



Full length article

Leading teams over time through space: Computational experiments on leadership network archetypes

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ARTICLE INFO

Keywords:

Shared leadership
Team mental models
Leadership networks

ABSTRACT

A key function of team leadership is building and sustaining shared mental models. Topological approaches to leadership identify structural patterns, such as decentralized and shared leadership that empower members to collectively lead themselves toward important goals, but an open question is the particular form of leadership that best promotes team mental models. We explored 8 leadership archetypes using a computational model fit on data from a unique sample of NASA analog space crews. Data from 4, 4-member crews living and working together for 45-days were used to parameterize the model which then accurately predicted mental models for the next set of 4-member crews. The validated model was used to conduct virtual experiments exploring the effects of leadership structures on mental models. We found shared leadership has the largest effect on shared mental models, followed by hierarchical and coordinated leadership. These findings extend shared leadership theory leveraging computational methods to examine leadership archetypes and suggest propositions about how they shape team functioning over time.

Introduction

Shared leadership is a dynamic process where team members collectively take responsibility for leading one another to achieve their goals (Carson et al., 2007; Pearce, 2004). The increasingly knowledge-based nature of work (DeNisi et al., 2003) requires an understanding of shared leadership as a way to self-organize teamwork (Mayo et al., 2003). Shared leadership approaches are especially relevant in an era where digital technologies and collaboration platforms are scaling up the size, complexity, and distributive nature of teamwork. Shared leadership benefits teams by enabling members to develop and maintain shared mental models, one of the strongest predictors of team effectiveness (DeChurch & Mesmer-Magnus, 2010). This benefit is especially critical in teams whose members have diverse expertise, skills, and other characteristics. Such teams can benefit from their diversity to the extent that members' disparate mental representations can be effectively integrated.

One such team that is composed of highly specialized experts is the space exploration team, some of whom will be venturing in a small spacecraft for a 3-year journey to Mars. Though the mission could be a decade or more into the future, social scientists are currently bringing computational tools to bear on helping design these teams. Deep space exploration teams will be largely self-managing with a high

degree of autonomy necessitated by the communication delays of as many as 21 min each way between mission control here on Earth and Mars. Team members will rely on one another to make decisions, creatively solve problems, and tackle countless unforeseeable challenges. Given the distributed expertise and highly interdependent mission, these teams could benefit from shared leadership structures that engage multiple individuals mutually leading one another as a way to develop and maintain shared mental models among a diverse team (DeChurch & Mesmer-Magnus, 2015; Mulhearn et al., 2016).

The purpose of this paper is twofold. First, we investigate 8 leadership archetypes and their effects on shared mental models. Though abundant prior work connects shared leadership to team outcomes, an open question is one of form. Using leadership archetypes, we advance work on shared leadership to understand how different leadership structures shape team mental models. Second, we advance computational approaches to leadership illustrating how models can be rooted in theory, validated in the field, and then used to conduct virtual "what if" experiments that explore the joint and iterative effects of a wide set of factors.

We leverage computational models to gain an advanced look at how leadership networks could affect a key predictor of team success, team mental models' convergence, over time. Convergence is a cognitive process experienced by teams throughout their operational life

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(Dionne et al., 2010; McComb, 2007) whereby a shift in processing information occurs from individual members to the level of team, where shared and similar understandings guide collective information processing (Dionne et al., 2010). A great deal of evidence has shown that converged mental models positively influence team performance (e.g., Edwards et al., 2006; Mathieu et al., 2000) because team members are more readily able to recognize one another's needs and information requirements (Stout et al., 1999).

Over the past two decades, a sizeable body of work has explored the consequences of shared leadership in teams, culminating in three meta-analyses (D'Innocenzo et al., 2016; Nicolaidis et al., 2014; Wang et al., 2014) supporting the conclusion that greater engagement by multiple team members in leading the team is positively associated with team performance. Much of this work has represented shared leadership as either a percentage of the team engaged in its leadership (e.g., leadership density) or the degree of differentiation among team members in the provision of leadership (e.g., leadership centralization). Engagement and differentiation are useful, albeit simplistic, representations of shared leadership in teams.

More recently, the concept of shared leadership has benefited from social network theories and methods which enable a rich conceptualization of social structure and form (Carter et al., 2015; Contractor et al., 2012; Sullivan et al., 2015). Social network approaches define elements of social structure that have long been theorized but seldom empirically studied in shared leadership research. Existing work on shared leadership has focused on relatively simple network concepts such as density, centralization, and transitivity (Carson et al., 2007; Crawford & LePine, 2013; Mathieu et al., 2015). Moreover, studies that expand the structural richness of shared leadership research faced the major limitation of requiring very large sample sizes (e.g., Mehra et al., 2006).

Posing questions about complex structural variables exponentially increases the required sample size for two reasons. First, enough observed networks are required to ensure variation on focal structures. Second, many of the structures are correlated with one another, such as leadership density and centralization (DeRue et al., 2015). This necessitates collecting data from a larger number of networks to effectively and adequately sample various combinations of different structural motifs.

Fortunately, computational methods provide a theory-building tool for leadership research that overcomes these challenges (Dionne et al., 2010; Hanneman, 1988; Monge & Contractor, 2003; Zhou et al., 2019). Computational modeling enables researchers to “reach beyond describing and explaining what is, to exploring what might be” (Burton & Obel, 2011, p. 1197), to artificially generate teams and experiment with their leadership structures in order to observe interactions and outcomes otherwise unobservable (Levine & Prietula, 2013).

Shared leadership: A network perspective

Bowers and Seashore (1966) noted long ago that leadership is meaningful only in the context of at least two people and the authors conceptualized leadership as the provision of four group functions: support (e.g., maintenance of group membership), interaction facilitation (e.g., develop mutually satisfying group relations), goal emphasis (e.g., meeting group's goal), and work facilitation (e.g., differentiation of supervisory roles, planning, scheduling). These ideas have now come to the fore of team leadership research, their importance underscored by the prevalence of teams in organizations. In this context, shared leadership is defined as an emergent team property where team members must be willing to not only provide leadership influence to others but must also recognize that there is value in relying on multiple team members for leadership (Carson et al., 2007). Network approaches define leadership as a relationship between two people

(Carter et al., 2015), a pattern of leadership in the team through influence processes that are independent of formal roles (Bedeian & Hunt, 2006). Shared leadership is an inherently relational phenomenon (Carson et al., 2007; Contractor et al., 2012; Day & Harrison, 2007; DeRue & Ashford, 2010; Mayo et al., 2003; Mehra et al., 2006) in which members are empowered to collectively lead themselves toward important goals.









Leadership topologies. Previous research on shared leadership has focused on specific configurations of leadership including hierarchical, distributed and fragmented leadership (Aime et al., 2014; Johnson et al., 2003; McIntyre & Foti, 2013; Mehra et al., 2006; Pearce & Conger, 2002). Conceptually, these forms differ in the degree to which team members are connected or fragmented by leadership influence relationships. In connected leadership networks, all team members are actively engaged in leading and following, either through direct or indirect relationships. The various forms of connected leadership share in common the ability to mobilize the whole group in a common direction, albeit with different challenges and efficiency arising from each specific form. In contrast, there are a number of leadership configurations studied in the literature that involve either faction within the team, or group members who are disengaged from the group, neither leading nor following.

We posit the dimension of leadership connectedness plays a critical role in promoting needed group properties like shared mental models. To the degree that leadership is connected, there are conduits of influence whereby all group members can come to align their understanding. In contrast, when there are factions in the group or isolates, it can be difficult to confront and align mental representations. Group members who are not engaged in leading and following are left to develop a schema that can, over time, become quite divergent from the core team. The same is true of leadership involving one or more isolated members who are neither leading nor following. In reviewing previous research, we identify eight stylized leadership archetypes that vary along the continuum of connectedness. We summarize and visualize these archetypes in Table 1, using a 4-person team.

Four connected leadership archetypes are shared leadership, hierarchical leadership, coordinated leadership, and cyclical leadership. *Shared leadership networks* are those structures in which leadership is distributed across all team members and they mutually recognize each other as leaders (Mehra et al., 2006; Pearce & Conger, 2002). *Hierarchical leadership networks* are represented as a leader-centered model or centralized leadership model, where leadership is enacted by one member, who is acknowledged by all team members (McIntyre & Foti, 2013; Mehra et al., 2006). *Coordinated leadership networks* represent those structures in which at least two team members are acknowledged as leaders by other team members and they recognize each other as leaders (McIntyre & Foti, 2013; Mehra et al., 2006). *Cyclical leadership networks* are those where each member directly or indirectly leads and follows one another. Imagine a leadership chain where the leader at the top of the chain is also a follower of the team member at the bottom of the chain. As such cyclical leadership denotes an anti-hierarchical structure and is unlikely to be observed empirically (Emery et al., 2011).

Three disconnected leadership archetypes are factionalized leadership, disenfranchised star, disenfranchised chain. *Factionalized leadership networks* are represented by structures in which the leadership network is divided into multiple subgroups or cliques (Johnson et al., 2003) that do not rely on one another for leadership. There are two types of disenfranchised leadership networks, both of which reflect a structure wherein at least one member does not accept leadership within the team (McIntyre & Foti, 2013; Mehra et al., 2006). In the case of the *disenfranchised star network*, leadership is enacted by one team member (i.e., star). With the *disenfranchised chain network*, leadership is provided by two members hierarchically (i.e., chain).

Table 1
Leadership topologies.

Leadership Form	Description	Visualization	Citation/studies
Connected	Shared		(McIntyre & Foti, 2013; Mehra et al., 2006; Pearce & Conger, 2002)
	Hierarchical		(McIntyre & Foti, 2013; Mehra et al., 2006)
	Coordinated		(McIntyre & Foti, 2013; Mehra et al., 2006)
	Cyclical		(Emery et al., 2011)
Fragmented	Factionalized		(Johnson et al., 2003; Mehra et al., 2006)
	Disenfranchised star		(McIntyre & Foti, 2013; Mehra et al., 2006)
	Disenfranchised chain		(McIntyre & Foti, 2013; Mehra et al., 2006)
	Absent		

The role of leadership in the emergence and evolution of shared mental models

Leadership plays an important role in developing and shaping shared mental models in teams. *Shared mental models* are properties of a group reflecting how members organize knowledge and understanding about the purpose of the team, the nature of the work, and how members work together. Shared mental models are established through common experience among team members regarding expected collective behavior patterns (Cannon-Bowers et al., 1990; Converse et al., 1993; Kleinman & Serfaty, 1989) and thus characterize the degree to which members hold similar knowledge structures about their task and team interactions (Baard et al., 2014; Burke et al., 2006).

