Ilgen & Hulin, 2000), yet virtually do not exist in the field's top journals (Harrison, Lin, Carroll, Carley, 2007). Computational models prove particularly useful in exploring complex phenomena involving multiple elements (e.g., individuals) interacting over time (Vancouver, Tamanini, & Yoder, 2010; Zoethout, Jager, & Molleman, 2008). Generally, the study of such complex phenomena proves intractable with the use of the experimental and correlational methodologies. Indeed, although organizational psychologists garnered much knowledge from traditional methodologies with respect to team inputs, processes, and outputs, exploring team dynamics may require focusing on case studies, as do the sports psychologists, or developing computational models, as do the physicists when they examine human dynamics. The present work develops a computational study of team collaboration and performance, but before doing so, a discussion of computational models and their advantages and how such models inform theory follows.

Computational Models and their Advantages

Computational models may specify mathematical relationships, such as equations, or sets of explicit rules generally in the form of logical if-then statements (Harrison et al., 2007). These rules or equations specify how a system changes from one time period to the next. In other words, the rules and equations of a computational model represent the processes responsible for system behavior (Vancouver et al., 2010; Vancouver, Weinhardt, & Schmidt, 2010). A key advantage of computational models stems from the ability to track system behaviors over time with greater ease than experimental and correlational methods. Not only do computational models provide more easily tractable system behavior over time, but they also more easily incorporate a large number of system features and processes that may simultaneously affect system behavior (Goldstone & Gureckis, 2009). This additionally offers greater possibilities for testing the effects of a greater range of parameter values on system dynamics and behavior. Similarly, constraints from sample size or unwanted influences (e.g., measurement error) do not present a problem for computational studies. Given the nature of teams, these advantages serve as a motivation to utilize computational models to understand the complexities involved in team dynamics and behaviors.

Deriving Knowledge from Computational Models

Harrison et al. (2007) discuss seven potential uses for computational models: prediction, proof, discovery, explanation, critique, prescription, and empirical guidance. In terms of prediction, computational studies reveal relationships among variables, which, in turn, may turn into empirically testable hypotheses. A computational model may serve as an existence proof by demonstrating that modeled processes produce certain system behaviors (e.g., a learning model of organizational change producing patterns of punctuated equilibrium in organizations). Alternatively, computational models may discover unexpected consequences of the interaction of system features and processes. Computational models may serve to test whether or not specified processes reproduce observed behaviors. If the modeled processes produce outcomes that fit observed behaviors, then the processes offer an explanation for the observed behaviors. In a similar vein, computational modeling may examine proposed explanations for given phenomena and possibly find simpler explanations or solutions. A computational model serves a prescriptive purpose when offering suggestions to improve system behavior. Finally, a computational model offers empirical guidance by uncovering connections between previously unlinked variables or by uncovering unexpected relationships between variables. Given the well-developed theoretical database on team inputs, processes, and outputs, and the general complexities involved in understanding a team of interacting individuals, a computation study of team dynamics may prove useful in all seven manners.

Model Development

The present work formulates a computational study from the extant literature on teams in organizational and sports psychology, and from the work by physicists modeling human dynamics, to examine the impact of team collaboration and individual characteristics on team outcomes. As one of the few instantiations of formal theorizing on teams, this computational model may serve several purposes. Although definitions of teams emphasize interacting individuals (e.g., Kozlowski & Bell, 2003), there exists a paucity of empirical research on interaction dynamics of teams, which may result from difficulties of designing experimental and correlational studies to observe enough teams over a sufficiently acceptable time frame (Mitchell & James, 2001). This suggests that systematic examinations may need to rely on computational methods to garner knowledge and to provide guidance in designing empirical work. Given the paucity of research on interaction dynamics, then one of the primary ways in which the computational effort in the present work advances knowledge and empirical design comes from deriving principles with regards to the effects of team collaboration structures and interaction modes on team performance. At the same time, the computational model developed here integrates well-studied effects of individual characteristics and investigates the combined effects of team collaboration and individual characteristics on team performance, yet another hitherto skimpily studied aspect of teams. Additionally, the computational modeling framework within the present work offers numerous extensions to explore the extreme regions of team theory. The sections that follow develop the various components of the computational model in the present work.

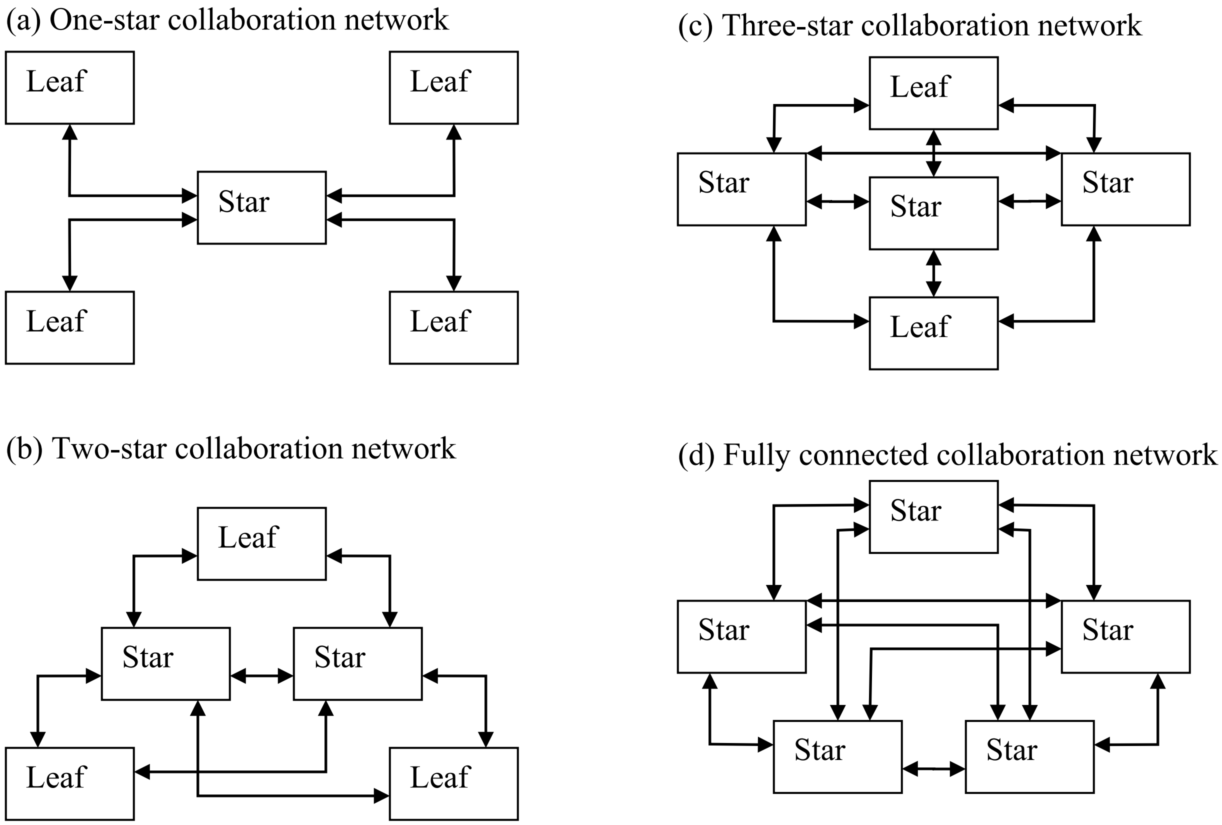
Team Collaboration

Case study research by sports psychologists on sports teams (e.g., Bourbousson et al., 2010; Passos et al., 2011) and physicists investigating human dynamics (e.g., Min et al., 2009; Oliveira & Vazquez, 2009) provide two important aspects of team collaboration: team collaboration structures and interaction modes. Team collaboration structures refer to which teammates may work with each other, whereas team interaction modes refer to the rules by which teammates engage in interaction. Both aspects provide unique contributions to team collaboration dynamics, and at the same time, provide interactive effects as well. The number of possible collaboration structures in a team depends on a team's size. For example, a three-person team offers five collaboration structures: one with no collaboration among any individual team members, three sets with two teammates interacting and the other person isolated, and one where everyone collaborates. On the other hand, a five-person team offers many more collaboration structures as demonstrated by the fact that there exist ten possible dyadic collaborations with the three other members isolated. This excludes other possible five-person team collaboration structures such as those involving triadic and quadratic collaboration among team members. Similarly, the number of possible interaction modes may loosely depend on team size, but yet, empirical (e.g., Bourbousson et al., 2010) and theoretical (e.g., Oliveira & Vazquez, 2009) work thus far only finds and considers a couple. Team size does not serve as a variable of interest in the present work, and modeling efforts focus only on teams of five agents with specific collaboration structures. This section reviews specific collaboration structures and interaction modes modeled in the present work.

Collaboration structures. A common notion with some empirical support (e.g., Losada, 1999; Passos et al., 2011) suggests that the higher the level of connectedness of a team's members, the more effective the team. In other words, the success of a team may depend on the number of connections or collaborative opportunities that exist in a team. Empirical work by Bourbousson et al. (2010) and theoretical work by Min et al. (2009) offers some of the various forms of collaborative structures that may exist among a group of interacting individuals. Figure 2 depicts four collaboration structures for a five-agent team modeled in the present work that represent varying levels of connectivity among team members. The first collaboration structure (Figure 2a), known as a star structure, provides the least number of connections amongst teammates. In particular, only one team member (a.k.a., the star) can interact with every other individual (a.k.a., a leaf) in the team, while these individuals, in turn, can only interact with the central member and not any other teammate. This collaborative structure provides a total of four connections among team members. One method for increasing the number of interactions in a team comes from allowing additional team members the ability to interact with all teammates. The second collaborative structure (Figure 2b), known as a two-star structure, allows two members of the team to possibly interact with every other teammate. This collaborative structure provides an additional three connections to the star structure for a total of seven connections among team members. The third collaborative structure (Figure 2c), known as a three-star structure, allows three team members to interact with every other teammate leaving only two teammates with the ability to interact with each other. This collaborative structure provides a total of nine connections amongst teammates. Finally, the fourth collaborative structure (Figure 2d), known as a fully connected structure, allows all team members to interact with each other, and it provides a total of ten connections amongst teammates. This set of collaborative structures offers an opportunity to examine the impact of connectivity among teammates on team performance. In particular, the star collaborative structure relies on the interactive capabilities of a single member with each team member and their interactive capabilities with the star, whereas the fully connected collaborative structure offers teams far more flexibility in terms of the degrees of freedom for interactive capabilities in the team. In other words, exposing (or alternatively, covering up) poor collaborative action may prove a more difficult (easier) task in a fully connected collaborative structure than a star structure. This, in turn, brings up the point that even though the star member in the single-star structure interacts with the same number (i.e., four

Figure 2

Four team collaboration networks.



in Figure 2) of teammates as he may in the fully connected structure, his responsibility in the star structure outweighs his responsibility in the fully connected structure as a result of his centrality in the single-star structure.

Collaboration modes. Theorists emphasize that team communication serves an important role in achieving teamwork (e.g., Eccles & Tenenbaum, 2004; Kozlowski & Bell, 2003). Various forms of team communication may provide differential benefits in terms of achieving collaboration and costs in terms of time and cognitive resources (Eccles & Tenenbaum, 2004). In their study of a youth basketball team, Bourbousson et al. (2010) observed two forms of dyadic collaboration via different forms of communication. One form of dyadic collaboration they labeled mutual dyadic collaboration wherein the two communicating teammates took account of each other to complete an action. This form of collaboration resulted from explicit (e.g., hand clapping) communication or practiced situations. The other form of dyadic collaboration they labeled unidirectional dyadic collaboration wherein one player took account of the actions of a teammate but the teammate did not reciprocate. This form of collaboration exemplifies implicit communication (Eccles & Tenenbaum, 2004).

Interestingly, the interaction modes in the theoretical work by Min et al. (2009) studying human dynamics capture the two forms of dyadic collaboration observed by Bourbousson et al. (2010). The AND interaction mode requires that both agents wish to interact with each other, while the OR interaction mode only requires that one agent wishes to interact with a teammate. Given the representativeness of these interaction modes, the present work models these two interaction modes as well. Interaction among team members in the mutual interaction protocol, wherein both teammates must initiate interaction, faces a more stringent barrier for collaboration than the unidirectional interaction protocol, wherein only one teammate needs to initiate interaction. Taking note of the interaction mode of a team seems particularly interesting when simultaneously considering the collaborative structure of a team. The connectedness of a team may only prove impactful under the less stringent unidirectional interaction protocol as the mutual interaction protocol may prove prohibitive in taking advantage of the complete interconnectedness of teammates in fully connected team collaborative structures.

Individual Characteristics

Much of research on teams in organizational psychology focuses on the individual characteristics of team members. Particular interest centers on the efficacy of skills for individual and collaborative action. Individual skills reflect the technical skills that allow individuals to complete the duties of their jobs, while collaboration skills reflect those skills that allow individuals to work effectively with teammates to accomplish common goals (Kozlowski & Bell, 2003). In other words, both individual and collaboration skills reflect capabilities of individuals, and thus, serve as two general pathways through which individuals may accomplish team goals and outcomes. Individual skills indicate the efficacy of accomplishing tasks individually, whereas collaboration skills indicate the ability of an individual to work with teammates. Yet, within or across teams, individuals may differentially prefer to rely on their individual and collaboration skills to accomplish team tasks. A successful team needs to maximize the resources of its individuals. This section reviews the implementation of individual skills, collaboration skills, and preference for collaboration in the present work.

Individual skills. Researchers in organizational psychology focus much of their attention on indicators of individual skills. For example, they find that cognitive ability serves as the most potent indicator of individual skills in terms of affecting individual and team performance (Barrick et al., 1998; Schmidt, 2002). A team composed of individuals with excellent individual skills may rely on the individual skills of its members to accomplish team tasks. Such a team may not need much interconnectedness to accomplish team goals and outcomes. As an example, a sports team (e.g., American national basketball team, Brazilian national soccer team) with many individually skilled players may need to solely rely on the individual talents of its players to win a game. This, in turn, suggests that although a team's members may share a unified team goal, its members may rely largely on individual actions to maximize team performance. In the present work, each agent possesses an individual skill level to accomplish a relevant team task by his own action. Specific conditions include teams consisting of agents all possessing high, medium, or low individual skills.

Collaboration skills. Individuals in a team may not only accomplish team relevant tasks by their own actions but also by interacting with another teammate. The efficacy of an individual's interactions depends on his collaboration skills, which, in turn, affect the quality of teamwork processes and emergence of behavioral, affective, and cognitive states in a team (Stout et al., 1997). A team composed of individuals with excellent collaboration skills may take advantage of a more interconnected collaborative structure, while, on the other hand, less collaborative structures may inhibit the use of collaboration skills. In the present work, along with possessing an individual skill level, each agent also possesses a collaboration skill level to accomplish a relevant team task. Given that collaboration skills belong to an individual, two teammates that may interact with each other need not possess the same collaboration accomplishment efficacy when they work together. A particular team member may possess higher collaboration skill levels than his teammates. In the present work, similar to individual skills, teams consist of agents all possessing high, medium, or low collaboration skills.

Preferences for collaboration. Meta-analytic results suggest that preference for collaboration serves as one of the more important dispositional predictors of task performance (Bell, 2007). Similar to task, goal, and outcome interdependence, preference for collaboration serves as an indicator of the level of interdependency among team members. Individuals within or across teams may differentiate themselves to the extent to which they wish to accomplish team tasks through collaboration as opposed to autonomous work (Wagner, 1995). A team composed of individuals wishing to work autonomously may only prove effective if individuals in the team possess quality individual skills. Similarly, a team composed of individuals preferring collaboration may only prove effective if individuals in the team possess quality collaboration skills. Teams in more interconnected collaborative structures may only take advantage of collaboration skills if individuals in the team prefer to work together to accomplish tasks. In the present work, similar to individual and collaboration skill levels, teams consist of agents all possessing a preference to work autonomously, all possessing a preference to work collaboratively, or teams consisting of agents with equal preference for autonomous and collaborative work.

Team Outcomes

The confluence of various specifications of team collaboration and individual characteristics generates varying team performance dynamics. In order to understand team performance dynamics, particular interest centers on the utilization of individual and collaboration skills by the members of a team as a function of collaborative structures, collaboration modes, and preferences for collaboration. Whether or not two teammates interact with each other depends on whether the collaborative structure and collaboration modes of the team and individual preferences for collaboration allow them to interact. The present work does not consider social interactions among team members unrelated to team performance. Collaborative structures determine which specific teammates in a team may interact; collaboration modes determine how teammates interact; individual preferences for collaboration determine if team members prefer to interact with one another. These factors combine to affect whether or not team members accomplish team relevant tasks working together or independently. The success of the team depends on the team maximizing its individual and collaboration skills. If a particular team consists of team members with excellent collaboration skills, then the team should utilize collaborative structures, collaboration modes, and hold appropriate preferences for collaboration to maximize the number of interactions that occur among team members. Team performance not only depends on team members possessing individual and collaboration skills to accomplish tasks, but it also depends on teams managing to maximally take advantage of those skills. Thus, in the present work, agents make a decision on whether to work with a teammate or independently to accomplish a team task, and then, utilize their individual or collaboration skills to perform. This section describes two team outcomes tracked in the computational model that reflect team effectiveness.

