Spring 6-14-2019

A Computational Cognitive Architecture for Exploring Team Mental Models

Neil Benoit Outland
DePaul University, noutland@depaul.edu

A Computational Cognitive Architecture for Exploring Team Mental Models

by

Neal Benoit Outland

A Dissertation Presented to
DePaul University
in Partial Fulfillment of the Requirements for the Degree of
Doctor of Philosophy

Psychology

2019

DePaul University
College of Science and Health

This dissertation was submitted by Neal Outland under the direction of the chair of the dissertation committee listed below. It was submitted to the College of Science and Health and approved in partial fulfillment for the degree of Doctor of Philosophy in Industrial-Organizational Psychology at DePaul University.

Approved:

June 5, 2019
Date of Defense

Goran Kuljanin, Ph.D.
Chair

Suzanne Bell, Ph.D.

David Allbritton, Ph.D.

Erich Dierdorff, Ph.D.

Grace Lemmon, Ph.D.

.

June 12, 2019
Date of Final Approval

Acknowledgments

I would like to thank my parents (William and Faunchetta) and sisters (Courtney and Dajuana) for their never-ending support, love and encouragement in everything I have done. I could not have hoped for a better foundation upon which to chase my wildest dreams. I would also like to thank Josiane Bernier for her companionship throughout both the happiest and most challenging periods of my life thus far. I am forever grateful for the fun and awe you have contributed to my life. Finally, I would like to thank my committee members of my dissertation— Goran Kuljanin, Suzanne Bell, Erich Dierdorff, Grace Lemmon, and David Allbritton— who have all contributed considerable resources to help me achieve a critical milestone in my personal and professional career.

Table of Contents

List of Tables

List of Figures

Abstract

Team Mental Models (TMM) are one of the strongest predictors of team behavior and performance. TMM direct team behaviors through the series of tasks they perform over time. Research in the area, although crucial in demonstrating the effect of TMM, has been largely static, failing to articulate specifically how TMM emerge or function in teams over time. This dissertation develops a computational model to explicate the process of TMM emergence and demonstrate necessary factors. First, I explain the core concepts of TMM emergence, including team composition, dyadic interactions, and contextual variables. Second, I develop a process-oriented theory of TMM development in narrative format. Third, I translate the narrative theory into a computational model proposed to explore how the core processes interact to influence TMM emergence.

Results of the model suggest that teams may simultaneously increase TMM similarity and decrease overall accuracy as a team. Additionally, team intelligence may be viewed as a liability in some respects. While intelligence in team members could facilitate more efficient, faster sharing of information, incorrect information spreads more quickly. As team members are more agreeable starting from the beginning of the simulation, members could be more susceptible to believing more incorrect information.

Chapter 1: Introduction

Mental models, the cognitive organization of relevant task and procedural team knowledge, drive behavioral and affective processes in individual team members and compile to produce team-level processes that are strongly related to team performance (Cannon-Bowers, Salas, & Converse, 1993; Klimoski & Mohammed, 1994; LePine, Piccolo, Jackson, Mathieu, & Saul, 2008). Relevant knowledge, skills, abilities, and other characteristics (KSAOs) present in individual team members, often considered individual difference variables, drive the degree to which individual mental models represent a team mental model (TMM), a mental model shared across multiple team members.

A TMM is an emergent construct that develops over time as a function of the interactions team members have with one another and the environment (McComb, 2007). TMM can be perceived as the outcome of a learning process by which members integrate disparate areas of knowledge and information. Integration of unique knowledge is the very quality of teams facilitating improved performance over individuals. Teams, as a unit, process information by acquiring information from the environment and passing it between other members via communicative processes (Hinsz, Tindale, & Volrath, 1997).

TMMs are established and reinforced by team processes, the behaviors and actions team members enact to accomplish team goals (Marks, Mathieu, & Zaccarro, 2001; Mathieu, Heffner, Goodwin, Cannon-Bowers, & Salas, 2000; Mathieu, Heffner, Goodwin, Salas 2005; Resick, Murase, Randall, & DeChurch, 2014; Smith-Jentsch, Kraiger, Cannon-Bowers, & Salas, 2009; Stout et al., 1999). Through team communication processes such as planning (Stout, Cannon-Bowers, Salas, &

Milanovich,1999), information sharing (Resick et al., 2014), or reflecting upon past behaviors (Smith-Jentsch et al., 2009), teams increase the degree of sharedness of TMM among team members. Precisely how communication processes impact the development of TMMs is a standing research question (Hinsz et al., 1997; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013). Timing, centrality, or variance in the behaviors may provide information as to the precise nature by which processes influence TMM emergence.

Once established, TMMs facilitate action processes, behaviors teams employ to best accomplish tasks such as coordination, backup behavior, performance monitoring, and adaptation to changing contexts (Burke, Stagl, Salas, Pierce & Kendall, 2006; Fisher, Bell, Dierdorff, & Belohlav, 2012; Rico, Sanchez-Manzanares, Gil, & Gibson, 2008; Schmiedtke & Cummings 2017). Across team types, contexts, and tasks, TMMs strongly influence future team processes, and performance (DeChurch & Mesmer-Magnus, 2010a; LePine et al., 2008).

Team processes are one focal group of TMM antecedents present in the literature; the other is team composition factors. Team composition represents the degree to which combinations of individual’s skills, knowledge, abilities, and other characteristics impact affective behavioral or cognitive team outcomes (Bell, Brown, Colaneri, & Outland, 2018). Although team composition factors have direct effects on TMM emergence, their impact derives predominantly through their effect on team processes (Edwards, Day, Arthur, & Bell, 2006; Fisher et al., 2012; Randall, Resick, & DeChurch, 2011; Resick et al, 2014). Behaviorally oriented composition factors, such as agreeableness, collectivism, or extraversion, are positively related to antecedent processes and TMM in a variety of settings (Fisher et al., 2012; Lim & Klein, 2006; Resick et al., 2014). Alternatively, ability-oriented composition factors, such as cognitive ability, have a direct relationship to TMM emergence. Similar to team processes, the specific mechanisms by which team composition factors impact TMM emergence directly and through the influence of team processes is a topic that requires further research.

Contemporary thought on the development of TMM has caused a divide in the literature concerning when, how, and if TMM should be expected to develop. While the overwhelming majority of research suggests that TMM increase either in the degree of similarity between team members or in the accuracy of the TMM overall, evidence has emerged that question these assumptions (Cooke, Gorman & Winner, 2013; Levesque, 1991). In fact, researchers challenge the existence of shared or collective cognition, questioning the utility of research aims in such aspirations. The split in the literature is contradictory and could disrupt the future of TMM research and practice. Uncovering the merits of each position is necessary to expand understanding of TMM with the goal of more impactful use of TMM in teams research.

A limitation to both camps of research lies in the reliance on cross-sectional studies (Mohammed, Ferzandi, & Hamilton, 2010). Additionally, longitudinal research in the area is limited in the number of time points collected, lacking ability to pinpoint how timing of measurements may impact interpretation (Li & Roe, 2012). In turn, these limitations restrict the ability of scientists to examine critical questions surrounding TMM development over time, such as the rate of TMM (non)convergence and the level at which TMM converge (McComb, 2007; Mohammed et al., 2010).

The level of TMM emergence represents the amount of convergence, in terms of similarity or accuracy between team members, necessary for team functioning (Mathieu et al., 2005; Mohammed et al., 2010). Similarity refers to the degree of overlap of mental models across team members; accuracy refers to the degree of overlap between individual mental models and expert mental models (Edwards et al, 2006; Mathieu et al., 2000; 2005). The rate of TMM convergence refers to the amount of time necessary for a team to reach optimal or necessary levels of TMM convergence. Identifying the process by which antecedent factors, such as individual differences and team processes, contribute to the pattern of TMM emergence can aid in predicting the both level and rate of TMM emergence.

Recent theoretical developments suggest that a better understanding of TMMs will be achieved through a multilevel examination of the emergence process; therefore, it is necessary to consider the role that lower-level phenomena such as individual differences, contextual influences, and dyadic relationships (Kozlowski et al. , 2013; Kozlowski & Chao, 2012; Kozlowski & Klein, 2000) play in emergence. Currently, multilevel examinations of TMMs are only partially conducted in TMM research. Knowledge of TMM development is dominated by understanding team-level relationships.

Through either aggregating individual behaviors (e.g. team mean individual reports of sharing information with others as representative of the amount of information sharing and team performs) or measuring team processes directly at the team-level (e.g. measuring the frequency of communication between team members), researchers examine the degree to which aggregate team behaviors impact the emergence of TMMs over time. Examining TMM development from the team-level perspective is important; it has developed the current field of TMM, yet it lacks the ability to answer contemporary questions posed, including (1) precisely how antecedents (e.g. team composition) influence TMM emergence, (2) how antecedents influence variation in TMM emergence, and (3) how process variations influence emergence (Kozlowski et al., 2013).

This dissertation addresses contemporary questions concerning TMM development, yielding two main deliverables. First, this dissertation develops a conceptual framework for integrating team composition and team processes to explain TMM development. The framework proposes a process-oriented theory of TMM development by which individual team member behavior compiles to yield measurable TMM outcomes.

Second, the conceptual framework is instantiated in a computational model to investigate TMM development under the variety of circumstances created by team composition or processes. The computational model is built on the basis of the proposed conceptual framework following the principles of computational cognitive architectures. Computational cognitive architectures are simulated cognitive environments constructed to mimic an individual's cognitive processes (Sun, 2008). In developing a computational cognitive architecture, this dissertation has multiple strengths that will advance both theoretical and practical research areas.

First, the cognitive architecture is flexible enough to represent any form of TMM, such as mental models focused on representing team member interactions or taskwork responsibilities (Cannon-Bowers et al., 1993). Second, the architecture will be able to model the emergence of transactive memory systems, a team cognition construct that is usually viewed as distinct from TMM. Third, TMM development may be reflected based on team composition information. The architecture will model team composition in terms of individual differences known to impact TMM development but will also have the capability to include additional individual difference variables that have not been included in previous studies.

Finally, the model is flexible to calibration and manipulation. Researchers may calibrate parameters of the model to better fit human subjects' data. Additionally, model parameters can be influenced through simulated interventions that influence how variables relate to one another or the processes by which behaviors unfold. A potential utility of this line of research is to develop interventions tailored to specific team compositions. Such an endeavor could inform interventions on human subjects for delivery into sub-optimally composed human teams.

Outline of this Dissertation

Chapter 2 discusses the theoretical foundation of the research work, including discussion of TMM theory, team processes that reciprocally impact TMM development, team composition as it relates to TMM development, and the rationale for applying computational models to this research.

Chapter 3 explores the construction of the computational model and outlines the rationale behind parameters, along with parameter settings. Here, description of the overall computational model is given, accompanied by the disparate areas of research that inform how the model simulates teamwork behavior.

Chapter 4 begins by validating model parameters impact on expected outcomes. The validation is followed by discussion of insights garnered from simulations of teams composed of different individual difference compositions. Implications of team composition on TMM similarity and accuracy are presented along with an example of more specific questions that could be posed using the model.

Chapter 5 discusses the implications of the insights discussed in chapter 4. This is followed by a constructive evaluation of the research as a whole. Future virtual experiments, limitations, and contributions of the research are discussed. The concluding comments discuss addressing limitations and how researchers can use the model's architecture in the future.

Chapter 2: Theoretical Foundation

Cognition in Organizations

Cognition research suggests one may best explain and predict human behavior by understanding an individual's cognition (Conant & Ashby, 1970). Individuals possess cognitions, such as mental models, that allow them to describe, explain, and predict their surrounding environment (Rouse & Morris, 1986). Mental models are cognitive structures that organize the various concepts inherent in an environment and the relationships between those concepts, including expected outcomes (Holyoak, 1984). Conceptually, one can view mental models as cognitive entities composed of content, which represent the concepts of the environment, and structure, which represents the relationships between content (Klimoski & Mohammed, 1994; Mohammed et al., 2010).

In individuals, the development of mental models is analogous to learning. Learning is the process by which individuals collect and organize knowledge. As individuals interact with others or the environment, they acquire knowledge that increases their ability to describe, predict or explain their surrounding context (Rouse & Morris, 1986). Learning is also a constructive, cumulative process; new knowledge is built upon previous knowledge. The availability of prior knowledge can serve as a basis or hindrance to learning. Similarly, mental models serve as both a facilitator and antagonist of prior knowledge (Rouse & Morris, 1986). In cases where new information is too dissimilar from the foundational mental model, integration of new information may not occur.

Mental models offer a variety of uses including allowing individuals to run mental experiments, find causes for observed events, predict future system states, and determine the correct actions to influence system states (Cannon-Bowers et al., 1993; Klimoski & Mohammed, 1994; Rouse & Morris, 1986). If individuals are able to understand the relationships between possible antecedents and observed outcomes, they might infer the preceding actions or system states (Rouse & Morris, 1986). Similarly, mental models may help predict future system states. Based on connections between system states and outcomes, an individual may utilize observations of the current context and predict the future environment. With this ability to model the context, individuals may plan for behaviors to influence their environment (Stout et al., 1999).

Overall, mental models serve as a representation of the surrounding context, including other individuals, resources, goals, and an understanding of how behavior may impact each (Cannon-Bowers et al., 1993). As mental models develop and change, they likely become more complex and match the complexity of the environment. In complex situations, individuals with more complex mental models, those composed of more content and structure, perform tasks more effectively and develop more accurate perceptions of the context (Curseu & Rus, 2005). Moreover, mental model complexity positively relates to organizational performance when the complexity matches that of the environment (Calori, Johnson, & Sarnin, 1994).

Team Mental Models

Given teams are often assembled to handle tasks too complex or difficult for any one individual, it takes the combined mental models of multiple individuals to match the complexity of the environment. The concept of team mental models (TMMs) serves as a team-level construct representing the shared cognition of groups (Cannon-Bowers et al., 1993). TMMs allow teams to predict, describe, and explain their environment (Cannon-Bowers et al., 1993; Cannon-Bowers & Salas, 2001). TMMs are often considered isomorphic to individual level mental models, operationalized as simple aggregations of individual mental models (DeChurch & Mesmer-Magnus, 2010b).

Team members enter a team with mental models of their own content and structure (Cannon-Bowers & Salas, 2001; McComb, 2007). The content of the mental models in question are the content relevant to the team or its tasks (e.g. goals, expertise and skills of other members). The content of individual mental models may be unique and completely distinct or shared to some extent. Additionally, individual mental models may vary in the degree to which they reflect true realities (Day, Arthur, & Gettman, 2001). Through collective activity, content and structure of the individual mental models may be shared across members (Edwards et al., 2006). Additionally, the content and structure are not inextricably linked; communicated content may be stored idiosyncratically, yielding multiple mental models that may share content but differ in structure. There also exists the possibility that individuals may communicate and come to share both content and structure of their mental models (McComb, 2007).

TMM Similarity

When members share mental model content and structure, it facilitates smoother team functioning through synergistic creation of behavior (McComb, 2007). The coherence among content and structure of mental models is considered mental model similarity and is positively related to processes, thus influencing how teams interact with one another, when, and under what circumstances (Cannon-Bowers et al., 1993). Similarity is also positively related to distal team outcomes in a variety of contexts, including sports, military, and organizational settings (Cooke, Kiekel & Helm, 2001; Lim & Klein, 2006; Marks, Sabella, Burke & Zaccaro, 2002; Marks, Zaccaro, & Mathieu, 2000; Mathieu et al., 2000; 2005; Rentsch & Klimoski, 2001; Webber, Chen, Payne, Marsh, & Zaccaro, 2000). For situations requiring team member interactions, similarity in mental models may determine team success or failure.

TMM similarity facilitates synergistic behaviors in teams; that is, TMM similarity facilitates coordination, communication and collaboration between team members (Uitdewilligen, Waller, & Zijlstra, 2010). Coordination refers to processes by which teams sequence behaviors and actions towards the accomplishment of a goal (Cannon-Bowers, Tannenbaum, Salas, & Volpe, 1995). When individuals share mental models of the task and strategies for goal accomplishment, they can predict the actions of others in the team and adjust their behaviors accordingly (Cannon-Bowers et al., 1993). Coordination as described here represents implicit coordination, particularly useful if teams must interact without the ability to explicitly provide direction to other team members (Rico et al., 2008). In sports teams and action teams, TMM similarity is positively related to team performance (Mathieu et al., 2000; 2005; Webber et al., 2000). In such teams, it is important that team members are able to predict the actions of other team members such that they can act dynamically in goal pursuit; TMM facilitates such dynamic action (Fisher et al., 2012).

In less dynamic contexts, teams may not need to rely on implicit coordination to manage team behaviors. Teams may directly communicate with one another to coordinate actions. TMM similarity facilitates both the timing and quality of communication between team members (Fussel & Krauss, 1989; Krauss & Fussell, 1991). For team members to effectively communicate, shared understanding of the task situation may allow members to understand when information is needed, by which other team member, and how to provide the information (Mohammed et al., 2010).

Finally, TMM similarity aids in collaboration processes of teams (Uitdewilligen et al., 2010). With similar TMM, teams may more efficiently reach consensus on decisions or future actions. For example, in less familiar teams, members may spend a large portion of time understanding team tasks and member capabilities (Bettenhausen & Murningham, 1985). However, if TMM are too similar, teams could experience rigidity in thoughts or ideas, possibly detrimental to performance. The extent to which similar mental models in teams may prove detrimental depends on whether or not the shared TMM are accurate depictions of the task situation (Mathieu et al., 2005).

TMM Accuracy

While it is important that mental models are shared between team members, it is equally important that the mental models accurately represent the context, similar to individual mental models (Day et al., 2001; Edwards et al., 2006). When mental models represent the team context well, they are said to be accurate. TMM accuracy ensures that teams possess true knowledge of the environment and facilitates behavior that most likely leads to goal achievement (Edwards et al., 2006).

TMM accuracy research explores the processes teams engage in following accurate representations of the context. Specifically, accuracy is much more relevant for intellective tasks, such as general performance tasks, where there is a demonstrable correct answer. Alternatively, accuracy is harder to operationalize for constructs such as teamwork and coordinating mechanisms given there may exist multiple optimal strategies for accomplishing the goal. In fact, some researchers suggest that accuracy of TMM may even be difficult to conceptualize for taskwork in circumstances where multiple effective strategies may likely exist (Mathieu et al., 2005).

TMM accuracy, along with TMM similarity, facilitates effective behaviors towards goal pursuit (Mohammed et al., 2010). The process by which accuracy impacts team-level outcomes also resembles that of TMM similarity. Whereas TMM similarity functions through similar conceptualizations of behaviors, accuracy functions through behaviors being correct or optimal for a task situation. However, as team members become more accurate in their construal of the task situation, they are also likely to become more similar (Edwards et al., 2006). When teams hold accurate TMMs, they are likely to exhibit higher performance (Edwards et al., 2006; Mathieu et al., 2005), better decision making (Lim & Klein, 2006), and higher quality strategies (Gary and Wood, 2011).

TMM Measurement

There exist multiple manners of collecting or eliciting TMM content and structure. These include Likert-type scales, concept mapping, card sorting, and qualitative methods (Mohammed et al., 2010). Common among all of the elicitation techniques is the goal to measure both the content and the structure of TMMs. However, no one method is found to be best for capturing TMMs and each comes with associated advantages and disadvantages.

Paired comparisons and Likert-type scales are utilized to examine how individuals rate the degree of relationship between content. In this case, content is provided by the researcher, and thus, may not accurately assess the content held idiosyncratically in individual team members. Paired comparison ratings primarily capture declarative knowledge at a descriptive level. Utilizing network metrics, researchers are able to quantify the amount of similarity between teammates' mental models. Likert-type scale questionnaires are generally regarded as elicitation tools but not as TMM measurement techniques given they do not simultaneously measure both content and structure (Mohammed et al., 2010).