Past empirical work has found that functional leadership behaviors promote shared mental models in teams (McIntyre & Foti, 2013; Murase et al., 2014), which are integral to team performance (DeChurch & Mesmer-Magnus, 2010). In their elaboration of team leadership, Zaccaro and colleagues explain that “a major responsibility of the team leader is to facilitate for team members an accurate shared understanding of their operating environment and how, as a team, they need to respond” (Zaccaro et al., 2001, p. 461). However, whereas prior work supports the role of leadership functions or behaviors aimed at regulating teamwork and taskwork, the question of how leadership topologies promote shared mental models remains an open question.

The structure of leadership may have important consequences for the development and maintenance of shared mental models over time. The act of offering leadership to others in order to achieve the purpose

of the team can lead to more commitment and information sharing within the team (Katz & Kahn, 1978), which can increase trust among team members, and improve team performance (Carson et al., 2007). However, as Mehra et al. (2006) found, this relationship is not as simple as it has been assumed. For example, though the authors found that shared leadership is no better than hierarchical (leader-centered) leadership, distributed-coordinated leadership (whereby several leaders emerge but with similar identities and thus acknowledge each other) tends to fare better than both fragmented leadership (leaders do not recognize each other) and hierarchical leadership.

Research on other team outcomes points out that the presence of multiple leaders within a group can have both positive and negative consequences (McIntyre & Foti, 2013). Some researchers argued that having multiple leaders in a team can lead to decentralized authority, less agreement, and more conflict. On the contrary, a single leader can regulate knowledge structures in accurate and similar ways, and foster better team responses (Marks et al., 2000). Others suggested that multiple leaders decrease the likelihood of groupthink and increase the quantity of information shared within the team (cf. Stewart & Manz, 1995). Along the same vein, Kozlowski and colleagues (Kozlowski et al., 1996; Kozlowski et al., 2009) posited that multiple leaders encourage communication and the spreading of crucial team knowledge.

The relational nature of shared leadership, characterized by mutual influence among team members, offers the opportunity to study shared leadership as a social network. Using social network theory and operationalization would allow us to examine the emergent and distributive attributes of shared leadership, and understand how these mechanisms affect shared mental models. In this study, we apply a

social network framework and operationalization to examine the effect of different leadership network structures on the emergence and evolution of shared mental models.

Connected vs fragmented leadership networks

Connected leadership presents several advantages over fragmented leadership that can lead to an improved similarity in team mental models. These advantages accumulate in the areas of conflict, accuracy, synchronization of effort, and cohesion/trust. For example, McIntyre and Foti (2013) showed that the boundaries among members of a shared leadership group are permeable allowing members to engage in reciprocal leadership processes that lead to less conflict or tension among members. Because leaders synchronize their efforts, they are more likely to agree with the information conveyed. Members' interactions are therefore positive in nature (Mathieu et al., 2015), increasing the trust and collegiality among team members, and resulting in a level of cohesion of the group that improves the similarity of the shared mental models. On the other hand, fragmented leadership results in various members that are recognized as leaders by different factions within the group. As a result, it is likely that communication among team members will get out of sync, resulting in lower coordination among members and dissimilarity in mental models within the team. Based on these arguments, we posit that:

Hypothesis 1. Teams with connected leadership networks develop more similar team mental models than do teams with fragmented leadership networks.

Shared vs hierarchical leadership networks

While shared leadership networks accrue all of the benefits of being a connected leadership network as discussed above (i.e., H1), hierarchical leadership networks, also a connected structure, confront a series of downsides that make them less desirable from the perspective of shared mental model development. There are at least three in particular. First, team members who share leadership may be more positively disposed to view things similarly. For example, Pearce, Yoo, and Alavi (2004) showed that members in teams who share leadership exhibit more positive relationships with one another than do team members with a single leader.

Second, shared leadership may advantage mental model convergence relative to hierarchical leadership because of the presence of multiple (or more) leaders. Shared leadership, as compared to hierarchical, involves more individuals in the direction setting and operational management of the team. The presence of multiple team leaders means that more individuals are actively engaged, explaining and persuading one another. Whereas with a single hierarchical team leader, shared mental models come about when followers adopt the leader's model, with multiple leaders, a shared mental model comes about through discourse and debate. Multiple individuals are actively participating both by sharing their perspectives and vetting others'. Hence due to the greater collective engagement present from having multiple leaders, we expect that greater sharedness will come about in teams with multiple as compared to a single leader.

Third, shared leadership may be especially advantageous for mental model convergence when expertise is distributed within the team. Whereas a hierarchical leadership structure would likely be superior or equivalent to a shared structure for teams wherein it is most desirable for the group to quickly converge on the leader's model, when expertise is distributed, teams need to continuously update mental models in ways that are adjusting for multiple team members, not only a central leader. For this reason, we would expect teams with shared leadership networks, and multiple leaders, are better able to develop shared mental models than their hierarchical counterparts.

Hypothesis 2. Teams with shared leadership networks develop more similar team mental models than do teams with hierarchical leadership networks.

Modeling the emergence and evolution of shared mental models

Computational models afford insights into emergent behavior resulting from actions and interactions that occur within complex systems (Macy & Willer, 2002). Computational models, and agent-based models, in particular, are useful for understanding the social context in the area of networks (Harrison et al., 2007; Monge & Contractor, 2003; Palazzolo et al., 2006) and teams (Ilgen & Hulin, 2000). In the case of teams, which is the focus of this study, computational modeling functions like an *in silico* laboratory and offers researchers the ability to "reach beyond describing and explaining what is, to explore what might be" (Burton & Obel, 2011, p. 1197). Researchers use computational modeling to experiment with synthetic teams whose structures and work processes (such as shared leadership processes) can be manipulated, thus being able to capture dynamic, multi-level, and complex relationships that occur within teams over time (Dionne & Dionne, 2008; Dionne et al., 2010; Sullivan et al., 2015). For example, Dionne et al. (2010) used agent-based modeling techniques to examine the complex and level-specific relationships between leadership and mental model convergence and team performance. Agent-based modeling has the inherent benefit of being able to vary elements and rules that cannot be manipulated in laboratory experiments while observing their interactions and their outcomes (Levine & Prietula, 2013). In addition, they have the benefit of being able to explore configurations that may not occur with sufficient frequency in field settings, and yet might be desirable (or deleterious) in terms of achieving desired outcomes.

In this study, we built an agent-based model to explicate how leadership affects task mental model development in teams over time. We parametrized the model using empirical data collected in a NASA space analog. Our model is validated by training and testing it on different subsets of the observed mission crews and by applying it on a different NASA space analog. Finally, we used the empirically parametrized model to conduct computational experiments. By varying leadership network structures and observing interactions and outcomes, we are thus able to understand processes that are difficult if not impossible to manipulate in the field or the laboratory.

Context: NASA's human exploration research analog

NASA's Human Exploration Research Analog (HERA, Cromwell & Neigut, 2014) represents an appropriate and fascinating context in which to examine how leadership networks affect the emergence and change in team mental models over time. HERA is a space analog located at Johnson Space Center in Houston, Texas. HERA mimics the context of a space mission in that crew members have highly structured daily tasks and live and work in an isolated and confined setting for an extended period of time. HERA members cannot leave the analog, and experience levels of isolation, confinement, and communication latency similar to those that would be expected in a space exploration mission. Crew members are confined to the inside of the capsule during the entirety of the mission. Each crew member has a small bunk in close quarters with bunks of the other 3 crew members. The crew shares a single "hygiene module".

We observed 4 crews, each composed of 4 members, that were part of HERA Campaign 4¹ (HERA C4). HERA C4 took place in 2017 and 2018. Crew members lived and worked in HERA for 45 days. The crews were on a hypothetical mission to land on an asteroid and collect soil samples, before returning home. As the crew traveled further from

¹ <https://lsda.jsc.nasa.gov/Mission/miss/1396>.

Earth, all communications in and out of the habitat, with mission control, experienced up to a five-minute delay each way. The delay gradually went away as the crew approached reentry to Earth. The communication delay started on mission day 16 and ended on mission day 28. There was no communication delay among crew members within the habitat. Additionally, the crew was exposed to sleep deprivation: The crew members slept 5 h per night during the workweek and 8 h on Saturday and Sunday.

Measures collected in HERA C4

Participants who enter the analog are selected based on similarity in their background to actual astronaut candidates (e.g., an advanced degree in STEM fields, experience in leading missions in extreme environments on Earth, military flight experience). One crew was composed of males only, and the other three crews were of mixed gender, for a total of 6 women and 10 men. Their ages varied from 29 to 56 ($M = 38.75$, $SD = 8.33$). Most participants were highly educated (13 participants out of 16 have graduate degrees) and 5 of them had previous military experience. Table 2 details all of the measures we collected in HERA C4 together with the data sources and survey questions used to assess the concepts in the model.

To assess participants' individual cognitive ability, we used NASA's Space Flight Cognitive Assessment Tool for Windows (WinSCAT; Kane et al., 2005). WinSCAT consists of a 5-test subset of the larger Automated Neuropsychological Assessment Metrics test system developed by the Department of Defense (Reeves et al., 2007). The cognitive domains assessed by these tests are (1) basic computational skills and working memory, (2) attention and working memory, (3) spatial processing and visuospatial working memory, (4) complex scanning, visual tracking, and attention, and (5) memory. The crew took the WinSCAT test between 4 and 6 times during the mission. At the end of each test, each crew member receives a score, called the index of cognitive efficiency ($M = 361$, $SD = 85.5$). Higher scores indicate higher cognitive ability.

In addition to individual characteristics, we also collected personal characteristics (i.e., agreeableness, conscientiousness, extraversion, openness, and psychological collectivism) and information about crew members' perceptions of team viability, team status conflict, and social relations. Every 5 days, the crew members completed a network survey asking about their leadership relations (i.e., "Who do you rely on for leadership?"), positive working relations (i.e., "Who do you enjoy working with?"), and negative working relations (i.e., "Who made it difficult for you to work on your task?"). The density of the leadership network varied greatly between crews and within crews, from 0.08 (very sparse network) to 1 (fully connected network). Additionally, the leadership network structures varied between crews. Table 3 presents a snapshot of the leadership network structures for the 4 crews over 5 points in time.

Finally, each individual's task mental model was collected every day, except Sundays, using the elicitation method. A task mental model represents the relationship among task procedures, strategies, and equipment needed to accomplish team goals (Cannon-Bowers & Salas, 2001; Converse et al., 1993; Mathieu et al., 2000) and is critical for team success especially for teams that have a pre-assigned task schedule such as NASA crews (Resick et al., 2010). Crew members were asked, on a scale of 1 (totally unrelated) to 7 (very strongly related), to report their perceptions of the relationships between a list of 8 task elements (Mathieu et al., 2005), which produced 28 dyadic values for each crew member for each day. We used the Euclidean Distance measure between each pair of astronauts to represent the degree to which their mental models are dissimilar. Then, we divided that distance by the maximum possible difference (i.e. if one person entered all '1s' and the other person entered all '7s'). This gave a number between 0 and 1 for a proportion of possible differences between two crew members. Finally, we inverted the number by subtracting it from 1 in order to get a proportion of possible similarity as opposed

to distance. The result was a dyadic, relational measure where ties are weighted indicators of shared cognition between each pair of crew members.