Individual and collaborative action. The nature of individual preferences for collaboration, team collaborative structure, and team collaboration mode determine the extent to which agents interact with each other or work independently to accomplish a team task. In other words, these three factors combine to affect the dynamics of how frequently team members interact with each other or take action on their own. Each team member possesses a skill level for individual and collaborative action, and an effective team maximizes the utility of team members' individual and collaboration skills. A team consisting of agents all possessing excellent individual skills but poor collaboration skills, or vice versa, requires a collaborative structure, collaboration mode, and preferences for independent work to take advantage of their strongest skills in order to maximize team performance. Tracking how frequently agents of a team work independently or together allows for an assessment of whether a team optimally utilizes team members' individual and collaboration skills. A team not meeting performance expectations may result from an inadequate utilization of team members' individual and collaboration skills, and thus, might require the team to alter what team members interact, how team members interact, or individual preferences for collaboration. The present work tracks the frequency of utilization of individual and collaboration skills by team members over a set time frame instead of using waiting times as frequency provides a more informative measure of optimal use of individual and collaboration skills.

Team performance. Researchers in both organizational and sports psychology argue that a team's performance consists of many performance episodes (Bourbousson et al., 2010; Kubatko, Oliver, Pelton, & Rosenbaum, 2007; Marks et al., 2001; Passos et al., 2011). In the academic workplace, a team of researchers may work on a research project for months to produce a publishable manuscript. Such a team project involves many performance episodes wherein team members work independently or together to complete an aspect of the whole enterprise. Whether or not a manuscript gets published depends on the research team successfully completing the many performance episodes that make up a manuscript. A research team unable to successfully complete at least some of the performance episodes pertinent to publishing may receive an infamous rejection letter from an editor. The computational model in the present work conceptualizes team performance in a similar manner. Team performance consists of many performance episodes that contribute to a team project wherein agents succeed or fail to complete each episode utilizing their individual and collaboration skills. The more performance episodes a team completes successfully, the more successful the team. Ultimately, the number of performance episodes a team completes successfully depends on the individual and collaboration skills of its team members and the degree to which the team's collaborative structure, collaboration mode, and individual preferences for collaboration take advantage of team members' most effective skills.

The types of tasks a team performs serves to provide boundary conditions on the definition of team performance (Kozlowksi & Bell, 2003). In the present work, each agent in the team contributes equally to team performance by working independently or interdependently with a teammate during any given performance episode. The choice of which agent acts during a single performance episode does not depend on his skill levels, his position in his team's collaboration network, his past performance, or any other factor in the present work. Instead, the factors that impact team collaboration determine whether each agent utilizes his individual or collaboration skills during any given performance episode. The collaboration factors serve as the mechanisms that determine the dynamics of agents utilizing their individual skill or their collaboration skills. The present work does not consider team tasks wherein one individual may complete the whole task such as the single-resource models tasks discussed by Steiner (1966, 1972) and Shiflett (1979) or the pooled interdependence tasks discussed by Van de Ven et al. (1976) and Saavedra et al. (1993) since the team project consists of numerous performance episodes that require the completion of various tasks. Similarly, the present work does not consider team tasks wherein team members serve different roles such as the multiple-resource models tasks discussed by Steiner (1966) and Shiflett (1979) or the sequential and reciprocal interdependence tasks discussed by Van de Ven et al. (1976) and Saavedra et al. (1993) since team members may complete all types of tasks, and therefore, do not serve strictly defined roles. These three types of task interdependencies do not really consider the notion that teammates may work together to complete specific tasks. However, team task interdependence, as described by Van de Ven et al. (1976) and Saavedra et al. (1993), does and most closely represents team performance in the present work. Although team performance in the present work does not strictly follow the definition of team performance for pooled, sequential, and reciprocal tasks, the principles developed in the present work may serve to understand the nature of team performance in these types of tasks as well.

Principles

The development of the computational model in the present work reveals two sets of components that impact team performance. Individual and collaboration skills reflect the individual capacities of team members they may utilize to successfully complete performance episodes. Team collaborative structures, collaboration modes, and individual preferences for collaboration form the set of collaboration parameters that reflect the degree to which team members utilize individual and collaboration skills. Understanding the way in which the collaboration parameters combine to impact individual and collaborative action and the manner in which collaboration parameters combine with individual and collaboration skills to affect team performance serve as the central goals of the present work. This section details arguments to formulate principles with respect to the impact of individual and collaboration skills, the effect of collaboration parameters, the fit between collaboration parameters and skills, and when the collaboration parameters provide the strongest impact on team performance. Importantly, these four set of principles offer a foundational basis that serve as starting points into examining model results. The present computational investigation reveals many nuanced findings and implications for each principle upon an examination of results.

Effect of Skill Levels

Team members may decide to utilize their individual or collaboration skills to accomplish team relevant tasks during performance episodes (Bourbousson et al., 2010; Stout et al., 1997). The individual skills of team members determine the success of individual actions during performance episodes, whereas collaboration skills determine the success of interactions between teammates in accomplishing the same tasks. Given that individual and collaboration skills provide the two pathways through which team members complete tasks, it follows that a team's performance results from the composite skill levels of team members. As an example, consider a team composed of individuals with low individual and collaboration skill levels. Such a team stands no chance of performing as well as a team composed of individuals with high skill levels.

Adequate team performance requires that at least some team members possess quality individual or collaboration skills.

Principle 1: A team's composite skills for individual and collaborative action determine team performance.

The present study examines nine combinations of skill levels wherein all team members possess low, medium, or high individual and collaboration skills. This principle reflects the main effect of skill levels on team performance. As an example, this principle considers conditions such as when two teams solely rely on collaborative action to accomplish work tasks. The principle predicts that the team consisting of members with higher collaboration skills performs best in this comparison. The importance of this prediction lies in the computational model replicating consistent findings in organizational psychology wherein researchers posit the positive impact of individual and collaboration skills on team performance (e.g., Bell, 2007; LePine et al., 2008; Stewart, 2006; Stout et al., 1997). Such replication lends validation to computational models (Harrison et al., 2007).

Effect of Collaboration Parameters

The three collaboration parameters of collaborative structure, collaboration mode, and preferences for collaboration effect the degree to which team members choose to act independently or work together to complete performance episodes. The team's collaborative structure indicates the level of interconnectivity among team members; the collaboration mode indicates how teammates initiate an interaction; individual preferences for collaboration indicate the degree to which team members wish to interact with various teammates. In terms of the collaborative structures considered in the present work, the fully connected collaborative structure provides the greatest number of opportunities for interaction since every team member may interact with every other teammate. The unidirectional interaction protocol only requires that one team member of an interacting dyad initiate interaction as opposed to the mutual interacton protocol where both teammates need to initiate interaction. Naturally, team members that hold preferences for collaboration wish to interact with teammates with greater frequency than team members who prefer to work independently. Frequent team member interaction, and therefore, the use of collaboraton skills, requires that the team's collaborative structure provide opportunities for interaction, that team members may initiate dyadic interactions with ease, and that team members hold preferences to work together.

> *Principle 2*: The occurrence of collaboration within a team depends on the team's collaborative structure and protocol and the agents' preferences for collaboration.

The present study examines twenty-four combinations of collaborative structure, collaboration mode, and preferences for collaboration. This principle reflects the collective effect of the collaboration parameters on team members choosing to complete tasks on their own or with the help of a teammate. A general finding in psychological team research contends that more interconnectivity among team members, such as the interconnectivity represented by the fully connected collaborative structure, leads to effective team performance resulting from the purportedly numerous effective interactions (Losada, 1999; Passos et al., 2011). Yet, the complete interconnectivity among team members in the fully connected collaborative structure may merely serve as a façade if not accompanied by an appropriately matched collaboration mode and team member preferences for collaboration. The mutual interaction protocol or team members holding preferences for independent work reduce the number of realized interactions in collaborative structures, and this effect may prove particularly dramatic for the most interconnected collaborative structures. The prediction from this principle, then, places boundary conditions on the general finding of a positive effect between team interconnectivity and performance.

Fit Between Collaboration Parameters and Skills

Collaboration parameters determine whether team members work independently or together, and team members' individual and collaborative skill levels determine the success of individual actions or interactions between teammates. In order for a team to perform effectively, an appropriate match must exist between collaboration parameters and skill levels of team members. A team consisting of members with excellent collaboration skills but poor individual skills, or vice versa, only performs well if the team's collaboration parameters provide opportunities for team members to utilize their most effective skills. This introduces an interesting phenomenon wherein a team may consist of team members who possess, overall, higher skill levels than another team, but yet, may perform worse if the collaboration parameters lead to ineffective use of team members' skills. For example, one team may consist of members with excellent individual skills and moderate collaboration skills, while another team may consist of members with poor individual skills and excellent collaboration skills. In this case, the team members in the former team possess higher skill levels when considering both individual and collaboration skills. Yet, this team may only perform better than the latter team if the collaboration parameters allow its members to utilize their most effective skills. If the collaboration parameters for both teams lead its members to utilize their collaboration skills, then the latter team consisting of team members possessing superior collaboration skills will perform better.

Principle 3: A team maximizes its team performance when it collaborates in a manner that utilizes agents' most effective skills.

This principle reflects the interactive effects of all five factors in the present study. On a general level, the principle predicts the need for complementary team skills and collaboration parameters. At the same time, it offers an explanation for a commonly discussed phenomenon in organizational psychology that the whole may exceed expectations generated from its parts (e.g., Tziner & Eden, 1985). A team consisting of more highly skilled members than another team may not necessarily perform better if the team's collaboration parameters ineffectively utilize their team skills. Indeed, the team with less skilled members in total may in fact perform better than the team with more skilled members if they possess an appropriate collaborative structure, collaboration mode, and preferences for their skill set. The root of this effect comes from the necessity of complementary team skills and collaboration parameters in order to achieve effective team performance.

Strongest Impact of Collaboration Parameters

Various collaboration parameters differentially utilize team members' individual and collaboration skills. Given a set of team member individual and collaboration skills, particular interest centers on when collaboration parameters matter most for maximizing team performance. When it comes to a team's own potential, a set of particular collaboration parameters more strongly impacts a team with members possessing excellent collaboration skills and poor individual skills than if the team's members possess excellent collaboration and individual skills. For the first team, a particular set of collaboration parameters leads to the team utilizing their weak skill set, while a different set of collaboration parameters leads to the team utilizing their strong skill set. However, for the second team, any set of collaboration parameters ultimately leads to using the same skill level. In other words, collaboration parameters provide the strongest impact on a team's own potential performance when team members possess large differences between their individual and collaboration skills, whereas collaboration parameters provide least impact on team performance when team members possess equal skill levels for individual and collaborative action.

> *Principle 4*: The form of team collaboration matters most when teams consist of agents with differential skill levels for individual and collaborative action.

This principle pinpoints the greatest impact of the collaboration parameters. In other words, they explicate when the collaboration parameters provide the most noticeable impact on team performance. A team consisting of team members with similar individual and collaboration skills will not find that changes in the nature of their collaboration leads to positive changes in team performance. However, a team with large differences in individual and collaboration skills will find large differences in team performance as a result of different forms of team collaboration. For two teams with large differences in team member composite skill levels competing either explicitly (e.g., basketball) or implicitly (e.g., academics) against each other, the less skilled team may find that changes in their collaboration may not lead to improved outcomes (e.g., winning a game or publishing their research) because of the large discrepancies in skill levels. However, for two teams with similar team member composite skill levels, both teams may find that changes in their team collaboration may lead to improved outcomes because particular forms of collaboration may more effectively utilize team members' skills. This offers another viewpoint into the importance of the fit between team skills and collaboration parameters. The collaboration parameters should lead team members to utilize their strongest skills.

METHOD

An agent-based simulation, implemented using the free statistical software R, serves as the basis for the computational study developed in the present work. Appendix A contains the R code for the computational model in the present work. In particular, the present work considers a team of agents working independently or interdependently to complete tasks relevant to a team project involving many performance episodes. This section details the parameters, outcomes, and analyses of the simulation.

Parameters

The present work considers two sets of parameters: collaboration parameters and agent skills. Collaboration parameters refer to the parameters that impact whether agents work independently or interdependently. In particular, three parameters determine the frequency of independent or interdependent work in a team of agents. The collaborative structure determines what teammates interact, the dyadic collaboration mode determines whether one or both teammates initiate an interaction, and individual preferences for collaboration express the degree to which agents wish to work alone or with teammates. The parameters pertaining to agent skills reflect the quality each agent possesses when it comes to working independently or with a teammate. In short, agents possess individual and collaboration skills. This section describes the specifics of each parameter in the simulation.

Collaboration Parameters

The collaborative structure of a team determines the level of interconnectivity between teammates. Figure 2 displays four collaborative structures considered in the present work. The star structure consists of a team wherein one agent (i.e., the star or the central node) may interact with all four of his teammates, and his teammates (i.e., the leaves) may only interact with him but not with each other. Each of the other three collaborative structures in Figure 2 represents an increasing level of interconnectivity between teammates. The two-star structure allows two agents to interact with all of their teammates and leaves three agents with the ability to only interact with the two stars, whereas the three-star structure allows three agents to interact with all of their teammates and leaves two agents with the ability to only interact with the three stars. Finally, the fully-connected structure allows all agents to interact with their teammates.

Each agent possesses a preference to work with each one of his teammates in the team's collaborative structure and a preference to work independently to accomplish team tasks during a performance episode. For the star-structure, this means that the star node possesses five preferences: one preference for working independently and four preferences to work with each one of his teammates. Each leaf node in the single star structure possesses two preferences: one preference for working independently and one preference to work with the star node. In other words, the number of preferences an agent possesses equals one plus the number of interacting partners resulting from the team's collaborative structure. This implies that one agent may possess a higher preference to work with a teammate than vice versa. The present work investigates three types of teams with respect to preferences for collaboration. Teams consist of all agents possessing a higher preference to work independently, all agents possessing a higher preference for teamwork, or all agents possessing equal preference for independent and interdependent work. To sample preferences, the simulation utilizes a continuous uniform distribution. The important characteristic of the sampling strategy pertains to whether for a particular agent his preferences for individual work overlap with his preferences for collaboration. Overlapping preferences imply the mixed condition wherein all agents hold equal preferences for individual and interdependent work, whereas non-overlapping preferences imply the other two conditions. Every time an agent acts independently or works with a teammate the simulation samples a new preference from the appropriate distribution.

The dyadic interaction protocol determines whether one or both agents in a dyad need to initiate an interaction. The mutual interaction protocol requires that both agents in a dyad each possess as their highest preference to interact with each other. This means that even in the condition when all agents possess preferences for collaboration, instead of independent work, that two agents may decide not to interact with each other if one of the agents in the dyad possesses a stronger preference to work with another teammate. The unidirectional interaction protocol only requires that one agent possesses as his highest preference to interact with a teammate for two particular teammates to work together. Under the unidirectional interaction protocol this implies that in the condition when all agents possess preferences for collaboration that a particular agent will interact with a teammate every time. In other words, the combination of the unidirectional interaction protocol with all agents possessing preferences for collaboration produces a condition wherein a team solely relies on its collaboration skills to accomplish tasks.

Agent Skills

Each agent possesses two types of skills: individual and collaboration skills. Individual skills reflect the probability of successfully completing tasks when an agent works independently, whereas collaboration skills reflect the probability of successfully completing tasks when an agent works with another teammate. Every agent possesses a single probability to represent his individual skill level and possesses as many probabilities to represent his collaborative skill levels as interacting partners in the team's collaborative structure. In other words, each agent possesses the same number of preferences for individual and collaborative action as the number of probabilities representing his individual and collaborative skill levels. Given that each individual agent possesses collaboration skills, one agent may possess a higher collaborative skill level when receiving assistance from a teammate to complete a task than vice versa. In the present work teams consist of agents with homogeneously poor or excellent individual and collaboration skills, and teams consist of agents with heterogeneous individual and collaboration skills. Specifically, the simulation creates these conditions by sampling individual and collaboration skills from a continuous uniform distribution. A drawn value indicates the probability of an agent successfully completing tasks via individual or collaboration skills during a single performance episode. Every time an agent acts independently or works with a teammate the simulation samples a new probability from the appropriate distribution. When drawing teams to create agents with high individual and collaboration skills, the simulation utilizes U(.6, .8), and when drawing teams to create agents with low individual or collaboration skills, the simulation utilizes U(.2, .4). The simulation utilizes U(.2, .8) to draw teams to create agents with medium individual and collaboration skill levels.

Outcomes

The set of parameter specifications result in agent action and interaction dynamics that ultimately lead to team performance dynamics. In terms of understanding action and interaction dynamics, the present work tracks the frequency with which agents utilize individual and collaboration skills. In short, this assessment indicates whether agents utilize their strongest skills and the efficiency with which they utilize them. Naturally, team performance indicates the effectiveness of agent individual and collaboration skills. This section describes the outcomes of the simulation.

Frequency of Individual and Collaborative Action

Agents engage in two types of activities: individual and collaborative action. Individual action occurs when an agent decides to work independently and utilize individual skills to complete tasks during a performance episode, whereas collaborative action occurs when an agent decides to work with a teammate and utilize collaboration skills to complete tasks during a performance episode. The simulation keeps track of the number of times agents utilize their task work and teamwork skills in order to assess agents' optimality of utilization of their skills. To achieve the greatest performance, agents in a team should utilize their strongest skills during each performance episode.

Team Performance

For each performance episode, the simulation randomly selects with equal probability a single agent in a team. This agent then orders his preferences for individual and collaborative action from the highest to lowest preference. If the agent possesses the highest preference for individual action, then the agent works independently and utilizes his individual skills to accomplish tasks during the performance episode. However, when the agent possesses the highest preference for collaboration with a particular teammate, then under the mutual interaction protocol, the agent works together with the teammate and utilizes his collaboration skills only if the selected teammate also possesses the highest preference for collaboration with the agent. Otherwise, the agent decides to work independently and utilize his individual skills to accomplish tasks during the performance episode. Under the unidirectional interaction protocol, the agent works together with the selected teammate and utilizes his collaboration skills irrespective of the teammate's preferences for collaboration. The simulation measures team performance by considering the performance of agents in a team during 100,000 performance episodes. Agents may succeed or fail to accomplish tasks during a performance episode via individual or collaboration skills. The more successful performance episodes completed by a team of agents, the more successful the team. In short, the simulation measures team performance by computing the total number of successfully completed performance episodes by a team of agents.