In card sorting and concept mapping techniques, participants sort content into meaning structures. This can include sorting cards into piles based on relationships or by sorting cards hierarchically (Mohammed et al., 2010). Through this method, researchers are able to elicit more complex structure of mental models (e.g. sequencing of behaviors). These techniques are powerful for examining complex relationships between content, but share the weakness that content is supplied to participants.

Qualitative approaches have been suggested as a method to elicit all types of mental model knowledge from participants. Qualitative approaches, such as coding team member statements or interactions, provide an effective mechanism of eliciting both content and structure of mental models from individuals. Qualitative approaches accurately capture emergent phenomenon also (Kozlowski et al., 2013; Mohammed et al., 2000). However, this approach is difficult to integrate across individuals (Mohammed et al., 2000). Due to differences in language and terminology in expressing relationships, it is currently difficult to compare idiosyncratic mental models of individuals into meaningful metrics such as accuracy or similarity.

Computational modeling of TMMs does not suffer from measurement issues in the manner that measurement impacts empirical studies. A model can provide full knowledge of individual mental models, mental model similarity and accuracy at all times, without error for the simulated environment. This, in turn, can help guide the development of improved empirical measurements of TMMs. For example, researchers could use computational models to improve timing of TMM measurement. Through modeling TMM emergence, a computational model could pinpoint areas of TMM change and stability, informing researchers when TMM change is most likely to occur.

TMM Development

Given TMM similarity and accuracy, researchers examine how and why TMM come to get shared across team members. TMM convergence is suggested to be a bottom-up process (Klimoski & Mohammed, 1994; Kozlowski & Klein, 2000). As members with idiosyncratic mental models form a team, each mental model, despite (in)completeness, describes a person's conceptualization of the relevant team domain (e.g. the individual members, team boundaries, surrounding context, team goals; Wenzel & Kraiger, 1997). Through interactions with other teammates and the environment, mental models become more similar in both content and structure (McComb, 2007). This effect, however, is conditioned on the extent team members experience the same context. For example, individuals that do not work on similar tasks or interact interdependently are less likely experience the same information. Thus, over time, their mental models become less similar.

Throughout their lifecycle, teams encounter new information. This information can result from interactions with the environment, through communication with other team members, through revision of team goals, or the addition of a new member with entirely new mental model content and structure. With the addition of new information, individuals may revise or update their mental models (McComb, 2007). While the change in information one may view as a team-level event, the mental model change occurs in the minds of individuals (Rentsch & Woehr, 2004). Previous research also suggests that mental model convergence may occur faster for content than for structure (McComb, 2007).

Specifically, researchers suggest the convergence process occurs in 3 stages: orientation, differentiation, and integration (McComb, 2007). Orientation represents the stage whereby individuals gather and pool new information. Individuals may gather information from the environment or through interaction with other team members. Differentiation describes encoding of information and registering information that may or may not share similarity to their own. Finally, during integration, individuals integrate disparate views or pieces of information into their mental model and use it to guide behavior.

TMM Convergence Process

The pooling of new information can occur through either communication between team members or collective interaction with the environment. This represents two types of information gathering that may occur: passive and active. Passive information gathering occurs when individuals collect information from others they did not themselves observe. Active information gathering occurs when individuals collect information from the environment through direct interaction.

Individuals may collect information through interaction with other team members. For example, individuals may engage in a verbal exchange of information (Hill & Levenhagen, 1995). Individuals may also collect information through observation, experimentation, inquiry, and interaction with the environment (Ostroff & Kozlowski, 1992). Through examining the behaviors of others, the outcomes of their behaviors, and inquiring about the content and structure of others' mental models, individuals garner an understanding of different aspects of the team context.

As new information gets presented to individual team members, they must integrate this information with the information currently composing their mental models. Individuals process information to examine similar, distinct, or novel bits of information to the current mental model's content and structure. Information with similar content and structure to an individual's mental model does not require change. In fact, confidence in the correctness of information (in this case, content and structure) increases as the same information is repeated by others or repeatedly experienced (Klayman, 1995). For information conflicting with current mental model content and structure, individuals process whether or not they should integrate new information into their mental model. A similar process occurs for new information wholly missing from an individual's mental model. A variety of factors explain this process. In general, individuals must determine the credibility of new information (Lucassen & Schraagen, 2012). Following the processing of information, integration represents the reconciliation of differences whereby individuals modify their own mental models. Based on the analysis of the credibility of information, individuals update their mental models to reflect conceptualizations of the most credible information (Rouse & Morris, 1986).

By understanding the process by which mental models develop in teams, natural questions with regard to TMM convergence emerge. Two factors impact the rate of convergence: (1) the amount of information processing required and (2) the speed at which individuals can process information (Schroder, Driver, & Streufert, 1967). The amount of task information held by the team and the amount of information shared amongst members impacts the amount of information processing required by a team. If the team brings with it a wide range of information, they more likely capture the task context well (Curseu & Rus, 2005). While some team members may still share information, the wider breadth of content will provide more information that the team will need to share. Thus, the breadth of task-relevant information, called mental model coverage, impacts the amount of information a team must process. Teams with higher mental model coverage process more information.

The amount of shared information a team possesses at the start of their work further impacts the amount of information processing required by a team (Gersick &

Hackman, 1990). Member familiarity or training may impact initial sharedness of mental models (McComb, 2007). If members worked together in the past, this likely increases the amount of shared content and structure by team members. This idea does not imply the accuracy of shared models. Training attempts to ensure team members possess similar structure and content (Cooke et al., 2001). Teams members that go through training likely receive exposure to similar content in a way that ensures similar structure (Smith-Jentsch, Cannon-Bowers, Tannenbaum, & Salas, 2008). Overall, most teams will include team members that share initial mental model similarity and some that do not. For teams with less similarity to begin, they require more information processing than teams beginning with more shared conceptualizations.

Finally, the speed of information processing may vary across teams. Speed of information processing in teams depends on the rate of learning and sharing between individuals (Grand, Braun, Kuljanin, Kozlowski, & Chao, 2016; Kozlowski & Bell, 2013; Kozlowski et al., 2013). Furthermore, the amount of unique information presented to members and the speed by which members differentiate and integrate information proves critical. Thus, speed of information processing in a team may depend on the both the amount of unique information each member receives and the amount of information individuals in the team can handle at different points in time. In this sense, much rests on the characteristics of team members as to how fast a team can process information (Grand et al., 2016; Ree, Carretta, & Teachout, 1995).

Team Processes in TMM Convergence

Researchers model and predict TMM convergence through two team phenomena: team processes and team composition. Team process research develops ideas surrounding the behaviors that teams engage in to ensure task success (LePine et al., 2008; Marks et al., 2001). Two type of team processes directly relate to team goal accomplishment: team transition and action processes. Team transition processes involve collective information sharing in teams and include the team's preparation for action episodes. Team action processes consist of collective behaviors that occur during action episodes, when teams actively perform tasks (Marks et al., 2001).

During transition processes, teams actively engage in information sharing and communication. Researchers use information sharing as a lens to understand the convergence of mental models. In multiple studies, the amount of information shared between teams positively relates to the level of TMM similarity (Randall et al., 2011; Resick et al., 2014). More than the amount of information sharing, the amount of unique information shared within the team proves particularly important (Mesmer-Magnus & DeChurch, 2009). Information sharing impacts the amount of information represented in the team and the amount of information the team needs to process. The more relevant information presented to the team, the more likely the team can come to shared conceptualizations and hold accurate perceptions of the context.

Team Composition in TMM Development

Similarly, researchers explain and predict the emergence of shared TMM by considering team composition (Bell et al., 2018). Team composition considers the relevant member qualities that impact team functioning and performance (Bell, 2007; Schneider & Angelmar, 1993). Previous research utilized a variety of approaches to explore the emergence of TMM in teams including: cognitive styles (Leonard, Beauvais, & Scholl, 2005), cognitive complexity (Curseu & Rus, 2005), and team member personality (Randall et al., 2011; Resick et al., 2014). Overall, research in this area leads to the conclusion that individual differences impact the emergence of TMM.

Member knowledge, skills, abilities, and other characteristics impact the degree to which teams need to engage in information processing. The knowledge individuals bring to a team dictates the requisite amount of information processing necessary by the team. Based on mental model coverage and accuracy, teams may need to discuss and process more or less information. Changing task environments may further impact the amount of necessary information processing. Given mental models constitute cognitive representations of the relevant task context, as context increases in dynamism or complexity, the amount of information required for processing may also increase. In this sense, both amount of initial mental model coverage and the amount of new or changing content in the task environment may impact the amount of necessary information processing.

For the speed of information processing, team member abilities such as learning or cognitive ability become increasingly important. Increases in team member abilities to process information impact the overall ability of teams to process information, and thus, produce accurate TMM (Edwards et al., 2006). As team members develop more accurate mental models, assuming only one correct manner to accomplish the task, mental models should also become more similar (Edwards et al., 2006; Mathieu et al., 2005). Utilizing student teams composed as a function of cognitive ability, Edwards and colleagues (2006) demonstrated team ability strongly relates to TMM accuracy.

Team composition also impacts the rate at which information becomes shared or integrated within teams. While cognitive ability impacts how much information members can process, it also influences the amount of information individuals can communicate effectively (Nisbett et al., 2012). Thus, teams composed of higher ability teams may possess the potential to integrate information faster than other teams. Reaching this potential depends on the component processes of mental model development (McComb, 2007). While higher ability teams may pool information more quickly, the differentiation and integration of that information depends on other factors.

The degree to which team members share information with one another influences the process of team members pooling information. Some team members may reluctantly share information while others may exhibit a propensity to further their ideas or to present particular information to the team (Driskell, Goodwin, Salas, & O'Shea, 2006). In particular, assertive individuals tend to provide their own ideas with a greater propensity. Assertive individuals, by speaking more frequently, can influence group decisions by controlling which information a team considers collectively. In terms of TMM, highly assertive individuals may more likely influence TMM development than individuals not as forthcoming with information.

Differentiation is the process by which individual team members distinguish between presented information in a team and previously held information (Bartunek, Gordon, & Weathersby, 1983; Gruenfeld & Hollingshead, 1993; McComb, 2007). In some cases, an individual's mental model may not hold prior conceptualizations of the information presented. Regardless of whether the information presented to team members exists in the idiosyncratic models of individuals, individuals must evaluate the credibility of information presented before updating their mental models. Factors that influence the degree to which individuals change their mental models based on incoming information include the confidence individuals hold in corresponding information, the level of credibility they hold for the presenter of the information, and, in the absence of credibility, beliefs in the presenter of the information (i.e. the propensity to trust in others).

Confidence is the strength of a person's belief that a specific statement or bit of information is correct or accurate (Peterson & Pitz, 1988). Internally, the more confidence an individual possesses in a particular topic (e.g., mental model content), the less likely he or she modifies beliefs without substantial influence (Stasser & Davis, 1981). Overall, confident individuals are less likely to respond to outside information, especially if incoming information is presented with low confidence (Zarnoth & Sniezek, 1997). Thus, highly confident team members may be less likely to update their mental models based on information from other team members.

An alternative to internal factors such as confidence, individuals may utilize information about others in a team as cues for social influence (Zarnoth & Sniezek, 1997). Particularly, information about other group members may impact the degree to which individuals view information as credible. For example, knowledge about an individual as an expert, or that an individual demonstrated credibility in the past, may increase the probability that one views the individual as credible in the future. Additionally, individuals may utilize the amount of confidence they perceive others to possess as a cue for accuracy (Zarnoth & Sniezek, 1997). Teams may utilize confidence to simplify decision-making processes, particularly true in situations of high trust with other team members. Trust in team members, emerging from either past interactions or knowledge of expertise of other members, facilitates beliefs in the credibility of information (Stewart & Stasser, 1995). As team members view information as credible, they may more likely accept information from others and update their mental models to become more similar to those that presented the information.

The process of viewing others as credible and then updating mental models may occur through two mechanisms. First, in the case of unfamiliarity between team members, a team member's propensity to trust may impact the degree to which they view information from others as credible. Propensity to trust is a subfacet of agreeableness and influences the degree to which individuals trust others (Costa & McCrae, 1985; Driskell et al., 2006). Absent interpersonal information, dispositions may dictate the likelihood someone views another as credible and whether to integrate information into a mental model.

Second, patterns of interaction allow for individuals to build empirical records of credibility. While the influence of propensity to trust may impact perceptions of credibility early on, they do not guarantee that perceptions of credibility remain stable over time (Mathieu, Tannenbaum, Donsbach, & Alliger, 2014). Over time, actual interactions between individuals begin to dictate perceptions of trustworthiness. Patterns of interactions, then, influence perceptions of credibility and whether or not an individual will integrate information presented by particular team members.

Computational Modeling

Sun (2008) suggests one cannot discover or understand processes and mechanisms of the mind purely on the basis of behavioral experiments since these tests inevitably amount to probing only relatively superficial features of human behavior that may change under the influence of individual/group differences and contextual factors. Given the complexity of human thought, as evident in behavioral flexibility, there exists a need for complex, process-based theories to explore and explain the intricate details of the human mind. Without process-based theories, experimentation lacks direction or focus: scientists may examine the outcomes of processes without understanding the sequences of steps that produced the behavior. Computational modeling provides succinct, precise, and meaningful understanding to data generated and helps guide empirical and theoretical evaluations (Grand et al., 2016; Newell, 1994; Sun, 2008, 2009).

In addition to providing succinct and precise steps arranged in flexible sequences (Sun, 2008), computational models explore, examine, predict, and explain scientific phenomena (Harrison, Lin, Carroll, & Carley, 2007). In this sense, computational models serve as a theory building tool by instantiating verbal-conceptual theory (Grand et al., 2016; Sun, 2008). Through this procedure, simulations can test the assumptions and predictions of multiple verbal theories against one another simultaneously.

Computational cognitive models provide a flexible manner to specify the complex and detailed theories of cognition. They may provide more detailed interpretations beyond what experimental and narrative theoretical approaches can provide.

One may argue that a fundamental goal in applied sciences consists of progressing from understanding a phenomenon to predicting it, followed by prescription or control (Sun, 2008). Computational modeling serves as a unique tool contributing to all three of these aims (Harrison et al., 2007). Computational models, through process-based simulation, may reveal dynamic aspects of cognition not otherwise discovered or described, allow a detailed look at constituent elements and the interactions between those elements, predict the outcomes of constituent interactions, and produce relevant data for applied contexts in real time (Sun, 2008). Such an exploration may lead to new hypotheses, predictions, and explanations for observed or theorized phenomena.

Contemporary theories of modeling emergent constructs require examination of iterative relationships between static and dynamic factors that contribute to emergence (Kozlowski et al., 2013; 2016). The degree of specificity in relationships between variables is influenced by the goals of the model. Thus, to model TMM emergence, specifications of individual-, dyadic-, and team-level relationships is necessary. Computational models accommodate various levels of detail and granularity of the inputs, outputs, and processes (Sun, Coward, & Zenzen, 2005). Currently, the levels of cognitive modeling are organized in a hierarchical structure to include inter-agent processes, individual/agent processes, intra-agent processes, and substrate processes (Sun et al., 2005). Further information on the levels of cognitive modeling are presented in Table 1.

Table 1
Levels of Cognitive Modeling

Level	Object of Analysis	Type of Analysis	Computational Units
1	Inter-Agent Processes	Social/Cultural	Collections of Agents
2	Agents	Psychological	Individual agents
3	Intra-Agent Processes	Componential	Modular Construction of Agents
4	Substrates	Physiological	Biological Representation of Modules

Note. From "Introduction to Computational Cognitive Modeling," by R. Sun, 2008, Cambridge Handbook of Computational Psychology, 98, p. 12.

The sociological- or cultural-level includes modeling inter-agent processes such as agents interacting with one another and their environment. Cognition, in part, develops under social/cultural processes (Sun, 2006). Ignoring socio-cultural processes could miss out on underlying determinants of individual cognition. For situations of interacting agents, individual cognition requires an understanding of socio-cultural processes. In teams, the socio-cultural level of analysis may be represented by general team culture, norms, previous cognitions, or beliefs. Indeed, these factors exhibit strong top-down influences on other levels of teamwork (Edmondson & Lei, 2014). At the psychological level, individual behaviors, beliefs, knowledge, concepts, skills, motivation, emotions, perceptions and other individual characteristics are modeled. Psychological level factors may both impact and be impacted by occurrences at the inter-agent (i.e. dyadic) level (Sun, 2008). The intra-agent processes, also known as the componential level of analysis, represent the various subprocesses by which psychological factors emerge or depend on for change. In this sense, components of psychological level phenomena explicate the process by which individual agent characteristics change. At this level, cognitive architectures are utilized, and cognitive functions are computed explicitly. The physiological level of analysis, the lowest level of analysis, represents the biological implementation of computation (Dayan, 2003). This level serves as the focus for a range of disciplines such as physiology, biology, and neuroscience. Biological-level phenomena are important in cognitive computational modeling as biological aspects may influence important indicators such as the amount of information an individual may possibly process (Nisbett et al., 2012). Overall, understanding the mechanisms of individual cognition can lead to better theories of social processes (Sun, 2008; Sun & Naveh, 2004).

A Computational Foundation of TMM Development

The following section outlines the process-oriented narrative theory of TMM development. Relevant processes are outlined to delineate the iterative steps teams progress through that influence TMM development. Within outlined processes, relevant factors are included to influence effectiveness of the processes. Relevant factors may be invariant and unlikely to change over the course of the teams' lifecycle (e.g. personality), or factors may be variable and fluctuate as the team interacts over time (e.g. dyadic perceptions of credibility). Further explication of the computational foundation can be found in Appendix B.

Information Selection

Before the process of information sharing can begin in teams, individuals select information to present. Individuals search available information to select what may be relevant for the group. To filter or direct their search, individuals may first look to information they are confident in. Confident information is readily available in the minds of individuals and may be more likely to be presented to other group members (Siemsen, Roth, Balasubramanian, & Anand, 2009). The amount of information an individual can communicate, however, is limited by their ability to hold and manipulate information (Baddeley, 2003; Nisbett et al., 2012). With information selected to present to the group, individuals speak to present that information, usually if no other individuals are talking. In this dissertation, agents have a quality, labelled intelligence, that impacts the amount of information an agent can communicate and process.

Information Sharing

Groups usually engage in turn-taking in conversational contexts with one team member presenting information to the group at a time (Stasser, Vaughn, & Stewart, 2000). Based on what is discussed or presented to the group, individuals may engage in the process of information selection again to determine what relevant information needs to be presented to the group. In this dissertation, the turn-taking process is cyclical over time as it continues until individuals either do not have more information to discuss, or individuals no longer have a desire to speak.

Information Processing

The process of information sharing is influenced by the amount of information there is to be processed, social factors inherent between the presenter of information and the receiver, and individual factors inherent in the receiver of information. As information is presented to the group, each member idiosyncratically processes the presented information. First, the amount of information influences how effectively it can be processed (Miller, 1956). Information composed of more content or more complex relationships is more difficult to process. Higher levels of cognitive ability allow individuals to handle more complex information (Nisbett et al., 2012).

Additionally, characteristics of both the presenter and the receiver can influence how information is processed. According to motivated information processing theory, individuals may be less likely to encode information from individuals based on their characteristics (van Knippenberg, De Dreu, & Homan, 2004). Specifically, individuals may attend to the relationship they share with the individual speaking. As senders and receivers have stronger relationships or positive interactions with one another, the receiver may be more likely encode the information.

History of interactions are not always available between individuals. As such, individuals have general propensities that may influence how they perceive the credibility of others. Particularly, a receiver’s propensity to trust may influence whether an individual treats information as credible and then encodes the information.

Updating Mental Models

Finally, individuals encode credible information. As the last step of information processing, individuals update the content and structure of their mental models to reflect newly integrated information. Processing information and updating mental models are idiosyncratic processes that occur in each member receiving information. As these members process information similarly, they are likely to develop similar TMM. Thus, through the idiosyncratic processing of individuals, a collective construct, TMM, may emerge.