The model

We began with a conceptual model explaining how mental models come about in teams, and the factors affecting them. This was based on an exhaustive search and integration of the extant research on shared cognition in teams. The team shared mental model characterizes the degree to which members hold similar knowledge structures about their task and team interactions. Shared mental models differentiate novice from expert teams, and are robust predictors of effective teamwork processes and performance (DeChurch & Mesmer-Magnus, 2010). Furthermore, the ability to adapt requires that members hold a similar understanding of taskwork and teamwork (Baard et al., 2014; Burke et al., 2006). There are a large number of factors that affect shared mental models, and many of these factors change over time, as the team develops and conditions change. We build our conceptual model starting with two sets of team mental model antecedents identified by Mohammed et al. (2010): team members' demographic and personality characteristics and contextual factors. Additionally, we include social relations (i.e., leadership, positive and negative relations) that have been shown to affect the emergence and evolution of shared mental models (Cartwright, 1968; Cialdini & Goldstein, 2004). We detail the model in the following sections.

Model structure

The model consists of 4 agents that work and live in a confined and isolated environment for 45 days. Each agent performs one of the 167 pre-assigned individual and collaborative tasks. An agent can work individually or collaborate with one or more agents. The model progresses in increments of 5 min for 45 days: 288 t ticks per day or 12,960 t ticks for 45 days. At every time t , the model updates each agent's mental model and computes the team shared mental model. The development of the computational model relies heavily on empirical data and was implemented in NetLogo (Wilensky, 1999). The pseudocode in Table 4 outlines the logical flow of the model. Descriptions of the steps follow next, when necessary.

Model initialization

Steps 1 to 4. When the model is initialized, each agent is assigned demographic and personality characteristics, and cognitive ability (i.e., intelligence). The agents have perceptions of team viability and team status conflict. The agents have social relations with other agents: informal leadership, positive, and negative relations. Finally, the agents have initial mental models. This measure represents each person's mental understanding of the tasks they perform.

Step 5. Next, the model imports the task log which contains all tasks performed by each agent at each moment in time over 45 days. Each task has attributes. Task workload and importance determine whether a task is perceived by agents as demanding and essential for the mission. Task workflow determines how interdependent the task is. Additionally, each task has assigned one or more of the 8 task elements included in the mental model ratings, based on which of the task elements are most likely to be activated when agents are working on that specific task.

Fig. 1(a) and 1(b) present examples of task elements associated with two tasks. For example, performing a task that involves flight simulation for an extravehicular activity to support an exploration mission scenario (MMSEV-EVA) activates the following task elements: Completing our individual work tasks, Completing our crew responsibilities, Communicating with mission control, Performing extravehicular activities, Participating in scientific studies, and Managing our time and staying on schedule. However, performing a battery of multitask tasks (between the crew and mission control) activates the following

Table 2
Description of Measures Collected in HERA C4.

Variable	Type	Source	Description	Mean	SD
Outcome variable					
Task mental model	Network	Questionnaire (repeated measure: data collected every day, except Sundays)	Mental model was collected using the elicitation method; the question was developed based on SME input: <i>Complete each of the open cells [in the matrix] by filling in a number from 1 to 7 that indicates how related the task element in the corresponding row is to the element in the corresponding column. Task elements:</i> <ul style="list-style-type: none"> ● Completing our individual work tasks; ● Completing our crew responsibilities; ● Communicating with mission control; ● Performing extravehicular activities; ● Ensuring crew health and safety; ● Performing maintenance activities; ● Participating in scientific studies; ● Managing our time and staying on task 	0.73	0.05
Predictor variables					
Leadership ties ^a	Network	Questionnaire (repeated measure: data collected every 5 days)	Question adapted from Carson et al. (2007): <i>Who do you rely on for leadership?</i>	0.59	0.25
Positive ties ^a	Network	Questionnaire (repeated measure: data collected every 5 days)	Question adapted from Sparrowe et al. (2001): <i>Who do you enjoy working with?</i>	0.79	0.17
Negative ties ^a	Network	Questionnaire (repeated measure: data collected every 5 days)	Question adapted from Sparrowe et al. (2001): <i>Who made it difficult for you to work on your task?</i>	0.23	0.19
Team viability	Individual	Questionnaire (repeated measure: data collected every 5 days)	Team's viability is measured using an eight-item construct that is adapted from previous work by Resick et al. (2010) and includes additional recommendations from Bell and Marentette (2011): <i>Please describe your perceptions of your HERA crew</i> <ul style="list-style-type: none"> ● I really enjoy being part of this HERA crew ● I feel like I am getting a lot out of being a member of this HERA crew ● I wouldn't hesitate to participate on another task with the same HERA crew ● If I could leave this team and work with another HERA crew, I would (reverse-worded) ● This HERA crew does not have what it takes to be effective in long-duration space exploration missions (reverse-worded) ● This HERA crew has the capacity for long-term success ● This HERA crew should not continue to function as a unit (reverse-worded) ● This HERA crew has positioned itself well for continued success 	4.50	0.58
Team status conflict	Individual	Questionnaire (repeated measure: data collected every 5 days)	Bendersky and Hays (2012), 4-item status conflict scale	2.58	1.15
Age	Individual	Demographics survey		38.75	8.33
Gender: Women	Individual	Demographics survey		0.38	0.50
Ethnicity	Individual	Demographics survey	16 Caucasian (non-Hispanic), 1 Caucasian (Hispanic), 1 East Asian, 1 Other		
Education	Individual	Demographics survey	3 Bachelor Degrees, 7 Master Degrees, 8 PhD degrees, 2 Professional Degrees (e.g., MD, JD)		
Military experience	Individual	Demographics survey		0.31	0.48
Agreeableness	Individual	Questionnaire	Big Five Aspect Scales (BFAS; DeYoung et al., 2007)	4.02	0.44
Conscientiousness	Individual	Questionnaire	Big Five Aspect Scales (BFAS; DeYoung et al., 2007)	4.15	0.48
Openness	Individual	Questionnaire	Big Five Aspect Scales (BFAS; DeYoung et al., 2007)	3.88	0.47
Extraversion	Individual	Questionnaire	Big Five Aspect Scales (BFAS; DeYoung et al., 2007)	3.77	0.41
Psychological collectivism	Individual	Questionnaire	Jackson et al. (2006), psychological collectivism scale	5.60	0.66
Cognitive ability	Individual	NASA-provided WinSCAT	NASA's Space Flight Cognitive Assessment Tool for Windows (WinSCAT, Kane et al., 2005)	361.00	85.00
Communication delay	Contextual	NASA-provided mission log			
Sleep deprivation	Contextual	NASA-provided mission log			
Task workflow	Contextual	SME-rated	NASA Task Load Index (NASA-TLX, Hart & Staveland, 1988)	2.29	1.05
Task workload	Contextual	SME-rated	NASA Task Load Index (NASA-TLX, Hart & Staveland, 1988)	3.79	1.26
Task importance	Contextual	SME-rated	NASA Task Load Index (NASA-TLX, Hart & Staveland, 1988)	3.42	0.61

Note. ^a The mean and standard deviation for social relationships are computed based on the network density.

task elements: Communicating with mission control, Ensuring crew health and safety, Participating in scientific studies, and Managing our time and staying on schedule.

Step 6. Finally, the model initializes the communication delay and the awake time as zero.

Model dynamics

Once the initialization is complete, the model increments the time (**Step 7**) and verifies whether there are any updates for individual characteristics, social relations, and perception on team characteristics in the empirical data and updates the information accordingly (**Step**

8). Next, the model updates the contextual factors: communication delay (**Step 9**) and sleep deprivation (**Step 10**). The communication delay is computed as:

$$C_{\text{delay}}(t) = \begin{cases} 0.1 & \text{if } 16 \geq t/d > 16 \text{ or } 28 \geq t/d > 29, \\ 0.2 & \text{if } 17 \geq t/d > 18 \text{ or } 27 \geq t/d > 28, \\ 0.4 & \text{if } 18 \geq t/d > 19 \text{ or } 26 \geq t/d > 27, \\ 0.6 & \text{if } 19 \geq t/d > 20 \text{ or } 25 \geq t/d > 26, \\ 1 & \text{if } 20 \geq t/d > 25, \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

Table 3
Observed leadership structures.

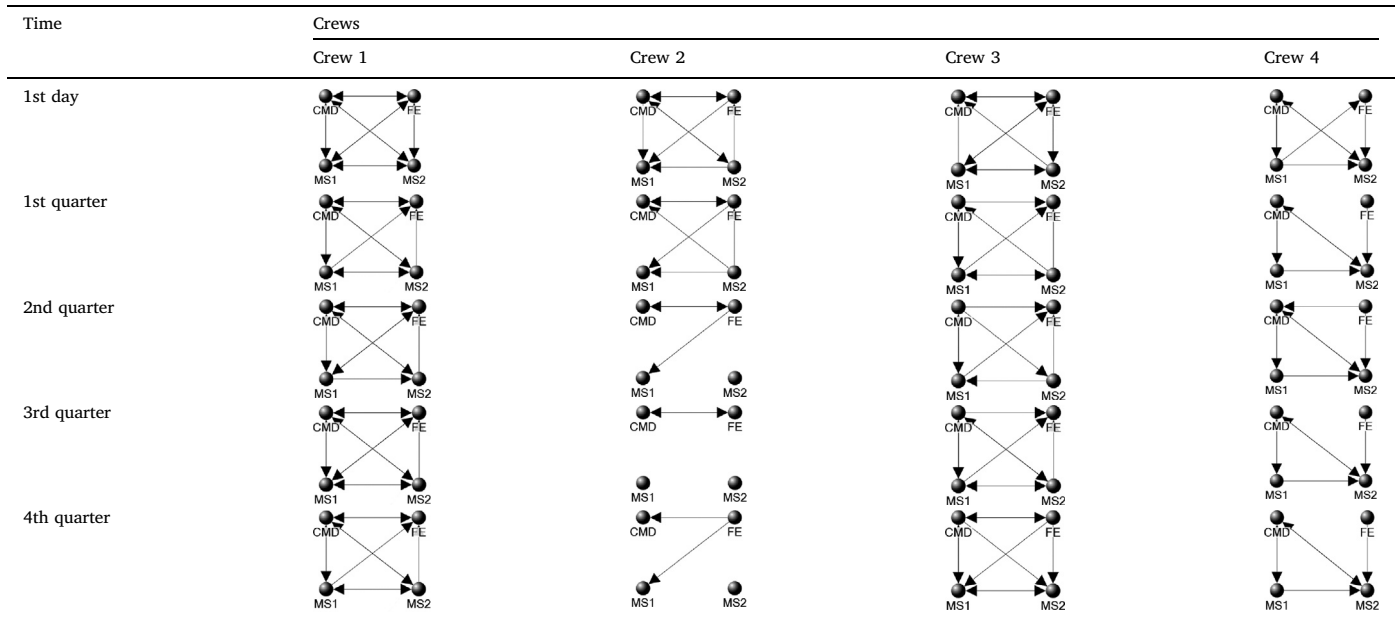


Table 4
Pseudocode for mental model algorithm.