Computations

The simulation consists of teams created from combinations of five factors to produce a total of 216 conditions: 4 (collaborative structures) x 2 (collaboration modes) x 3 (preferences for collaboration) x 3 (individual skills) x 3 (collaboration skills). Each condition consists of 1,000 teams observed over 100,000 performance episodes for a total of 216,000 teams and 21,600,000,000 performance episodes. The results of the present work come from a set of computations: mathematically computing the probability that a team selects individual or collaborative action during the first performance episode, computing the probability of a team selecting individual or collaborative action during the first fifty performance episodes via the computational model, computing the frequency of individual and collaborative action via both mathematics and the computational model, and mathematically computing team performance. This section describes each of these computations.

Computing Probabilities of Individual and Collaborative Action

Graph theory represents a major area of modern mathematical research that concerns itself with developing mathematics for the types of collaborative structures presented in Figure 2. In the present work, each agent makes a decision to act independently or work together with a teammate to complete tasks. The decision for each agent functions as a result of the combination of the number of partners for interaction, the collaboration mode, and preferences for collaboration. When considering these three factors, there exists a mathematical formulation to determine the probability of each agent, and therefore, the team as a whole, selecting to work independently or with a teammate. Yet, as a result of the fact that only one agent or dyad completes tasks, and therefore updates their preferences, during any given performance episode, this probability may change from one performance episode to the next conditional on prior random samplings of preferences for teamwork across all non-acting agents. An explanation of the exact computation of this probability for the first performance episode exists in the Results and Appendix B. The Results offer a description of the computation for the collaboration conditions that lead to non-trivial initial probabilities, while Appendix B contains more detailed information on the computation of initial probabilities for each of the 24 collaboration conditions.

Some of the conditions of present study lead to unchanging probabilities across performance episodes providing the opportunity to offer a complete mathematical representation of them, and thereby, simplifying the presentation of simulation results. For those conditions where the probability changes over time, Appendix C provides simulation R code that focuses the computational model in the present work on the first fifty performance episodes. This simulation tracks the number of teams out of 10,000 teams that choose individual or collaborative action for each of the first fifty performance episodes with 30 replications of the simulation to provide a stable computation. The simulation in Appendix A focuses on tracking 1,000 teams for 100,000 performance episodes, while the simulation in Appendix C tracks 10,000 teams for 50 performance episodes with 30 iterations. The simulation in Appendix C offers a more stable computation of the probability of teams selecting individual or collaborative action for the first 50 performance episodes than the simulation in Appendix A. Fifty performance episodes provide enough of a time frame to model the changing nature of the probability of a team selecting individual or collaborative action over time. The present work fits various statistical models to capture the changing nature of this probability for various collaboration conditions.

Computing the Frequency of Individual and Collaborative Action

To compute the frequency of individual and collaborative action, the present work relies on mathematical computation for those conditions that lead to trivial collaboration dynamics and relies on computation by simulation for those conditions with non-trivial collaboration dynamics. In particular, the simulation in Appendix A tracks the average, across 1,000 teams, number of times that a team selected to undertake individual and collaborative interaction across 100,000 performance episodes. These computations serve to inform on the dynamics of the 24 collaboration conditions in the present work.

Computing Team Performance

Upon mathematical and simulation computation of the frequency of individual and collaborative interaction, then a mathematical computation describes the nature of team performance in the 216 conditions of the present work. The 24 collaboration conditions lead to teams differentially utilizing individual and collaborative action. The nine skills conditions determine the efficacy of individual and collaborative actions. Therefore, to compute team performance requires multiplying the average skill level for individual and collaborative action by the frequency with which a team chooses to execute individual and collaborative actions, respectively.

RESULTS

The collaboration parameters of collaborative structure, collaboration mode, and preferences for collaboration impact the frequency with which agents choose to complete tasks independently or interdependently, while the skills parameters of individual and collaboration skills determine the frequency with which agents successfully complete tasks either independently or interdependently. This implies that the impact of the 24 conditions obtained from the combinations of the collaboration parameters focus on one dependent variable (i.e., frequency of agents choosing to work independently or interdependently), while the nine conditions obtained from the skills parameters focus on a different dependent variable (i.e., performance). This section first focuses on the impact of collaboration parameters on agents choosing to complete tasks independently or interdependently, and then focuses on how various forms of team collaboration maximize agents' skill levels. The description of results relies on mathematical computation whenever possible and on computation from simulation otherwise. A demonstration of the principles of the present work follows the presentation of computations.

Frequency of Individual and Collaborative Action

The first set of results to understand pertains to the frequency of individual and collaborative action that comes from the three collaboration parameters. For all conditions there exists a logical mathematical derivation to assess the initial (i.e., at the first time step) probability of agents selecting to do individual or collaborative action. This probability for some conditions changes at each time step while for other conditions it remains static. For those conditions where the probability changes over time, computations from simulation capture this dynamism. Computing the frequency of individual and collaborative action informs on the similarities and differences of the 24 collaboration conditions and serves as a fundamental component to determining team performance. This section first focuses on the mutual interaction protocol and then on the unidirectional interaction protocol.

Mutual Interaction Protocol

The derivation of the probability that agents initially select individual or collaborative action follows from the choice of collaboration parameters and the initial random assignment of all preferences across all agents from a continuous uniform distribution. Under the mutual interaction protocol, a selected agent selects to work interdependently (i.e., perform collaborative action) with another agent only if both agents hold the highest preference to work with each other, otherwise the selected agent chooses to work independently (i.e., perform individual action). If an agent holds the highest preference to work independently, then the agent does so. Results for each of the preference scenarios in the present study follow.

Preferences for individual action. Under the mutual interaction protocol and preference scenario where each agent holds the highest preference for individual action at each point in time, all agents always select individual action and never select collaborative action regardless of the collaboration structure of the agents. This result follows logically since every selected agent always possesses the highest preference for individual action which implies that the agent always chooses to perform independently. Thus, the frequency of individual action equals the length of observation, while the frequency of collaborative action equals zero. The efficacy of these types of teams rests on the individual skill levels of agents.

Preferences for collaborative action. Under the mutual interaction protocol and preference scenario where each agent holds the highest preference to work with one of his teammates at each point in time, then the initial probability of agents selecting to do individual or collaborative action depends on the team collaboration structure. Equations 1a and 1b calculate the initial probability that a set of star nodes performs individual and collaborative action, respectively, with appropriate adjustments made for different collaboration structures, while Equations 1c and 1d calculate the initial probability that a set of leaf nodes performs individual and collaborative action, respectively. Where P_0 equals the initial probability, IA equals individual action, CA equals collaborative action, T_N equals the total number of nodes (i.e., five in all cases), S_N equals the number of star nodes, L_N equals the number of leaf nodes, $S_{N\text{-Team}}$ equals the number of interacting partners each star node holds, and $L_{N\text{-Team}}$ equals the number of interacting partners each leaf node holds, then

$$P_0\left(IA_{Star}\right) = \frac{S_N}{T_N}\left(\frac{1}{S_{N\text{-Team}}} * \frac{S_{N\text{-Team}}\text{-}1}{S_{N\text{-Team}}}(S_N\text{-}1) + \frac{1}{S_{N\text{-Team}}} * \frac{L_{N\text{-Team}}\text{-}1}{L_{N\text{-Team}}} * L_N\right), \quad (1a)$$

$$P_0\left(CA_{Star}\right) = \frac{S_N}{T_N}\left(\left(\frac{1}{S_{N\text{-Team}}}\right)^2 (S_N\text{-}1) + \frac{1}{S_{N\text{-Team}}} * \frac{1}{L_{N\text{-Team}}} * L_N\right), \quad (1b)$$

$$P_0\left(IA_{Leaf}\right) = \frac{L_N}{T_N}\left(\frac{1}{L_{N\text{-Team}}} * \frac{S_{N\text{-Team}}\text{-}1}{S_{N\text{-Team}}} * S_N\right), \text{ and} \quad (1c)$$

$$P_0\left(CA_{Leaf}\right) = \frac{L_N}{T_N}\left(\frac{1}{L_{N\text{-Team}}} * \frac{1}{S_{N\text{-Team}}} * S_N\right). \quad (1d)$$

For the fully-connected collaboration network, there exists a 25% chance that two agents in a team work interdependently during the first time step and a 75% chance that an agent of the team works independently. Indeed, the probability of agents working independently equals one minus the probability of agents working interdependently, or vice versa, as at every time step either a single agent works independently or two agents work interdependently. Calculating for the remaining three collaboration networks, the probability of a team working interdependently at the first time step equals 27.5%, 32.5%, and 40% in a three-star, two-star, and one-star, respectively, collaboration network. An examination of the initial probabilities demonstrates an interesting pattern. Although the fully-connected collaboration network possesses the most connections among teammates, under the mutual interaction protocol it offers the lowest probability of a team working interdependently. In fact, the collaboration network with the least number of connections, the one-star collaboration network, offers the highest probability of teammates working together.

Examining what happens to the initial probabilities over time provides additional insight into the combined impact of the collaboration parameters. Finding the probability of individual and collaborative action at each point in time informs on the expected number of times that each collaboration condition leads to teams utilizing individual and collaboration skills across the performance episodes of their team task. In the one-star collaboration network each leaf node holds only two preferences: one preference to work with the star node and one preference to work independently. In this scenario, each node holds the highest preference for collaboration at every time point. This means that for the one-star collaboration network that each leaf node always wants to interact with the star node. The star node, in turn, always wants to interact with one of the leaf nodes. In fact, the probability of the star node working independently equals zero. All of this, in turn, implies that the initial probability of 40% chance of a one-star collaboration network working interdependently never changes over time. In other words, for the one-star collaboration network the probability of agents working interdependently equals 40% for every time period, which, in turn, implies that the probability of agents working independently equals 60% for every time period. Thus, the probability of working interdependently (or independently) remains static over time for the one-star collaboration network. However, for the three other collaboration networks, the initial probability of working interdependently changes over time according to an exponential decay function. Where P_t equals the probability of working interdependently at time t, P_0 equals the initial probability of working interdependently, and λ equals the decay constant, then

$$P_t=P_0e^{-\lambda t}. \quad (2)$$

The computation of the probability of working interdependently at each time point comes from the simulation code in Appendix C estimated by computing the number of teams that worked interdependently at each point in time. The exponential decay function explains at least 98% of the variance in probabilities for each of the three collaboration networks of interest here and $\hat{\lambda}$ equals 0.223, 0.199, and 0.134 for the fully connected, three-star, and two-star collaboration networks, respectively. The sum of the infinite series, $\sum_{t=1}^{\infty} P_t = \frac{P_0}{1-e^{-\lambda}}$, indicates the expected number of times a team works interdependently. Utilizing the lambda estimate, the expected number of times a team works interdependently equals 1.25, 1.52, and 2.59 for the fully connected, three-star, and two-star collaboration networks, respectively. These estimates, reported in Table 1, match closely the simulation results reported in Table 2, which presents the average frequency for each collaboration network. Although the present work does not logically derive Equation 2 as it does Equations 1a-d, the almost perfect fit of Equation 2 to simulation data indicates that there may exist a logical derivation of the probability of working interdependently at each point in time. Certainly, the nearly matching results in Tables 1 and 2 indicate that Equation 2 offers an accurate mathematical description of the collaboration conditions discussed in this section. A mathematical derivation of the probability of working interdependently at each point in time may lead to a completely mathematical theory of team collaboration dynamics. The present work serves as a starting point for developing such a mathematical theory. As a whole, these results indicate that only the one-star collaboration network allows teams to utilize their collaboration skills beyond three times.

Table 1

Initial probabilities of teammates working interdependently, the exponential decay constants of the change in initial probabilities, and the expected number of interactions between teammates in the mutual interaction protocol with preferences for collaboration.

Collaboration Network	P_0(Collaboration)	$\hat{\lambda}$	$\frac{P_0}{1-e^{-\lambda}}$
One-star	0.40	-	-
Two-star	0.325	0.134	2.59
Three-star	0.275	0.199	1.52
Fully-connected	0.25	0.223	1.25

Note. P_0 = initial probability; $\hat{\lambda}$ = the estimate of the decay constant from Equation 2.

Table 2

Average frequency of individual and collaborative action across 1,000 teams for 100,000 time periods in the mutual interaction protocol with preferences for collaboration.

	Frequency	
Collaboration Network	Collaborative Action	Individual Action
One-star	40,000.42	59,998.58
Two-star	2.70	99,997.30
Three-star	1.63	99,998.37
Fully-connected	1.32	99,998.68

Equal preferences. Under the mutual interaction protocol and preference scenario where each agents holds equal preferences for individual and collaborative action at each point in time, then the initial probability of agents selecting to do individual or collaborative action follows a new set of formulae. Equations 3a and 3b calculate the initial probability that a set of star nodes performs individual and collaborative action, respectively, with appropriate adjustments made for different collaboration structures, while Equations 3c and 3d calculate the initial probability that a set of leaf nodes performs individual and collaborative action, respectively. Where $S_{N\text{-}Tot}$ equals the total number of preferences each star node holds (i.e., five in all cases), $L_{N\text{-}Tot}$ equals the total number of preferences each leaf node holds, and all other terms defined previously, then

$$P_0\left(IA_{Star}\right)=\frac{S_N}{T_N}\left(\frac{1}{S_{N\text{-}Tot}}+\left(\frac{S_{N\text{-}Team}}{S_{N\text{-}Tot}}\right)^2\frac{1}{S_{N\text{-}Team}}(S_N\text{-}1)+\frac{S_{N\text{-}Team}}{S_{N\text{-}Tot}}\right.$$
$$\left.*\frac{1}{S_{N\text{-}Team}}*\frac{L_{N\text{-}Team}}{L_{N\text{-}Tot}}*L_N\right), \tag{3a}$$

$$P_0\left(CA_{Star}\right)=\frac{S_N}{T_N}\left(\left(\frac{S_{N\text{-}Team}}{S_{N\text{-}Tot}}\right)^2\left(\frac{1}{S_{N\text{-}Team}}\right)^2(S_N\text{-}1)+\frac{S_{N\text{-}Team}}{S_{N\text{-}Tot}}\right.$$
$$\left.*\frac{1}{S_{N\text{-}Team}}*\frac{L_{N\text{-}Team}}{L_{N\text{-}Tot}}*\frac{1}{L_{N\text{-}Team}}*L_N\right), \tag{3b}$$

$$P_0\left(IA_{Leaf}\right)=\frac{L_N}{T_N}\left(\frac{1}{L_{N\text{-}Tot}}+\frac{L_{N\text{-}Team}}{L_{N\text{-}Tot}}*\frac{1}{L_{N\text{-}Team}}*\frac{S_{N\text{-}Team}}{S_{N\text{-}Tot}}*S_N\right),\text{ and} \tag{3c}$$

$$P_0\left(CA_{Leaf}\right)=\frac{L_N}{T_N}\left(\frac{L_{N\text{-}Team}}{L_{N\text{-}Tot}}*\frac{1}{L_{N\text{-}Team}}*\frac{S_{N\text{-}Team}}{S_{N\text{-}Tot}}*\frac{1}{S_{N\text{-}Team}}*S_N\right). \tag{3d}$$

For the fully connected collaboration network, there exists a 16% chance that two agents in a team work interdependently during the first time step, and therefore, an 84% chance that an agent of the team works independently. Calculating for the remaining three collaboration networks, the probability of a team working interdependently at the first time step equals 16.8%, 17.6%, and 16% in a three-star, two-star, and one-star, respectively, collaboration network. Unlike the scenario where each agent holds preferences for collaboration, when each agent holds equal preferences for individual and collaborative action, then all collaboration networks provide similar initial probabilities of collaboration, which still implies that although the fully-connected collaboration network possesses the most connections among teammates, the one-star collaboration network offers the same probability of teammates working together even though this network involves less connections between teammates.

Under the scenario where each agent holds preferences for collaboration the initial probability of collaboration under the one-star collaboration network did not change over time. In that case the star node never performed an individual action since he held the highest preference to work with one of the leaf nodes and each leaf node held the highest preference to interact with the star node. However, in this scenario where each agent holds equal preferences for individual and collaborative action a leaf node does not interact with the star node if it holds the highest preference for individual action, which implies that the star node will perform an individual action every time a leaf node rejects to interact with him. This leads to a different set of dynamics for the one-star collaboration network under this scenario than in the case where each agent holds preferences for collaboration. In this scenario, the initial probability for collaboration in the one-star collaboration network changes over time. Yet, the form of the change in the initial probability of the one-star collaboration network differs from the change in the initial probability of the other three collaboration networks. The initial probability of working interdependently for the one-star collaboration network changes over time according to a power function. Where P_t equals the probability of working interdependently at time t, P_0 equals the initial probability of working interdependently, and γ equals the power exponent, then

$$P_t=P_0t^{-\gamma}. \tag{4}$$

Note that Equation 4 represents a different power function than the power-law function of waiting times discussed by physicists (e.g., Min et al., 2009). Equation 4 serves to accurately model the probability of an agent choosing to work interdependently in the one-star collaboration network. As mentioned, in the present work, a focus on figuring out the probability of an agent working interdependently provides a more informative measure in terms of determining whether a particular form of collaboration leads to the optimal use of individual and collaboration skills by a team of agents. Indeed, a power function explains 99% of the variance in the probability of agents working interdependently over time in the one-star collaboration network with $\hat{\gamma} = 0.236$. Whenever $\gamma \leq 2$, then the mean of P_t goes to infinity (Newman, 2005). In other words, the number of times agents work interdependently does not converge to a finite sum. The change in probability for the other three collaboration networks still follows an exponential decay function. In this scenario, the exponential decay function explains at least 95% of the variance in probabilities over time for these three collaboration networks. Table 3 presents the estimated decay constants. Comparing the results in Table 3 with those in Table 4, it again demonstrates that Equation 2 offers an accurate mathematical description of the number of times agents collaborate in the two, three, and fully-connected collaboration networks. Table 4 confirms the difference in terms of the number of times agents work interdependently in the one-star collaboration network as opposed to the other three collaboration networks. Indeed, the difference in the frequency of collaboration in the one-star collaboration network as opposed to the other three collaboration networks serves to describe the difference in the collaboration dynamics represented by Equations 4 and 2, respectively.