Computational Architecture for Team Mental Model Development

The computational architecture for examining TMM development is a framework by which researchers can explore the development of TMM. Three notable features provide reality and robustness to the architecture. First, the framework depicts the hierarchical nature of organizations by specifying distinct levels of analysis. Second, factors relevant to TMM development are delineated for each level of analysis. Third, the nature of factors is specified to understand how the factor may change over the course of simulation. Finally, the relationship between factors is specified. This yields four decisions for the modeler to make when using this architecture: choice of levels to simulate, variables to utilize, typology of selected variables, and nature of variable relationships.

Levels of Analysis

For this architecture, factors are grouped along levels of analyses representative of those used in empirical research (e.g. individual, dyad, team, organization). Levels of analyses capture the hierarchical nature of social systems (Mathieu & Chen, 2011). Each additional layer of analysis can be conceptualized as the proximal context for lower levels of analysis. For example, organizations create the context in which teams operate while teams create the environment by which individuals perform. For this architecture, factors are grouped along levels of analyses representative of those used in empirical research (e.g. individual, dyad, team, organization). For example, organizations create the context in which teams operate while teams create the environment by which individuals perform. A selective summary of potential variables that could be used in a computational architecture to model teams can be found in Appendix F.

Organizational-Level. Organizations create the context by which teams perform. Generally referred to as strategy or human resource practices, organizations provide resources, structure the work environment, institute rewards for behaviors and outcomes, and foster collective perceptions (e.g. culture) that direct the behavior of employees and teams (Schneider, Brief, Guzzo, 1996).

Team-Level. Team-level constructs are collective phenomenon that utilize the team as the focal unit. Team-level factors may include affective (e.g. cohesion, efficacy), behavioral (e.g. processes, norms), or cognitive (e.g. climate) elements. Team-level factors could also be aggregated measures of individual (e.g. personality) or dyadic factors (e.g. familiarity) as was a common research practice previously (Chan, 1998; Kozlowski & Klein; Mohammed et al., 2010).

Dyadic-Level. Dyadic factors are inherent in teams and represent the nature of relationships between pairs of team members (Kozlowski et al., 1999). Dyadic factors may include interactions between individuals (e.g. sharing information), perceptions between dyads (e.g. liking) or may have be related to individual-level factors (e.g. similar demographics).

Individual-Level. Individual-level variables describe both the KSAOs of individual team members and the specific behaviors individuals may engage in. KSAOs could include knowledge members hold, preferences or personalities, cognitive ability, previous work experience, or task relevant expertise. KSAOs may then influence relevant individual behaviors such as asking questions, proactively providing information to others, or elaborating.

Factor Typology

Two major characteristics describe the nature of factors at each level: dynamism and latency. First, factors are either dynamic or static over the course of the eventual computational simulation. Dynamic factors may fluctuate over the course of the model. This may be the result of dynamism in other factors or of time within the simulation. Static factors remain constant throughout a simulation.

Second, factors may be either observable or latent. Latent factors are analogous to latent variables measured in psychological research (e.g. personality) that can be measured but are generally unobservable. Observable factors are analogous to behaviors or characteristics that could be perceived by others (e.g. gender, speaking frequency). Taken together, four distinct groups of factors are used in the architecture. Table 2 depicts an example 2x2 of the nature of factors included in the architecture for the individual level.

The choice of whether a factor is dynamic or static over the course of a simulation is a decision based on the modeler and research question (Sun, 2008). To isolate the effects of particular factors, modelers may choose to hold other factors constant; thus, factors may be categorized differently based on the goals of a model derived from this architecture. Although outside of the scope of the current research, similar decisions could be made for what are traditionally latent variables in empirical research. For example, latent variables such as motivation could be modeled as an observable feature in a model.

Nature of Variable relationships

The computational model developed from this architecture will simulate a system through explication of or examination of how the system may function. Following the selection of relevant variables, relationships must be specified among variables both within and across levels of analysis. Such specification yields a complete theory of how a system of interest operates and may be compared to alternative theories of the same system (Harrison et al., 2007).

Table 2
Individual-Level Factors

	Observable	Latent
Static	Factors that do not change over the course of the simulation. Represent phenomena observable to other agents (e.g. demographics)	Factors unobservable to other agents yet that impact system behavior (e.g. personality, culture).
Dynamic	Factors representing observable phenomena that may recur throughout the	Variables that fluctuate over the course of simulation and impact other factors yet are

	course of simulation (e.g. behaviors, interaction)	unobservable to agents (e.g. efficacy, cognition, trust)
	Observable	Latent

Rationale

TMM develop as new information is presented to the team through either the members of the team or through interactions with the environment. As new information enters a team, each member undergoes a three-phase mental model development process of orientation, differentiation, and integration. Team processes influence the development of TMM through their emphasis on information sharing (e.g. transition processes), while, TMM influence how and when particular types of processes (e.g. action processes) are utilized.

Team composition also impacts the development of TMM (Edwards et al., 2006; Fisher et al., 2012; Randall et al., 2010; Resick et al., 2014). Individual differences of cognitive ability, assertiveness, and propensity to trust each influence various aspects of the mental model development process. Assertiveness influences the degree to which individuals share information in pursuit of their own goals, thoughts, or ideas (Driskell et al, 2006). Propensity to trust influences the degree to which, without information, an individual will perceive the information from other individuals as credible (Driskell et al., 2006). Finally, cognitive ability influences the degree to which individuals can handle and process large amounts of information (Ones, Dilchert, & Viswesvaran, 2012). Overall, I assert that a team’s intelligence is positively related to the rate of information processing that can occur; propensity to trust is positively related to initial rates of integration; and relative assertiveness among team members influences the balance of information sources.

In addition to these discussed outcomes, social influences also impact the development of TMM (Dionne et al., 2010). First, dyadic perceptions of credibility influence the degree to which individuals view others as trustworthy (Robert, Denis, & Hung, 2009). As individuals view each other as trustworthy, they more likely integrate information into their mental models (Fisher et al., 2012). Thus, trustworthiness between team members influences the rate of integration of information. Confidence in information influences integration as well (Zarnoth & Sniezek, 1997). As individuals gain confidence in information, it requires more effort or credibility on behalf of other team members to change one's mental model. Thus, as confidence increases in individual team members, teams may decrease mental model updating of content or structure.

The multitude of intervening factors aim to model the process by which TMM develop in detail. Through a process-oriented computational architecture, it is possible to answer questions previously unassailable to the team cognition literature. First, the model may speak to the rate of TMM convergence. The amount of information and the rate of information processing are both useful in understanding how TMM emerges in teams and on what time scale. This model demonstrates how team composition impacts the rate of convergence. Second, the level of convergence is of particular importance. While some teams may converge at a particular rate, the level at which they converge, if they do, is equally important. Level of convergence conceptually represents the degree to which teams come to share TMM in terms of similarity and accuracy.

The rate and level describe patterns that could emerge in TMM development. Important questions addressed with respect to team composition include whether or not teams achieve high levels of TMM accuracy or similarity; the amount of time necessary for teams to maximize TMM emergence; whether teams show little or no convergence over time; and whether teams show dynamic patterns of emergence. For example, some combinations of agent cognitive ability, propensity to trust, and assertiveness may yield high levels of similarity and accuracy but take a longer time than other compositions that achieve similar levels. Alternatively, teams may maximize their level of similarity or accuracy in relatively short periods. Moreover, the characteristics of agents and the social mechanisms could create subgroups whereby one member develops different mental models than other team members. Exploring these questions can qualify the level of TMM with the amount of time teams will need to achieve that level, expressing efficiency. In addition to the patterns of emergence that may be inherent, there exists the possibility that some compositions will demonstrate equifinality of outcomes. Compositions may influence differential patterns of dyadic similarity while still producing similar levels of team TMM accuracy. This introduces the primary research question.

> *Research Question 1*: How does the combination of three individual characteristics (i.e., cognitive ability, propensity to trust, and assertiveness) impact the development of team mental model similarity and accuracy?

Chapter 3: Research Method

Computational Model Construction

Agents share information with team members they consider as true information about their work. As a whole, teams share information continuously throughout simulated team interactions but TMM changes may stagnate. This could occur through multiple mechanisms. First, if all agents updated information to be similar, it is expected that no further changes to mental models would occur. Secondly, if all members become entrenched in their mental models such that no degree of confidence or credibility of other agents could cause an agent to update its mental model, TMM development should stabilize at a certain level and discontinue change. Finally, some interaction of the above mechanisms can occur. Dyads could become similar to one another and become entrenched in their beliefs, leaving other team members unable to impact the TMM.

The simulation will examine a 3 (cognitive ability) x 3 (propensity to trust) x 3 (assertiveness) fully-crossed design of individual differences in teams of 5 agents each, resulting in 161,911 unique compositions. Of the total unique compositions, 1,500 simulations were conducted. First, agglomerative clustering was conducted on the 161,911 potential simulations and yielded 500 clusters, from which 2 simulations each were selected. The remaining 500 simulations were selected randomly from the remaining simulations. The sample was chosen to ensure minimal and maximum heterogeneity for each level of individual difference factors among agents (e.g. maximal heterogeneity on assertiveness by ensuring all levels of assertiveness were present in the team).

For each composition, 200 teams were simulated. Table 3 represents the procedural steps of the computational model followed by all agents. Additionally, the model for this dissertation is constructed upon assumptions concerning team communication, summarized in Table 4. The assumptions here are selective, using only a subset of potential variables presented in Appendix D.

Table 3

Procedural Steps for Computational Model of TMM Development

Step	Conceptual Action	Computational Representation
1	Generate agents (team members) with specific attributes (Cognitive Ability, Propensity to Trust, Assertiveness, Perceptions of credibility in other agents)	Create 200 teams of 5 agents each. Agent composition should match one of 27 compositions.
2	Generate Task Environment	Create 25 x 25 square matrix to represent task environment. Fill with 0 and 1 to demonstrate structure.
3	Add Mental Model information from task environment	Sample agents with 70% of content and structure.
4	Assign confidence to agents	Randomly select confidence levels with equal probabilities for values between 0-.99
5	Team members each select information to present to the team individually	Sample topics to present based on confidence in information
6	Select a speaker	Sample a speaker from agents based on confidence in information and assertiveness
7	Information sharing	Speaker presents information to the group with degree of confidence (calculated form confidence in information and assertiveness)

8	Team members distinguish information based on credibility, what they agree with, and what they believe is wrong (Differentiation)	Credibility in information based on past history of credibility (dyad effect) and propensity to trust (individual difference). Information categorized into agreed, disagreed, and unknown.
9	Team members update mental models, perceptions of credibility, and confidence in information	Agreed information receives boost in confidence. Disagreed and unknown information are probabilistically accepted based on speaker's confidence. Newly accepted information inherits confidence level equal to speaker's confidence.
10	Return to step 5	Repeat steps 5-9 for 200 rounds

A true mental model, demonstrating the relationship between 25 pieces of content, was generated for all teams. Agents mental models are sampled from the true mental model with specific level of mental model coverage (i.e. amount of potential content space covered), and accuracy. Specifically, agents in this simulation are sampled from 70% of the task environment, with a 70% accuracy rate. These factors allow for teams to approach 100% coverage of mental content across members and excite learning of both content and structure. Additionally, the 70% accuracy rate ensures variability in the beliefs of structure across agents. Thus, agent's mental models have some degree of overlap in content and some degree of similarity, albeit not perfect. Agents begin the simulation without any prior interaction history with one another, thus limiting dyadic effects early in the simulation.

Mental models are represented as matrices with content representing both the rows and columns. As individuals learn new content, empty rows and columns are filled to accommodate the content and structure. Structural linkages are specified by 0's and 1's in the interior of the matrix. Zero's represent the absence of a relationship between content pairs and 1 represents a connection. Conceptually, 0's suggest that an agent believes two factors from the team's environment are unrelated to one another while a 1 suggests the agent believes that they are.

Table 4
Assumptions of Computational Model

	Assumption	Rationale
1	Agents have drive to share information with one another.	For purpose of this simulation, all agents aim to contribute to group goal by sharing information.
2	Confidence in information is positively related to information selected to be discussed.	Individuals are more likely to share information they are confident in (Siemsen et al., 2009).
3	Confidence in information fluctuates over time.	As new information is presented and discussion unfolds, confidence in what is correct or incorrect changes.

4	Groups exhibit turn-taking in communication with one person speaking per turn.	Groups have demonstrated turn-taking in experimental research (Stasser et al., 2000). For the sake of the model, interruptions would result in information not being effectively communicated and is not a focal aspect of research questions.
5	Assertiveness interacts with confidence in information to contribute to confident statement of information.	Assertive individuals communicate with authoritarian tones (Driskell et al., 2006) which may be interpreted as confidence. Confidence is utilized as a social cue by others to interpret the credibility of information (Zarnoth & Sniezek, 1997).

6	Propensity to trust has a non-linear relationship with perceptions of credibility over time.	Propensity to trust serves as an initial indicator upon which more situation-specific trust builds (Merritt & Ilgen, 2008).

Note. *Variable relationships in alternative models could be explained differently. The choice of variable relationships relies on theoretical understanding and goals of the modeler. For example, confidence in information could, alternatively, be considered inconsequential in determining what information is shared. Instead a modeler could use a factor such as previous experience to dictate how and when agents share information.*

Independent Factors

Intelligence. Intelligence is used to operationalize differences in the amount of information an individual agent can effectively process and communicate. Agents are assigned a particular intelligence level (low, moderate, high) that dictates the number of pieces of content that can be communicated or processed at a time. The categories implemented are for conceptual understanding; intelligence can be sampled on a continuum of ability levels. Following research on human working memory, the amount of information for each intelligence level is 5, 7, and 9 respectively (Miller, 1956). The influence of intelligence levels on information communication and processing can be found in Appendix B.

Propensity to Trust. Propensity to trust is used to operationalize the probability that information is perceived as credible without influence of dyadic information. Agents are assigned levels of propensity to trust (low, moderate, high) that dictate the probability of perceiving information as credible. Propensity to trust does not change over the course of simulations. However, the impact of propensity to trust is formulated to decrease over time. The influence of propensity to trust on probabilities of accepting information can be found in Appendix B.

Assertiveness. To operationalize the general propensity individual agents have to share their own thoughts, I used assertiveness. Agents were assigned levels of Assertiveness (low, moderate, high) that dictates the probability of attempting to present information to the group. Additionally, assertiveness positively impacts the amount of confidence individuals convey when speaking. The influence of assertiveness on speaking probability and confidence can be found in Appendix B.

Model Processes

Using information from the extant team cognition, communication, and composition literature, the present dissertation examines the interactive effects of the various factors related to TMM. By modeling the interactive factors that contribute to the emergence of team cognition, the aim is to accurately describe the process by which TMM emerges. An accurate modeling of the process can serve multiple purposes. Specifying the process over time provides information to the rate of convergence and the general temporal dynamics of TMM development. Additionally, through examining dyad-level effects, the model allows for the examination of differential effects among dyads within a team, possibly uncovering subgrouping within teams.

The unit of time for virtual simulations is a speaking round. In each unit of time, one agent speaks and presents information while the other agents process information. The next round begins when the next agent speaks. Each simulation will contain 200 speaking rounds. A summary of model processes can be found in Appendix C. A conceptual figure representing the relationships between core concepts can be found in Appendix A.

Selecting a Speaker. For team members to share information, individuals must speak and present information to one another. Research on group interactions demonstrates teams do not contribute equally (Stasser & Vaughn, 2014). Instead, research suggests stable patterns exist with respect to team member contributions as a function of team member individual characteristics (Parker, 1988; Stasser & Vaughn, 2014). In this model, individuals hold a desire to speak or present information to the team based on the confidence they hold in information and their level of assertiveness.

The question of member selection addresses who speaks and what information they present. Individual agents present information based on their confidence in the information. More confident information is more likely to be discussed. Agents present specific mental model content and proposed structural linages. Confidence held in information by agents is used to sample the information that may be presented to the group. Thus, if there are multiple areas in which the agent is confident, the each of these areas are likely to be presented to the group. Members also communicate a certain amount of information. The amount of information that individuals may present is limited by their level of cognitive ability. The confidence from the selected information is multiplied by the agent's assertiveness. The resulting score, which is limited between 0 and 1, presents a "speaking drive" or desire for agents to speak. In sum, agents select a topic based on confidence which ranges from 0 to 1; select the amount information based on their cognitive ability (5, 7, or 9 pieces of information); and communicate that information with a degree of confidence. This process yields a speaking drive score which directly related to the relative probability that the agent will speak in a given round. The speaking drive formula is represented as such:

A speaker is sampled probabilistically based on the drive level relative to other team members. Thus, individuals that have a stronger drive to speak are more likely to present information to the group. The selected speaker then presents the previously selected information to the group with a confidence level equal to the calculated speaking drive. The communicated confidence holds a value between 0 and 1, with 0 representing no confidence in the information and 1 representing absolute full confidence in the presented information. Only one agent speaks each turn.

Differentiating and Integrating Information. After information is presented to the group, agents each process the information individually. As a function of cognitive ability, agents may only process a subset of the information presented. In the event that more information is presented than an agent can process, information is selected randomly, up to the ability of the agent, for processing. Thus, no matter the quantity of information presented, the maximum amount of information processed is determined by cognitive ability.

The first step in processing information is determining its credibility. Agents determine credibility of information as a function of perceived trustworthiness of the speaker, and the confidence with which the information was presented. Perceived trustworthiness of the speaker is calculated as a function of a receiving agent's propensity to trust and any previous interactions between the speaker and receiving agent. The specific function for credibility has 2 parts: (1) the impact of propensity to trust and (2) the interaction between speakers' confidence and interaction history. The function used to capture this effect in the model is presented in Appendix B.

This function highlights the differential impact of individual differences based on previous interactions. The function is conceptually designed to demonstrate the asymptotic relationship that individual differences have over time and the extent to which dyadic interactions compile to influence future interactions. Specifically, by positioning propensity to trust in the denominator and multiplying it by the round number, the denominator is constantly increasing each round, causing the influence of propensity to trust to decrease over time. Such conceptualizations address calls for finer detailed relationships over time (Humphrey & Aime, 2014; Mathieu et al., 2014). Alternatively, the confidence with which a speaker presents information is expected to have a linear relationship on the perceived credibility of information. As the speaker's confidence increases, the probability of viewing information as credible increases (Zarnoth & Sniezek, 1997). However, this effect interacts with the interaction history between agents and cannot be examined singularly.

Finally, interaction history demonstrates a nonlinear relationship with perceptions of trust in information. The one-third exponent is utilized to demonstrate an asymptotic trajectory of trust based on past interactions. For example, early interactions of trustworthy information will cause swift increases in trust and will eventually stabilize, not increasing indefinitely. Alternatively, patterns of untrustworthy information are set to an asymptotic number close to 0, .0001. Thus, if information from another source is overwhelmingly untrustworthy, it becomes very unlikely for future information to be perceived as trustworthy. The interaction between confidence and interaction history allows agents to discount confidence in information presented based on whether or not the speaker has been credible in the past.

Agents must next determine how incoming information resonates with current mental models. Incoming information can be equivalent, different, or absent from current mental models. To assess this, agents search for the content in their mental models and the corresponding structure. If the content is found in an agent's mental model, then the information can be either equivalent or different in terms of the structural relationship. For information that is equivalent, agents increase their confidence in the information and no further processing is necessary. If information is different from currently held information, agents must select which information to maintain. Maintained information is probabilistically selected based on level of confidence in the information currently held and the assertiveness of the speaker. As a speaker communicates with more confidence, others are likely to view the information as credible (Zarnoth & Sniezek, 1997). Additionally, to the extent that an agent is highly confident in the information at hand, the more credibility needs to be communicated to instigate a change in the mental model. Finally, if information is new to the current agent's mental model, the credibility of the information is utilized to probabilistically select or reject information. As the speaker's confidence in presented information increases, the probability that the information will be integrated increases.