Step	Action	Equation
Model initialization: based on empirical data		
1	Initialize time $t = 0$	
2	Import one crew with 4 agents	
3	Agents receive time-invariant characteristics <ul style="list-style-type: none"> ● roles: commander (CMD), flight engineer (FE), mission specialist 1 (MS1) or mission specialist 2 (MS2), ● demographic characteristics, and ● personality characteristics 	
4	Agents receive time-dependent characteristics at time $t = 0$ <ul style="list-style-type: none"> ● intelligence, ● team viability and team status conflict, ● social relations: informal leadership, positive, and negative relations, and ● task mental model: a list with 28 dyadic values representing the pairwise similarity ratings between 8 task elements 	
5	Import HERA C4 task log which contains all tasks performed by each agent at each moment in time over 45 days. Each task is assigned a task characteristic and the corresponding task elements associated with the task	
6	Assign communication delay as zero seconds and awake time as zero	
Model dynamics		
7	Increment time to $t = t + 1$	
8	Update agents' time-dependent characteristics <ul style="list-style-type: none"> ● intelligence ● team viability and conflict ● social relations: informal leadership, positive, and negative relations 	
9	Compute communication delay effect	eq. (1)
10	Compute sleep deprivation effect	eq. (2)
11	Set current task according to the task log	
12	Compute agents' task mental model	eq. (3)
13	Compute shared mental model	eq. (4)
14	If $t < 12,960$, then go to step 7	
Model ends		
15	END	

Note. t = time point (i.e., tick in NetLogo; 5 min in empirical data)

where t represents the current tick and $d = 288$ (i.e., number of ticks in a day). The communication delay function follows the HERA analog setting: 30 s delay on Mission Days (MDs) 16 and 28, 60 s delay on MDs 17 and 27, 120 s delay on MDs 18 and 26, 240 s delay on MDs 19 and 25,

and 300 s delay between MD 20 and 24. For example, given that each tick is 5 min or 300 s, the 30-second delay on MD 16 or MD 28 results in a communication delay of 0.1 (i.e. 30/300).

The sleep deprivation is computed as:

$$C_{sleep}(t) = \begin{cases} 0 & \text{if } awake_t \leq 192, \\ \frac{(awake_t - 192)}{96} \times day_{t-1} \times 0.0225 & \text{if } awake_t > 192. \end{cases} \quad (2)$$

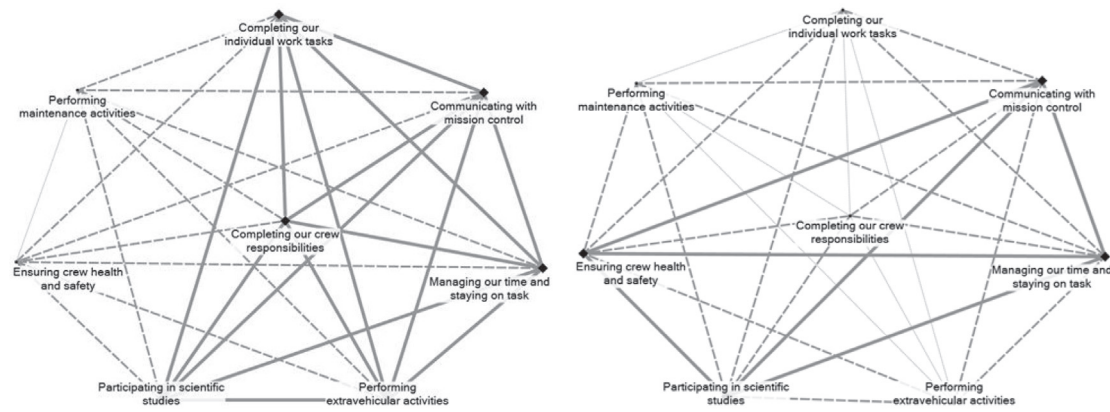
where $awake_t$ represents the time an agent is awake at time t . 192 represents the number of ticks (5 min apart) equivalent to 16 h of awake time (Lim & Dinges, 2008). Hence as long as the crew member is not awake for more than 16 h straight, there is no sleep deprivation. 96 represents the number of ticks equivalent to 8 h of sleep time, and day_t represents the day number corresponding to tick t . The sleep deprivation formula follows Lim and Dinges (2008) and is based on HERA settings: the crew members slept 5 h per night during the workweek and 8 h on Saturday and Sunday.

Finally, the model sets the current task according to the task log (Step 11) and updates (Step 12) agents' mental model based on prior agents' mental model, the contextual, individual, and social factors depending on the type of task: individual, collaborative, or no task (e.g., sleep). In the next sections, we describe the factors that influence the change in the mental model. Table A1 in Appendix summarizes the factors that influence the change in the mental model and their implementation in the computational model.

Individual mental model (Step 12).

Contextual characteristics. The first set of factors to influence an agent's mental model are contextual factors. *Communication delay* (C_{delay}) represents the degree to which team members are separated by time-related boundaries (O'Leary & Cummings, 2007). Research showed that temporal dispersion weakens mental models, as teams have a more difficult time communicating with one another (Cramton, 2001; Hinds & Weisband, 2003). It may also be the case that communication delays could heighten members' motivation and attention, thereby having a positive effect on mental model convergence.

Physical stress, such as *sleep deprivation* (C_{sleep}), puts a physical strain on team members (Driskell et al., 2018) and weakens team cognition, as it weakens the scope of members and also decreases the time they have to coordinate with one another (Ellis, 2006; Marques-



Node shape:

- Diamond: the element is associated with the task
- Circle: the element is not associated with the task

Link style:

- Solid: both elements are associated with the task
- Dash: one element is associated with the task, the other element is not associated with the task
- Dot: both elements are not associated with the task

Fig. 1. (a) Task elements associated with MMSEV-EVA task. (b) Task elements associated with Multiteam Task Battery task.

Quinteiro et al., 2013). Research showed that failures in performance appear after 16 h awake and this effect is accentuated by the number of days spent in sleep deprivation and the number of hours awake over time (Lim & Dinges, 2008). Thus, sleep deprivation has a negative effect on cognition.

Working in an environment with high workload (C_{load}), important (C_{imp}), and interdependent (i.e., workflow C_{flow}) tasks may influence the development of mental models. For example, a high workload environment may be detrimental to team mental models. As team members' workload increases, it is more difficult to observe what is happening within the team (Entin & Entin, 2000). However, results from Stout et al. (1999) showed that a high workload environment has no effect on team mental models. Furthermore, task workflow, defined as a highly interdependent task where team members must work together to perform a task, may require a high level of team cognitive workload which may weaken the team's mental model. Given the evidence that workload affects mental model formation, we included it in the model.

Individual learning. The second set of factors that affects an agent's mental model are individual learning factors. *Cognitive ability* (I_{ca}) represents an individual's capacity to learn quickly, to recognize the information stored, and to use it in new situations (Hunter, 1986; Kanfer & Ackerman, 1989; Schmidt et al., 1986). Individuals with high cognitive ability are able to distinguish those task priorities important for the job, and therefore see the task elements associated with the assigned task to be more similar than those task elements not associated with the assigned task (Resick et al., 2010).

Social learning. The third and final set of factors to influence the agent's mental model are social learning factors. Agents work on pre-assigned tasks with other agents. While they work together, their mental models can get closer or further away. The extent to which they converge or diverge through the course of working together could be affected by a variety of relational and dyadic characteristics, each explained next.

Social relations. Generally, there is a positive relationship between cognition and motivational-affective states. Individuals pay more

attention to the views of experts than non-leaders (S_{rload}), and are more likely to adjust their mental models to be more congruent with those whom they view as experts (Cartwright, 1968; Cialdini & Goldstein, 2004). Furthermore, trust increases knowledge sharing (Chowdhury, 2005) and has been suggested as a key factor in the formation of team cognition (Sánchez-Manzanares et al., 2008). Therefore, a positive social relation (S_{rpos}) will increase the shared mental models, while a negative relation (S_{rneg}) will decrease the shared mental models.

Team processes. Team cognition is positively related to team behavioral processes (DeChurch & Mesmer-Magnus, 2015; Niler et al., 2017) and motivational states, and in particular with cohesion. Therefore, team members with high perceptions of team viability (S_{viabi}) and lower perceptions of team status conflict (S_{conft}) may have more shared mental models.

Demographic characteristics. Team heterogeneity is negatively correlated with team cognition as variance in surface-level diversity increases divergence of cognitive architectures (Levesque et al., 2001; Rentsch & Klimoski, 2001). In this model, we implemented the following surface-level effects: gender (S_{hgen}), ethnicity (S_{hethn}), and education homophily (S_{heduc}), as well as age difference (S_{dage}). Additionally, we implemented one measure of deep-level diversity: military experience (S_{hme}). Homophily describes whether the two agents working together on a task have the same gender, ethnicity, education degree, or military experience.

Personality characteristics. We included five personality traits found to be important to teamwork: agreeableness, conscientiousness, extraversion, openness, and psychological collectivism (Bell, 2007). Agreeable members have a strong tendency towards compliance and consensus within the group (Hogan et al., 1994; Judge et al., 2002). Highly agreeable members see themselves as responsible for keeping up morale and bringing everyone together on common ground (Hogan et al., 1994). Team agreeableness (S_{sim_a}) increases team mental model similarity (Resick et al., 2010) and transactive memory (Guchait et al., 2014) over time. Conscientious members like organizing activities, so they are more likely to want to coordinate efforts towards a common goal, especially when the structure of the task is

loosely defined (Judge et al., 2002). Team conscientiousness (S_{sim_c}) predicts initial team transactive memory (Guchait et al., 2014) though the positive relationship is not sustained over time (Guchait & Hamilton, 2013; Resick et al., 2010). Extraverted members are active, outgoing, emotionally positive, energetic, and inclined to assert themselves on a broader level within groups and to influence the group (Judge et al., 2002). Team extraversion (S_{sim_e}) promotes cooperation and increases shared team mental models (Reilly et al., 2002). Individuals high on openness are much more likely to want to brainstorm, think outside the box, and try to come up with novel ideas (Judge et al., 2002). Thus, individuals high on openness (S_{sim_o}) are more likely to provide divergence from the group and decrease the team mental model.

Finally, psychological collectivism (S_{pc}) is defined as the degree to which a member is concerned with developing norms and goals within the team (Jackson et al., 2006). Individuals high in psychological collectivism see themselves as members of one or multiple “in-groups,” and their behavior is categorized by five facets: preference for in-groups, reliance on in-groups, concern for in-groups, acceptance of in-group norms, and prioritization of in-group goals (Jackson et al., 2006). Therefore, people with high psychological collectivism are more likely to have mental models that are close to their team members’ mental models.