Table 3

Initial probabilities of teammates working interdependently, the exponential decay constants of the change in initial probabilities, and the expected number of interactions between teammates in the mutual interaction protocol with equal preferences for individual and collaborative action.

Collaboration Network	P_0(Collaboration)	$\hat{\lambda}$	$\frac{P_0}{1-e^{-\lambda}}$
One-star	0.16	-	-
Two-star	0.176	0.097	1.90
Three-star	0.168	0.144	1.25
Fully-connected	0.16	0.163	1.06

Note. P_0 = initial probability; $\hat{\lambda}$ = the estimate of the decay constant from Equation 2.

Table 4

Average frequency of individual and collaborative action across 1,000 teams for 100,000 time periods in the mutual interaction protocol with equal preferences for individual and collaborative action.

	Frequency	
Collaboration Network	Collaborative Action	Individual Action
One-star	1,120.66	98,879.34
Two-star	2.72	99,997.28
Three-star	1.73	99,998.27
Fully-connected	1.36	99,998.64

Unidirectional Interaction Protocol

Under the unidirectional interaction protocol, if a selected agent holds the highest preference to work with a teammate, then he interacts with his teammate without regard to whether his teammate holds the highest preference to work with him. If an agent holds the highest preference to work independently, then the agent does so. Results for each of the preference scenarios in the present study follow.

Preferences for individual action. Under the unidirectional interaction protocol and preference scenario where each agent holds the highest preference for individual action at each point in time, all agents always select individual action and never select collaborative action regardless of the collaboration structure of the agents. Similarly to the scenario under the mutual interaction protocol and preferences for individual action, this result follows logically since every selected agent always possesses the highest preference for individual action which implies that the agent always chooses to perform independently. Thus, the frequency of individual action equals the length of observation, while the frequency of collaborative action equals zero. The efficacy of these types of teams rests on the individual skill levels of agents.

Preferences for collaborative action. Under the unidirectional interaction protocol and preference scenario where each agent holds the highest preference for collaboration at each point in time, all agents always select collaborative action and never select individual action regardless of the collaboration structure of the agents. A similar logic applies as to the case when agents hold preferences for individual action. In this scenario every selected agent always possesses the highest preference for collaboration which implies that the agent always chooses to perform interdependently. Thus, the frequency of collaboration equals the length of observation, while the frequency of individual action equals zero. The efficacy of these types of teams rests entirely on the collaboration skill levels of agents.

Equal preferences. Under the unidirectional interaction protocol and preference scenario where each agents holds equal preferences for individual and collaborative action at each point in time, then the initial probability of agents selecting to do individual or collaborative action depends on the team collaboration structure. Equations 5a and 5b calculate the initial probability that a set of star nodes performs individual and collaborative action, respectively, with appropriate adjustments made for different collaboration structures, while Equations 5c and

5d calculate the initial probability that a set of leaf nodes performs individual and collaborative action, respectively. With all terms defined previously, then

$$P_0\left(IA_{Star}\right)=\frac{S_N}{T_N}\left(\frac{1}{S_{N\text{-}Tot}}\right), \tag{5a}$$

$$P_0\left(CA_{Star}\right)=\frac{S_N}{T_N}\left(\frac{S_{N\text{-}Team}}{S_{N\text{-}Tot}}*\frac{1}{S_{N\text{-}Team}}*S_{N\text{-}Team}\right), \tag{5b}$$

$$P_0\left(IA_{Leaf}\right)=\frac{L_N}{T_N}\left(\frac{1}{L_{N\text{-}Tot}}\right), \text{ and} \tag{5c}$$

$$P_0\left(CA_{Leaf}\right)=\frac{L_N}{T_N}\left(\frac{L_{N\text{-}Team}}{L_{N\text{-}Tot}}*\frac{1}{L_{N\text{-}Team}}*S_N\right). \tag{5d}$$

For the fully-connected collaboration network, there exists a 80% chance that two agents in a team work interdependently during the first time step, and therefore, a 20% chance that an agent of the team works independently. Calculating for the remaining three collaboration networks, the probability of a team working interdependently at the first time step equals 78%, 72%, and 56% in a three-star, two-star, and one-star, respectively, collaboration network. Under the unidirectional interaction protocol with equal preferences for individual and collaborative action, the team collaboration structure impacts the number of interactions among teammates. As opposed to the situation under the mutual interaction protocol, in this scenario the fully-connected collaboration structure leads to the highest initial probability of teammates interacting (i.e., 80%), and the one-star collaboration structure leads to the lowest initial probability of teammates interacting (i.e., 56%).

The change in probability of doing teamwork for the one-star collaboration network in the mutual interaction protocol and equal preferences for individual and collaborative action followed a power function, while the change in probability of doing teamwork for the other three collaboration networks followed an exponential decay function. Under the unidirectional interaction protocol and equal preferences for individual and collaborative action a power function with a positive exponent best captures the change in probability of doing teamwork. Where P_t equals the probability of working interdependently at time t, P_0 equals the initial probability of working interdependently, and γ equals the power exponent, then

$$P_t=P_0t^{\gamma}. \tag{6}$$

Note that γ only takes on positive values to capture the fact that the probability of collaborating under this scenario gradually increases over time but yet never converges to 1 for all collaboration networks. This power function explains about 90% of the variance in probability of doing teamwork over time across the different collaboration networks. Table 5 reports the estimate of γ in Equation 6 for each collaboration network.

Table 5

Initial probabilities of teammates working interdependently and the power constant of the change in initial probabilities in the unidirectional interaction protocol with equal preferences for individual and collaborative action.

Collaboration Network	P_0(Collaboration)	$\hat{\gamma}$
One-star	0.56	0.026
Two-star	0.72	0.022
Three-star	0.78	0.019
Fully-connected	0.80	0.017

Note. P_0 = initial probability; $\hat{\gamma}$ = the estimate of the power constant from Equation 6.

The large discrepancy in the initial probability of doing teamwork in the one-star collaboration network as opposed to the other three collaboration networks leads to a large frequency discrepancy, demonstrated in Table 6, in the number of times teams collaborate in the one-star collaboration network as opposed to the other three. As opposed to the case under the mutual interaction protocol, the one-star collaboration network leads to the least number of interactions in a team. Comparing the mutual and unidirectional interaction protocols under equal preferences for individual and collaborative action, Table 4, which considers the mutual interaction protocol, demonstrates a large advantage for those teams consisting of agents high in individual skills. Table 6, which considers the unidirectional interaction protocol, demonstrates a large advantage for those teams consisting of agents high in collaboration skills but yet not to the same degree as the mutual interaction protocol across all collaboration networks.

Table 6

Average frequency of individual and collaborative action across 1,000 teams for 100,000 time periods in the unidirectional interaction protocol with equal preferences for individual and collaborative action.

	Frequency	
Collaboration Network	Collaborative Action	Individual Action
One-star	83,376.19	16,623.81
Two-star	97,166.97	2,833.03
Three-star	98,854.19	1,145.81
Fully-connected	99,094.89	905.11

Team Performance

Team performance follows directly from knowledge of the number of times a team worked independently and interdependently and the average individual and collaboration skill levels of agents in a team. Where TP equals team performance, T equals the total number of time observations, P_{CA} equals the probability of working interdependently, P_{IA} equals the probability of working independently, S_{CA} equals the average probability of successful collaborative action, and S_{IA} equals the average probability of successful individual action, then

$$TP=T(P_{CA}*S_{CA}+P_{IA}*S_{IA}). \tag{7}$$

In the present work T equals 100,000, P_{CA} and P_{IA} come from the results in the previous section, and S_{CA} and S_{IA} equals 0.3, 0.5, or 0.7, which represents the mean of the respective skills distributions, depending on whether agents in a team possess low, medium, or high, respectively, individual and collaboration skills. P_{CA} equals zero for the mutual and unidirectional interaction protocols under preferences for individual action, while P_{IA} equals zero for the unidirectional interaction protocol under preferences for collaboration. For all other cases, P_{CA} and P_{IA} compute from the frequency columns of Tables 2, 4, and 6. This section reveals the nature of team performance when agents in a team possess equal and differential skill levels for individual and collaborative action.

Equal Skill Levels for Individual and Collaborative Action

For the situation when agents in a team possess equal skill level for individual and collaborative action, then Equation 7 reduces to

$$TP=T*S, \tag{8}$$

where S equals the average probability of success for individual and collaboration skills and all other terms defined previously, since P_{CA} plus P_{IA} always equals one. For the present work, the implications of Equation 8 indicate that there exist 24 different forms of team collaboration that lead to the same team performance for each of the three sets of equal skills levels. When a team consists of agents with low individual and collaboration skills, then TP = 100,000*.3 = 30,000. A similar computation reveals that the team performance of teams consisting of agents with simultaneous medium or high individual and collaboration skills equals 50,000 and 70,000, respectively. In total, this explains the team performance of 72 conditions.

Differential Skill Levels for Individual and Collaborative Action

Equation 7 reduces to

$$TP=T^*S_{IA} \tag{9}$$

for the mutual and unidirectional interaction protocol under preferences for individual action since P_{CA} equals zero and P_{IA} equals one in that case. Equation 9 indicates that team performance, for the eight collaboration networks under the mutual and unidirectional interaction protocol and preferences for individual action, depends only on the average probability of successful individual action without regard to the average probability of successful collaborative action. For the 16 conditions when a team consists of agents with low individual skills, then TP = 100,000*.3 = 30,000. A similar computation reveals that the team performance for the 32 conditions of teams consisting of agents with simultaneous medium or high individual skills equals 50,000 and 70,000, respectively. In total, this explains the team performance of 48 conditions.

For the unidirectional interaction protocol under preferences for teamwork, then Equation 7 reduces to

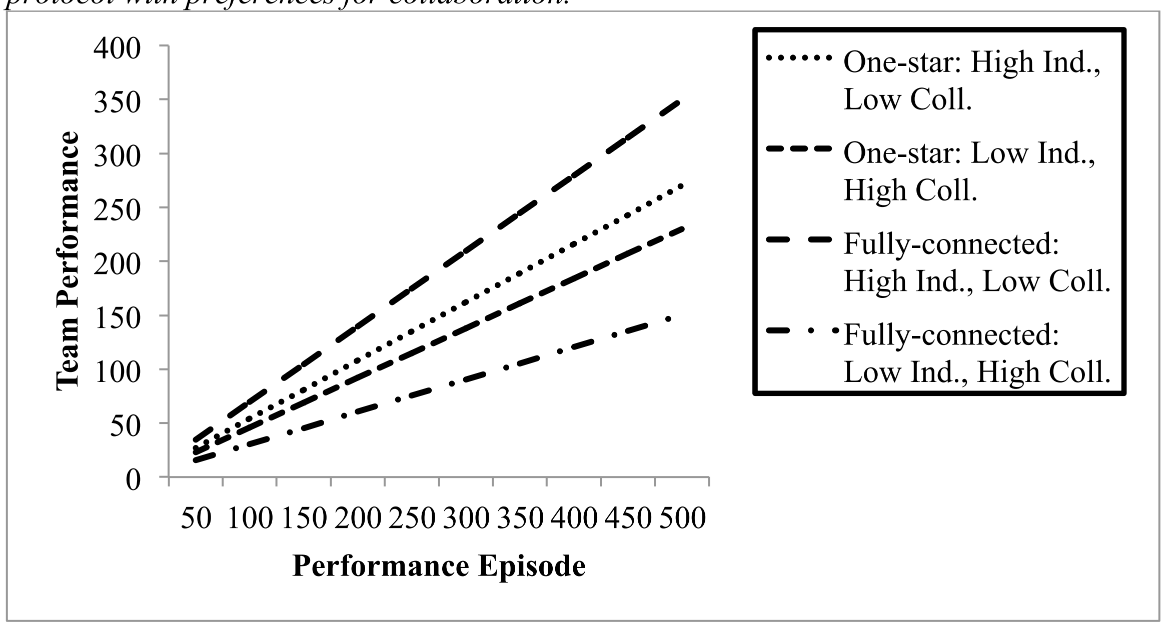
$$TP=T^*S_{CA} \tag{10}$$

since P_{IA} equals zero and P_{CA} equals one in that case. Equation 10 indicates that team performance, for the four collaboration networks under the unidirectional interaction protocol and preferences for collaboration, depends only on the average probability of successful collaborative action without regard to the average probability of successful individual action. For the eight conditions when a team consists of agents with low collaboration skills, then TP = 100,000*.3 = 30,000. A similar computation reveals that the team performance for the 16 conditions of teams consisting of agents with simultaneous medium or high collaboration skills equals 50,000 and 70,000, respectively. In total, this explains the team performance of 24 conditions.

The remaining 72 conditions consist of the 12 collaboration conditions consisting of the four different collaboration networks each under the mutual interaction protocol with preferences for collaboration, the mutual interaction protocol with equal preferences for individual and collaborative action, and the unidirectional interaction protocol with equal preferences for individual and collaborative action for each of the six combinations of individual and collaboration skill levels. Team performance for these 72 conditions follows Equation 7 wherein the frequency columns of Tables 2, 4, and 6 weigh the average probability of successful individual and collaborative action. Figures 3, 4, and 5 display team performance during the first 500 performance episodes for the one-star and fully-connected collaboration networks with agents possessing high individual skills and low collaboration skills, or vice versa, under different combinations of interaction protocols and preference structures. Figure 3 considers the mutual interaction protocol with preferences for collaboration. In this scenario, the fully-connected collaboration network with high individual skills and low collaboration skills performs best. The fully-connected collaboration network benefits from high individual skills but suffers from low individual skills as opposed to the one-star collaboration network since the fully-connected network leads to much greater individual action. Figure 4 considers the mutual interaction protocol with equal preferences for individual and collaborative action. In this scenario, the fully-connected and one-star collaboration networks lead to much more similar team performance for a team of agents that possess high skills for individual action and low skills for collaborative action than under the mutual interaction protocol with preferences for collaboration. The one-star collaboration network leads to much less collaborative action under equal preferences for individual and collaborative action than under preferences for collaborative action. Figure 5 considers the unidirectional interaction protocol with equal preferences for individual and collaborative action. In this scenario, the fully-connected collaboration network with high skills for collaborative action and low skills for individual action performs best. The fully-connected collaboration network benefits from high collaboration skills but suffers from low collaboration skills as opposed to the one-star collaboration network since the fully-connected network leads to much greater collaborative action.

Figure 3

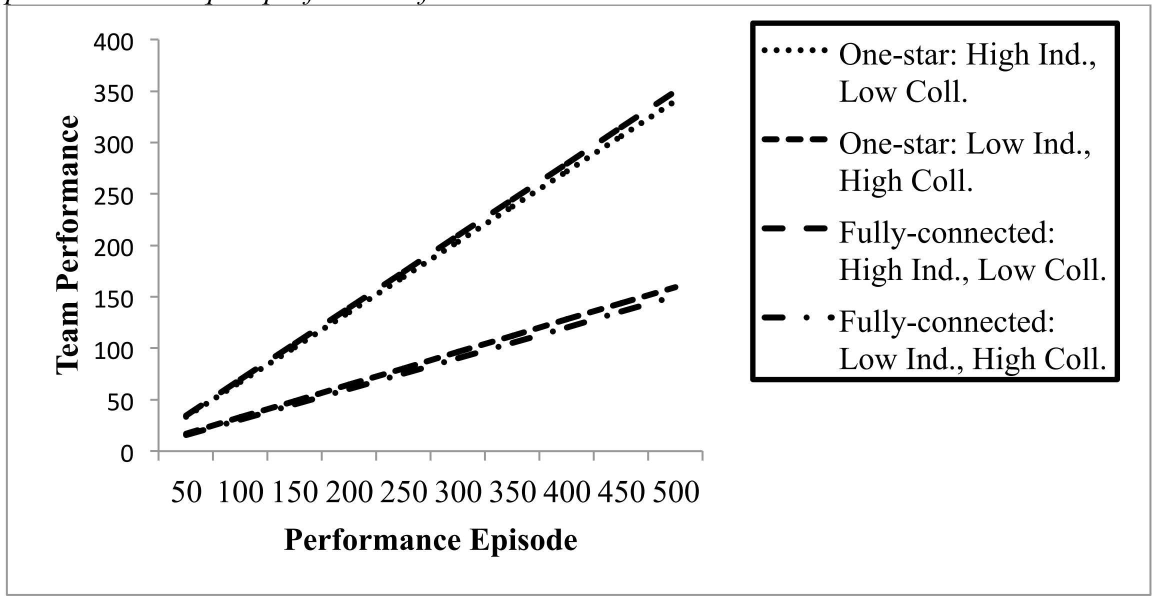
Team performance during the first 500 performance episodes under the mutual interaction protocol with preferences for collaboration.



Note. High Ind. = High individuals skills; Low Ind. = Low individual skills; High Coll. = High collaboration skills; Low Coll. = Low collaboration skills.