Model Metrics

A process-oriented theory of TMM emergence allows simultaneous examination of multiple levels within a team. To measure the various dynamics present during TMM emergence, a number of metrics will be utilized. Accuracy metrics will be used to examine the degree to which mental models of individuals and teams are correct. Similarity metrics will be utilized to measure the degree to which team members share similar mental models. In addition to the team level, dyad level similarity will also be examined to capture potential dyad-specific similarity that may occur. Overall, the metrics below aim to measure both individual- and team-level dynamics in the process of TMM emergence. Model metrics are summarized in Table 28.

Individual Accuracy. Accuracy metrics are assessed through direct comparison of agents' mental model content and structure with the true mental model content and structure. Individual accuracy will be measured by directly assessing the amount of correctly identified structural information between content pairs. Accuracy will count the total number of correctly specified structural linkages. Thus, if an agent holds all 25 content items in its mental model, 625 items will be compared to the true mental model. The number of correct linkages will be divided by the total number of possible correct linkages, 625, to yield a score of accuracy for the total task model.

Team Accuracy. Team accuracy will be analyzed using metrics of collective accuracy common in the teams literature, and through the collective presence of correct information (Mohammed et al., 2010). First, the team mean accuracy can be calculated as the average accuracy across team members. This involves the individual accuracy calculations above. This metric will be referred to as team average accuracy.

Team accuracy will also be assessed holistically by examining if the correct information is present in any individual mental model. This will be called team total accuracy. By simultaneously examining how each agent in a team conceptualizes a piece of content, a holistic accuracy metric can inform whether the correct information was available to team members. This metric helps qualify team accuracy metrics by demonstrating whether or not the team could have achieved accuracy in content based on the information distributed among all members. This is similar to the hidden-profile paradigm used in group decision-making research (Stasser et al., 2000).

Team Similarity. Team similarity will be calculated using the mean of the similarity between all possible dyads in the team. Team similarity is the mean aggregation of the dyadic similarity calculations described above. Mean similarity is a common measurement for TMM similarity (Mohammed et al., 2010). Team mean similarity will be used to understand the influence of individual characteristics and dyadic interactions on overall TMM emergence.

Table 5

Computational Model Metrics

Metric	Description	Calculation
Total Individual Accuracy	Accuracy of individual mental model content and structure.	Number of correct content and structure / 625
Conditional Individual Accuracy	Accuracy of individual mental model content and structure conditioned on the size of the agent's mental model	Number of correct content and structure / number content and structure in agent's mental model

Total Team Accuracy	Average total individual accuracy	Sum of individual accuracy / team size
Conditional Team Accuracy	Presence of accurate information among team members. If even one agent has correct information, teams will be considered accurate for that combination of content and structure.	Number of correct content and structure / 625
Team Similarity	Mean dyadic similarity	Sum of dyadic similarity divided by number of unique dyads.

Model Evaluation

Validation is a crucial aspect of computational model development. As computational models of themselves can be used to represent a theory of a phenomenon of interest, computational models are subject to the same scrutiny as theories. Validation of computational models centers around generative sufficiency, the notion that under the purveyance of plausible rules, with plausible agents, one can examine and reproduce similar social patterns on a timescale of interest (Epstein, 1999; 2006). For my example, validating a computational model includes assessing the accuracy of the functional relationships present in the model and the accuracy of model outputs.

To assess the accuracy of functional relationships present in the model, it is suggested that the functional forms, the calculations used to represent variable interactions, either be generated utilizing empirically generated estimates as specifications of relationships or that relationships between variables are informed from relevant literature (Epstein, 1999). The role of utilizing literature to inform relationships between variables is necessary in the case that current conceptualizations of variable relationships are unavailable. This is the case for many of the relationships specified in this dissertation. For example, while, theoretically, propensity to trust is an individual difference that is likely to lose influence on interactions over time, estimates of how much loss is expected over time or the degree to which there are individual differences in the amount of loss is unavailable. Including empirical correlations to represent the relationships between variables is an example of using empirically generated estimates. For example, an alternative specification of the effect of propensity to trust in this model may be to include correlations between propensity to trust and perceptions of credibility calculated from an empirical study.

Conceptual Similarity to Empirical Data

Relationships between input variables and outputs must be assessed to ensure that aspects of the model act in the intended ways. Thus, the data generated by the model must, at least conceptually, match expectations of influence on outcome variables. This introduces the concept of generative sufficiency where I tested if modelled variables operated in expected ways (Epstein, 1999). To begin, I examine if modelled variables impact system outcomes in expected ways. For example, assertiveness should increase the amount of speaking an agent does over the course of simulation.

Expectations of Model Outputs

Speaker Analysis. Speaking is designed to be a function of an agent's level of assertiveness which influences desire to share thoughts and further one's own agenda. Neither agreeableness nor intelligence are theoretically linked to speaking turns taken. It is expected that only levels of assertiveness are associated with differences in number rounds used by agents.

Assertiveness. It is expected that assertiveness impacts the opportunity agents have to consume information. Agents with higher levels of assertiveness speak more, and thus, have fewer opportunities to consume information than agents with lower levels of assertiveness. Agents with low levels of assertiveness likely have many more opportunities to consume information since they have lower probabilities of speaking information. However, given that the amount of information that may be integrated is a function of the speaker's intelligence, the recipient agents' intelligence, and the agreeableness of the recipient agents, the effect of assertiveness may be negligible at the global level. However, on average, increases in assertiveness should yield decreases in the amount of information integrated and rejected because agents will not have the opportunity to process as much information.

Agreeableness. It is expected that agreeableness impacts the degree to which agents view information as credible. Agents with higher levels of agreeableness are more likely to view information presented as credible. However, there are two factors that impact the influence of agreeableness on integrated information. First, as agents interact over time, they accept information based on historical credibility of the speaker. Thus, by the end of simulation, agreeableness is a minor aspect of determining credibility. Second, agents' current beliefs impact likelihood of accepting new information. Agents who believe strongly in a particular aspect of their mental model are less likely to change their mind, despite credibility perceptions.

Agent agreeableness is likely impactful early in simulations. In turn, early interactions could influence future credibility perceptions as credibility perceptions accumulate over time. However, with the multiple intervening factors, it is expected that differences in integrated information are negligible at the global level. Still, on average, higher levels of agreeableness should yield increases in integrated information and decreases in rejected information. Alternatively, lower levels of agreeableness should be associated with lower levels of integrated information and higher levels of rejected information.

Intelligence. Information impacts the amount of information an agent can process during a simulated round. Higher levels of intelligence provide agents the opportunity to both integrate and reject more information. Higher levels of intelligence, should, on average, yield higher levels of both accepted and rejected information.

Chapter 4: Results

Generative Sufficiency

I follow the validation procedures outlined by (Epstein, 1999). This process begins with generative sufficiency. Generative sufficiency establishes the degree to which model processes and parameters have intended relationships with model outcomes. Isolating inputs to examine effects on model outputs facilitates the discovery of whether inputs have intended effects on the data produced by the model.

Generative sufficiency does not include strict cutoffs for its determination. Examining statistical significance for simulated data would additionally be fruitless as the sample size ensures that any metric would be deemed as significant. Thus, the following review will use common metrics and visual examinations to discuss the degree to which model inputs yield expected outputs.

I review the model features of speaking turns used, integrated information, and rejected information to assess generative sufficiency. These features are the core of the modeled team communication process and are impacted by the qualities of agents composing the team. Given the model only varied the composition of teams, understanding how individual agent compositional features (i.e. agent personality) impact team process features reveal whether the model generates theoretically realistic data. Reviews of each model feature include a description of the impact that various agent characteristics have on the feature, expected outcomes of the feature based on agent characteristics, and whether or not simulated data match expectations.

Speaker Analysis

Speaking is designed to be a function of an agent's level of assertiveness which influences desire to share thoughts and further one's own agenda. Neither agreeableness nor intelligence are theoretically linked to speaking turns taken. Figure 2 outlines each personality variable modeled along with the level of each personality level. The values depicted represent the average number of speaking turns for agents with the associated levels of personality across compositions.

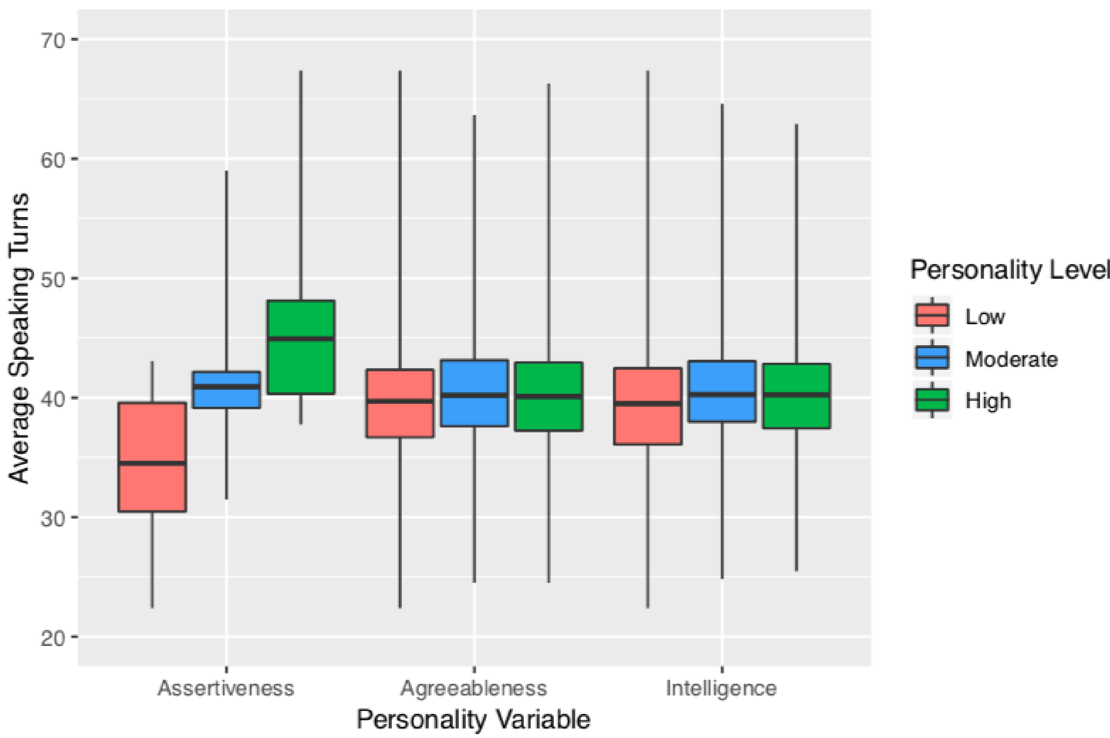


Figure 2. Mean Speaking Turns by Personality Level

Mean Levels of Speaking Turns

Given teams of 5 agents, 40 is the expected number of rounds to be taken by agents assuming equal distribution of speaking. Examining mean speaking turns by personality levels of Agreeableness, Assertiveness, and Intelligence reveals variance in mean speaking turns among agents only across levels of Assertiveness. Agents with low (*M* = 34.5), moderate (*M* = 40.9), and high (*M* = 44.9) levels of assertiveness differed in number of speaking terms used in the expected direction. Alternatively, across levels of Agreeableness, means were similar. Low (*M* = 39.7), moderate (*M* = 40.2), and high (*M* = 40.9) levels of agreeableness produced indiscernible levels of speaking turns. Means were also similar across levels of Intelligence with low (*M* = 39.5), moderate (*M* = 40.3) and high (*M* = 44.92) levels producing similar means to one another and expected number of rounds. Aligned with expectations, mean speaking rounds for moderate levels of Assertiveness (*M* = 40.9) are similar to mean levels of all levels of Agreeableness and Intelligence. From this perspective, only Assertiveness influences the degree to which agents took speaking turns in the simulation, as intended.

Differences in Mean Speaking Turns

Table 6 shows the descriptive statistics of agent personality facets on speaking turns taken. Specifically, for variance, the range of speaking turns for assertiveness is lower than that of agreeableness and intelligence. This aligns with expectations given the direct relationship theorized between assertiveness and speaking turns. It demonstrates that the impact of assertiveness is not influenced by the level of other personality factors.

Table 6
Descriptive Information of Agent Speaking Turns

	Level	Mean Rounds	SD of Mean Rounds	Max of Mean Rounds	Min of Mean Rounds	Range of Mean Rounds
Assertiveness						
	Low	34.50	4.75	43.07	22.39	20.68

	Moderate	40.91	3.48	59.01	31.48	27.53
	High	44.92	5.38	67.39	37.76	29.63
Agreeableness						
	Low	39.70	6.42	67.39	22.39	45.00
	Moderate	40.19	6.36	63.66	24.49	39.17
	High	40.10	6.24	66.28	24.48	41.80
Intelligence						
	Low	39.49	7.00	67.39	22.39	45.00
	Moderate	40.25	6.23	64.59	24.82	39.77
	High	40.23	5.74	62.91	25.48	37.43

Note. Descriptive information summarizes mean levels of 200 simulation iterations for 1,500 simulation conditions.

Information Dynamics

Theoretically, all factors were predetermined to have an effect on the amount of information integrated and rejected. First, intelligence impacts the amount of information an agent can communicate and process. This impacts the degree to which an agent can consume large amounts of information. It is expected that higher levels of intelligence will increase the amount of information an agent has the opportunity to process and, thus, the amount of information potentially integrated and rejected. However, the amount of information integrated or rejected will be determined by the levels of agreeableness of the agent as well. Agents with lower levels of agreeableness will see less information as credible, and thus, will reject more information. Rejecting information also makes it impossible to integrate that information. Therefore, increases (decreases) in rejected information simultaneously decreases (increases) the amount of integrated information.

Finally, assertive agents are more likely to speak and share information, during which time they are not processing information. Thus, higher levels of assertiveness, which can impact the degree to which an agent speaks, may be associated with lower levels of both integration and rejection since agents that are speaking more have fewer opportunities to process information from others. In sum, it is expected that each personality variable affects differences in mean levels of integrated and rejected information.

Information Exchange

Information exchange measures the amount of information an agent accepts or rejects over the course of team interactions. For integrated information, it is information an agent both perceives as credible and incorporates into its mental model. Rejected information measures the amount of information that is perceived as discreditable, and therefore, it is not incorporated into an agent's mental model. Intelligence represents the amount of information an agent could process per round. Thus, as intelligence increases, the amount of potential information integrated or rejected also increases. However, the amount of information integrated depends on the amount of information communicated by the speaker, also limited by a speaker's intelligence.

Information Integration

Information integration measures the amount of communicated information trusted and incorporated into an agent's mental model. Measurements of integrated information included switching back and forth between beliefs about types of information. Agents could switch their beliefs on pieces of information multiple times as they were convinced by other agents. Thus, the amount of integrated information may exceed the amount of information in the true mental model (i.e., 625 pieces of information).

Information Rejection

Rejected Information measures the amount of information viewed as discreditable. Rejected information measurement includes information presented multiple times that is repeatedly viewed as discreditable. Thus, the amount of rejected information may exceed the amount of information contained in the true mental model.

Two considerations should be noted before evaluating information integration and rejection. First, the likelihood that information is viewed as credible, and thereby, integrated into agent mental models is higher than for the rejection of information. This is particularly true during early stages of the simulation as many agents do not have overlapping mental models. Lack of overlapping mental models therefore suggests that the information received will be new to an agent. When information is new, this model posits that agents will rely on historical credibility, which will be limited during early interactions, and an agent's agreeableness.

Evaluating Generative Sufficiency of Integrated Information

Figure 3 is a graphical depiction of integrated information by assertiveness, agreeableness, and intelligence. Within each are the three levels of each personality from low to high. Table 6 provides corresponding numeric data. Visually examining the amount of integrated information at the end of the simulation, it is clear that personality variables impact integrated information in expected ways.

Differences in mean levels for assertiveness and agreeableness are minimal but still in the expected direction. As assertiveness levels increase, there are small but noticeable differences in mean levels of integrated information. Low assertiveness (M = 169.01) was associated with more integrated information than moderate (M = 155.25) and high (M = 151.01) levels of assertiveness.

Agreeableness was expected to be positively related to information integration such that increases in agreeableness levels correspond to increases in integrated information. This expectation was met. High agreeableness (M = 170.50) was associated with more information integration than moderate (M = 159.44) and low (M = 144.99) levels.

Intelligence also exhibited effects in the expected direction. Increases in levels of intelligence coincide with increases in mean levels of integrated information. High intelligence (M = 225.01) yielded more integrated information integration than moderate (M = 165.99) and low (M = 84.80) intelligence.

Table 7

Mean Integrated Information by Personality Level

	Level	Mean Integrated Info.	SD of Integrated Info.	Max of Mean Integrated Info.	Min of Mean Integrated Info.	Range of Mean Integrated Info.
Assertiveness						
	Low	169.01	92.83	487.93	41.71	446.22
	Moderate	155.25	84.37	415.79	37.14	378.65
	High	151.01	81.23	403.89	37.27	366.62
Agreeableness						
	Low	144.99	84.04	447.90	37.14	410.76

	Moderate	159.44	86.76	458.83	44.34	414.49
	High	170.50	86.97	487.93	49.31	438.62
Intelligence						
	Low	84.80	20.40	164.12	37.14	126.98
	Moderate	165.99	55.03	325.78	50.44	275.34
	High	225.01	95.56	487.93	49.66	438.27

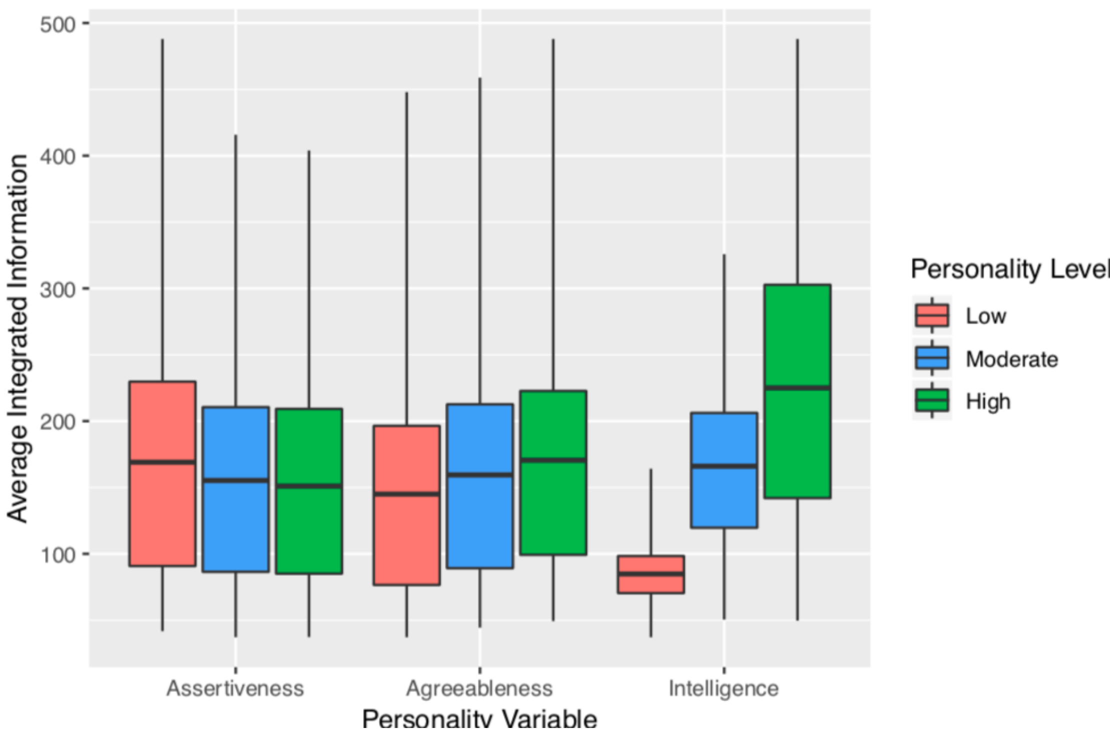


Figure 3. Mean Integrated Information by Personality Level

Evaluating Generative Sufficiency of Rejected Information

Figure 4 shows the distribution of mean rejected information across personality factors and levels. Visually examining the amount of integrated information at the end of the simulation, it is clear that personality variables produce effects in expected directions. Table 8 provides descriptive information for mean levels of information rejection.