As mentioned previously, the mental model is represented as pairwise similarity ratings between 8 task elements. As such one can consider each team member’s mental model as being represented as a network where the nodes are the 8 task elements. The strength of the ties in this network is the pairwise similarity ratings provided by each crew member on a scale of 1 (totally unrelated) to 7 (very strongly related). The computational model updates the rating between task element i and task element j at time t if task i is associated with task k and task j is either associated or not associated with that specific task². Equation (3) presents the mathematical representation of updating the mental model³.

$$\begin{aligned}
 MM_A TE_{i \neq j}^{ij} = & MM_A TE_{i \neq j}^{ij} + \alpha_{delay} \times C_{delay} + \alpha_{sleep} \times C_{sleep} + \alpha_{flow} \times C_{flow_k} \\
 & + \alpha_{load} \times C_{load_k} + \alpha_{imp} \times C_{imp_k} + \alpha_{ca_{sim}}(ij) \times I_{ca_A} + \alpha_{ca_{diff}}(ij) \times I_{ca_A} \\
 & + R_{AB} \times (\alpha_{sr_{load}} \times S_{sr_{load}_{A,B}} + \alpha_{sr_{pos}} \times S_{sr_{pos}_{A,B}} + \alpha_{sr_{neg}} \times S_{sr_{neg}_{A,B}} \\
 & + \alpha_{stabil} \times S_{stabil_{A,B}} + \alpha_{conf} \times S_{conf_{A,B}} + \alpha_{d_{agg}} \times S_{d_{agg}_{A,B}} + \alpha_{h_{gen}} \times S_{h_{gen}_{A,B}} \\
 & + \alpha_{h_{ethn}} \times S_{h_{ethn}_{A,B}} + \alpha_{h_{educ}} \times S_{h_{educ}_{A,B}} + \alpha_{h_{me}} \times S_{h_{me}_{A,B}} + \alpha_{sim_a} \times S_{sim_{a,A,B}} \\
 & + \alpha_{sim_c} \times S_{sim_{c,A,B}} + \alpha_{sim_e} \times S_{sim_{e,A,B}} + \alpha_{sim_o} \times S_{sim_{o,A,B}} + \alpha_{pc} \times S_{pc_A}) \quad (3)
 \end{aligned}$$

where $MM_A TE_{i \neq j}^{ij}$ represents the pairwise similarity rating at time t between task element i and task element j for agent A while performing task k . $1 \leq MM_A TE_{i \neq j}^{ij} \leq 7$. E_k represents all task elements associated with task k with task element $i \in E_k$, while task element $j \in E_k$ or $j \notin E_k$. $R_{AB} \sim U[0, \Delta]$ is a random variable that is uniformly distributed between 0 and the difference Δ . Δ represents the difference between the pairwise similarity rating at time $t-1$ between task element i and task element j for agent A and the pairwise similarity rating at time $t-1$ between task element i and task element j for agent B , normalized with the maximum distance possible between any two agents a and b .

Shared mental model (Step 13). We use the Euclidean distance to compute the distance between agents’ mental models. As such one can view the extent to which two agents share a mental model as the overlap between each agent’s representation of the network connection among the task elements. Given that the measure computed is a distance measure, and we are interested in a shared mental model, we

subtracted the distance from 1. Sharedness is computed for each dyad at each time t and takes values between 0 and 1, with 1 representing the highest shared mental model. Finally, the dyadic shared mental model is averaged at the team level to compute the team shared mental model (Eq. (4)).

$$SMM(t) = AVG \left[\sum_{A,B \in team, A \neq B} \left(1 - \frac{\sqrt{\sum_{i,j=1, i \neq j}^8 (MM_A TE_{i \neq j}^{ij} - MM_B TE_{i \neq j}^{ij})^2}}{\sqrt{28 \times (7-1)^2}} \right) \right] \quad (4)$$

where $SMM(t)$ represents the shared mental model at team level at time t . $MM_A TE_{i \neq j}^{ij}$ represents the pairwise similarity rating at time t between task element i and task element j for agent A while performing task k . $\sqrt{28 \times (7-1)^2}$ represents the maximum Euclidean distance in pairwise similarity rating between two agents.

Model calibration

After the agent-based model was specified, the parameters were estimated using empirical data collected from the 4 HERA analogs to assess the importance of the generative mechanisms. As Smith and Rand (2017) indicated, using data generated from human subjects’ experiments is the ideal method to design and calibrate the parameters that are encoded in the agent-based model’s rules and mechanisms. Although having a larger sample size would have been an ideal scenario, the NASA context poses insurmountable limits to our discretion to do so. This is, however, one of the very few social science papers, especially on team and leadership research that use empirical data to calibrate their agent-based models, as most studies determine ABM’s parameters based on either theory or practical recommendations. For example, in a 2007 review of computer models of leadership, Hazy (2007) shows that none of articles that used modeling for leadership and teams had parameters estimates using empirical data. Taken together with the very hard to reach but fascinating NASA context, we see the benefits of our study far outweighing the drawbacks posed by the unavoidable smaller sample.

Parameters estimation

The parameters were fitted using the BehaviorSearch tool (Stonedahl & Wilensky, 2010). The BehaviorSearch tool allows for the specification of an objective function that is minimized or maximized according to some set of constraints in order to “calibrate” the model. Calibration simply describes the process of manipulating a model to get closer to the desired behavior. In this case, the desired behavior is matching the simulated individual and shared mental model to the empirical mental models as closely as possible. The objective function chosen was therefore the mean squared error (MSE) between simulated mental models and empirical mental models. The MSE was calculated separately for the individual mental model and shared mental models, then averaged to ensure the error was minimized for both types of mental models simultaneously.

The BehaviorSearch software has the ability to use several search algorithms to find the optimal combination of variables that most closely minimize this error term. To find the parameters for this model, each of the different search algorithms was tested, with the standard genetic algorithm yielding the best results. The optimization function was measured as the minimum objective function over 200 simulations. Each simulation contained 10,000 model runs with 10 replications of each previous best model obtained. Two separate analyses were performed to fit the model based on the empirical data. First, the error term was modified to be calculated for the entire data set. This modification essentially finds the set of parameters that most closely matches the mental models across all crews in HERA C4. This

² The description of the task elements associated with a specific task is available in Step 5.

³ At each time t , the model updates a random number of selected pairwise similarity ratings. The model does not update the pairwise similarity rating between two task elements if none of them is associated with the task performed.

analysis yielded one set of parameters. Additionally, the BehaviorSearch minimization was run for each crew separately to determine the set of parameters that best fit the simulated mental models to the observed mental models in each crew. This yielded one set of parameters for each crew.

All variables were weighted to fall between 0 and 1. Additionally, all parameters were specified to range between -1 and 1 to investigate the positive or negative relationships of the mechanisms described in the model. This analytical strategy allowed us to directly compare the “standardized” effect sizes of all estimated parameters. The magnitude of the parameter is a measure of the effect size for each mechanism and describes how important each factor is relative to the others. Table 5 shows the value of parameters estimated using the BehaviorSearch tool for each crew and the entire HERA C4.

It is important to note that unlike traditional statistical inferential techniques, estimates obtained from BehaviorSearch algorithms are not accompanied by standard errors and hence are not amenable to standard significance tests (Antone et al., 2020). However, to assess the robustness of the estimated parameters, we run the model for each parameter P while keeping constant all other parameters as they were estimated by BehaviorSearch but letting parameter P vary over its range (from -1 to 1) using enough replications to compute the mean fit error. For example, to test the significance of the leadership parameter for Crew 1, we ran the model 200 times using the parameters determined by BehaviorSearch (e.g., leadership parameter is 0.51). Then, we ran the model 200 times with all but the leadership parameter kept constant at the value they were estimated. However, the value of the leadership parameter was allowed to vary over its range (from -1 to 1). Finally, a one-sided one sample t -test was performed to determine whether the set of errors estimated with the fit parameter (0.51) are less than those estimated allowing the parameter to vary (from -1 to 1). If the errors estimated with all parameters fixed is significantly lower than the errors from the model where the one parameter (in this case, leadership) were allowed to vary, we can conclude that the leadership variable has a statistically significant effect. The sign and magnitude of the effect are given by the parameter estimated, which in this example for Crew 1 would be 0.51 for leadership. The positive and significant value for the leadership parameter, in this case, suggests that if two agents are linked via a leadership tie it will have a positive impact on the two agents having a shared mental model. The procedure is repeated for all estimated parameters for each crew and for all four missions in HERA Campaign 4 (C4).

As noted above, the computational model shows that among the social relations factors, leadership ties are consistent predictors of shared mental models: Relying on a task collaborator for leadership increases the shared mental model between the two individuals. Among demographic characteristics, only age is a significant predictor: the closer the age between task collaborators, the higher the overlap of their mental models. Among personality characteristics, agreeableness and openness similarity are consistent predictors of shared mental models: the higher the difference in personality traits between task collaborators, the higher the overlap of their mental models. Furthermore, the results show that cognitive ability is an important predictor of mental model similarity. Crew members with high cognitive ability form more accurate mental models by perceiving the concepts associated with the task closer together, while those not associated with the task are perceived further away. Finally, among the contextual factors, task workload and task workflow are constant predictors of shared mental models.

Model validation

Once the model is calibrated, the next step is to assess the validity of the model. There are three types of validation we focus on (Rand & Rust, 2011). We first confirm face validity which represents the extent to which the proposed variables and mechanisms are theoretically plausible based on existing research. One such example is the effect

of cognitive ability on shared mental models. Our results show that cognitive ability has a positive effect on identifying those task priorities important for the job (Antone et al., 2020; Resick et al., 2010). Such results help confirm the face validity of our model.

Next, we seek to confirm internal validity or the extent to which simulation results from our computational model provide a useful reflection of observed data. Specifically, we compare the simulated mental models with empirical mental models for the same data set. This is analogous to a goodness of fit test. Finally, we consider external validity or the extent to which the model performs well at making predictions for a separate crew that was not used to calibrate the model. This assesses its generalizability. To assess external validity, we first use cross-validation in HERA C4, similarly to k -fold cross-validation used in machine learning (Rand & Rust, 2011; Sargent, 2010; Stonedahl & Rand, 2014): We estimate our models' parameters using data from one of the four crews, and then use this set of parameters to simulate the other three crews. Next, we apply the model estimated on the entire HERA C4 on a set of teams outside of the HERA C4 that engaged in activities under somewhat different circumstances. We collected additional data from HERA Campaign 5 (HERA C5)⁴. HERA C5 took place in 2019 and 2020. We observed 4 crews of 4 people that were part of HERA C5 and we collected data on individual characteristics, social relations, and tasks. Crew members lived and worked in HERA for 45 days. Unlike previous campaigns, crews in C5 were not under a sleep deprivation condition. However, they had less privacy in their crew quarters and in the hygiene module.