Figure 4

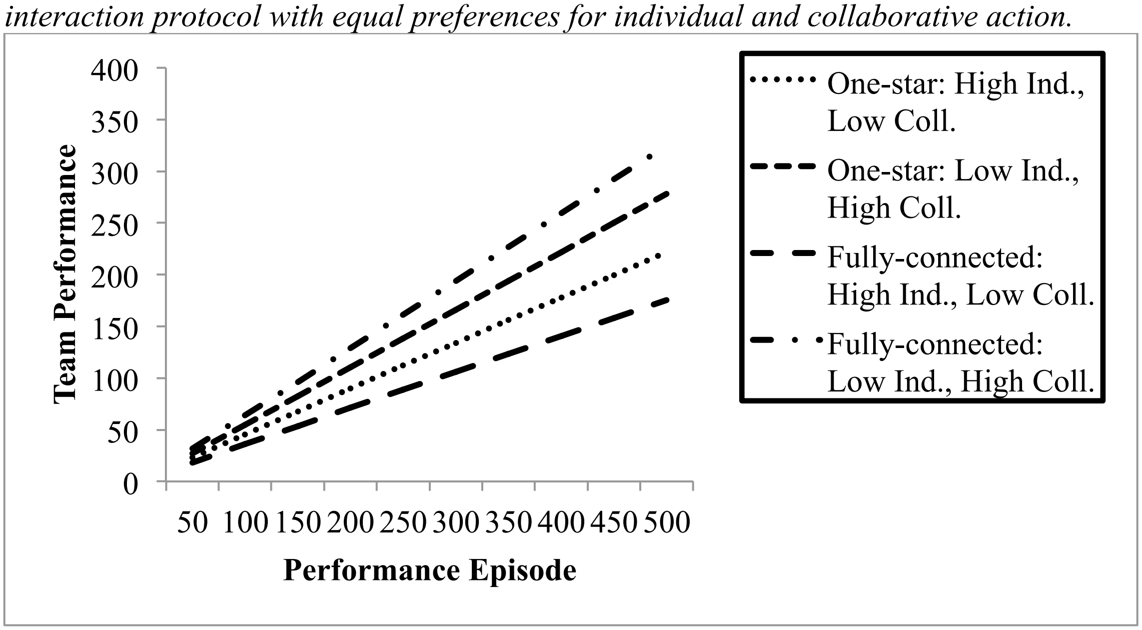
Team performance during the first 500 performance episodes under the mutual interaction protocol with equal preferences for individual and collaborative action.



Note. High Ind. = High individuals skills; Low Ind. = Low individual skills; High Coll. = High collaboration skills; Low Coll. = Low collaboration skills.

Figure 5

Team performance during the first 500 performance episodes under the unidirectional interaction protocol with equal preferences for individual and collaborative action.



Note. High Ind. = High individuals skills; Low Ind. = Low individual skills; High Coll. = High collaboration skills; Low Coll. = Low collaboration skills.

Demonstration of Principles

The four principles presented in the Introduction consider the nature of the mechanisms responsible for team collaboration and performance. The computational results may serve to offer a demonstration of these four principles. This section links the computational results with each principle. In turn, these principles lead to numerous implications, presented in the Discussion, important for the study of teams.

Principle 1

The first principle states that a team's composite skills for individual and collaborative action determine team performance. The present work demonstrates this principle in two ways. In the case when agents possess equivalent skills for individual and collaborative action, then their team performance follows Equation 8. This equation demonstrates that teams consisting of agents that possess high skills for both individual and collaborative action outperform those teams that consist of agents with medium skills who, in turn, outperform those teams that consist of agents with low skills. In the case when a team of agents collaborate in a manner to only utilize one set of skills, either their skills for individual action or their skills for collaborative action, then their team performance follows Equation 9 or Equation 10. Equation 9 demonstrates that for those collaboration conditions that lead to agents only utilizing their skills for individual action, then those teams consisting of agents with high skills for individual action outperform those teams consisting of agents with medium skills who, in turn, outperform those teams consisting of agents with low skills. Similarly, Equation 10 demonstrates that for those collaboration conditions that lead to agents only utilizing their skills for collaborative action, then those teams consisting of agents with high skills for collaborative action outperform those teams consisting of agents with medium skills who, in turn, outperform those teams consisting of agents with low skills. Thus, the present work demonstrates a team's composite skills for individual and collaborative action determine team performance.

Principle 2

The second principle states that the occurrence of collaboration within a team depends on the team's collaboration structure and protocol and the agents' preferences for collaboration. The first sub-section of the Results presents the number of times the 24 collaboration conditions in the present work leads a team of agents to utilize individual and collaborative action. Under the mutual or unidirectional interaction protocols with agents holding preferences for individual action, a team of agents only choose to utilize individual action for every performance episode. On the other hand, under the unidirectional interaction protocol with agents holding preferences for collaborative action, a team of agents only choose to utilize collaborative action for every performance episode. Therefore, the occurrence of collaboration within a team occurs most frequently under the unidirectional interaction protocol with agents holding preferences for collaborative action. For the 12 other collaboration conditions in the present work, teams display at least a little mixture of individual and collaborative action. Under the mutual interaction protocol and equal preferences for individual and collaborative action, agents predominantly choose individual action with the one-star collaboration network leading to the most occurrences of collaborative action. The one-star collaboration network leads to a much greater occurrence of collaborative action when agents hold preferences for collaborative action under the mutual interaction protocol, while the other three coordination networks lead to the same very small number (i.e., about 1 to 3) of collaborative actions as when agents hold equal preferences for individual and collaborative action. When a team operates under the unidirectional interaction protocol and agents hold equal preferences for individual and collaborative action, then a reversal happens where agents predominantly choose collaborative action. Again, the one-star collaboration network differs from the other three collaboration networks in that in this case it leads to greater individual actions than the other three collaboration networks. Taken as a whole, the present work demonstrates that the occurrence of collaboration within a team depends on the team's collaboration structure and protocol and the agents' preferences for collaboration.

Principle 3

The third principle states that a team maximizes its team performance when it collaborates in a manner that utilizes agents' most effective skills. Equation 8 implies that whenever all agents possess equivalent skills then the nature of team collaboration does not matter in terms of team performance. Stated alternatively, when all agents possess exactly the same skills, then all forms of team collaboration maximize team performance. However, whenever teams consist of agents with differential skills then different forms of team collaboration maximize team performance. In the present work, agents possessed differential skills in terms of individual and collaborative action. For such teams to maximize their team performance, then they should collaborate in a manner that leads to choosing the more effective skill set every single time. If a team possesses higher skills for individual action, then the agents may collaborate under the mutual or unidirectional interaction protocols and any collaboration network as long as they hold preferences for individual action. On the other hand, if a team possesses higher skills for collaborative action, then the agents may collaborate under unidirectional interaction and any collaboration network as long as they hold preferences for collaborative action. The present work does not investigate the case where some agents in a team hold a higher preference for individual action and other agents in the team hold a higher preference for collaborative action. However, the lessons from the present work apply to this case too. In order to maximize team performance in such a case, then the team would need to collaborate in a manner that leads to agents utilizing their most effective skill. This would require that the group of agents holding higher skills for individual action choose to utilize their skills for individual action and that the group of agents holding higher skills for collaborative action choose to utilize their skills for collaborative action. Indeed, this case presents a more general case than the one studied in the present work. Whenever agents in a team vary in their skill levels for individual and collaborative action, then agents with the highest skills for individual action should execute individual actions and agents with the highest skills for collaborative action should execute collaborative actions in order to maximize team performance. Thus, the present work demonstrates that a team maximizes its team performance when it collaborates in a manner that utilizes agents' most effective skills.

Principle 4

The fourth principle states that the form of team collaboration matters most when teams consist of agents with differential skill levels for individual and collaborative action. Equation 8 demonstrates that if a team consists of all agents possessing equivalent skill levels for both individual and collaborative action, then all forms of team collaboration lead to the same team performance. This presents the principle of equifinality in open systems (von Bertalanffy, 1968). However, whenever a team consists of agents who differ either in their skills between individual and collaborative action, their skills for individual action, or their skills for collaborative action, then particular forms of team collaboration serve to maximize team performance. The present work only investigated the case when agents differ in their skills between individual and collaborative action. Take, for example, a team consisting of agents with high skills for collaborative action but medium skills for individual action. This team should collaborate in a manner to utilize their skills for collaborative action such as operating under the unidirectional interaction protocol with agents holding preferences for collaboration. Yet, a team that consists of agents with high skills for individual action but medium skills for collaborative action should collaborate in a manner to utilize their skills for individual action. For this team, the mutual or unidirectional interaction protocol leads to agents utilizing their skills for individual action as long as the agents hold preferences for individual action. Although the present work does not examine the case when agents possess differences in their skills for individual action or differences in their skills for collaborative action, it follows that to maximize team performance the agents with highest skills should act. Thus, the present work demonstrates that the form of team collaboration matters most when teams consist of agents with differential skill levels for individual and collaborative action.

DISCUSSION

The present work undertook a computational study of team collaboration dynamics based on research from organizational (e.g., Bell, 2007) and sports (e.g., Passos et al., 2011) psychology and recent research on human dynamics by physicists (e.g., Min et al., 2009), and the integration of research from these various areas provides one of the contributions of the present work. The problem that the present work set out to solve considered how a team of individuals combine their efforts to maximally utilize their team competencies. In order to solve this problem, the present work investigated how various forms of team collaboration utilize team members' individual and collaboration skills. This section reviews and synthesizes findings, develops implications, and considers limitations and future directions before concluding.

Review and Synthesis of Results

The twenty-four collaboration conditions determined the frequency with which agents in a team worked independently and interdependently, while the nine skills conditions determined agents' success of working independently and interdependently. The interplay of these two sets of conditions determines whether or not a team of agents maximizes its team performance. In order for a team to achieve maximum team performance, the results indicate two general strategies. A team that develops both high individual and collaboration skills need not worry about the nature of their team collaboration. Indeed, as demonstrated by Equation 8, any time a team consists of equal individual and collaborative skill levels then the nature of team collaboration does not moderate team performance. Alternatively, a team that develops either high individual or collaboration skills, but not both, should develop a specific form of collaboration. In terms of a strict definition of maximum, then to maximize the performance of a team consisting of agents with high individual skills the team of agents should strive to develop preferences for individual action, whereas to maximize the performance of a team consisting of agents with high collaboration skills the team of agents should strive to develop preferences for collaboration under the unidirectional interaction protocol as these collaboration conditions lead to agents utilizing the appropriate high skill level. With a slightly less strict definition of maximum, then a team consisting of agents with high individual skills may also maximize team performance under any preference structure and collaboration network under the mutual interaction protocol other than the one-star collaboration network under preferences for collaboration (see Table 2) and the one-star collaboration network under equal preferences for individual and collaborative action (see Table 4).

Although the three collaboration parameters that make up the collaboration conditions all simultaneously impact the extent to which a team of agents works independently and interdependently, the results in the present work shed light on the impact of each collaboration parameter as well. Consider first the interaction protocol of a team. The results clearly indicate that for combinations of collaboration networks and preference structures that the mutual interaction protocol favors teams consisting of agents with high individual skills. The mutual interaction protocol restricts the number of opportunities for interaction since both agents must hold the highest preference to work with each other before they interact. The unidirectional interaction protocol, on the other hand, allows the preference structure and the collaboration network to determine the number of interactions that occur in a team. Indeed, the differential dynamics of team collaboration under the unidirectional interaction protocol with preferences for individual action, on the one hand, and preferences for collaboration, on the other hand, demonstrate that preference structure serves as the driving force in the resulting team collaboration dynamics wherein teams completely utilize individual skills in the former and collaboration skills in the latter case. These results align with the findings from Bourbousson et al.'s (2010) study of the frequency of different forms of collaboration in a basketball team. Bourbousson et al. (2010) found that when basketball teammates interacted with each other the far more dominant mode of interaction consisted of unidirectional dyadic interaction as opposed to mutual dyadic interaction. In other words, the unidirectional interaction protocol, on the whole, leads to greater number of interactions in a team than the mutual interaction protocol consistent with the findings from the present study.

As mentioned, the impact of the preference structure of a team comes to the forefront under the unidirectional interaction protocol. Under the unidirectional interaction protocol if agents hold preferences for individual action then agents work independently regardless of the collaboration network of the team, and similarly, if agents hold preferences for collaboration then agents work interdependently regardless of the collaboration network of the team. The impact of the preference structure of a team also comes to the forefront under the mutual interaction protocol when comparing the one-star collaboration network under preferences for collaboration versus the one-star collaboration network under equal preferences for individual and collaborative action. In the case when a team consists of agents with preferences for collaboration, then the initial probability of the team working interdependently equals 40% (see Table 1) and this probability remains constant over time. However, in the case when a team consists of agents with equal preferences for individual and collaborative action, then the initial probability equals 16% (see Table 3) and this probability slowly decays over time. In the one-star collaboration network each leaf node holds two preferences. Under the mutual interaction protocol and preferences for collaboration, though, each leaf node always wishes to interact with the star node, and the star node always interacts with one of the leaf nodes since it too holds the highest preference for collaboration. This leads to the star node always working interdependently. Under the mutual interaction protocol with equal preferences for individual and collaborative action, however, the leaf nodes no longer always prefer to interact with the star node, and the star node does not always interact with the leaf nodes. As a result, the probability of working interdependently in the one-star collaboration network under the mutual interaction protocol proves much higher at every point in time when agents hold preferences for collaboration as opposed to holding equal preferences for individual and collaborative action. If a team consists of agents with high collaboration skills, then the sacrificing nature of the star node under the scenario wherein agents hold preferences for collaboration marries up with research findings that suggest preferences for collaboration lead to effective team performance (e.g., Bell, 2007; Jung & Sosik, 1999) as this scenario leads to greater collaboration than the scenario wherein agents hold equal preferences for individual and collaborative action.

Similar to the preference structure of a team, the impact of the collaboration network of a team clearly comes to the forefront under the unidirectional interaction protocol with equal preferences for individual and collaborative action. In this collaboration condition, the collaboration network of the team serves as the driving force behind determining the frequency of collaboration. Examining Table 6 one may see that the frequency of collaboration trends upwards as the interconnectivity of a team increases wherein the one-star collaboration network represents the least interconnected team and the fully-connected collaboration network represents the most interconnected team. This result coincides with the results from the study by Passos et al. (2011). In their observation of a water polo game wherein equal preferences for individual and collaborative action and the unidirectional interaction protocol serve as reasonable assumptions, they found that the team that interacted more won the game. In other words, the team that more often took advantage of the collaboration skills of its players won the game. Under the unidirectional interaction protocol with equal preferences for individual and collaborative action, the fully-connected collaboration network leads to the greatest number of interactions and ultimately leads to success for teams consisting of agents with high collaboration skills. However, the interconnectivity of a team may not always lead to the greatest number of interactions as clearly demonstrated in Table 2 under the mutual interaction protocol and preferences for collaboration. In this collaboration condition, the least interconnected team, the one-star collaboration network, leads to the greatest number of interactions among teammates and leads to dramatically different team collaboration dynamics than the other three collaboration networks. This happens because under preferences for collaboration the leaf nodes do not possess competing collaboration preferences. All leaf nodes can only interact with one star node. Yet, for the other three collaboration networks every node possesses at least two competing collaboration preferences. For example, in the two-star collaboration network, the three leaf nodes possess two competing collaboration preferences. Given the restrictive nature of the mutual interaction protocol, this quickly leads to a preference grid-lock wherein each agent wants to interact with an agent who, in turn, wants to interact with a third agent. Min et al. (2009) labeled this situation "dynamic freezing" as at a certain point agents only execute individual actions.

The three collaboration parameters in the present work represent three potential mechanisms of team collaboration that impact the extent to which agents utilize their set of skills. Previous research finds that preferences for collaboration (e.g., Jung & Sosik, 1999), interconnectedness of teammates (e.g., Losada, 1999), and interaction protocol (e.g., Bourbousson et al., 2010) may all lead to effective team performance. Yet, the present work demonstrates that these descriptive findings only hold under certain collaboration conditions but not others. One cannot merely say that teams should always consist of individuals holding preferences for collaboration or greater interconnectedness always leads to effective team performance or that a particular interaction protocol always proves most effective. Instead, one requires a nuanced understanding of how these three collaboration parameters simultaneously impact the nature of team collaboration and how that ultimately leads to the effectiveness with which individuals utilize team competencies. The present work offers such a nuanced and integrative understanding of team collaboration dynamics and the resulting consequences for team performance.

Implications

The computational theory developed in the present work, underlined by its principles, serves to inform on numerous questions pertinent to the study of teams. This section reviews how the present work may apply to understanding some of the biggest issues in the team literature. These issues range from explaining team phenomena such as group process loss to answering practical questions such as selecting individuals for teams.

When the Whole May Exceed the Sum of its Parts

One key question for team researchers considers when the whole exceeds the sum of its parts (e.g., Tziner & Eden, 1985). In the present work, teams consist of agents possessing skills for individual and collaborative actions. Consider one team that consists of agents possessing high skill levels for both individual and collaborative actions and another team that consists of agents possessing high skill levels for collaborative actions but low skill levels for individual actions. The former team, on the whole, possesses higher skill levels than the latter team. As demonstrated in the Results, the former team performs well without regard to collaboration condition. The latter team, although on the whole possessing less skill, may achieve the same performance level as the former team if the latter team operates under unidirectional interaction with preferences for collaboration. Under alternative collaboration conditions the latter team does not achieve the same level of performance as the former team. In other words, there exist specific collaboration conditions that serve to maximize the latter team's skills, and thereby, achieve performance levels equivalent to a team that, on the whole, consists of more skillful agents. Consider a second example where one team consists of agents with moderate skill levels for individual actions and high skill levels for collaborative actions and the other team consisting of agents as the latter team in the previous example. Just as in the previous case, the former team, on the whole, consists of more skillful agents than the latter team. However, the former team in this case can only maximize its performance potential under a specific set of collaboration conditions just like the latter team. In fact, both teams in this case maximize their performance under unidirectional interaction and preferences for collaboration. If, however, the former team operated under unidirectional interaction and preferences for individual action while the latter team operates under the optimal collaboration condition, then the more skilled team would perform worse than the less skilled team. Thus, both examples serve to demonstrate how the present work answers when the whole exceeds the sum of its parts wherein a less skilled team may outperform or perform equally as well as a more skilled team.