Assertiveness yields demonstrable levels of rejected information. As assertiveness increases, mean levels of rejected information decrease, similar to the distributions of integrated information. Low assertiveness (*M* = 40.42) produced higher levels of rejected information than moderate (*M* = 35.23) and high (*M* = 31.68). The effect is similar, higher levels of assertiveness decrease the opportunity to reject information.

Agreeableness yielded the largest differences in means between levels. As agreeableness increases, levels of rejected information decrease, as expected. Low agreeableness (*M* = 50.32) yielded higher mean levels of rejected information than both moderate (*M* = 34.14) and high (*M* = 22.8) levels. This effect is best explained by the self-reinforcing feedback loop created by agreeableness. Higher levels of agreeableness cause positive feedback loops with each successive round of information by a particular agent more likely to be accepted while lower levels of agreeableness yield the opposite effect.

Increases in levels of intelligence coincide with increases in mean levels of rejected information. Low intelligence (*M* = 28.07) yielded lower mean levels of rejected information than moderate (*M* = 37.91) and high (*M* = 41.29) levels. This effect is due to opportunity. Increases in intelligence generally provides more opportunities to reject information.

Table 8

Mean Rejected Information by Personality Level

	Level	Mean Rejected Info.	SD of Rejected Info.	Max of Mean Rejected Info.	Min of Mean Rejected Info.	Range of Mean Rejected Info.
Assertiveness						

	Low	40.42	16.31	110.40	15.27	95.13
	Moderate	35.23	14.33	83.68	13.37	70.31
	High	31.68	12.99	73.75	11.70	62.05
Agreeableness						
	Low	50.32	13.12	110.40	23.88	86.52
	Moderate	34.14	8.56	65.92	18.34	47.58
	High	22.80	6.95	51.92	11.70	40.22
Intelligence						
	Low	28.07	10.17	57.99	11.70	46.29
	Moderate	37.91	14.47	80.45	13.16	67.29
	High	41.29	16.46	110.40	12.64	97.76

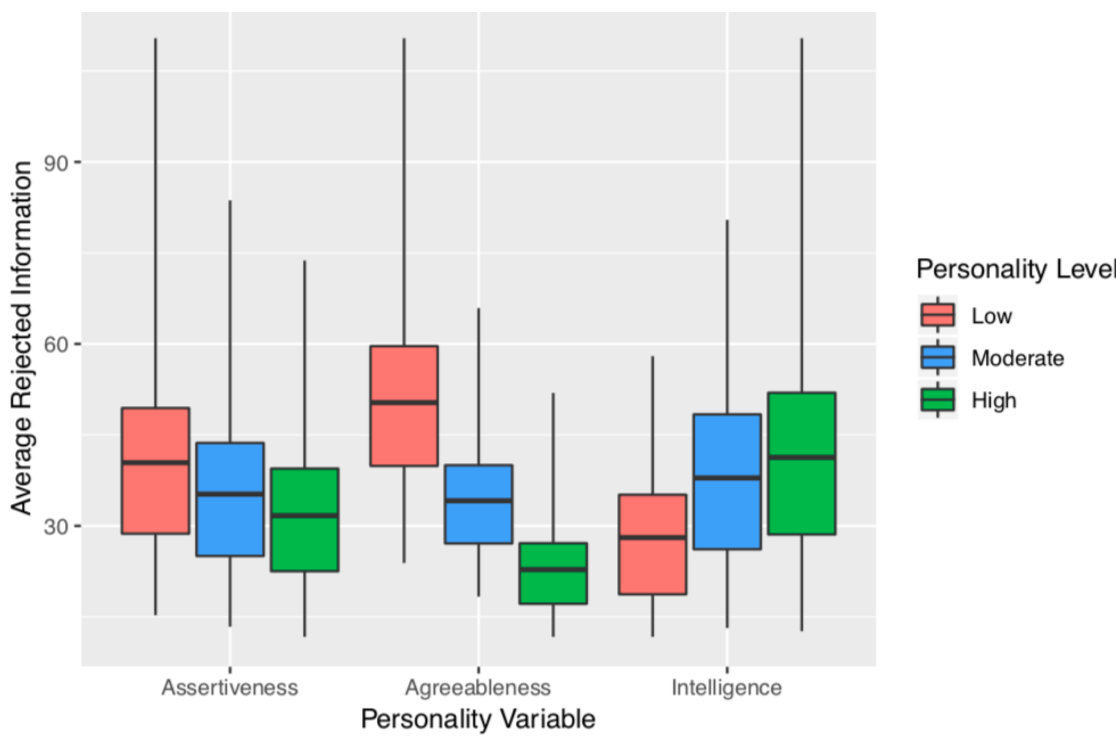


Figure 4. Mean Rejected Information by Personality Level

Correlations between Personality and Team Outcomes

Correlations of modelled data and outcomes can be found in Tables 8-10. Each table depicts the mean correlation and confidence interval for correlations between team-level personality factors and TMM outcomes. Four metrics, commonly used in empirical research to operationalize team composition, are described: team mean, team minimum, team maximum and standard deviation. For each variable and operationalization, confidence intervals are provided for both the mean and standard deviation of TMM similarity.

Similarity

Intelligence and Similarity. Intelligence exhibited strong relationships with mean TMM similarity in the simulations, with correlations ranging from -.36 to .87 in the model. Team mean 95% CI [.84,.87], minimum 95% CI [.85,.88], and maximum 95% CI [.49, .57] intelligence exhibited positive relationships with mean TMM similarity. Each also produced negative relationships with standard deviations of TMM similarity. Alternatively, team standard deviation of intelligence produced negative relationships with mean TMM similarity 95% CI [-.36, -.26] and positive relationships with TMM similarity standard deviation 95% CI [.72, .77]. Results are presented in Table 8.

Table 9

Correlation between Intelligence and TMM Similarity

	Similarity Metric	LL 95% CI	Average Correlation	UL 95% CI
Team Mean Intelligence				
	Mean	.84	.86	.87
	SD	-.13	-.07	-.02

Team Minimum Intelligence				
	Mean	.85	.86	.88
	SD	-.61	-.57	-.53
Team Maximum Intelligence				
	Mean	.48	.53	.57
	SD	.18	.24	.29
Team Intelligence SD				
	Mean	-.36	-.31	-.26
	SD	.72	.74	.77

Note. LL 95% CI = Lower Lever of 95% Confidence interval; UL 95% CI = Upper Lever of 95% Confidence interval

Agreeableness and Similarity. Team mean agreeableness here produced confidence intervals suggest small relationships with similarity. Team mean agreeableness 95% CI [.27, .37], team minimum agreeableness 95% CI [.16, .27], maximum agreeableness 95% CI [.24, .34], and agreeableness SD 95% CI [.01, .13] share small to moderate relationships with TMM similarity. Results are presented in Table 10.

Table 10

Correlation between Agreeableness and TMM Similarity

	Similarity Metric	LL 95% CI	Average Correlation	UL 95% CI
Team Mean Agreeableness				
	Mean	.27	.32	.37
	SD	-.17	-.11	-.06
Team Minimum Agreeableness				
	Mean	.16	.22	.27
	SD	-.11	-.06	.00

Team Maximum Agreeableness				
	Mean	.24	.29	.34
	SD	-.19	-.14	-.08
Team Agreeableness SD				
	Mean	.01	.07	.13
	SD	-.12	-.07	-.01

Note. LL 95% CI = Lower Lever of 95% Confidence interval; UL 95% CI = Upper Lever of 95% Confidence interval

Assertiveness and Similarity. Team mean assertiveness exhibited positive relationships with mean TMM similarity 95% CI [.13, .24] and no discernible relationship with the standard deviation of TMM similarity as confidence intervals include zero 95% CI [-.11, .006]. Team minimum assertiveness produced negligible relationships with mean TMM similarity 95% CI [-.003, .11] and positive relationships with standard deviation of TMM similarity 95% CI [.03, .15]. Team maximum assertiveness produced moderate positive relationships with TMM similarity 95% CI [.17, .28] and negative relationships with standard deviation of TMM similarity 95% CI [-.22, -.11]. Finally, standard deviation of assertiveness produced small relationships with mean TMM similarity 95% CI [.10, .21] and negative relationships with standard deviation in TMM similarity 95% CI [-.28, -.17]. Results are represented in Table 11.

Table 11

Correlation between Assertiveness and TMM Similarity

	Similarity Metric	LL 95% CI	Mean r	UL 95% CI
Team Mean Assertiveness				
	Mean	.13	.18	.24

	SD	-.11	-.05	.01
Team Minimum Assertiveness				
	Mean	.00	.05	.11
	SD	.03	.09	.15
Team Maximum Assertiveness				
	Mean	.17	.22	.28
	SD	-.22	-.17	-.11
Team Assertiveness SD				
	Mean	.10	.16	.21
	SD	-.28	-.23	-.17

Note. LL 95% CI = Lower Lever of 95% Confidence interval; UL 95% CI = Upper Lever of 95% Confidence interval

Total Accuracy

Intelligence and Total Accuracy. Intelligence exhibited strong negative relationships with mean TMM total accuracy. Team mean 95% CI [-.86, -.83], minimum 95% CI [-.85, -.88], and maximum 95% CI [-.56, -.52] intelligence exhibited negative relationships with mean TMM accuracy. Each also produced negative relationships with standard deviations of TMM accuracy, the standardized variance in accuracy across agents. In contrast, team standard deviation of intelligence produced positive relationships with both mean TMM total accuracy 95% CI [.27, .37] and TMM total accuracy standard deviation 95% CI [.25, .35]. Results are presented in Table 12.

Table 12
Correlation between Intelligence and TMM Total Accuracy

	Accuracy Metric	LL 95% CI	Mean r	UL 95% CI
Team Mean Intelligence				
	Mean	-.86	-.85	-.83

	SD	-.83	-.81	-.79
Team Minimum Intelligence				
	Mean	-.88	-.86	-.85
	SD	-.84	-.82	-.80
Team Maximum Intelligence				
	Mean	-.56	-.52	-.48
	SD	-.55	-.50	-.46
Team Intelligence SD				
	Mean	.27	.32	.37
	SD	.25	.30	.35

Note. LL 95% CI = Lower Lever of 95% Confidence interval; UL 95% CI = Upper Lever of 95% Confidence interval

Agreeableness and Total Accuracy. Agreeableness exhibited negligible relationships with mean TMM total accuracy, with correlations ranging from -.02 to .06. Team mean 95% CI [-.02, -.06], minimum 95% CI [-.03, -.05], and maximum 95% CI [-.02, -.06] agreeableness each included zero in confidence intervals of relationships with TMM accuracy. Each also produced negative relationships with standard deviations of TMM accuracy. Results are presented in Table 13.

Table 13
Correlation between Agreeableness and TMM Total Accuracy

	Accuracy Metric	LL 95% CI	Mean r	UL 95% CI
Team Mean Agreeableness				
	Mean	-.02	.02	.06
	SD	-.02	.02	.06
Team Minimum Agreeableness				
	Mean	-.03	.01	.05
	SD	-.03	.01	.05

Team Maximum Agreeableness				
	Mean	-.02	.02	.06
	SD	-.02	.02	.06
Team Agreeableness SD				
	Mean	-.03	.01	.05
	SD	-.03	.01	.05

Note. LL 95% CI = Lower Lever of 95% Confidence interval; UL 95% CI = Upper Lever of 95% Confidence interval

Assertiveness and Total Accuracy. Assertiveness exhibited small to moderate positive relationships with mean TMM total accuracy, with correlations ranging from -.03 to .28. Team mean 95% CI [.13, .24], minimum 95% CI 0, .11], maximum 95% CI [.17, .28], and standard deviation 95% CI [.10, .21] assertiveness exhibited positive relationships with TMM accuracy.

In terms of the variance of TMM total accuracy, results varied. Mean assertiveness exhibited confidence intervals that included zero suggesting that there may be no relationships between team mean assertiveness and the standard deviation of TMM total accuracy, 95% CI [-.11, .01]. Team minimum assertiveness had small positive correlations 95% CI [.03, .15] with the standard deviation of TMM total accuracy. Both, team maximum 95% CI [-.22, -.11], and team standard deviation, 95% CI [-.28, -.17], of assertiveness were negatively related to the standard deviation of total accuracy with Results are presented in Table 14.

Table 14

Correlation between Assertiveness and TMM Total Accuracy

	Similarity Metric	LL 95% CI	Mean r	UL 95% CI
Team Mean Assertiveness				
	Mean	.13	.18	.24
	SD	-.11	-.05	.01
Team Minimum Assertiveness				
	Mean	.00	.05	.11
	SD	.03	.09	.15
Team Maximum Assertiveness				
	Mean	.17	.22	.28
	SD	-.22	-.17	-.11
Team Assertiveness SD				
	Mean	.10	.16	.21
	SD	-.28	-.23	-.17

Note. LL 95% CI = Lower Lever of 95% Confidence interval; UL 95% CI = Upper Lever of 95% Confidence interval

Mean Accuracy

Correlations between Intelligence and Mean Accuracy. Team mean 95% CI [-.88, .90], minimum 95% CI [.88, .90], and maximum 95% CI [.52, .60] intelligence exhibited positive relationships with mean TMM accuracy. Each also produced positive relationships with standard deviations of TMM accuracy.

In contrast, team standard deviation of intelligence produced positive relationships with both mean TMM accuracy 95% CI [-.36, -.25] and TMM mean accuracy standard deviation 95% CI [-.37, -.27]. Results are presented in Table 15.

Table 15
Correlation between Intelligence and TMM Mean Accuracy

	Accuracy Metric	LL 95% CI	Mean r	UL 95% CI
Team Mean Intelligence				
	Mean	.88	.89	.90
	SD	.86	.88	.89
Team Minimum Intelligence				
	Mean	.88	.89	.90
	SD	.87	.88	.90
Team Maximum Intelligence				
	Mean	.52	.56	.60
	SD	.49	.54	.58
Team Intelligence SD				
	Mean	-.36	-.31	-.25
	SD	-.37	-.32	-.27

Note. LL 95% CI = Lower Lever of 95% Confidence interval; UL 95% CI = Upper Lever of 95% Confidence interval

Agreeableness and Mean Accuracy. Agreeableness exhibited negligible relationships with mean TMM total accuracy, with correlations ranging from -.03 to .06. Team mean 95% CI [-.02, .06], minimum 95% CI [-.03, .05], maximum 95% CI [-.02, -.6], and SD 95% CI [-.03, .05] agreeableness exhibited identical relationships with mean TMM accuracy. Each also produced negative relationships with standard deviations of TMM accuracy. Results are presented in Table 16.

Table 16
Correlation between Agreeableness and TMM Mean Accuracy

	Accuracy Metric	LL 95% CI	Mean r	UL 95% CI

Team Mean Agreeableness				
	Mean	-.02	.02	.06
	SD	-.02	.02	.06
Team Minimum Agreeableness				
	Mean	-.03	.01	.05
	SD	-.03	.01	.05
Team Maximum Agreeableness				
	Mean	-.02	.02	.06
	SD	-.02	.02	.06
Team Agreeableness SD				
	Mean	-.03	.01	.05
	SD	-.03	.01	.05

Note. LL 95% CI = Lower Lever of 95% Confidence interval; UL 95% CI = Upper Lever of 95% Confidence interval

Assertiveness and Mean Accuracy. Assertiveness exhibited mostly small positive relationships with TMM mean accuracy, with correlations ranging from -.28 to .28. Team assertiveness mean 95% CI [.13, .24], minimum 95% CI [0, .11], maximum 95% CI [.17, .28], and standard deviation 95% CI [.10, .21] exhibited positive relationships with mean TMM accuracy. Team assertiveness standard deviation yielded a negative relationship with SD of TMM accuracy 95% CI [-.28, -.17]. Results are presented in Table 17.

Table 17

Correlation between Assertiveness and TMM Mean Accuracy

	Accuracy Metric	LL 95% CI	Mean r	UL 95% CI

Team Mean Assertiveness				
	Mean	.13	.18	.24
	SD	-.11	-.05	.01
Team Minimum Assertiveness				
	Mean	.00	.05	.11
	SD	.03	.09	.15
Team Maximum Assertiveness				
	Mean	.17	.22	.28
	SD	.22	-.17	-.11
Team Assertiveness SD				
	Mean	.10	.16	.21
	SD	-.28	-.23	-.17

Note. LL 95% CI = Lower Lever of 95% Confidence interval; UL 95% CI = Upper Lever of 95% Confidence interval

Computational Model Results

The current computational model was constructed to simulate team interactions and answer the question of whether teams would be more likely to develop more similar or dissimilar TMM over time. Additionally, the model sought to explore the degree of accuracy that should be expected to develop as teams interact. The following paragraphs explore conclusions that may be inferred from simulation results. Beginning with similarity expectations, the discussion will explore what general trends exist across all simulated compositions before focusing on the characteristics of compositions that yield desirable outcomes.

TMM Similarity

Overall TMM Similarity. Visual depictions of TMM similarity over time display the variance in trajectories of TMM development over time. Table 18 describes the beginning and ending similarity of team compositions. Across all modelled simulations, all teams increased in TMM similarity over time. On average teams began with a similarity of 31% and completed the simulation with an average similarity of 69%. This means, on average, all pairs of dyads within a team agreed upon 69% of information by the end of simulation, an average increase of 38%. No compositions exhibited decreases in TMM similarity. Thus, the model suggests that teams generally increase in TMM similarity over time.

Final TMM similarity exhibited a wide range of outcomes. At the end of 200 rounds, 89% represented the maximum value of TMM similarity. The minimum value was 44%. Thus, the largest TMM increase in similarity was 58% while the minimum increase was 13%. To explore the characteristics of the teams that yielded the highest and lowest similarity over time, the top and bottom 5% of teams were examined. Figure 6 shows the average trajectory of TMM similarity development for the top and bottom 5% of teams.

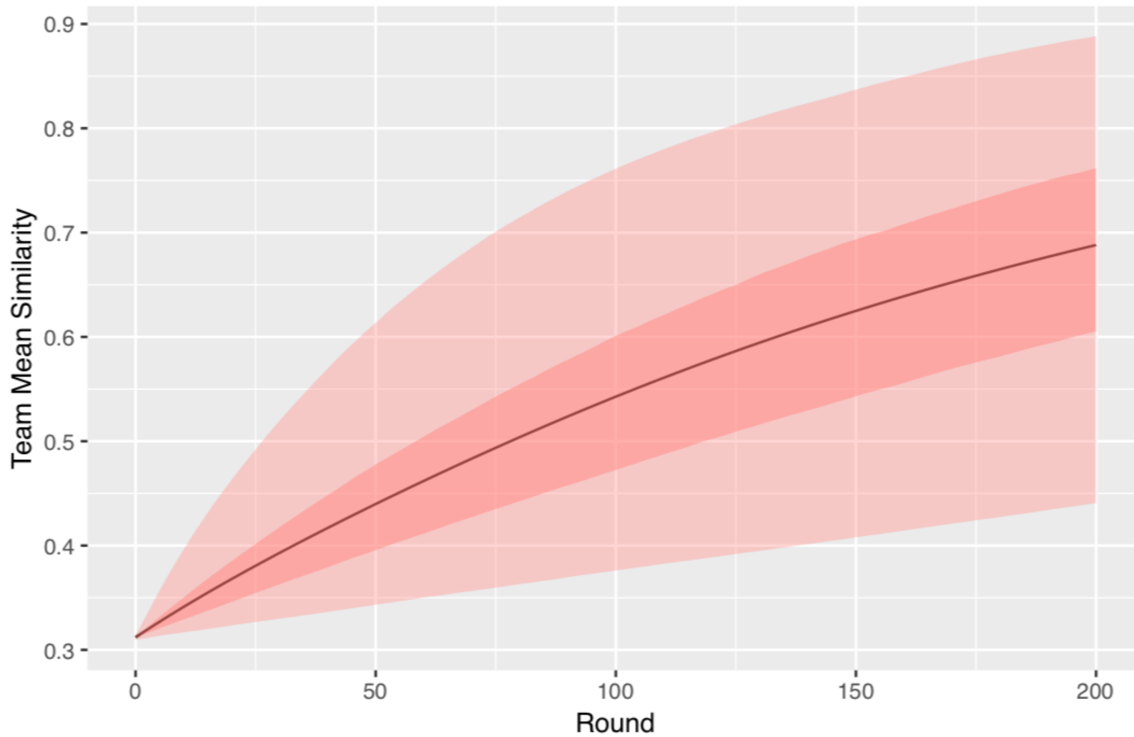


Figure 5. TMM Mean Similarity over Time

Table 18

TMM Similarity Development Over Time

Round	Mean Similarity	25% Quartile Mean Similarity	75% Quartile Mean Similarity	Maximum Similarity	Minimum Similarity
0	31%	31%	31%	31%	31%
200	69%	76%	61%	89%	44%

Note. Agents started with identical similarity across simulations.