For each HERA C4 crew, we ran 4×200 simulations using the model parameterized on each crew in C4. Additionally, for comparison purposes, we ran 200 simulations using a null model where all parameters varied randomly from -1 to 1 . Next, we computed the mean squared error (MSE) between simulated and observed mental models. The MSE characterizes the accuracy of the estimates and can vary between 0, representing a perfect estimation of the observed data, and 1 representing complete failure in simulations (e.g., at each time t an individual rated the pairwise similarity between elements as 1 while the model estimated pairwise similarity as 7). The average MSE for internal validity (on the training data set) was 0.15, the average MSE for external validity (on the test data set in C4) was 0.19, and the average MSE for a null model was 0.51. Fig. A1(a) to A1(d) in the Appendix present the results for the internal and external validation in HERA C4. By training and testing the model on different subsets of the observed mission crews, we were able to demonstrate the validity and the across-crew generalizability of the model.

Next, for each crew in HERA C4 and C5 we ran 200 simulations using the model parameterized on the entire HERA C4. The average MSE for the HERA C4 was 0.19 while the average MSE for HERA C5 was 0.21. Fig. A2 in the Appendix presents the validation results in HERA C4 and C5 using the model parameterized on all crews in HERA C4.

Computational study: How leadership networks affect the team's shared mental model

We use virtual experiments to test our hypotheses. Our computational study was a single factor, fixed effect experiment manipulating leadership networks. For each crew, we manipulated eight conditions of leadership structures: The first four structures representing the connected structures (i.e., shared, hierarchical, coordinated, and cyclical) have been previously investigated in studies of team leadership (Carson et al., 2007; Mehra et al., 2006). The next three represent leadership structures that are fragmented and have been described in ethnographic research on small groups who live together in isolation for extended periods of time: factionalized (i.e., two subgroups), disen-

⁴ <https://lsda.jsc.nasa.gov/Mission/miss/2409>.

Table 5
Model parameters estimated from the empirical data.

		Crew 1		Crew 2		Crew 3		Crew 4		Overall	
Social relations											
$\alpha_{sr_{lead}}$	Leadership	0.51	***	0.39	***	0.51	***	0.44	***	0.63	***
$\alpha_{sr_{pos}}$	Positive	0.76	***	−0.03		0.18	***	0.11	***	0.36	***
$\alpha_{sr_{neg}}$	Negative	−0.67	***	0.79	***	−0.24	***	−0.83	***	−0.61	***
Team processes											
α_{viabil}	Team viability	0.27	**	0.06	***	0.08	***	−0.09	+	0.32	
α_{confl}	Team status conflict	−0.79		0.96	+	0.87		−0.71		0.24	
Demographic characteristics											
$\alpha_{d_{age}}$	Age difference	−0.31	***	−0.14	***	−0.36	***	−0.08		−0.63	*
$\alpha_{h_{gen}}$	Gender homophily	−0.92	***	0.28	+	0.54	***	0.30		−0.06	
$\alpha_{h_{ethn}}$	Ethnicity homophily	0.48	***	−0.39	+	−0.33		−0.62	*	0.31	**
$\alpha_{h_{educ}}$	Education homophily	0.23		0.48	*	−0.98	***	−0.15		0.71	***
$\alpha_{h_{mex}}$	Military experience homophily	0.87		0.60	***	0.58		0.44		0.82	
Personality characteristics											
α_{sim_a}	Agreeableness similarity	−0.73	***	−0.36	*	−0.01	***	−0.54	***	−0.54	***
α_{sim_c}	Conscientiousness similarity	0.15	*	−0.94	***	−0.71	***	−0.09	*	−0.05	***
α_{sim_o}	Openness similarity	−0.41	***	0.63	***	−0.19	***	−0.11	**	−0.99	***
α_{sim_e}	Extraversion similarity	−0.40	***	0.28	***	0.43	***	0.96	***	−0.64	***
α_{pc}	Psychological collectivism	−0.80	***	−0.46	***	0.34	***	−0.82	***	0.60	***
Cognitive ability											
$\alpha_{ca_{sim}}$	Effect on similar element dyads	0.80	***	0.69	***	0.98	***	0.60	***	0.97	***
$\alpha_{ca_{diff}}$	Effect on different element dyads	−0.88	***	−0.71	***	−0.88	***	−0.86	***	−0.83	***
Context characteristics											
α_{delay}	Communication delay	−0.01	***	0.02	***	−0.04	***	0.00	***	−0.04	***
α_{sleep}	Sleep deprivation	0.41	***	0.53	***	−0.05	***	−0.33	***	−0.23	***
$\alpha_{t_{flow}}$	Task workflow (interdependence)	−0.18	+	−0.57		−0.67	***	0.33		−0.22	+
$\alpha_{t_{load}}$	Task workload	0.37	***	0.81	***	0.25	***	0.60	***	0.23	***
$\alpha_{t_{imp}}$	Task importance	0.68	***	0.27	***	0.52	***	0.51	***	0.53	***

Note. Model parameters are being fit to predict shared mental model convergence in the empirical data; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$ (t -test performed for robustness test).

franchised star (i.e., a star with one isolate), and disenfranchised chain (i.e., chain with one isolate). Finally, for comparison, the eighth structure captured the case where there were no leadership relations within the team. All other crew and task characteristics were held constant, as in the observed crews.

Next, we used our computational model to simulate the emergence and evolution of a shared mental model across 45 days, a timespan identical to that of the mission for which empirical data were collected. The parameters of the model were the same as those fitted to the HERA C4. The individual and shared mental model were predicted at 5 min intervals (or each tick) and it was aggregated at the day level. We repeated the experiment with 100 replications for each leadership network structure for a total of 3,200 runs (i.e., 4 crews and 8 leadership structures).

We used Hierarchical Linear Modeling (HLM) to detect statistically significant differences in the resulting shared mental models across the four mission crews based on different leadership network structures. HLM is appropriate because of the nesting of the shared mental model data (Level 1) which was collected at multiple points in time (Level 2) for each of the four missions (Level 3). We used the command *mixed* in STATA 16.1 to analyze a three-level random coefficient model that tests Hypotheses 1 and 2. This analytical approach can account for variation that is introduced by each of the three levels. We use Akaike Information Criterion (AIC) to assess model fit. The reduction in the AIC is significant for all models. Table 6 shows the results for the four models used to test Hypotheses 1 and 2.

The first step in multilevel analysis is to construct a null model without any explanatory variables to see if and how the variance is distributed over different levels of analysis — in this case time (Level 2) and mission (Level 3). The model defines the amount of variance that exists around the mean of the dependent variable, shared mental model, at the mission level, and the time level. This is calculated as an Intraclass Correlation Coefficient. Model 1 represents the Null

model for Hypothesis 1. The Null model revealed that 39 % of the variance in the shared mental model could be explained at the mission and time level. The intercept component is significant, which means that the ICC is also significant, indicating that a multi-level analysis using HLM is an appropriate strategy.

Model 2 adds to Model 1 the leadership type as a Level 1 predictor of a shared mental model. Hypothesis 1 predicted that teams with connected leadership networks develop more similar mental models than do teams with fragmented leadership networks. As predicted, connected leadership did produce a higher shared mental model than fragmented leadership ($r = 0.015$, $p < 0.001$), which produced a higher shared mental model than the no leadership structure, thus supporting Hypothesis 1. Fig. 2 illustrates the leadership structures over time.

Model 3 represents the Null model for Hypothesis 2. The Null model revealed that 49% of the variance in the shared mental model could be explained at the mission and time level. Model 4 adds to Model 3 the shared and hierarchical connected leadership structures as Level 1 predictors of the shared mental model. Hypothesis 2 predicted that teams with shared leadership networks develop more similar team mental models than do teams with hierarchical leadership networks. As predicted, shared leadership produced a higher shared mental model than hierarchical leadership ($r = 0.004$, $p < 0.001$). Therefore, Hypothesis 2 is statistically supported although the magnitude of the effect makes its substantive import questionable. Fig. 3 illustrates the connected leadership structures over time. Fig. A3 in the Appendix presents the shared mental model across all leadership structures.

Discussion

The past two decades have witnessed an abundance of interest in and enthusiasm for shared and heterarchical approaches to team lead-

Table 6
Hierarchical linear modeling (HLM) testing effects of leadership network structures on team shared mental model.

	Model 1		Model 2		Model 3		Model 4	
	Null		Leadership type		Null		Connected leadership	
<i>Fixed-effects</i>								
Intercept	0.702	***	0.698	***	0.716	***	0.714	***
	(0.0150)		(0.0150)		(0.0157)		(0.0157)	
H1: Leadership type (ref. Fragmented)								
Connected			0.015	***				
			(0.0002)					
Absent			−0.031	***				
			(0.0003)					
H2: Connected leadership (ref. Hierarchical)								
Shared							0.004	***
							(0.0004)	
<i>Random-effects</i>								
Variance Components								
Residual	0.0014	***	0.0012	***	0.0011	***	0.0011	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Mission	0.0009	***	0.0009	***	0.0010	***	0.0010	***
	(0.0007)		(0.0007)		(0.0008)		(0.0008)	
Time	0.0001	***	0.0001	***	0.0001	***	0.0001	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Additional Information								
ICC: Mission	0.37				0.45			
ICC: Mission & Time	0.39				0.49			
Observations	140,800		140,800		35,200		35,200	
Wald Chi2			25,825	***			150	***
AIC	−521210		−544888		−139590		−139724	

Note. Standard errors in parentheses, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

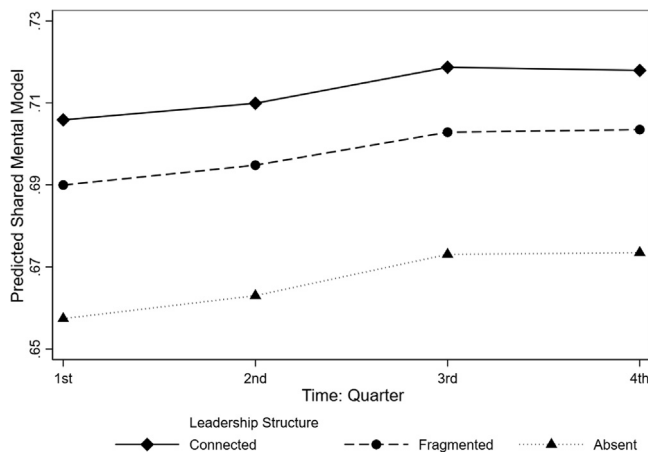


Fig. 2. Effect of Leadership Structures on Shared Mental Model.