Group Process Loss

One of the most common findings in the group and team research literature indicates that teams often underperform as a result of group process loss (Hill, 1982). A team that does not utilize the most potent abilities of its members suffers from group process loss (Kerr & Tindale, 2004). In the present work, Equation 8 demonstrates that when a team consists of agents equal on skill level for individual and collaborative actions, then any collaboration condition leads to the same team performance. Such teams do not experience any group process loss. However, whenever a team consists of agents who do not possess equivalent skill levels for individual and collaborative actions, then teams may experience group process loss. Take, for example, a team consisting of agents with high skills for individual action but low skills for collaborative action. If this team operates under unidirectional interaction and preferences for collaboration, then this team does not maximize its performance potential because all team members would utilize their less potent skills. In other words, when a collaboration condition does not maximize the skills of a team, then it offers an example of group process loss. The present work indicates that group process loss may only occur when a team consists of agents with varying skill levels. For teams consisting of agents with varying skill levels, then any underperformance typifies group process loss resulting from the inability of a team to collaborate in a manner to utilize team members' most potent skills. Thus, the present work identifies what collaboration conditions lead to group process loss for a given team skill set.

Equifinality

A key idea in the study of open systems such as teams considers the notion of equifinality (von Bertalanffy, 1968). The notion of equifinality says that for a given open system there may exist several different means or pathways to the same end. The present work demonstrates the notion of equifinality when two teams achieve the same team performance while operating under different collaboration conditions. In particular, equifinality occurs in the present work whenever teams possess the same skill levels (i.e., high, medium, or low) for individual and collaborative action. In each of these cases, every single collaboration condition leads to the same team performance. Yet, there exists still another way that equifinality manifests itself in the present work. Take for example one team consisting of agents with high skill levels for individual action but low skill levels for collaborative action and another team with the opposite set of skills. This case presents a situation where two teams possess different skill sets. The first team achieves its maximal performance under unidirectional interaction and preferences for individual action or under mutual interaction and preferences for individual action, which again demonstrates that teams may achieve the same team performance via different collaboration conditions. In addition to that type of equifinality, the second team achieves the same team performance as the first team if it operates under unidirectional interaction and preferences for collaborative action. This presents a case where two teams possess different skill sets but yet still achieve the same team performance. In other words, different skill sets may lead to the same team performance via different forms of team collaboration. Thus, the present work demonstrates the key notion of equifinality in open systems such as teams.

Diversity of Skills

One of the key questions in the team literature considers the impact of the diversity of skills of team members on team performance (e.g., Gladstein, 1984). The present work considers agents with two sets of skills: one set of skills for individual action and another for collaborative action. When the agents possess the same skill level on both sets of skills, then the team's performance only depends on their skill level as demonstrated by Equation 8. These teams represent homogenous teams with respect to skill levels. Homogenous teams may lead to good performance if a team consists of agents with high skill levels for both individual and collaborative action, while homogenous teams may lead to poor performance if a team consists of agents with low skill levels for both individual and collaborative action. For teams heterogenous in their skill sets, then the team's performance depends on the nature of team collaboration. Heterogenous teams succeed when they collaborate in a manner to utilize their most effective skills, and they fail when they collaborate in a manner that does not utilize their most effective skills. The present work focuses on teams maximizing their skills across two skill sets. Within each of those two skill sets teams consist of all agents possessing high, medium, or low skills levels for individual and collaborative action. If teams consisted of agents with diverse levels of skills for individual and collaborative action, then such teams would maximize their performance if they utilize team members with the highest skills for individual action and if they utilize team members with the highest skills for collaborative action. Although the difficulty of the maximization problem of finding team members with the highest skills increases when agents may possess differential skills for individual action and differential skills for collaborative action, the principle of utilizing the skills of the most able team members remains the same. Hence, the present work speaks to the impact of diversity of skills within a team.

Backing-up Behavior

Recent research indicates that backing-up behavior in teams may not prove beneficial when it leads to team members neglecting their own responsibilities (Barnes et al., 2008). In the present work, the unidirectional mode of interaction under preferences for collaboration always leads teammates to choose to ask a teammate for help in completing tasks. Yet, this proves effective only if teammates possess skill at collaborative actions. If teammates possess greater skill at individual action, then this would lead teammates to neglect to utilize their most effective skills. Ultimately, it would lead to non-optimal team performance. The mutual form of interaction does a much better job of protecting team members from neglecting their skills for individual actions even when team members hold preferences for collaborative action. Indeed, in the mutual form of interaction an agent that asks another agent to complete a task only receives help if the other agent possesses the highest preference to work with the requester. In this way, the present work captures the notion that teammates helping each other may not prove beneficial to team success.

Centrality of Team Members

In any given team some team members may prove more central than other team members. The centrality of a team member may relate to the influence of that team member with regard to important team outcomes such as team performance (Klein, Lim, Saltz, & Mayer, 2004). The level of interconnectedness of a team member indicates his centrality. In the present work, star nodes could interact with any teammate while leaf nodes could only interact with star nodes. Star nodes represent central team members in the present work. In the one-star collaboration network there exists only one agent who may interact with all of his teammates, and therefore, all interactions involve him. The fully-connected collaboration network represents the case when all nodes possess equal influence in terms of the number of interactions in the team. A single star alters the nature of team collaboration under both mutual and unidirectional interaction. In the case of mutual interaction, the one-star collaboration network leads to a situation where the star node never undertakes an individual action if all team members hold preferences for collaboration. If all team members hold equal preferences for individual and collaborative action, then the single star still prohibits the extinction of interaction in the team as opposed to the other three collaboration networks. Under the case of unidirectional interaction and team members holding equal preferences for individual and collaborative action, the single star network now leads to much more individual action than the other three collaboration networks. Thus, a team consisting of a single central team member possesses rather different team collaboration dynamics than teams with at least two central team members. Hence, the present work highlights the impact of centrality of team members on team performance.

Selecting Individuals to a Formed Team

Another important question for teams considers the consequences of one team member leaving a team and another team member joining the team (Morgeson et al., 2005). In the present work, an agent possesses three individual characteristics: degree of preference for collaboration, skill level for individual action, and skill level for collaborative action. To the extent that a new team member differs in the individual characteristics from an outgoing team member, then the nature of team collaboration and performance would change. If a new team member differs in his degree of preference for collaboration than an outgoing member, then the nature of team collaboration changes. For instance, if the team operates under unidirectional interaction and all team members possess a preference for collaboration, then this team would always utilize its skills for collaborative action. However, if one of these team members leave and a new team member holds preference for individual action, then the team would no longer always utilize its skill for collaborative action. Instead, whenever the new team member completes tasks during a performance episode he will utilize his individual skills. Team performance would change for the better if the outgoing and new team member both possessed strongest skills for individual action as only the new team member would use his most effective skills. Similarly, team performance would change for the worse if the outgoing and new team member both possessed strongest skills for collaborative action as only the outgoing team member would use his most effective skills. Thus, the present work demonstrates the impact of switching out an outgoing team member with a new team member.

Newly Formed Teams

The team members of a newly formed team may require some time before developing the necessary skills for individual and collaborative actions required of their team task (Ilgen et al., 2005). The present work assumes that agents already possess developed skills. Yet, if the skills of the agents changes over performance episodes, then maximal team performance would require that at each performance episode agents utilize their strongest skills. If an agent possesses stronger skills for individual action at an initial performance episode and that same agent possesses stronger skills for collaborative action at a later performance episode, then maximal performance would require the agent to utilize his skills for individual action initially and his skills for collaborative action later. In order for agents to utilize their most effective skills during each performance episode, this would mean that the manner in which teammates collaborate would need to change to allow agents to utilize their most effective skills. A team would need to change their preferences for individual and collaborative action or their interaction protocol and collaboration network to take advantage of team members' strongest skills. To the extent that a team does not collaborate in a manner to utilize agents' most effective skills, then the team's performance suffers and may serve as an another example of group process loss. Thus, the present work informs on how a newly formed team may navigate its way toward maximizing team performance as team members develop their skills.

Limitations and Future Directions

The limitations of computational studies serve both to place boundaries on results, and, at the same time, offer opportunities for new investigations. Consider the measurement of team performance in the present work. For each performance episode a selected agent either contributes to team performance by working independently or by working interdependently with a teammate each with a certain probability of success. In this case, on average, each agent performs the same number of times, and thus, each agent contributes, on average, equally to team performance. In pooled interdependence tasks (see Saavedra et al, 1993; Van de Ven et al., 1976) each individual completes the whole task on their own. Tasks that a team of individuals may complete with a single-resource (see Steiner, 1966; Shiflett, 1979) do not require interaction among team members. In the present work, agents possessed general skills which allowed them to complete various tasks composing a team project by working independently or together with a teammate. Yet, single team members did not complete the whole task on their own. Interestingly, pooled interdependence tasks represent a special case of Equation 9 wherein team performance rests on the individual skills of a single individual in the team as opposed to the whole team like in the present work. All such teams whose team performance follows Equation 9 may merely represent teams by name but not by action. In other words, such teams do not consist of interacting individuals, which often forms a fundamental aspect in definitions of teams (e.g., Kozlowski & Bell, 2003).

As mentioned, in the present work, agents possessed general skills to complete tasks composing a team project by working independently or together with a teammate. Yet, the completion of tasks may require specific roles. Tasks defined by sequential and reciprocal workflow may necessitate team members to possess specific expertise, and therefore, serve a particular role. Such interdependence, though, does not lead to team members collaborating to complete tasks making up the team project, but instead, leads to teammates providing inputs for each other to use on the next task (e.g., Van de Ven., 1976). This presents a situation where team members utilize individual skills, but their performance depends on other team members. In sequential workflow, each person must correctly complete their task before the product goes on to the next teammate. Similarly, reciprocal workflow requires team members to coordinate their individual actions, which serve as inputs to a teammate. Thus, sequential and reciprocal workflow requires a team to complete a project consisting of sequenced or coordinated tasks. The present work, though, assumes that agents may complete tasks during each performance episode via their individual or collaboration skills. If nothing prevents teammates working on a sequenced or coordinated set of tasks from collaborating with each other, then the results from the present work may inform team performance in such tasks as well. However, if constraints exist that prevent collaboration among team members then the present work may not adequately speak to such tasks.

The manipulations of the three collaboration parameters in the present work often led to trivial team collaboration dynamics as exemplified by those collaboration conditions that follow Equations 9 and 10. This may result from strong manipulations in the present work. However, numerous possible combinations exist that probably lead to different and less trivial collaboration dynamics than some of those observed here. For example, in the present work teams consisted of all agents holding preferences for collaboration or all agents holding preferences for individual action or all agents holding equal preferences for individual and collaborative action. Teams composed of some agents holding preferences for collaboration and other agents holding preferences for individual action may lead to new and interesting team collaboration dynamics. Similarly, even for a five-person team, many different collaboration networks may exist. For instance, Bourbousson et al., (2010) found that the basketball team in their investigation often worked in a network with two teammates forming a dyad and three teammates forming a triad. Such a network may lead to a different form of team collaboration dynamics than those observed here. Along the same lines, a particular dyad may operate under the mutual interaction protocol while another dyad or perhaps triad may operate under the unidirectional interaction protocol. This too should lead to a different set of, and perhaps, less trivial team collaboration dynamics than those observed in the present work.

Teams consisted with all agents possessing low, medium, or high individual and collaboration skills. For example, one team consisted of all agents possessing high individual skills and medium collaboration skills. However, teams could all consist of agents with some possessing low individual skills and others possessing high individual skills, while at the same time the agents in a team may vary with respect to their collaborative skill levels. Finding a collaboration condition to maximize team performance under this scenario would prove more difficult than for the skills conditions in the present work. Most likely it would require each agent possessing the exact same pattern of preferences for collaboration and individual action as the pattern of their collaborative and individual skill levels under the unidirectional interaction protocol as this protocol allows preferences to dominate in determining whether agents act independently or interdependently.

With regard to interactions, the present work only considers dyadic interaction. Yet, teammates may interact as part of triads or even greater groupings. Naturally, the performance of a team may depend on some dyadic interactions and some triadic interactions. Additionally, interactions in a team may follow a particular pattern. A sequential pattern might mean that one agent may need the help of another agent to complete certain tasks, but that agent, in turn, needs the help of a third agent to complete a different set of tasks (e.g., Saavedra et al., 1993). On the other hand, a hierarchical pattern might mean that an agent interacts only with agents at the level above and below him but not with any other agents.

All five independent variables in the present study remained static over time. Although preferences for collaboration and skill levels updated after an agent performed, the updates only remained in the specified preference (i.e., preference for collaboration, preference for individual action, or equal preferences for individual and collaborative action) and skill level (i.e., low, medium, or high) range for that agent. A team of individuals may change the nature of their collaboration network as they learn certain individuals work best with each other; they may change their preferences for collaboration and individual action as they learn the nature of other individuals and the tasks at hand; and they may change their interaction protocol depending on task and individual restraints. If each performance episode consists of tasks that require a different skill set, then the individual and collaborative skill levels of individuals in the team may change over time as well. Making each independent variable in the present work dynamic would certainly lead to non-trivial team collaboration dynamics and provide a rather difficult maximization of team performance problem. Additionally, several different mechanisms may determine the nature of the dynamics of each independent variable in the present work, and each mechanism may lead to different team collaboration dynamics.

Conclusion

The present work developed a computational study of team collaboration dynamics and set out to solve how teammates may collaborate to maximally utilize their team competencies to yield effective team performance. Results suggest that the solution to this problem requires a nuanced understanding of team collaboration mechanisms. A team's collaboration network and interaction protocol and the preference structure of the individuals in a team all simultaneously impact the extent to which team members utilize individual and collaboration skills. Effective team performance rests on a team developing team collaboration dynamics that lead to the team's members utilizing their most effective skills. Numerous implications important to the study of teams follow from the set of principles developed in the present work, while limitations of the present work offer numerous extensions to develop a more complete computational theory of team collaboration and performance.

APPENDICES

APPENDIX A

R Simulation Code for the Computation of Frequency of Individual and Collaborative Action

Mutual Interaction Protocol

```
m = 1000 # number of teams
t = 100000 # number of time steps
n = 5 # number of nodes
z <- array(0,dim=c(n+1,m*t)) # data matrix

for (j in 1:m) {
k = 25 # number of priorities/preferences for fully-connected collaboration network
# k = 23, 19, and 13 for three-star, two-star, and one-star collaboration networks
w <- array(0,dim=c(k,4))
### fully-connected collaboration network
w[,1] <- c(1,1,1,1,1,2,2,2,2,2,3,3,3,3,3,4,4,4,4,4,5,5,5,5,5)
w[,2] <- c(1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,5)
### three-star collaboration network
#w[,1] <- c(1,1,1,1,1,2,2,2,2,2,3,3,3,3,3,4,4,4,4,5,5,5,5)
#w[,2] <- c(1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,1,2,3,5)
### two-star collaboration network
#w[,1] <- c(1,1,1,1,1,2,2,2,2,2,3,3,3,4,4,4,5,5,5)
#w[,2] <- c(1,2,3,4,5,1,2,3,4,5,1,2,3,1,2,4,1,2,5)
### one-star collaboration network
#w[,1] <- c(1,1,1,1,1,2,2,3,3,4,4,5,5)
#w[,2] <- c(1,2,3,4,5,1,2,1,3,1,4,1,5)

###sets preferences
for (i in 1:k) {
	if (w[i,1] == w[i,2]) {
		w[i,3] = runif(1,.6,.8) # preference for individual action
	}
	if (w[i,1] != w[i,2]) {
		w[i,3] = runif(1,.2,.4) # preference for collaboration
	}
}
###sets skill levels
for (i in 1:k) {
	if (w[i,1] == w[i,2]) {
		w[i,4] = runif(1,.6,.8) # skill level for individual action
	}
	if (w[i,1] != w[i,2]) {
		w[i,4] = runif(1,.6,.8) # skill level for collaborative action
```

```
		}
}
w <- data.frame(w)
names(w) <- c("Queue","Task","Priority","Skill")

### mutual interaction protocol
for (l in 1:t) {
	q <- sample(1:n, 1, replace = TRUE, prob = c(.2,.2,.2,.2,.2))
	g <- w[w$Queue == q,]
	gByPriority <- g[rev(order(g[,"Priority"])),]
	###individual action
	if (q == gByPriority[1,]$Task) {
		perf <- sample(c(0,1), 1, replace = TRUE, prob = c(1-gByPriority[1,]$Skill,
			gByPriority[1,]$Skill))
		z[n+1,(t*(j-1)+l)] <- perf
		z[q,(t*(j-1)+l)] <- q
		w[w$Queue == q & w$Task == q,]$Priority <- runif(1,.6,.8)
		w[w$Queue == q & w$Task == q,]$Skill <- runif(1,.6,.8)
	 }
	###collaborative action
	if (q != gByPriority[1,]$Task) {
		h <- w[w$Queue == gByPriority[1,]$Task,]
		hByPriority <- h[rev(order(h[,"Priority"])),]
		if (hByPriority[1,]$Task == q) {
			perf <- sample(c(0,1), 1, replace = TRUE, prob = c(1-
				gByPriority[1,]$Skill, gByPriority[1,]$Skill))
			z[n+1,(t*(j-1)+l)] <- perf
			z[q,(t*(j-1)+l)] <- gByPriority[1,]$Task
			w[w$Queue == q & w$Task == gByPriority[1,]$Task,]$Priority <-
				runif(1,.2,.4)
			w[w$Queue == gByPriority[1,]$Task & w$Task == q,]$Priority <-
				runif(1,.2,.4)
			w[w$Queue == q & w$Task == gByPriority[1,]$Task,]$Skill <-
				runif(1,.6,.8)
			w[w$Queue == gByPriority[1,]$Task & w$Task == q,]$Skill <-
				runif(1,.6,.8)
		}
		###individual action
		if (hByPriority[1,]$Task != q) {
			perf <- sample(c(0,1), 1, replace = TRUE, prob = c(1-w[w$Queue == q &
				w$Task == q,]$Skill, w[w$Queue == q & w$Task == q,]$Skill))
			z[n+1,(t*(j-1)+l)] <- perf
			z[q,(t*(j-1)+l)] <- q
			w[w$Queue == q & w$Task == q,]$Priority <- runif(1,.6,.8)
			w[w$Queue == q & w$Task == q,]$Skill <- runif(1,.6,.8)
		}
```

```
		}
}
}
```