Top and Bottom 5% of Teams in terms of Final TMM Similarity. Table 19 shows the characteristics of the top and bottom 5% of teams for TMM similarity development. On average, the least similar teams ended the simulation with 51% overlap in TMM. Teams exhibiting highest levels of TMM similarity ended with 87% similarity. In terms of differences between ending similarities, more similar teams were less variable in ending similarity yielding a maximum value of 89% and a minimum value of 85%. Alternatively, the bottom 5% of teams displayed a wider range of potential outcomes, ranging from a maximum value of 54% and a minimum of 44%. Thus, the range of values for the bottom 5% of team is double than the range of values for the highest 5% of teams.

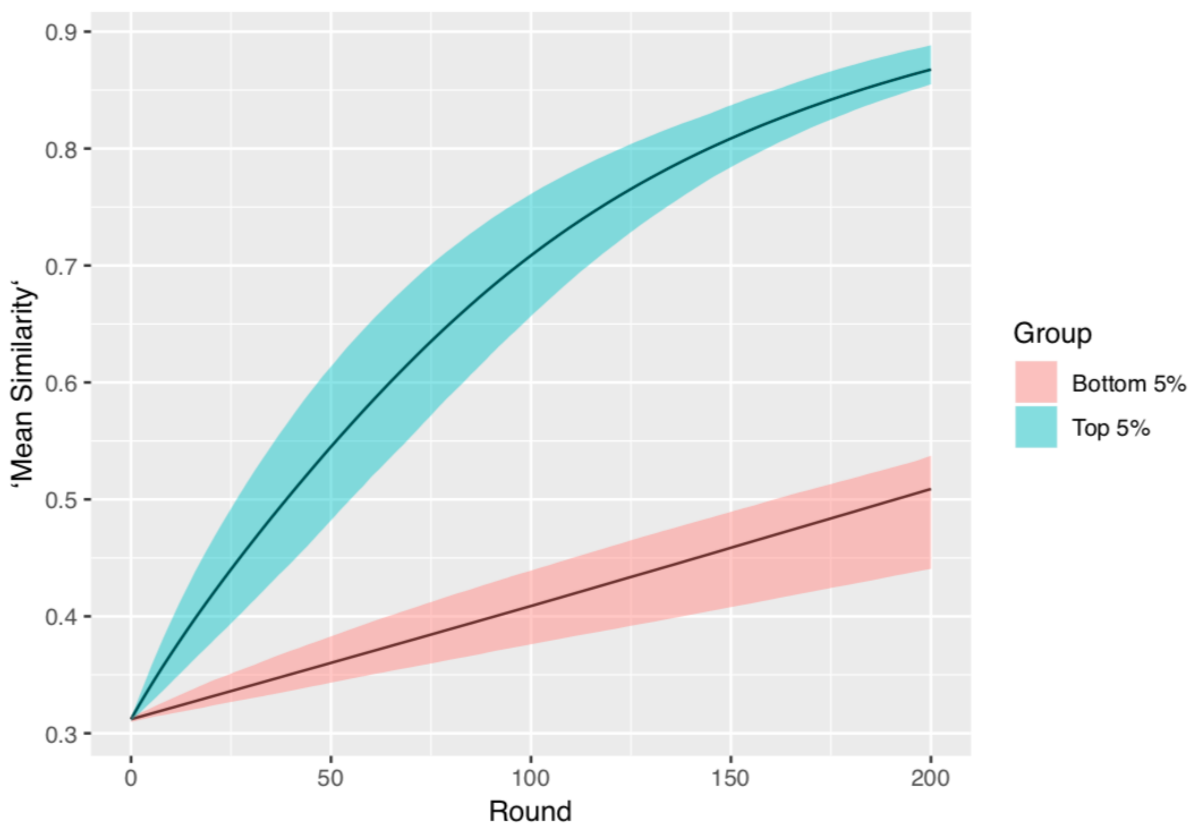


Figure 6. TMM Similarity over Time for Top and Bottom 5% Teams in Final Similarity

Table 19

TMM Similarity Development Over Time for Top and Bottom 5% Teams

Group	Mean Similarity	25% Quartile Mean Similarity	75% Quartile Mean Similarity	Maximum Mean Similarity	Minimum Mean Similarity
Bottom 5%	51%	50%	52%	54%	44%
Top 5%	87%	86%	87%	89%	85%

Note. Agents started with identical similarity across simulations.

Table 20 shows the compositional characteristics of teams within the top and bottom 5% of TMM similarity at the end of simulation. Mean values of team composition metrics (e.g. mean, minimum, maximum, standard deviation) were used to quantify differences in team compositions across the two groups. Means of summary statistics were calculated across teams within each group. Thus, average values of team mean, minimum, maximum, and standard deviation of team-level personality factors were used to quantify differences between the two groups. Values describe the overarching compositions of team constituent agents.

For the bottom 5% of teams, team mean agreeableness (*M* = .30), assertiveness (*M* = .39), and intelligence (*M* = 3.78) suggest the teams were primarily composed of individuals low in these three characteristics. Maximum values suggest that agents did not exceed moderate levels in any personality characteristics with average maximum values for agreeableness, assertiveness, and intelligence yielding .49, .6, and 6.11, respectively. Cutoff scores for modelled variables levels can be found in Table 28.

Alternatively, the top 5% of teams yielded higher means for agreeableness (*M* = .52), assertiveness (*M* = .53) and intelligence (*M* = 9.01). Instead of uniformly high levels of all characteristics, the top performing teams demonstrate a mix. From mean levels, team members were high in intelligence, but moderate in assertiveness and agreeableness. Mean maximum values of agreeableness (*M* = .75) and assertiveness (*M* = .75) suggest that some teams did have agents with high levels of these characteristics. However, mean minimum values demonstrate that teams also contained members with low levels of agreeableness (*M* = .27) and assertiveness (*M* = .27) but high levels of intelligence (*M* = 8.14).

Table 20

Team Composition of Top and Bottom 5% Teams for TMM Similarity

Variable	Group	Mean	Minimum	Maximum	SD
Agreeableness					
	Top 5%	.52	.27	.75	.20
	Bottom 5%	.30	.16	.49	.14
Assertiveness					
	Top 5%	.53	.27	.75	.20
	Bottom 5%	.39	.21	.60	.16
Intelligence					
	Top 5%	9.01	8.14	9.87	.79
	Bottom 5%	3.78	2.23	6.11	1.66

An alternative exploration of team composition is the proportional composition of team members. This approach describes teams in terms of the percentage of members who hold particular levels of characteristics (e.g. percentage of members with high levels of cognitive ability). Figure 7 and Figure 8 display the proportional composition of the top and bottom 5% of teams with highest levels of ending similarity, respectively. Specifically, each figure depicts the percentage of agents high or low on each personality factor. This helps understand computational contingencies that the computational model suggests may lead to particular outcomes. Such an analysis directly contributes to examination of equifinality in team compositions that can lead to the highest levels of TMM similarity.

Figure 7 and 8 are arranged such that the x-axis represents the percentage of agents with a particular level of a personality factor. The y-axis represents the percentage of compositions that make up the top and bottom 5% of cognitively similar teams. Red bars represent agents with high levels of a trait, while blue bars represent agents with low levels of a trait. To accentuate differences and ease processing, moderate values are excluded from the figures. Thus, not all descriptions of the sample will yield 100% of team compositions accounted for. As an example, Figure 7 shows that 100% of teams in the sample are composed entirely (100%) of agents high in intelligence. Also, 100% of teams are composed without and (0%) agents low in intelligence. The figure also shows a very small percentage of teams are fully (100%) composed of agents high in assertiveness. More results are discussed below.

Composition of Top 5% of Teams in TMM Similarity. Examining Figure 7, a striking conclusion can be drawn. One-hundred percent of teams with the highest levels of TMM similarity are composed of agents that are high in intelligence. This suggests that the model predicts that intelligence is a necessary condition to achieve the highest levels of TMM similarity.

Distributions for assertiveness and agreeableness suggest neither highly agreeable nor highly assertive agents are requisite compositions for achieving high levels of TMM similarity. Teams composed of agents uniformly high in either assertiveness or agreeableness make up fewer than 10% of the teams achieving the highest levels of TMM similarity. The percentage of teams composed of uniformly highly assertive agents is 5.3%. The percentage of teams composed of uniformly high agreeable teams is 4%.

Teams composed such that 80% of agents were high in agreeableness composed 9.3% of the high TMM similarity sample. Teams composed 60%, 40%, 20%, or 0% by agents high in agreeableness composed of 22.67%, 37.33%, 16%, and 10.67% of the sample, respectively. Thus, few teams composed of an overwhelming majority of agents high in agreeableness (i.e. 80% and above) achieved the highest levels of TMM similarity. The majority of teams in the top 5% of TMM similarity were composed of either 60% or 40% members high in agreeableness. This would suggest that moderate levels of agents high in agreeableness could be optimal for TMM similarity.

Teams composed of 80% of agents low in agreeableness made up 1.33% of teams in the included in the top 5% of TMM similarity. Teams composed such that 60% of agents were low in agreeableness composed 9.33% of the sample of most cognitively similar teams. The bulk of team compositions for this realm suggest that lower percentage compositions of low agreeableness members may be common at higher levels of TMM similarity with teams composed of 40%, 20%, or 0% of agents low in agreeableness combining for 89.34% of the most cognitively similar teams. Thus, it may be optimal for teams to minimize members low in agreeableness.

Teams' compositions of assertive agents followed similar patterns to agreeableness. Teams composed of 80% of agents high in assertiveness made up 13.33% of the sample, followed by 28% of the sample for teams composed of both 60% and 40% of agents high in assertiveness. Finally, teams composed of 20% agents high in assertiveness composed 17.33% of the most cognitively similar teams while teams without any individuals high in assertiveness contributed to 8% of the The majority of teams simulated who achieved the highest levels of TMM similarity were composed of either 60% or 40% of agents high in assertiveness. Moderate levels of agents high in assertiveness seem to be optimal to achieve the highest levels of TMM similarity.

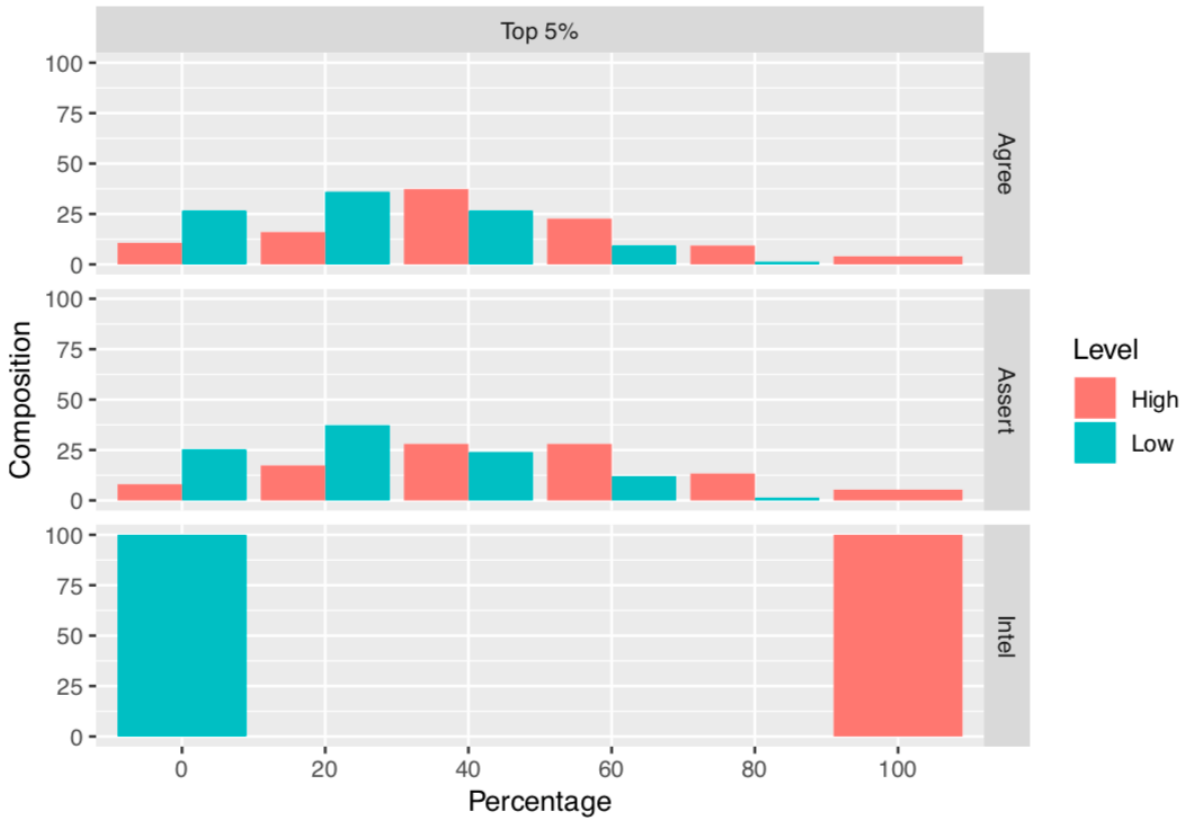


Figure 7. Team Composition Distributions for Top 5% Teams: TMM Similarity
Note: Agree = Agreeableness; Assert = Assertiveness; Intel = Intelligence; colors distinguish between high and low levels of each personality characteristic; x-axis represents percentage of members in a team with a personality characteristic; y-axis represents the percentage of simulated teams in the sample that match the percentage of each characteristic; moderate levels of each characteristic are excluded.

Compositions of low assertiveness agents also followed similar patterns to agreeableness. 1.33% of teams composed with 80% of agents low in agreeableness were a part of the most similar teams. 12% of teams were composed such that agents low in assertiveness composed 60% of the teams' members. Again, the majority of highly cognitively similar teams were composed of 40% or fewer agents low in assertiveness.

Teams composed such that 40%, 20%, and 0% of agents were low in assertiveness composed 24%, 37.33%, and 25.33% of teams in the sample, respectively for a total of 86.66% of teams. Again, minimizing the percentage of agents low in assertiveness is suggested to be optimal to achieve TMM similarity.

Composition of Bottom 5% of Teams in TMM Similarity. Compositions for the bottom 5% of teams in terms of ending TMM similarity differ primarily in the characteristics of agents that compose the majority within a team. Beginning again with intelligence, the majority of teams are composed at least at level of 60% by members low in intelligence. Collectively, team composed 60%, 80%, and 100% of members low in intelligence represent 95.99% of teams in the sample of teams lowest in TMM similarity. No teams composed of less than 40% low intelligence agents, which made up 4% of these teams, were present in the sample of lowest similarity teams.

Alternatively, high intelligence agents did not compose more than 40% of any teams in the low similarity sample. Teams composed of 40% high intelligence agents represented 4% of the total sample while teams composed of 20% highly intelligent agents composed 26.67% of the sample. Finally, highly intelligent agents were completely absent from 69.33% of teams. In the same sense that highly intelligent compositions were present in every team that achieved high similarity, teams with a dearth of intelligent members composed a large part of the low similarity sample.

Assertiveness composition was more distributed in the low similarity teams. Teams composed entirely of agents with low assertiveness were 24% of the sample. Teams composed of 80% of low assertive agents were 9.33% of the sample. Teams composed of 60% or lower of agents low in assertiveness combined for the remaining 67.67%. Teams composed 60%, 40%, 20%, and 0% of agents low in assertiveness composed 16%, 22.67%, 10.67%, and 17.33% of the sample respectively.

Agents high in assertiveness rarely exceeded 40% of a team's composition for teams low in TMM similarity. Teams composed of 60% or more of assertive agents were 8% of the sample. Alternatively, teams composed 40% or below of assertive agents made up 92% of the sample with 22.67% contributed to the sample by teams composed with 40%, 25.33% contributed by teams composed 20%, and 44% by teams without any highly assertive agents. Together, that teams with a dearth of low assertive agents and teams low in highly assertive agents does not paint a coherent picture for how composition of low and high assertive agents impact TMM similarity.

Agents low in agreeableness composed a large majority of teams that achieved low levels of similarity. 42.67% of teams were fully composed of agents low in agreeableness. 16% of teams were composed at a level of 80% by low agreeable agents while 25.33%, 13.33%, and 2.67% of the sample were composed of 60%, 40%, and 20% low agreeable agents respectively.

Finally, very few agents were high in agreeableness on any teams in this sample. No teams were composed of more than 60% highly agreeable agents. Teams that were composed at 60% by agreeable agents only occurred in 1.33% of the sample. Next, teams composed of 40% agreeable agents made up 2.67% of the sample. This increased with 24% of teams being composed at a level of 20% agreeable individuals. However, the overwhelming majority, 72% of teams, did not contain any highly agreeable agents.

Overall, teams composed primarily of disagreeable agents and teams composed minimally of highly agreeable agents yielded severely limited levels of TMM similarity.

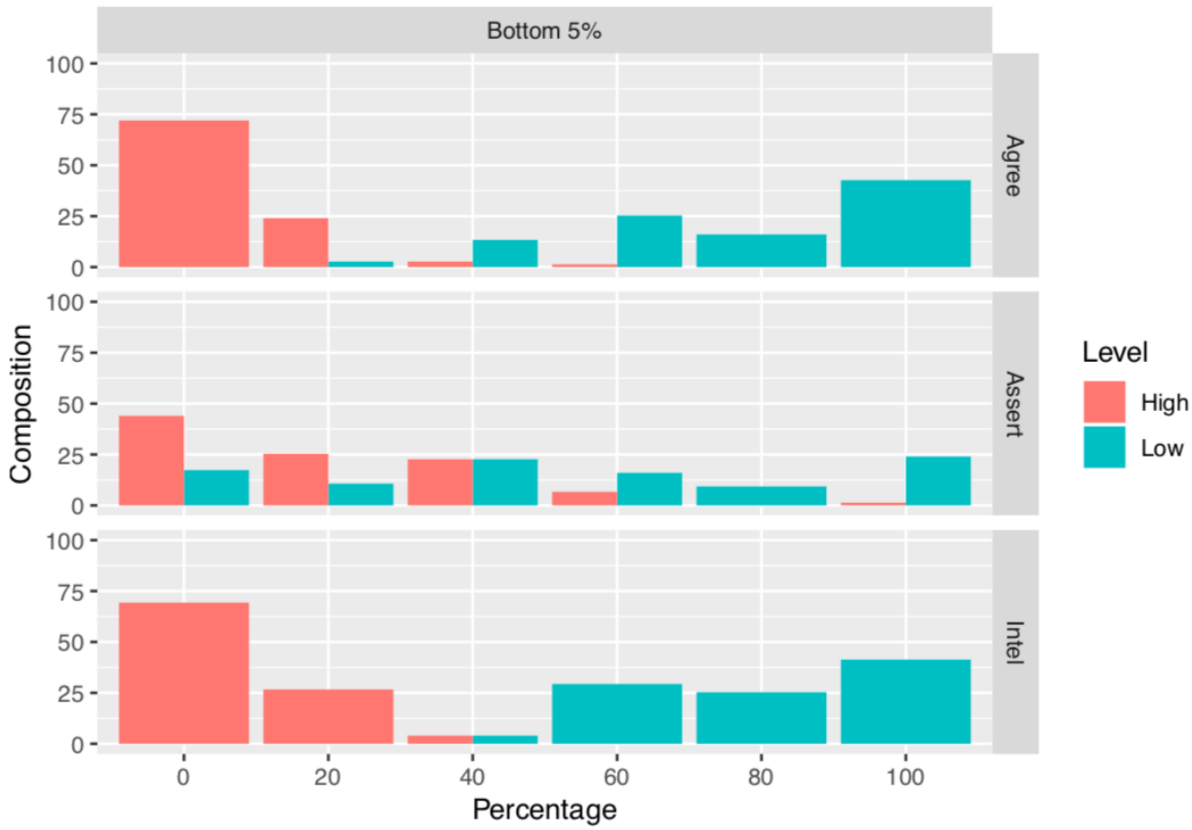


Figure 8. Team Composition Distributions for Bottom 5% Teams: TMM Similarity
Note: Agree = Agreeableness; Assert = Assertiveness; Intel = Intelligence; colors distinguish between high and low levels of each personality characteristic; x-axis represents percentage of members in a team with a personality characteristic; y-axis represents the percentage of simulated teams in the sample that match the percentage of each characteristic; moderate levels of each characteristic are excluded.