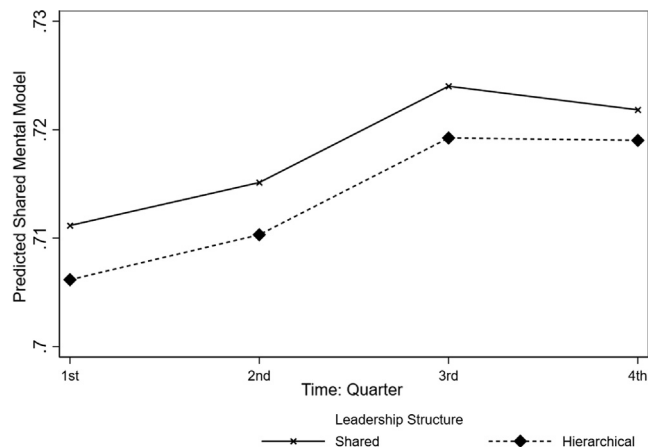


Fig. 3. Effect of Connected Leadership Structures on Shared Mental Model.

ership. In parallel, research on team effectiveness has arrived at a mature state, where much is presently understood about the antecedents, processes, and properties that enable teams to adapt and perform effectively (Kozlowski, 2018; Kozlowski & Ilgen, 2006). Leadership and shared mental models are two pivotal components of high-performance teams. A key function of team leadership is building and sustaining shared mental models, necessary for team performance. In this study, we build upon recent advances in leadership theory to examine how various leadership structures affect the development of shared mental models in teams over time. We do so using state of the art computational modeling techniques deployed in an interesting context: space exploration. Computational approaches are a game-changer for leadership in the digital era. As our study illustrates, we used intensive daily data collected on 8 analog space crews over two years. Each crew was observed for 45 days, and crews lived in the habitat sequentially. This approach allows us to extrapolate the effects of a multitude of leadership structures, generating a sample of 3,200 synthetic teams, a sample that would have taken 800 years were it not for computation.

Although leveraging computational approaches can hasten advances in leadership in any setting, the space context is especially challenging because it is simply not possible to observe thousands and thousands of teams en route to Mars, in order to understand how leadership networks underpin team mental model formation and change over time. Though a computational approach is critical for space travel, it is also exceptionally relevant back on earth where observing large numbers of teams in carefully controlled conditions are technically plausible, they are not practically feasible. Using computational methods, we can build on the current state of knowledge on shared leadership and team mental models to build a computer model that is empirically validated and can then be used to interrogate “what if” questions using synthetic teams created *in silico*.

This is not to say that space exploration is the *only* situation that stands to benefit from computational approaches to leadership. On the contrary, space merely presents an extreme case. Leadership scholars can use computational approaches as a theory-building tool, testing out relations, and examining possibilities that may be difficult to

observe in the field. Leadership practitioners can use these approaches, as we are developing for use by NASA, as a decision support tool. Our model allows us to look at leadership networks as an antecedent of team mental models. A similar approach has been used to compare the effects of participative versus differentiated leadership on team mental model convergence (Dionne et al., 2010), and to understand the ways situational factors shape leader goal striving behaviors (Zhou et al., 2019).

Our study sought to understand how the structure of leadership networks in teams would affect shared mental models over time as teams develop. We followed the lives of four teams of 4 people, living in a NASA space analog for 45 days, measuring their leadership structures, team mental models, and neighboring constructs in the nomological network. We built an agent-based model to explicate how leadership network structures affect mental model development in teams over time. We parameterized the model using data from the four crews. We then used the model parameterized on four crews to predict the next NASA analog mission with four new crews. The magnitude of the error between the model predictions and the empirical data were similar whether the model had been parameterized on the same crews or the previous crews. We then used the validated model to conduct “what if” computational experiments on teams manipulating the leadership network structures and observing their effects on shared mental models over time. At this point, the computer model is akin to a team leadership exploratorium, where we can manipulate leadership structures and observe what happens next. This paper makes two contributions to the leadership literature.

Contribution #1: Leadership network connectedness

The first contribution is to extend shared leadership research to include the connectedness dimension. A key function of team leadership is building and sustaining shared mental models (Zaccaro et al., 2001). Team members pay more attention to the beliefs and attitudes of those whom they consider being leaders, they seek advice from these individuals, and ultimately, shift their own beliefs to align with those whom they view as having influence within the group. This study adds a structural lens, showing the relevance of how leadership is patterned. How many team members are engaged in leadership? Do the leaders also rely on one another for leadership? The pattern or arrangement of leadership relations is an important driver of team mental models.

Shared leadership structures are believed to empower team members to collectively lead one another; they engender greater mutual accountability for team success (Carson et al., 2007). This study finds shared structures provide benefits to teams in terms of allowing members' cognitive schema to synchronize over time. Particularly as teams grow, an open question has remained, what constitutes shared leadership? Do all members need to lead and follow, or a subset of the team? Mehra et al. (2006) found that though all members did not necessarily need to lead and follow, having multiple leaders who are connected to one another is beneficial. The current findings build on their conclusion that structures matter. A key conclusion of that work is that “distributed leadership structures can differ with regard to important structural characteristics, and these differences can have important implications” (Mehra et al., 2006, p. 232). This study advances understanding of what these structural characteristics are, namely connectedness.

The current work also builds on that of Dionne et al. (2010), who used a computational model to understand how participative and differentiated (i.e., LMX) leadership affect team mental models. This work modeled teams of size 10 with a single leader and looked at how communication networks allowed for shared mental models to develop. A key conclusion being that participative networks outperformed differentiated ones. Whereas Dionne and colleagues were looking at a single team leader conveying meaning within teams with different communication networks, we extend this approach to under-

stand the patterning of leadership networks in self-managing teams. Dionne et al. found participative networks are superior to differentiated ones for conveying leader schema to team members. Our findings are consistent, in that shared leadership networks best promote shared mental models.

However, we found hierarchical and coordinated leadership networks are also better at promoting shared cognition than networks with either factions or isolates. Results of computational experiments support the proposition that shared leadership results in the most shared mental models, followed by hierarchical leadership, and then coordinated leadership; factionalized and disenfranchised leadership structures result in the least shared mental models. The insight that hierarchical leadership results in a more similar shared mental model than coordinated leadership is especially noteworthy and perhaps counter-intuitive.

Contribution #2: Computational approaches to leadership

The second contribution is to advance the use of computational approaches in leadership research. Over the past decade, computational social science has emerged as a viable and valuable component of our methodological suite (Contractor, 2019; Lazer et al., 2009; Lazer et al., 2020). Although the focus has been on leveraging computational approaches for “big data,” there is a growing awareness of the potential for leveraging these approaches for developing complex computational models that can be used to conduct “what-if” computational experiments. Until recently, the vast preponderance of computational models in general, and agent-based models in particular, were used to conduct thought experiments using relatively simple stylized models. These intellectual models are now being joined by a greater effort to create emulative models which are much more complex models that emulate (i.e. are grounded in) empirical contexts. Even more recent is the development of emulative models where the parameters are empirically estimated rather than being specified by the researcher. The approach utilized in this study represents one of the first efforts to bring these recent advances to the study of leadership.

Using the space exploration context, we elaborated a complex array of leadership structures and modeled their effects on team mental models over time. This allowed us to leverage an intensive longitudinal data collection alongside agent-based modeling to fast-track an understanding of how the manner in which leadership is configured in a team affects one of the most robust predictors of team performance: shared mental models. In doing so, we provided theory-guided practice for “what-if” types of team interventions in a context in which team (in)effectiveness will have dire consequences. To achieve these contributions in such a context required us to include computational science in the study of leadership. This way, we were able to incorporate more variables than a human mind can process and test a number of cases that would otherwise not be possible in lab experiments, all the while adding necessary precision to lab experiments.

Future directions

A consistent set of findings in leadership research is that connected leadership positively affects team performance (D'Innocenzo et al., 2016; Nicolaidis et al., 2014; Wang et al., 2014). The assumption of these studies is that such effects occur through the intermediating mechanism of shared mental models. In our study, we addressed directly the mechanism of influence, showing that connected leadership is more effective in the creation of shared mental models than fragmented leadership. However, we also show that different types of fragmented leadership structures can differentially affect a team's shared mental model with factionalized leadership being the least effective. Thus, although connected leadership structures are the most

effective, the great variety and number of fragmented leadership structures in modern-day teams and organizations suggest that there is benefit in future research focus on the effects of less desirable fragmented leadership structures on team performance and on the emergence and evolution of shared mental models. In particular, an interesting question to ask is: Are fragmented leadership structures damaging to a team's mental models, and if so, which type should be avoided?

The second area of future work suggested by these findings is to examine the role of shared leadership in larger teams. Though size has been a focal variable in group and team research for some time (Asch, 1956; Gerard et al., 1968; Ingham et al., 1974; Thomas & Fink, 1963), it is often treated as context, or as a control variable. Team size may fundamentally shift team leadership needs, rendering different topologies better and worse suited to supporting teams. When it comes to team leadership, we can think about how the team's functional needs change as a function of team size (i.e., size as a moderator), but also how team size cues different interaction patterns among team members (i.e., size as an antecedent).

A third interesting direction is to explore the natural self-organizing tendencies of leadership networks. Do they trend toward or away from hierarchy? Are isolates and factions inevitable in teams? In what ways do these tendencies depend on team size? For example, it may be the case that factions are most likely as team size exceeds 8 to 10 members. Though our model focuses on the outcomes of leadership networks, the question of antecedents is equally important. It is also possible that mental models serve as a basis for accepting and providing leadership to one another in teams. In fact, this is a possible self-organizing principle for leadership. Furthermore, it may be harder to develop shared mental models in groups with factions because disagreement could become normalized. This highlights the need for future work that explores both antecedents of leadership networks, as well as temporal shifts over time. Recent work has outlined that emergent leadership structures change over (Bendersky & Pai, 2018; Gerpott et al., 2019), and this suggests fruitful research opportunities that focus on the intersection between leadership structures, shared mental models, and changes in each of these over time.

The fourth area for future research is to explore leadership-based interventions to improve shared mental models. From a practical perspective, it would be useful to identify specific interventions that can be performed, and when they would need to be implemented, in order to improve mental model convergence in teams.

Caveats and limitations

Though the current findings advance theory on shared leadership in teams, there are a number of important caveats and limitations to consider. The first is that we studied shared leadership networks and shared mental models in a very particular context: teams that are isolated, confined, and in extreme environments. To test the validity of our model, we applied our parameterized model on a completely different set of teams outside of the four focal ones and we predicted their shared mental model with good accuracy. Specifically, we collected data from a different HERA analog. Although the new teams were still isolated and confined, they differed in their daily routines and exposure to stressors (e.g., they had less privacy in their crew quarters and in the hygiene module). Therefore, our findings are likely to be most generalizable to teams operating in contexts that mirror the kinds of tasks, cohabitation, and isolation experienced by these teams. For example, teams deployed in the military or working in extreme contexts like the deep sea or Antarctica.