Unidirectional Interaction Protocol

```
m = 1000 # number of teams
t = 100000 # number of time steps
n = 5 # number of nodes
z <- array(0,dim=c(n+1,m*t)) # data matrix

for (j in 1:m) {
k = 25 # number of priorities/preferences for fully-connected collaboration network
# k = 23, 19, and 13 for three-star, two-star, and one-star collaboration networks
w <- array(0,dim=c(k,4))
### fully-connected collaboration network
w[,1] <- c(1,1,1,1,1,2,2,2,2,2,3,3,3,3,3,4,4,4,4,4,5,5,5,5,5)
w[,2] <- c(1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,5)
### three-star collaboration network
#w[,1] <- c(1,1,1,1,1,2,2,2,2,2,3,3,3,3,3,4,4,4,4,5,5,5,5)
#w[,2] <- c(1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,1,2,3,5)
### two-star collaboration network
#w[,1] <- c(1,1,1,1,1,2,2,2,2,2,3,3,3,4,4,4,5,5,5)
#w[,2] <- c(1,2,3,4,5,1,2,3,4,5,1,2,3,1,2,4,1,2,5)
### one-star collaboration network
#w[,1] <- c(1,1,1,1,1,2,2,3,3,4,4,5,5)
#w[,2] <- c(1,2,3,4,5,1,2,1,3,1,4,1,5)

###sets preferences
for (i in 1:k) {
	if (w[i,1] == w[i,2]) {
		w[i,3] = runif(1,.6,.8) # preference for individual action
	}
	if (w[i,1] != w[i,2]) {
		w[i,3] = runif(1,.2,.4) # preference for collaboration
	}
}
w <- data.frame(w)
names(w) <- c("Queue","Task","Priority","Skill")

### unidirectional interaction protocol
for (l in 1:t) {
	q <- sample(1:n, 1, replace = TRUE, prob = c(.2,.2,.2,.2,.2))
	g <- w[w$Queue == q,]
	gByPriority <- g[rev(order(g[,"Priority"])),]
	###individual action
```

```
        if (q == gByPriority[1,]$Task) {
                perf <- sample(c(0,1), 1, replace = TRUE, prob = c(1-gByPriority[1,]$Skill,
                        gByPriority[1,]$Skill))
                z[n+1,(t*(j-1)+l)] <- perf
                z[q,(t*(j-1)+l)] <- q
                w[w$Queue == q & w$Task == q,]$Priority <- runif(1,.2,.4)
                w[w$Queue == q & w$Task == q,]$Skill <- runif(1,.6,.8)
         }
        ###collaborative action
        if (q != gByPriority[1,]$Task) {
                perf <- sample(c(0,1), 1, replace = TRUE, prob = c(1-gByPriority[1,]$Skill,
                        gByPriority[1,]$Skill))
                z[n+1,(t*(j-1)+l)] <- perf
                z[q,(t*(j-1)+l)] <- gByPriority[1,]$Task
                w[w$Queue == q & w$Task == gByPriority[1,]$Task,]$Priority <- runif(1,.6,.8)
                w[w$Queue == gByPriority[1,]$Task & w$Task == q,]$Priority <- runif(1,.6,.8)
                w[w$Queue == q & w$Task == gByPriority[1,]$Task,]$Skill <- runif(1,.6,.8)
                w[w$Queue == gByPriority[1,]$Task & w$Task == q,]$Skill <- runif(1,.6,.8)
        }
}
}
```

APPENDIX B

Computing the Initial Probability of Individual and Collaborative Action

P = Probability
CA = Collaborative action
IA = Individual action

<u>Mutual Interaction Protocol, Preferences for Collaboration, and Fully-Connected Collaboration Network</u>

P(CA) = P(Selecting Node 1)*P(Selecting CA for Node 1)*P(Node 1 Selecting CA with Node 2)*P(Selecting CA for Node 2)*P(Node 2 Selecting CA with Node 1)*(Number of CA Preferences)*(Number of Nodes) = .2*1*.25*1*.25*4*5 = .25

P(IA) = [P(Selecting Node 1)*P(Selecting IA for Node 1) + P(Selecting Node 1)*P(Selecting CA for Node 1)*P(Node 1 Selecting CA with Node 2)*P(Selecting CA for Node 2)*P(Node 2 NOT Selecting CA with Node 1)*(Number of CA Preferences)]*(Number of Nodes) = (.2*0 + .2*1*.25*1*.75*4)*5 = .75

<u>Mutual Interaction Protocol, Preferences for Collaboration, and Three-Star Collaboration Network</u>

P(CA_{STAR}) = [P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Leaf Nodes) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Star Node)*P(Selecting CA for Other Star Node)*P(Other Star Node Selecting CA with Star Node)*(Number of Other Star Nodes)]*(Number of Star Nodes) = (.2*1*.25*1*.33*2 + .2*1*.25*1*.25*2)*3 = .175

P(CA_{LEAF}) = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*1*.33*1*.25*3*2 = .1

P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = .275

P(IA_{STAR}) = [P(Selecting Star Node)*P(Selecting IA for Star Node) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node NOT Selecting CA with Star Node)*(Number of Leaf Nodes) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other

Star Node)*P(Selecting CA for Other Star Node)*P(Other Star Node NOT Selecting CA with Star Node)*(Number of Other Star Nodes)]*(Number of Star Nodes) = (.2*0 + .2*1*.25*1*.67*2 + .2*1*.25*1*.75*2)*3 = .425

$P(IA_{LEAF})$ = [P(Selecting Leaf Node)*P(Selecting IA for Leaf Node) + P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node NOT Selecting CA with Leaf Node)*(Number of Star Nodes)]*(Number of Leaf Nodes) = (.2*0 + .2*1*.33*1*.75*3)*2 = .3

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = .725$

<u>Mutual Interaction Protocol, Preferences for Collaboration, and Two-Star Collaboration Network</u>

$P(CA_{STAR})$ = [P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Leaf Nodes) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Star Node)*P(Selecting CA for Other Star Node)*P(Other Star Node Selecting CA with Star Node)*(Number of Other Star Nodes)]*(Number of Star Nodes) = (.2*1*.25*1*.5*3 + .2*1*.25*1*.25*1)*2 = .175

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*1*.5*1*.25*2*3 = .15

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = .325$

$P(IA_{STAR})$ = [P(Selecting Star Node)*P(Selecting IA for Star Node) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node NOT Selecting CA with Star Node)*(Number of Leaf Nodes) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Star Node)*P(Selecting CA for Other Star Node)*P(Other Star Node NOT Selecting CA with Star Node)*(Number of Other Star Nodes)]*(Number of Star Nodes) = (.2*0 + .2*1*.25*1*.5*3 + .2*1*.25*1*.75*1)*2 = .225

$P(IA_{LEAF})$ = [P(Selecting Leaf Node)*P(Selecting IA for Leaf Node) + P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node NOT Selecting CA with Leaf Node)*(Number of Star Nodes)]*(Number of Leaf Nodes) = (.2*0 + .2*1*.5*1*.75*2)*3 = .45

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = .675$

Mutual Interaction Protocol, Preferences for Collaboration, and One-Star Collaboration Network

$P(CA_{STAR})$ = P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Leaf Nodes) = .2*1*.25*1*1*4 = .2

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*(Number of Leaf Nodes) = .2*1*1*1*.25*4 = .2

P(CA) = $P(CA_{STAR})$ + $P(CA_{LEAF})$ = .4

$P(IA_{STAR})$ = P(Selecting Star Node)*P(Selecting IA for Star Node) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node NOT Selecting CA with Star Node)*(Number of Leaf Nodes) = .2*0 + .2*1*.25*1*0*4 = 0

$P(IA_{LEAF})$ = [P(Selecting Leaf Node)*P(Selecting IA for Leaf Node) + P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node NOT Selecting CA with Leaf Node)]*(Number of Leaf Nodes) = (.2*0 + .2*1*1*1*.75)*4 = .6

P(IA) = $P(IA_{STAR})$ + $P(IA_{LEAF})$ = .6

Mutual Interaction Protocol, Preferences for Individual Action, and Fully-Connected Collaboration Network

P(CA) = P(Selecting Node 1)*P(Selecting CA for Node 1)*P(Node 1 Selecting CA with Node 2)*P(Selecting CA for Node 2)*P(Node 2 Selecting CA with Node 1)*(Number of CA Preferences)*(Number of Nodes) = .2*0*.25*0*.25*4*5 = 0

P(IA) = [P(Selecting Node 1)*P(Selecting IA for Node 1) + P(Selecting Node 1)*P(Selecting CA for Node 1)*P(Node 1 Selecting CA with Node 2)*P(Selecting CA for Node 2)*P(Node 2 NOT Selecting CA with Node 1)*(Number of CA Preferences)]*(Number of Nodes) = (.2*1 + .2*0*.25*0*.75*4)*5 = 1

Mutual Interaction Protocol, Preferences for Individual Action, and Three-Star Collaboration Network

$P(CA_{STAR})$ = [P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star

Node)*(Number of Leaf Nodes) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Star Node)*P(Selecting CA for Other Star Node)*P(Other Star Node Selecting CA with Star Node)*(Number of Other Star Nodes)]*(Number of Star Nodes) = (.2*0*.25*0*.33*2 + .2*0*.25*0*.25*2)*3 = 0

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*0*.33*0*.25*3*2 = 0

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = 0$

$P(IA_{STAR})$ = [P(Selecting Star Node)*P(Selecting IA for Star Node) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node NOT Selecting CA with Star Node)*(Number of Leaf Nodes) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Star Node)*P(Selecting CA for Other Star Node)*P(Other Star Node NOT Selecting CA with Star Node)*(Number of Other Star Nodes)]*(Number of Star Nodes) = (.2*1 + .2*0*.25*0*.67*2 + .2*0*.25*0*.75*2)*3 = .6

$P(IA_{LEAF})$ = [P(Selecting Leaf Node)*P(Selecting IA for Leaf Node) + P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node NOT Selecting CA with Leaf Node)*(Number of Star Nodes)]*(Number of Leaf Nodes) = (.2*1 + .2*0*.33*0*.75*3)*2 = .4

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = 1$

Mutual Interaction Protocol, Preferences for Individual Action, and Two-Star Collaboration Network

$P(CA_{STAR})$ = [P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Leaf Nodes) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Star Node)*P(Selecting CA for Other Star Node)*P(Other Star Node Selecting CA with Star Node)*(Number of Other Star Nodes)]*(Number of Star Nodes) = (.2*0*.25*0*.5*3 + .2*0*.25*0*.25*1)*2 = 0

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*0*.5*0*.25*2*3 = 0

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = 0$

$P(IA_{STAR})$ = [P(Selecting Star Node)*P(Selecting IA for Star Node) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node NOT Selecting CA with Star Node)*(Number of Leaf Nodes) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Star Node)*P(Selecting CA for Other Star Node)*P(Other Star Node NOT Selecting CA with Star Node)*(Number of Other Star Nodes)]*(Number of Star Nodes) = (.2*1 + .2*0*.25*0*.5*3 + .2*0*.25*0*.75*1)*2 = .4

$P(IA_{LEAF})$ = [P(Selecting Leaf Node)*P(Selecting IA for Leaf Node) + P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node NOT Selecting CA with Leaf Node)*(Number of Star Nodes)]*(Number of Leaf Nodes) = (.2*1 + .2*0*.5*0*.75*2)*3 = .6

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = 1$

Mutual Interaction Protocol, Preferences for Individual Action, and One-Star Collaboration Network

$P(CA_{STAR})$ = P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Leaf Nodes) = .2*0*.25*0*1*4 = 0

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*(Number of Leaf Nodes) = .2*0*1*0*.25*4 = 0

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = 0$

$P(IA_{STAR})$ = P(Selecting Star Node)*P(Selecting IA for Star Node) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node NOT Selecting CA with Star Node)*(Number of Leaf Nodes) = .2*1 + .2*0*.25*0*0*4 = .2

$P(IA_{LEAF})$ = [P(Selecting Leaf Node)*P(Selecting IA for Leaf Node) + P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node NOT Selecting CA with Leaf Node)]*(Number of Leaf Nodes) = (.2*1 + .2*0*1*0*.75)*4 = .8

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = 1$

Mutual Interaction Protocol, Equal Preferences for Individual and Collaborative Action, and Fully-Connected Collaboration Network

P(CA) = P(Selecting Node 1)*P(Selecting CA for Node 1)*P(Node 1 Selecting CA with Node 2)*P(Selecting CA for Node 2)*P(Node 2 Selecting CA with Node 1)*(Number of CA Preferences)*(Number of Nodes) = .2*.8*.25*.8*.25*4*5 = .16

P(IA) = [P(Selecting Node 1)*P(Selecting IA for Node 1) + P(Selecting Node 1)*P(Selecting CA for Node 1)*P(Node 1 Selecting CA with Node 2)*P(Node 2 NOT Selecting CA with Node 1)*(Number of CA Preferences)]*(Number of Nodes) = (.2*.2 + .2*.8*.25*.8*4)*5 = .84

Mutual Interaction Protocol, Equal Preferences for Individual and Collaborative Action, and Three-Star Collaboration Network

P(CA_{STAR}) = [P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Leaf Nodes) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Star Node)*P(Selecting CA for Other Star Node)*P(Other Star Node Selecting CA with Star Node)*(Number of Other Star Nodes)]*(Number of Star Nodes) = (.2*.8*.25*.75*.33*2 + .2*.8*.25*.8*.25*2)*3 = .108

P(CA_{LEAF}) = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*.75*.33*.8*.25*3*2 = .06

P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = .168

P(IA_{STAR}) = [P(Selecting Star Node)*P(Selecting IA for Star Node) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Leaf Node NOT Selecting CA with Star Node)*(Number of Leaf Nodes) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Star Node)*P(Other Star Node NOT Selecting CA with Star Node)*(Number of Other Star Nodes)]*(Number of Star Nodes) = (.2*.2 + .2*.8*.25*.75*2 + .2*.8*.25*.8*2)*3 = .492

P(IA_{LEAF}) = [P(Selecting Leaf Node)*P(Selecting IA for Leaf Node) + P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Star Node NOT Selecting CA with Leaf Node)*(Number of Star Nodes)]*(Number of Leaf Nodes) = (.2*.25 + .2*.75*.33*.8*3)*2 = .34

P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = .832

Mutual Interaction Protocol, Equal Preferences for Individual and Collaborative Action, and Two-Star Collaboration Network

$P(CA_{STAR})$ = [P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Leaf Nodes) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Star Node)*P(Selecting CA for Other Star Node)*P(Other Star Node Selecting CA with Star Node)*(Number of Other Star Nodes)]*(Number of Star Nodes) = (.2*.8*.25*.66*.5*3 + .2*.8*.25*.8*.25*1)*2 = .096

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*.66*.5*.8*.25*2*3 = .08

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF})$ = .176

$P(IA_{STAR})$ = [P(Selecting Star Node)*P(Selecting IA for Star Node) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Leaf Node NOT Selecting CA with Star Node)*(Number of Leaf Nodes) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Star Node)*P(Other Star Node NOT Selecting CA with Star Node)*(Number of Other Star Nodes)]*(Number of Star Nodes) = (.2*.2 + .2*.8*.25*.66*3 + .2*.8*.25*.8*1)*2 = .304

$P(IA_{LEAF})$ = [P(Selecting Leaf Node)*P(Selecting IA for Leaf Node) + P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Star Node NOT Selecting CA with Leaf Node)*(Number of Star Nodes)]*(Number of Leaf Nodes) = (.2*.33 + .2*.66*.5*.8*2)*3 = .52

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF})$ = .824

Mutual Interaction Protocol, Equal Preferences for Individual and Collaborative Action, and One-Star Collaboration Network

$P(CA_{STAR})$ = P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Leaf Nodes) = .2*.8*.25*.5*1*4 = .08

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*(Number of Leaf Nodes) = .2*.5*1*.8*.25*4 = .08

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = .16$

$P(IA_{STAR})$ = P(Selecting Star Node)*P(Selecting IA for Star Node) + P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Leaf Node)*P(Leaf Node NOT Selecting CA with Star Node)*(Number of Leaf Nodes) = .2*.2 + .2*.8*.25*.5*4 = .12

$P(IA_{LEAF})$ = [P(Selecting Leaf Node)*P(Selecting IA for Leaf Node) + P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*P(Star Node NOT Selecting CA with Leaf Node)]*(Number of Leaf Nodes) = (.2*.5 + .2*.5*1*.8)*4 = .72