TMM Accuracy

TMM accuracy represents the degree to which TMM overlap with the true mental model created for comparison. While teams may increase in TMM similarity through interaction, accuracy is not guaranteed to also increase (Mathieu et al., 2000). The previous section outlined individual differences that impact TMM similarity development and team compositions that may optimize the development. This section will explore how and when teams become more accurate through their interaction.

TMM accuracy was measured in two manners: total accuracy, which measures whether or not the correct information is present somewhere within the team, and mean accuracy, which measures the average accuracy of each team member in comparison to the true mental model. These two metrics are analogous to measurement that could occur for human subjects TMM. Specifically, total TMM accuracy measures whether the correct information is within the group and mean accuracy is a common metric used to operationalize TMM accuracy (Mohammed et al., 2010).

Figure 9 shows the trajectories for both TMM total accuracy and TMM mean accuracy over the course of simulations. Table 21 describes TMM total accuracy levels at the beginning and end of simulated interaction. It is evident from visual inspection that across simulations, mean accuracy generally increased while total accuracy decreased. On average, teams began with a total accuracy of 90% and completed the simulation with an average of 85% total accuracy. Thus, as teams continued interacting, the upper limit on their ability to have the correct conceptualization of the problem decreased. The model suggests teams decrease in total accuracy over time. In fact, no teams demonstrated increases in TMM total accuracy over the course of simulation.

Final TMM total accuracy yielded a range of 11%. Thus, teams were all within 11% of one another in terms of total accuracy at the end of simulation. The minimum total accuracy was 78% and the maximum was 89%. Thus, the teams that were the worst in maintaining total accuracy lost, on average 12% of their total accuracy while the best teams lost only 1%. On average, teams lost between three and seven percent of total accuracy.

Table 21
TMM Total Accuracy Development Over Time

Round	Total Accuracy	25% Quartile Mean Total Accuracy	75% Quartile Mean Total Accuracy	Maximum Total Accuracy	Minimum Total Accuracy
0	90%	90%	90%	90%	90%
200	85%	83%	87%	89%	78%

Note. Agents started with identical accuracy across simulations.

Table 22 describes the TMM mean accuracy over the course of simulation. On average, teams began with 37% average accuracy and ended with 54%, yielding a 17% average increase. The minimum value for ending mean accuracy was 43% while the maximum value was 64%. Half of the simulated teams ended between 50% and 57% mean accuracy. Thus, the model suggests that teams generally increase in the amount of average accuracy as team members interact with one another.

Table 22
TMM Mean Accuracy Development Over Time

Round	Mean Accuracy	25% Quartile Mean Accuracy	75% Quartile Mean Accuracy	Maximum Mean Accuracy	Minimum Mean Accuracy
0	37%	37%	37%	37%	37%
200	54%	50%	57%	64%	43%

Note. Agents started with identical accuracy across simulations.

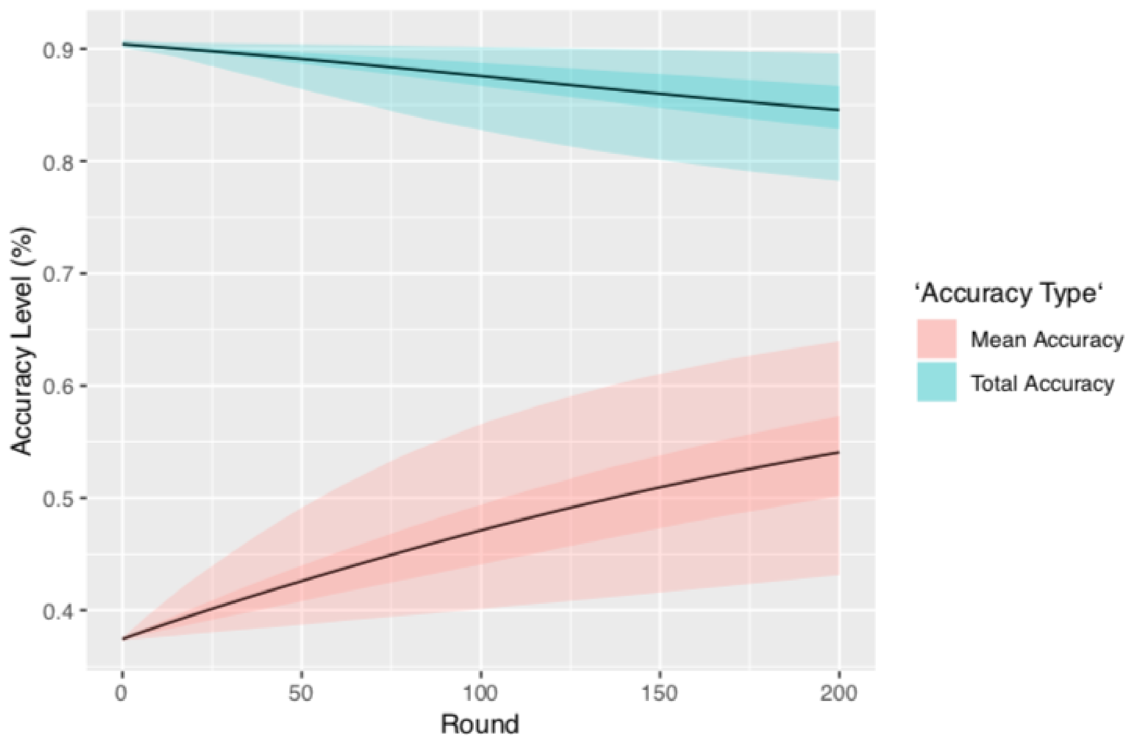


Figure 9. TMM Accuracy over Time
Note. Mean Accuracy = Average accuracy percentage of all team members when compared to true model; Total Accuracy = Percentage of true mental model that is present in any team members

Across all simulations, total accuracy and mean accuracy exhibit a negative relationship with one another. As total accuracy generally decreases over time, mean accuracy generally increases. The correlation between total accuracy and mean accuracy is strong and negative 95% CI [-.96, -.95].

Table 23
95% Confidence Interval for Correlation between TMM Total Accuracy and TMM Mean Accuracy

	LL 95% CI	Mean Correlation	UL 95% CI
	-.96	-.96	-.95

Total Accuracy. Figure 10 depicts the characteristics of the top and bottom 5% of teams for TMM total accuracy and Table 24 provides numeric descriptions. Here, the best teams are those that demonstrate the lowest levels of TMM total accuracy because decreases in total accuracy insinuate teams converging on the wrong TMM content. Teams performing the best lost 2.07% of total accuracy, on average. This suggest converging on the wrong answer for 13 pieces of information out of 625. No team in the top 5% lost more than 2.55% of total accuracy and the very best lost only 1.07%.

Alternatively, the bottom 5% of teams lost 10.92% of total accuracy on average, converging incorrectly on approximately 64 pieces of information out of 625. No team lost less than 10.39% of total accuracy. The worst teams, however, lost 11.84% of total accuracy, approximately 74 pieces of incorrect information.

Table 24
TMM Total Accuracy Development for Top and Bottom 5% Teams

Group	Mean Total Accuracy Change	25% Quartile Total Accuracy Change	75% Quartile Total Accuracy Change	Maximum Total Accuracy Change	Minimum Total Accuracy Change
Bottom 5%	-10.92%	-10.67%	-11.11%	-11.84%	-10.39%
Top 5%	-2.07%	-1.92%	-2.29%	-2.55%	-1.07%

Note. Agents started with identical total accuracy across simulations.

Compositions of Top and Bottom 5% of TMM Total Accuracy Teams. Table 25 shows the compositional characteristics of teams within the top and bottom 5% of TMM total accuracy. Again, mean values of team composition metrics (e.g. mean, minimum, maximum, standard deviation), calculated across teams within each group, were used to quantify differences in team compositions across the two groups.

Overall, compositional metrics are almost identical between the best and worst performing teams in terms of TMM total accuracy. For the bottom 5% of teams, team mean agreeableness (*M* = .40), assertiveness (*M* = .49), and intelligence (*M* = 6.32) suggest that the lowest performing teams were composed, on average, of moderate levels of all variables. The top 5% of teams suggest similarly: mean agreeableness (M = .43), assertiveness (*M* = .43), and intelligence (*M* = 6.36) all suggest that team members approximate to moderate levels of each personality variable.

Similarities continue for mean levels of minimum and maximum composition values. Team minimum agreeableness for the bottom 5% teams (*M* = .21) was indistinguishable from top 5% teams (*M* =.22) and suggests both teams had minimum values suggesting the presence of low agreeable team members. Average maximum values for agreeableness of both the bottom (*M* = .61) and top (*M* = .64) teams suggest teams were composed of moderately agreeable individuals at most.

For assertiveness, minimal and maximal values mimicked agreeableness. Average minimum values for bottom 5% teams (*M* = .27) and top 5% teams (*M* = .22) suggest teams had minimum members low in assertiveness. Maximal values for the bottom 5% teams (*M* = .71) were further from top 5% teams (*M* = .64) but yield the same interpretation: teams were composed of moderately assertive individuals, on average.

Table 25
Team Composition of Top and Bottom 5% Teams for TMM Total Accuracy

Variable	Group	Mean	Minimum	Maximum	SD
Agreeableness					
	Top 5%	.41	.21	.62	.17
	Bottom 5%	.50	.28	.71	.18
Assertiveness					

	Top 5%	.40	.23	.58	.15
	Bottom 5%	.52	.29	.75	.19
Intelligence					
	Top 5%	4.00	2.28	6.22	1.69
	Bottom 5%	8.90	7.83	9.85	.90

Finally, for intelligence, mean minimum intelligence for the bottom 5% of teams (M = 5.13) was indistinguishable from the top 5% teams (M = 5.18). Mean maximum values for bottom 5% teams (M = 7.88) was also highly similar to mean maximum values of intelligence for top 5% (M = 7.80) teams. Across all metrics here, the implication is that teams held moderate levels of all variables in both samples of teams.

Exploring team composition further, the next sections explore how proportions of members high and low in individual differences compose the top and bottom 5% of teams. Although mean levels across the two groups did not yield substantial information to distinguish teams from one another, proportional composition information may illuminate insights. Again, moderate levels of variables are excluded and only proportions of high and low levels of individual differences are presented.

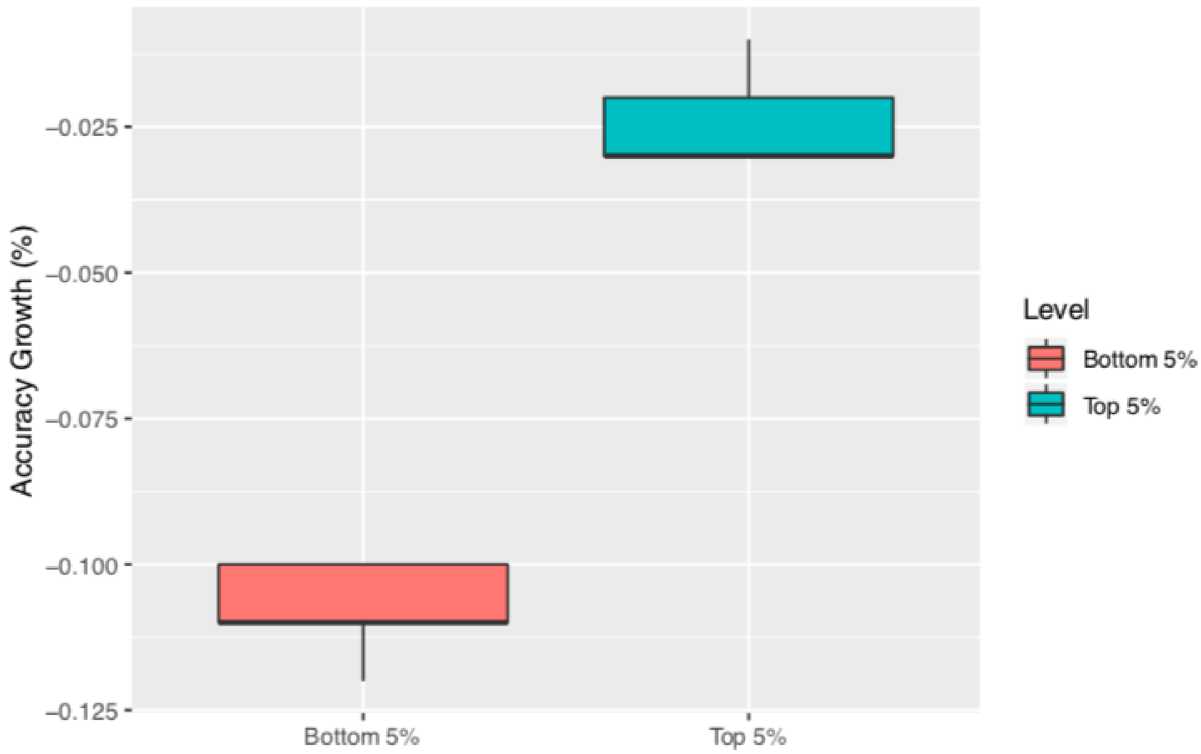


Figure 10. TMM Total Accuracy Change

Compositions for Top 5% of Total Accuracy. Exploring team composition of the top 5% teams in terms of proportions of members with certain qualities illuminates the complexity of TMM total accuracy change. Figure 11 depicts the proportional distributions of agents low and high in each individual difference variable. From visual inspection, teams in the top 5% of teams are comparatively more composed of individuals low in agreeableness, assertiveness, and intelligence than high in these traits.

Distributions for agreeableness suggest that members high in agreeableness rarely compose the majority of team compositions for this group. The majority (86.76%) of team compositions in the top 5% of TMM total accuracy teams were composed 40% or less agents high in agreeableness. The remaining 13.23% of compositions were not composed of more than 80% agents high in agreeableness.

For agents low in agreeableness, more even distributions are present. Teams composed solely of agents low in agreeableness comprised 18.29% of the sample and teams composed of 80% low agreeable agents comprised 6.61% of the sample. Agents composed of 60% agents low in agreeableness were 16.34% of the sample. Slight increases were noted for teams composed of 40% and 20% agents low in agreeableness as they were 21.40% and 25.29% of the sample respectively. Finally, 12.06% of teams did not include a low agreeable agent.

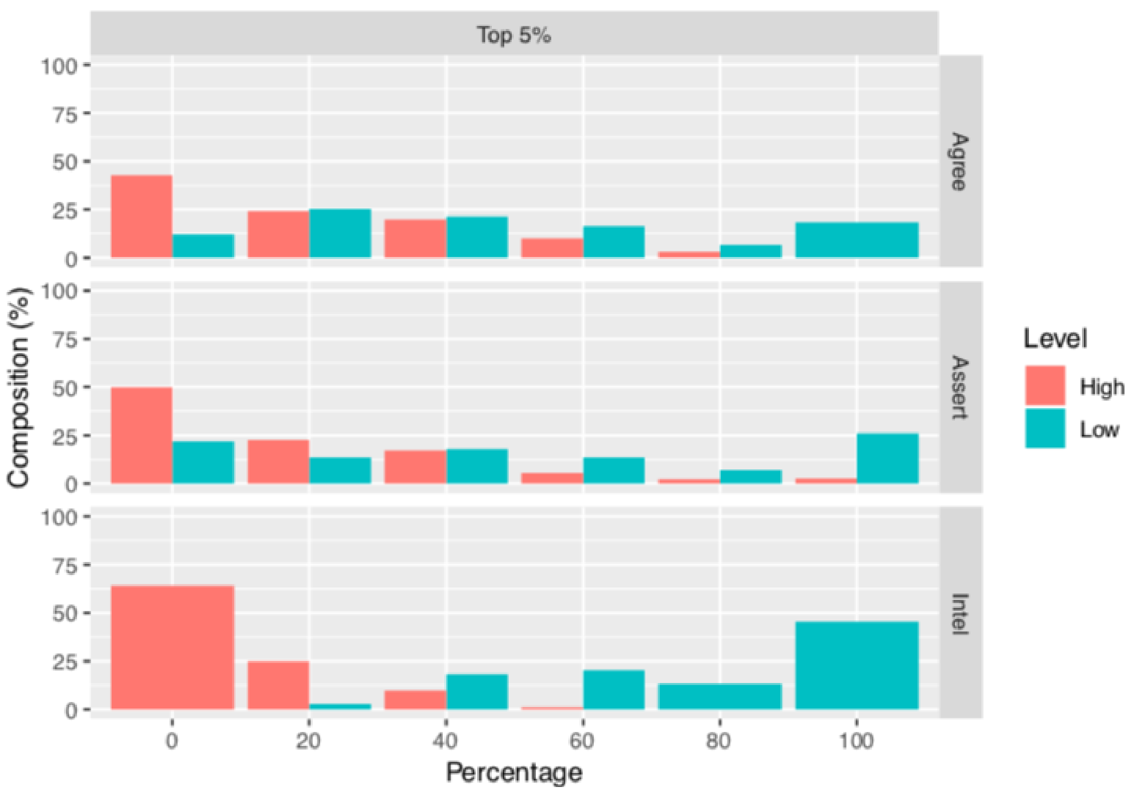


Figure 11. Team Composition Distributions for Top 5% Teams: TMM Total Accuracy

Note: Agree = Agreeableness; Assert = Assertiveness; Intel = Intelligence; colors distinguish between high and low levels of each personality characteristic; x-axis represents percentage of members in a team with a personality characteristic; y-axis represents the percentage of simulated teams in the sample that match the percentage of each characteristic; moderate levels of each characteristic are excluded.

Assertiveness compositions mimic the distributions of agreeableness. The majority of teams were composed of 40% agents high in assertiveness or lower. This group comprised 89.5% of teams in the top 5%. For the remaining compositions, 60, 80, and 100 percent composed of highly assertive agents made 5.45%, 2.33%, and 2.72% of teams in the sample, respectively.

Team compositions of low assertiveness agents were more evenly spread across the potential composition levels. Teams not containing any low assertive agents comprised 21.79% of the sample. Teams comprised of 20%, 40%, and 60% of low assertive agents represented 13.62%, 17.9%, and 13.62% of the sample respectively, Finally, teams composed of 80% agents low in assertiveness comprised 7.00% of the sample and teams fully composed of low assertiveness agents represented 26.07% of teams in the top 5% of teams in terms of total accuracy.

Intelligence was absent from the majority of teams in the top 5% of TMM total accuracy. 64.2% of teams in the sample did not contain any agents with high intelligence. Additionally, no teams were composed of more than 60% highly intelligent agents, which made only 1.17% of the sample. Teams composed of 20% and 40% highly intelligent agents comprised 24.90% and 9.73% of the sample respectively.