A second important aspect of the study was the lack of a formal leadership hierarchy. The crews did have an appointed commander role, though there was no formal authority attached to this individual. Leadership in these teams developed informally and relationally over time. In many extreme contexts in the military and space, the leadership model is formal and hierarchical. However, the laws of physics

will inevitably challenge this leadership approach when small teams venture beyond low Earth orbit, to destinations like Mars (Mulhearn et al., 2016). The distance will require unprecedented levels of autonomy, and with a possible crew size of between 4 and 8, there will be limited overlap in expertise. These teams will be highly expert, specialized, interdependent, and autonomous: all features favoring shared leadership structures.

Third, whereas computational methods allow the simulation of thousands of teams, the simulation used in this study is based on four teams with specific features and operating in a specific context. Furthermore, real-world teams may not conform exactly to the eight archetypes proposed and other variations clearly exist which may impact shared mental model development. While our focus on the eight archetypes was dictated by both the prior literature on the topic and by a need for model parsimony, actual teams may in fact exhibit lesser degrees of shared leadership than the one studied here. Therefore, we caution that generalizations to other types of teams performing different tasks and under different conditions should be made judiciously.

Fourth, we studied the effects of leadership archetypes on mental model convergence, but were not able to explore their effects on accuracy. This decision was based on prior work identifying the similarity of mental models as an important factor that enables teams to work together effectively, though mental model accuracy has also been found to predict team performance (DeChurch & Mesmer-Magnus, 2010; McIntyre & Foti, 2013). Our measure of mental models was developed with NASA SME input to capture mental representations of taskwork that are important to a space mission (e.g., safety, science, communication with mission control center). This measure was designed with the aim of understanding convergence, though a key limitation is that there is not a "ground truth" correctness to the model. Hence, it is important to interpret these findings with regard to mental representations where convergence is believed to be essential, independent of an objective degree of accuracy. Furthermore, an interesting future research direction is to explore the role of team leadership archetypes on mental model accuracy, as well as other team states like cohesion, team potency, and collective efficacy.

Fifth, we are using observed data to calibrate our model, even though the NASA context posed severe restrictions on our sample size. We strongly believe that our study represents a step forward towards empirically calibrating ABMs. Taken together with the very hard to reach but fascinating NASA context, we see the benefits of our study far outweighing the drawbacks posed by the unavoidable smaller sample.

Conclusion

Leading teams over time through space presents leadership scholars with a fascinating puzzle. The extremity of the context challenges the field to leverage advances in computational modeling and to sharpen current theories. Inspired by the NASA aim of sending space crews into deep space, we leveraged computational modeling to answer the important practical question: What kind of leadership structure best supports the development and maintenance of team shared mental models? This work not only illustrates an advance for leadership research, building on and integrating theories through computational approaches, but also extends leadership theory suggesting connectedness as an important dimension of shared leadership. This finding advances topological perspectives of leadership and computational approaches to study them.

Acknowledgements

This work was supported by the National Aeronautics and Space Administration under awards No. 80NSSC18K0221, 80NSSC18K0276,

and NNX15AM32G. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Aeronautics and Space Administration. We are grateful to George Banks and three anonymous reviewers for providing insightful developmental feedback on earlier versions of this paper. We also thank Gabriel Plummer, Mar-

lon Twyman, Lauren Landon, Sarah Huppman, and Ashley Johnson for their contributions to this research.

Appendix A

See Table A1, Figs. A1–A3.

Table A1

Factors that influence the change in mental model.

Variable	Parameter	Variable implementation
Contextual factors		
Communication delay	α_{delay}	C_{delay} = Eq. (1)
Sleep deprivation	α_{sleep}	C_{sleep} = Eq. (2)
Task workflow	α_{tflow}	C_{tflow} = Task workflow
Task workload	α_{tload}	C_{tload} = Task workload
Task importance	α_{timp}	C_{timp} = Task importance
Individual learning		
Cognitive ability		
Effect on similar element dyad	$\alpha_{ca_{sim}}$	I_{ca} = WinSCAT score
Effect on different element dyad	$\alpha_{ca_{diff}}$	I_{ca} = WinSCAT score
Social learning (dyadic level)		
Social relations		
Leadership	$\alpha_{sr_{lead}}$	$S_{sr_{lead}}$ = 1 if there is a leadership tie between two agents; 0 otherwise
Positive	$\alpha_{sr_{pos}}$	$S_{sr_{pos}}$ = 1 if there is a positive tie between two agents; 0 otherwise
Negative	$\alpha_{sr_{neg}}$	$S_{sr_{neg}}$ = 1 if there is a negative tie between two agents; 0 otherwise
Team processes		
Team viability	α_{viabil}	S_{viabil} = 1 if both agents have perception on team viability higher than mean team perception; 0 otherwise
Team status conflict	α_{confli}	S_{confli} = 1 if both agents have perception on team status conflict higher than mean team perception; 0 otherwise
Demographic characteristics		
Age difference	$\alpha_{d_{age}}$	$S_{d_{age}}$ = Absolute difference between agents age
Gender homophily	$\alpha_{h_{gen}}$	$S_{h_{gen}}$ = 1 if same gender; -1 otherwise
Ethnicity homophily	$\alpha_{h_{ethn}}$	$S_{h_{ethn}}$ = 1 if same ethnicity; -1 otherwise
Education homophily	$\alpha_{h_{educ}}$	$S_{h_{educ}}$ = 1 if same education; -1 otherwise
Military experience homophily	$\alpha_{h_{mex}}$	$S_{h_{mex}}$ = 1 if same military experience; -1 otherwise
Personality characteristics		
Agreeableness similarity	α_{sim_a}	S_{sim_a} = Absolute difference between the agreeableness score of the two agents
Conscientiousness similarity	α_{sim_c}	S_{sim_c} = Absolute difference between the conscientiousness score of the two agents
Extraversion similarity	α_{sim_e}	S_{sim_e} = Absolute difference between the extraversion score of the two agents
Openness similarity	α_{sim_o}	S_{sim_o} = Absolute difference between the openness score of the two agents
Psychological collectivism	α_{pc}	S_{pc} = Psychological collectivism of the agent

Note. All variables are normalized (i.e., values between 0 and 1).

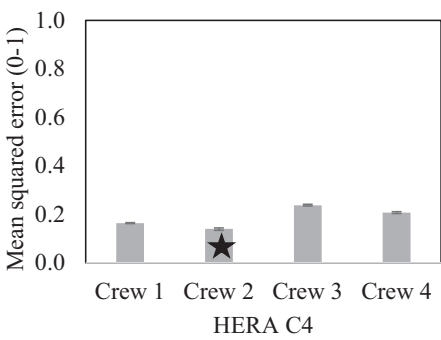
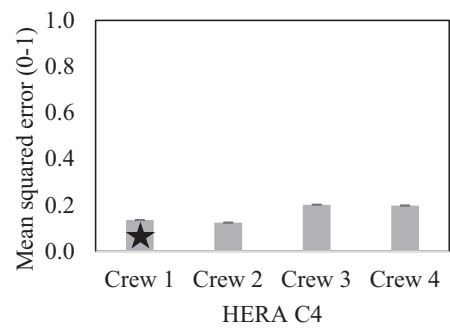


Figure A1(c) Model estimated on Crew 3

Figure A1(d) Model estimated on Crew 4

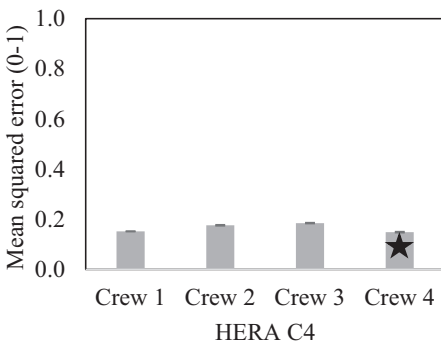
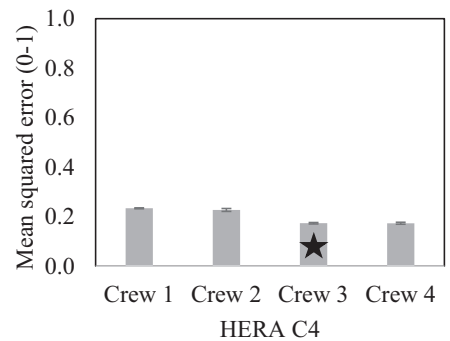


Fig. A1. (a) Model estimated on Crew 1, (b) Model estimated on Crew 2, (c) Model estimated on Crew 3, (d) Model estimated on Crew 4.

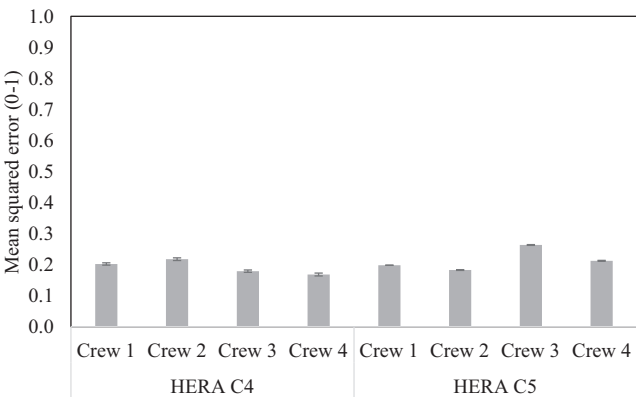


Fig. A2. Mean squared error between mental models simulated using the model parametrized on HERA C4 and observed mental models in HERA C4 and HERA C5.

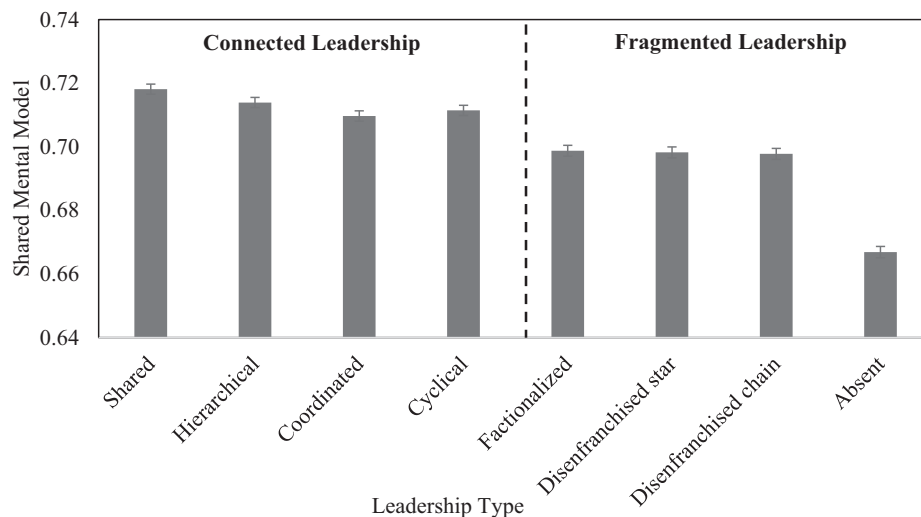


Fig. A3. Shared mental model by leadership type.

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