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = .84$

Unidirectional Interaction Protocol, Preferences for Collaboration, and Fully-Connected Collaboration Network

P(CA) = P(Selecting Node 1)*P(Selecting CA for Node 1)*P(Node 1 Selecting CA with Node 2)*(Number of CA Preferences)*(Number of Nodes) = .2*1*.25*4*5 = 1

P(IA) = P(Selecting Node 1)*P(Selecting IA for Node 1)*(Number of Nodes) = .2*0*5 = 0

Unidirectional Interaction Protocol, Preferences for Collaboration, and Three-Star Collaboration Network

$P(CA_{STAR})$ = P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Node)*(Number of CA Preferences)*(Number of Star Nodes) = .2*1*.25*4*3 = .6

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*1*.33*3*2 = .4

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = 1$

$P(IA_{STAR})$ = P(Selecting Star Node)*P(Selecting IA for Star Node)*(Number of Star Nodes) = .2*0*3 = 0

$P(IA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting IA for Leaf Node)*(Number of Leaf Nodes) = .2*0*2 = 0

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = 0$

Unidirectional Interaction Protocol, Preferences for Collaboration, and Two-Star Collaboration Network

$P(CA_{STAR})$ = P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Node)*(Number of CA Preferences)*(Number of Star Nodes) = .2*1*.25*4*2 = .4

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*1*.5*2*3 = .6

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = 1$

$P(IA_{STAR})$ = P(Selecting Star Node)*P(Selecting IA for Star Node)*(Number of Star Nodes) = .2*0*2 = 0

$P(IA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting IA for Leaf Node)*(Number of Leaf Nodes) = .2*0*3 = 0

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = 0$

Unidirectional Interaction Protocol, Preferences for Collaboration, and One-Star Collaboration Network

$P(CA_{STAR})$ = P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Node)*(Number of CA Preferences)*(Number of Star Nodes) = .2*1*.25*4*1 = .2

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*1*1*1*4 = .8

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = 1$

$P(IA_{STAR})$ = P(Selecting Star Node)*P(Selecting IA for Star Node)*(Number of Star Nodes) = .2*0*1 = 0

$P(IA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting IA for Leaf Node)*(Number of Leaf Nodes) = .2*0*4 = 0

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = 0$

Unidirectional Interaction Protocol, Preferences for Individual Action, and Fully-Connected Collaboration Network

P(CA) = P(Selecting Node 1)*P(Selecting CA for Node 1)*P(Node 1 Selecting CA with Node 2)*(Number of CA Preferences)*(Number of Nodes) = .2*0*.25*4*5 = 0

P(IA) = P(Selecting Node 1)*P(Selecting IA for Node 1)*(Number of Nodes) = .2*1*5 = 1

Unidirectional Interaction Protocol, Preferences for Individual Action, and Three-Star Collaboration Network

$P(CA_{STAR})$ = P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Node)*(Number of CA Preferences)*(Number of Star Nodes) = .2*0*.25*4*3 = 0

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*0*.33*3*2 = 0

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = 0$

$P(IA_{STAR})$ = P(Selecting Star Node)*P(Selecting IA for Star Node)*(Number of Star Nodes) = .2*1*3 = .6

$P(IA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting IA for Leaf Node)*(Number of Leaf Nodes) = .2*1*2 = .4

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = 1$

Unidirectional Interaction Protocol, Preferences for Individual Action, and Two-Star Collaboration Network

$P(CA_{STAR})$ = P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Node)*(Number of CA Preferences)*(Number of Star Nodes) = .2*0*.25*4*2 = 0

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*0*.5*2*3 = 0

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = 0$

$P(IA_{STAR})$ = P(Selecting Star Node)*P(Selecting IA for Star Node)*(Number of Star Nodes) = .2*1*2 = .4

$P(IA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting IA for Leaf Node)*(Number of Leaf Nodes) = .2*1*3 = .6

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = 1$

<u>Unidirectional Interaction Protocol, Preferences for Individual Action, and One-Star Collaboration Network</u>

$P(CA_{STAR})$ = P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Node)*(Number of CA Preferences)*(Number of Star Nodes) = .2*0*.25*4*1 = 0

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*0*0*1*4 = 0

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = 0$

$P(IA_{STAR})$ = P(Selecting Star Node)*P(Selecting IA for Star Node)*(Number of Star Nodes) = .2*1*1 = .2

$P(IA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting IA for Leaf Node)*(Number of Leaf Nodes) = .2*1*4 = .8

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = 1$

<u>Unidirectional Interaction Protocol, Equal Preferences for Individual and Collaborative Action, and Fully-Connected Collaboration Network</u>

P(CA) = P(Selecting Node 1)*P(Selecting CA for Node 1)*P(Node 1 Selecting CA with Node 2)*(Number of CA Preferences)*(Number of Nodes) = .2*.8*.25*4*5 = .8

P(IA) = P(Selecting Node 1)*P(Selecting IA for Node 1)*(Number of Nodes) = .2*.2*5 = .2

Unidirectional Interaction Protocol, Equal Preferences for Individual and Collaborative Action, and Three-Star Collaboration Network

$P(CA_{STAR})$ = P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Node)*(Number of CA Preferences)*(Number of Star Nodes) = .2*.8*.25*4*3 = .48

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*.75*.33*3*2 = .30

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = .78$

$P(IA_{STAR})$ = P(Selecting Star Node)*P(Selecting IA for Star Node)*(Number of Star Nodes) = .2*.2*3 = .12

$P(IA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting IA for Leaf Node)*(Number of Leaf Nodes) = .2*.25*2 = .1

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = .22$

Unidirectional Interaction Protocol, Equal Preferences for Individual and Collaborative Action, and Two-Star Collaboration Network

$P(CA_{STAR})$ = P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Node)*(Number of CA Preferences)*(Number of Star Nodes) = .2*.8*.25*4*2 = .32

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*.66*.5*2*3 = .4

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = .72$

$P(IA_{STAR})$ = P(Selecting Star Node)*P(Selecting IA for Star Node)*(Number of Star Nodes) = .2*.2*2 = .08

$P(IA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting IA for Leaf Node)*(Number of Leaf Nodes) = .2*.33*3 = .2

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = .28$

Unidirectional Interaction Protocol, Equal Preferences for Individual and Collaborative Action, and One-Star Collaboration Network

$P(CA_{STAR})$ = P(Selecting Star Node)*P(Selecting CA for Star Node)*P(Star Node Selecting CA with Other Node)*(Number of CA Preferences)*(Number of Star Nodes) = .2*.8*.25*4*1 = .16

$P(CA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting CA for Leaf Node)*P(Leaf Node Selecting CA with Star Node)*(Number of Star Nodes)*(Number of Leaf Nodes) = .2*.5*1*1*4 = .4

$P(CA) = P(CA_{STAR}) + P(CA_{LEAF}) = .56$

$P(IA_{STAR})$ = P(Selecting Star Node)*P(Selecting IA for Star Node)*(Number of Star Nodes) = .2*.2*1 = .04

$P(IA_{LEAF})$ = P(Selecting Leaf Node)*P(Selecting IA for Leaf Node)*(Number of Leaf Nodes) = .2*.5*4 = .4

$P(IA) = P(IA_{STAR}) + P(IA_{LEAF}) = .44$

APPENDIX C

R Simulation Code for the Computation of Probability of Individual and Collaborative Action for the First Fifty Performance Episodes

Mutual Interaction Protocol

```
f = 30 # number of monte carlo runs
m = 10000 # number of teams
t = 50 # number of time steps

mc_time_data <- array(0,dim=c(f*t,12)) # monte carlo data matrix

for (s in 1:f) {

n = 5 # number of nodes
z <- array(0,dim=c(n+1,m*t)) # team data matrix

for (j in 1:m) {
k = 25 # number of priorities/preferences for fully-connected collaboration network
# k = 23, 19, and 13 for three-star, two-star, and one-star collaboration networks
w <- array(0,dim=c(k,4))
### fully-connected collaboration network
w[,1] <- c(1,1,1,1,1,2,2,2,2,2,3,3,3,3,3,4,4,4,4,4,5,5,5,5,5)
w[,2] <- c(1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,5)
### three-star collaboration network
#w[,1] <- c(1,1,1,1,1,2,2,2,2,2,3,3,3,3,3,4,4,4,4,5,5,5,5)
#w[,2] <- c(1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,1,2,3,5)
### two-star collaboration network
#w[,1] <- c(1,1,1,1,1,2,2,2,2,2,3,3,3,4,4,4,5,5,5)
#w[,2] <- c(1,2,3,4,5,1,2,3,4,5,1,2,3,1,2,4,1,2,5)
### one-star collaboration network
#w[,1] <- c(1,1,1,1,1,2,2,3,3,4,4,5,5)
#w[,2] <- c(1,2,3,4,5,1,2,1,3,1,4,1,5)

###sets preferences
for (i in 1:k) {
	if (w[i,1] == w[i,2]) {
		w[i,3] = runif(1,.6,.8) # preference for individual action
	}
	if (w[i,1] != w[i,2]) {
		w[i,3] = runif(1,.2,.4) # preference for collaboration
	}
```

```
}
###sets skill levels
for (i in 1:k) {
	if (w[i,1] == w[i,2]) {
		w[i,4] = runif(1,.6,.8) # skill level for individual action
	}
	if (w[i,1] != w[i,2]) {
		w[i,4] = runif(1,.6,.8) # skill level for collaborative action
	}
}
w <- data.frame(w)
names(w) <- c("Queue","Task","Priority","Skill")

### mutual interaction protocol
for (l in 1:t) {
	q <- sample(1:n, 1, replace = TRUE, prob = c(.2,.2,.2,.2,.2))
	g <- w[w$Queue == q,]
	gByPriority <- g[rev(order(g[,"Priority"])),]
	###individual action
	if (q == gByPriority[1,]$Task) {
		perf <- sample(c(0,1), 1, replace = TRUE, prob = c(1-gByPriority[1,]$Skill,
			gByPriority[1,]$Skill))
		z[n+1,(t*(j-1)+l)] <- perf
		z[q,(t*(j-1)+l)] <- q
		w[w$Queue == q & w$Task == q,]$Priority <- runif(1,.6,.8)
		w[w$Queue == q & w$Task == q,]$Skill <- runif(1,.6,.8)
	}
	###collaborative action
	if (q != gByPriority[1,]$Task) {
		h <- w[w$Queue == gByPriority[1,]$Task,]
		hByPriority <- h[rev(order(h[,"Priority"])),]
		if (hByPriority[1,]$Task == q) {
			perf <- sample(c(0,1), 1, replace = TRUE, prob = c(1-
				gByPriority[1,]$Skill, gByPriority[1,]$Skill))
			z[n+1,(t*(j-1)+l)] <- perf
			z[q,(t*(j-1)+l)] <- gByPriority[1,]$Task
			w[w$Queue == q & w$Task == gByPriority[1,]$Task,]$Priority <-
				runif(1,.2,.4)
			w[w$Queue == gByPriority[1,]$Task & w$Task == q,]$Priority <-
				runif(1,.2,.4)
			w[w$Queue == q & w$Task == gByPriority[1,]$Task,]$Skill <-
				runif(1,.6,.8)
			w[w$Queue == gByPriority[1,]$Task & w$Task == q,]$Skill <-
				runif(1,.6,.8)
		}
		###individual action
```

```
            if (hByPriority[1,]$Task != q) {
                perf <- sample(c(0,1), 1, replace = TRUE, prob = c(1-w[w$Queue == q &
                    w$Task == q,]$Skill, w[w$Queue == q & w$Task == q,]$Skill))
                z[n+1,(t*(j-1)+l)] <- perf
                z[q,(t*(j-1)+l)] <- q
                w[w$Queue == q & w$Task == q,]$Priority <- runif(1,.6,.8)
                w[w$Queue == q & w$Task == q,]$Skill <- runif(1,.6,.8)
            }
        }
}
}

###compute probability of individual and collaborative action for each time point
time_data <- array(0,dim=c(t,12))

for (a in 1:t) {

        team_freq_time_taskwork <- NULL

        team_freq_time_teamwork <- NULL

        for (b in 1:n) {

                time <- z[b,seq(a,m*t,by = t)]

                time_taskwork <- which(time == b)
                freq_time_taskwork <- length(time_taskwork)
                team_freq_time_taskwork <- c(team_freq_time_taskwork, freq_time_taskwork)

                time_teamwork <- which(time != b & time != 0)
                freq_time_teamwork <- length(time_teamwork)
                team_freq_time_teamwork <- c(team_freq_time_teamwork,
                                            freq_time_teamwork)

                time_data[a,(2*(b-1)+1):(2*b)] <- c(freq_time_taskwork, freq_time_teamwork)

        }

        tot_freq_time_taskwork <- sum(team_freq_time_taskwork)

        tot_freq_time_teamwork <- sum(team_freq_time_teamwork)

        time_data[a,11:12] <- c(tot_freq_time_taskwork, tot_freq_time_teamwork)

}
```

```
mc_time_data[(t*(s-1)+1):(t*s),] <- time_data

}
```

Unidirectional Interaction Protocol

```
f = 30 # number of monte carlo runs
m = 10000 # number of teams
t = 50 # number of time steps

mc_time_data <- array(0,dim=c(f*t,12)) # monte carlo data matrix

for (s in 1:f) {

n = 5 # number of nodes
z <- array(0,dim=c(n+1,m*t)) # team data matrix

for (j in 1:m) {
k = 25 # number of priorities/preferences for fully-connected collaboration network
# k = 23, 19, and 13 for three-star, two-star, and one-star collaboration networks
w <- array(0,dim=c(k,4))
### fully-connected collaboration network
w[,1] <- c(1,1,1,1,1,2,2,2,2,2,3,3,3,3,3,4,4,4,4,4,5,5,5,5,5)
w[,2] <- c(1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,5)
### three-star collaboration network
#w[,1] <- c(1,1,1,1,1,2,2,2,2,2,3,3,3,3,3,4,4,4,4,5,5,5,5)
#w[,2] <- c(1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,1,2,3,5)
### two-star collaboration network
#w[,1] <- c(1,1,1,1,1,2,2,2,2,2,3,3,3,4,4,4,5,5,5)
#w[,2] <- c(1,2,3,4,5,1,2,3,4,5,1,2,3,1,2,4,1,2,5)
### one-star collaboration network
#w[,1] <- c(1,1,1,1,1,2,2,3,3,4,4,5,5)
#w[,2] <- c(1,2,3,4,5,1,2,1,3,1,4,1,5)

###sets preferences
for (i in 1:k) {
	if (w[i,1] == w[i,2]) {
		w[i,3] = runif(1,.6,.8) # preference for individual action
	}
	if (w[i,1] != w[i,2]) {
		w[i,3] = runif(1,.2,.4) # preference for collaboration
	}
}
w <- data.frame(w)
names(w) <- c("Queue","Task","Priority","Skill")
```

```
### unidirectional interaction protocol
for (l in 1:t) {
        q <- sample(1:n, 1, replace = TRUE, prob = c(.2,.2,.2,.2,.2))
        g <- w[w$Queue == q,]
        gByPriority <- g[rev(order(g[,"Priority"])),]
        ###individual action
        if (q == gByPriority[1,]$Task) {
                perf <- sample(c(0,1), 1, replace = TRUE, prob = c(1-gByPriority[1,]$Skill,
                        gByPriority[1,]$Skill))
                z[n+1,(t*(j-1)+l)] <- perf
                z[q,(t*(j-1)+l)] <- q
                w[w$Queue == q & w$Task == q,]$Priority <- runif(1,.2,.4)
                w[w$Queue == q & w$Task == q,]$Skill <- runif(1,.6,.8)
         }
        ###collaborative action
        if (q != gByPriority[1,]$Task) {
                perf <- sample(c(0,1), 1, replace = TRUE, prob = c(1-gByPriority[1,]$Skill,
                        gByPriority[1,]$Skill))
                z[n+1,(t*(j-1)+l)] <- perf
                z[q,(t*(j-1)+l)] <- gByPriority[1,]$Task
                w[w$Queue == q & w$Task == gByPriority[1,]$Task,]$Priority <- runif(1,.6,.8)
                w[w$Queue == gByPriority[1,]$Task & w$Task == q,]$Priority <- runif(1,.6,.8)
                w[w$Queue == q & w$Task == gByPriority[1,]$Task,]$Skill <- runif(1,.6,.8)
                w[w$Queue == gByPriority[1,]$Task & w$Task == q,]$Skill <- runif(1,.6,.8)
        }
}
}

###compute probability of individual and collaborative action for each time point
time_data <- array(0,dim=c(t,12))

for (a in 1:t) {

        team_freq_time_taskwork <- NULL

        team_freq_time_teamwork <- NULL

        for (b in 1:n) {

                time <- z[b,seq(a,m*t,by = t)]

                time_taskwork <- which(time == b)
                freq_time_taskwork <- length(time_taskwork)
                team_freq_time_taskwork <- c(team_freq_time_taskwork, freq_time_taskwork)
```

```
        time_teamwork <- which(time != b & time != 0)
        freq_time_teamwork <- length(time_teamwork)
        team_freq_time_teamwork <- c(team_freq_time_teamwork,
                                     freq_time_teamwork)

        time_data[a,(2*(b-1)+1):(2*b)] <- c(freq_time_taskwork, freq_time_teamwork)

    }

    tot_freq_time_taskwork <- sum(team_freq_time_taskwork)

    tot_freq_time_teamwork <- sum(team_freq_time_teamwork)

    time_data[a,11:12] <- c(tot_freq_time_taskwork, tot_freq_time_teamwork)

}

mc_time_data[(t*(s-1)+1):(t*s),] <- time_data

}
```

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