Low intelligence agents were dominant in the top 5% of teams for total accuracy. No teams were absent a member of low intelligence. 2.72% of teams were composed with one (20% composition) agent low in intelligence. From there, 20.23% of teams were composed of 60% low intelligence agents. Teams composed of 80% low intelligence agents represented 13.24% of the sample while the most representative teams were fully composed of agents low in intelligence making 45.53% of the sample. The proportion of agents with low levels of intelligence and the dearth of agents with high levels of intelligence contribute to the least amount of loss in total TMM over the course of the simulation.

Compositions for Bottom 5% of Total Accuracy. Teams in the bottom 5% of teams in total accuracy TMM were those that lost the most of their total TMM over the course of interaction. Teams in the bottom 5% of TMM total accuracy demonstrate more equal distributions between high and low members of agreeableness and assertiveness but not intelligence. Additionally, it was rare in this sample for agents low or high in agreeableness or assertiveness to exceed 80% of the team's composition.

Agents high in agreeableness were distributed across composition levels. Teams without any agents high in agreeableness composed 23.48% of teams in the sample. Teams composed of 20% low agreeable agents were 16.67% of the sample. Teams composed of 40% low agreeable agents represented 28.79% of teams. Finally, teams composed of 80% or fully composed of low agreeable agents composed 12.88% of the sample together with 6.82% being teams composed 80% of low agree agents.

In terms of low agreeable agents, teams were distributed more heavily towards lower percentage compositions. Teams composed without low agreeable agents, 20% low agreeable agents, and 40% low agreeable agents were similarly representative of 29.55%, 28.03%, and 25.76% of all teams in the sample. Teams composed on 60% low agreeable agents comprised 15.15% of the sample, followed by .76% of the sample for teams composed at levels of 80% or 100%.

Teams high in assertiveness were most predominant within the range of 20% to 60% composition. These compositions comprised for a combined 68.94% of this sample of teams. Teams without any highly assertive agents composed 9.85% of the sample. Teams with 80% or 100% composition of highly assertive agents composed 21.21% of the sample.

Team composition for low assertive agents was most representative for lower proportions. Teams composed 40% or less of low assertive agents composed 80.3% of the sample. Teams composed of low assertive agents at a level of 60% represented 17.42% of the sample of the bottom 5% of TMM total accuracy teams while no teams were composed fully of low assertive agents.

Team composition in terms of intelligence was polarized for the bottom 5% of teams in terms of TMM total accuracy. For teams composed disproportionately of high intelligence agents (i.e. more than 60% composition), 100% of the sample was represented. Teams composed at 60% of high intelligence were 3.79%; teams composed at 80% composed 9.85%; and teams fully composed of highly intelligent agents represented 86.36% of the sample. Finally, no teams in the sample were represented by an agent low in intelligence.

The distributions of proportional representation for the agents is difficult to decipher for all factors except intelligence. While only few teams were dominated by agents high in assertiveness or agreeableness, all teams were predominantly high in intelligence. Again, the model suggests a strong influence of intelligence on team outcomes.

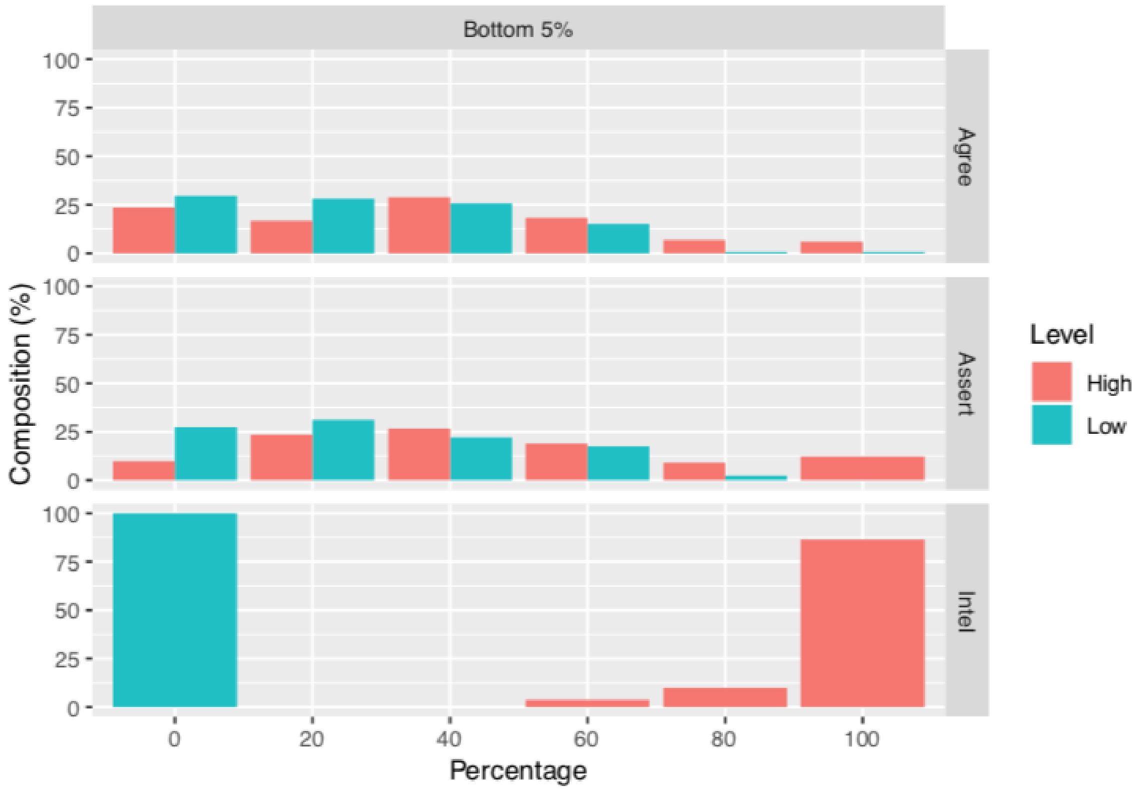


Figure 12. Team Composition Distributions for Bottom 5% Teams: TMM Total Accuracy

Note: Agree = Agreeableness; Assert = Assertiveness; Intel = Intelligence; colors distinguish between high and low levels of each personality characteristic; x-axis represents percentage of members in a team with a personality characteristic; y-axis represents the percentage of simulated teams in the sample that match the percentage of each characteristic; moderate levels of each characteristic are excluded.

In sum, teams that converged on the most inaccurate information across members were generally characterized by high degree of agents high in intelligence. Paired with this, no agents on these teams were low in intelligence. Finally, many teams were composed of a mix of agents in terms of agreeableness and assertiveness instead of being predominantly composed of one or the other.

Average Accuracy. Figure 13 depicts the characteristics of the top and bottom 5% of teams for TMM average accuracy at the end of simulation. Table 26 describes the range of outcomes for average accuracy change for the most and least accurate teams at the end of simulation. Here the best teams are those that demonstrate the greatest increases of average accuracy. Increases in average accuracy indicate that team members are integrating correct information from others. The top 5% best performing teams for average accuracy increased accuracy by 25.4% over the course of the simulation. The full range of growth in average accuracy was between 25.21% and 26.40%. This range equates to teams increasing average accuracy by .55% each round.

By contrast, the bottom 5% performing teams regarding mean accuracy increased by 8.57% on average. The full range for these teams was between a minimum of 5.82% increase to a maximum 9.67% increase. Over the course of the 200-round simulation, this results in an average increase of .042% per round. Thus, the bottom 5% of teams were learning slower than the top 5% of teams by a factor of more than 13.

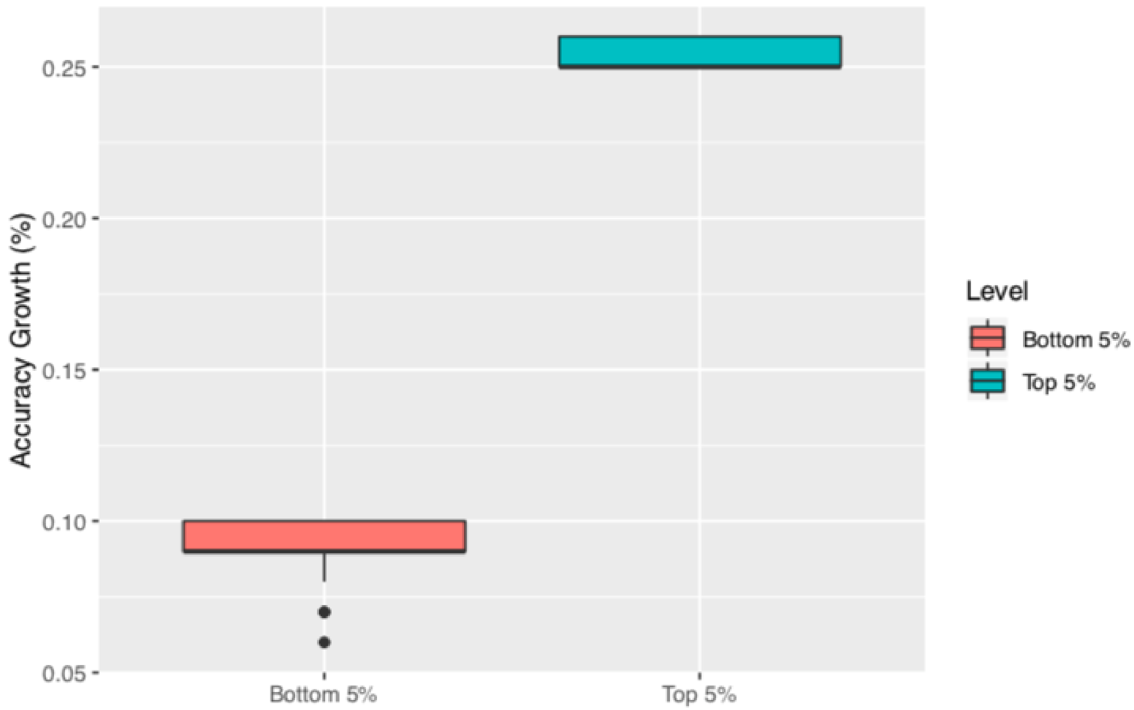


Figure 13. TMM Mean Accuracy Change: Top and Bottom 5%

Team Mean Compositions and Average Accuracy. Table 27 shows the descriptive statistics for composition of teams within the top and bottom 5% of teams for mean accuracy change over the course of simulation. The metrics reveal notable differences between groups in levels of intelligence.

Teams in the bottom 5% of ending TMM average accuracy were generally composed of agents low in intelligence (M = 3.62) and moderate in both agreeableness (M = .35) and assertiveness (M = .43). Alternatively, teams in the top 5% were composed of highly intelligent agents (M = 9.01), and moderate mean levels of both agreeableness (M = .50) and assertiveness (M = .48). It appears that the major difference in attaining higher levels of team TMM average accuracy is intelligence.

In addition to mean differences in intelligence, the standard deviation of groups' intelligence was telling. The standard deviation of intelligence in teams that were the least accurate (M = 1.49) was almost double that of the most accurate teams (M = .79). For standard deviation of the bottom 5% of accurate teams, both agreeableness and assertiveness yielded mean standard deviations of .16. The top 5% of teams, yielded similar estimates as well with agreeableness (M = .19) and assertiveness (M = .20) producing marginally higher standard deviations.

Minimum and maximum values of agreeableness for the bottom 5% of team suggest that teams ranged from agents low in agreeableness to moderate. Mean minimum score across the bottom 5% of TMM average accuracy teams was low (M = .18) and the mean maximum score across teams remained within moderate levels (M = .56). For assertiveness, a similar pattern emerged. Mean minimum scores on assertiveness suggest teams were composed of agents low (M = .25) in assertiveness while mean maximum assertiveness approached high levels (M = .64).

Minimum and maximum values of agreeableness and assertiveness for the top 5% of teams showed a greater disparity on average. Average minimum agreeableness for the top teams also suggested more agents lower in agreeableness (M = .26); however, maximum values ranged well into high scores (M = .72). Mean minimum assertiveness also suggested lower agent assertiveness (M = .24), but mean maximum assertiveness suggest high levels of assertiveness present (M = .71). Considering the present information, teams composed of agents low in all traits yield the lowest amounts of TMM average accuracy.

Table 26

TMM Mean Accuracy Development for Top and Bottom 5% Teams

Group	Mean Total Accuracy Change	25% Quartile Total Accuracy Change	75% Quartile Total Accuracy Change	Maximum Total Accuracy Change	Minimum Total Accuracy Change
Bottom 5%	8.57%	8.09%	9.19%	9.67%	5.82%
Top 5%	25.60%	25.36%	25.82%	26.40%	25.21%

Note. Agents started with identical mean accuracy across simulations.

Table 27

Team Composition of Top and Bottom 5% Teams for TMM Average Accuracy

Variable	Group	Mean	Minimum	Maximum	SD
Agreeableness					
	Top 5%	.50	.26	.72	.19
	Bottom 5%	.35	.18	.56	.16
Assertiveness					
	Top 5%	.48	.24	.71	.20
	Bottom 5%	.43	.25	.64	.16
Intelligence					
	Top 5%	9.01	8.14	9.87	.79
	Bottom 5%	3.62	2.20	5.68	1.49

Team Proportional Compositions for Top 5% Average Accuracy Teams. Figure 14 depicts the proportional compositions of teams in the top 5% of TMM average accuracy. For agreeableness and assertiveness, distributions are similar across composition levels. Low and high levels of agreeableness and assertiveness are both more prominent smaller proportions of teams but no level of composition (e.g. 40%, 60%) exceeds more than 35% of the total sample. However, intelligence demonstrates polar effects.

Teams composed of all levels of agreeableness composition are present in the sample. Although only 3.5% of the total sample of the top 5% of teams, teams completely composed of agents high in agreeableness are present. Slightly more prominent are teams composed of 80% agents high in agreeableness which make up 7.08% of the entire sample. The following compositions are similar in levels of representativeness: teams composed 60% and below (i.e. 40%, 20%, & 0%) of agents high in agreeableness composed 20.35%, 31.86%, 16.81%, and 20.35% respectively.

Team compositions of low agreeableness mimicked distributions of high agreeableness. A small portion of the sample (.88%) was composed of 80% agents low in agreeableness and no teams in the sample were composed fully of agents low in agreeableness. Teams composed of 60% low agreeable agents made 12.39% of the sample. The majority of teams were composed of 40% low agreeable agents and below, yielding 29.20% represented by teams composed at 40%, 35.40% of the sample by teams composed at 20%, and 22.12% of teams without low agreeable agents.

Assertiveness compositions are concentrated towards lower levels of concentration for both agents high and low in the traits. Teams composed of at least 80% agents high in assertiveness compose 12.39% of the total sample (3.54% for full compositions; 8.85% for 80% compositions). Teams 60% composed of highly assertive agents compose 21.4% of the sample. Teams composed at 40% and 20% produced similar estimates, representing 23.89% and 23.01% respectively. Finally, teams without any highly assertive agents represented 19.47% of the sample.

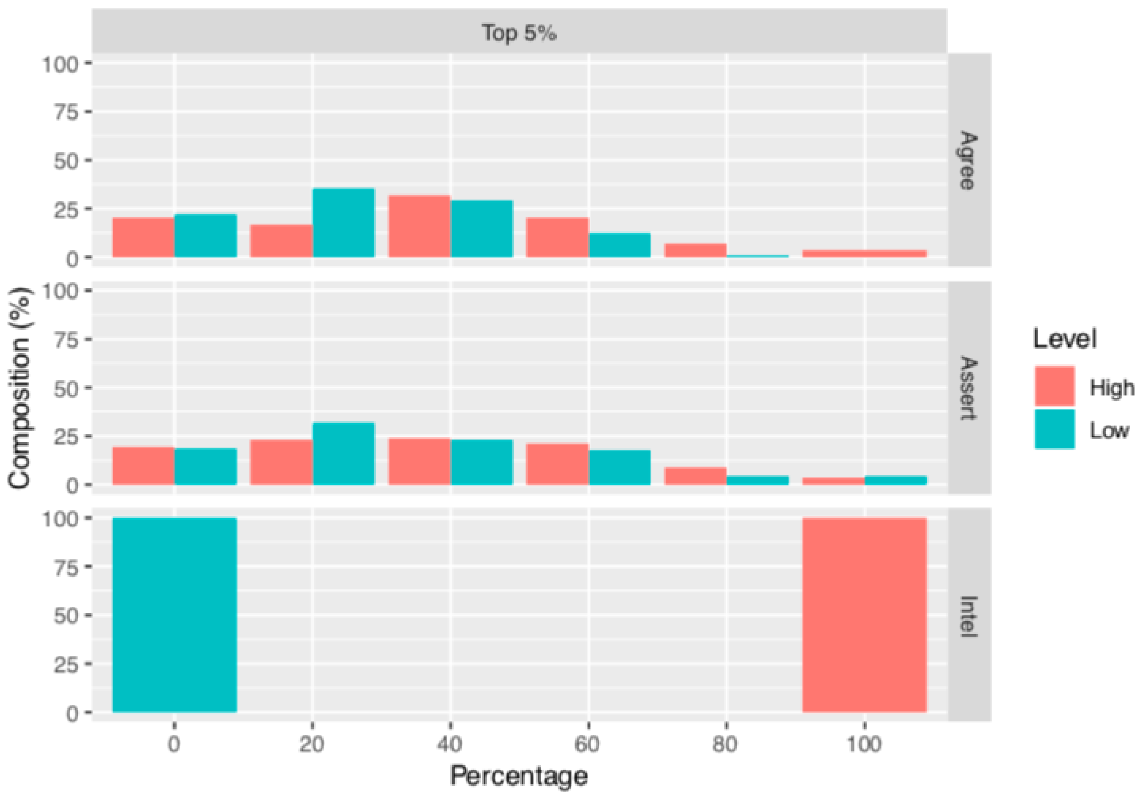


Figure 14. Team Composition Distributions for Top 5% Teams: TMM Mean Accuracy
Note: Agree = Agreeableness; Assert = Assertiveness; Intel = Intelligence; colors distinguish between high and low levels of each personality characteristic; x-axis represents percentage of members in a team with a personality characteristic; y-axis represents the percentage of simulated teams in the sample that match the percentage of each characteristic; moderate levels of each characteristic are excluded.

Team compositions of low assertive agents rarely (8.84%) exceeded 60%, with 4.42% represented by both each 80% compositions and teams fully composed of low assertive agents. Teams composed of 60% low assertive agents comprised 17.70% of the sample. Compositions 40% low assertive agents and below combined for 73.46% with 23.01% representing samples of 40% low assertive members, 31.86% representing teams of 20% low assertive members, and 18.58% representing teams without any low assertive members.

Team Proportional Compositions for Bottom 5% of Average Accuracy Teams. Team proportional compositions for the bottom 5% of teams were polarized in that many teams were composed minimally of agents high in agreeableness, assertiveness or intelligence. On the same note, teams were composed predominantly of agents low in these qualities. Visual depictions of proportional composition information are available in Figure 15. Descriptive information is presented in Table 27.

Teams composed of highly agreeable agents were absent from the bottom 5% of teams for TMM average accuracy. Teams without any high agreeableness individuals composed 58.54% of teams in the sample. Teams containing 20% composition of high agreeable members composed 27.64% of the sample. Teams containing 40% or 60% comprised of 13.01% and .81% of the sample. No teams contained more than 60% of highly agreeable agents.

Low agreeableness told an alternate story. Instead of concentrating to one level of proportional composition, low agreeable agents were present at each level. 4.88% of teams were not composed of any low agreeable agents while 13.82% of teams were composed of 20% low agreeable agents. Teams composed of 40% low agreeable agents composed 20.33% of the sample, similar to teams composed of 60% which composed

22.76% of the sample. Team composed of 80% low agreeable agents represented 11.38% and teams fully composed of low agreeable agents composed 26.83% of teams in the bottom 5% of TMM mean accuracy.

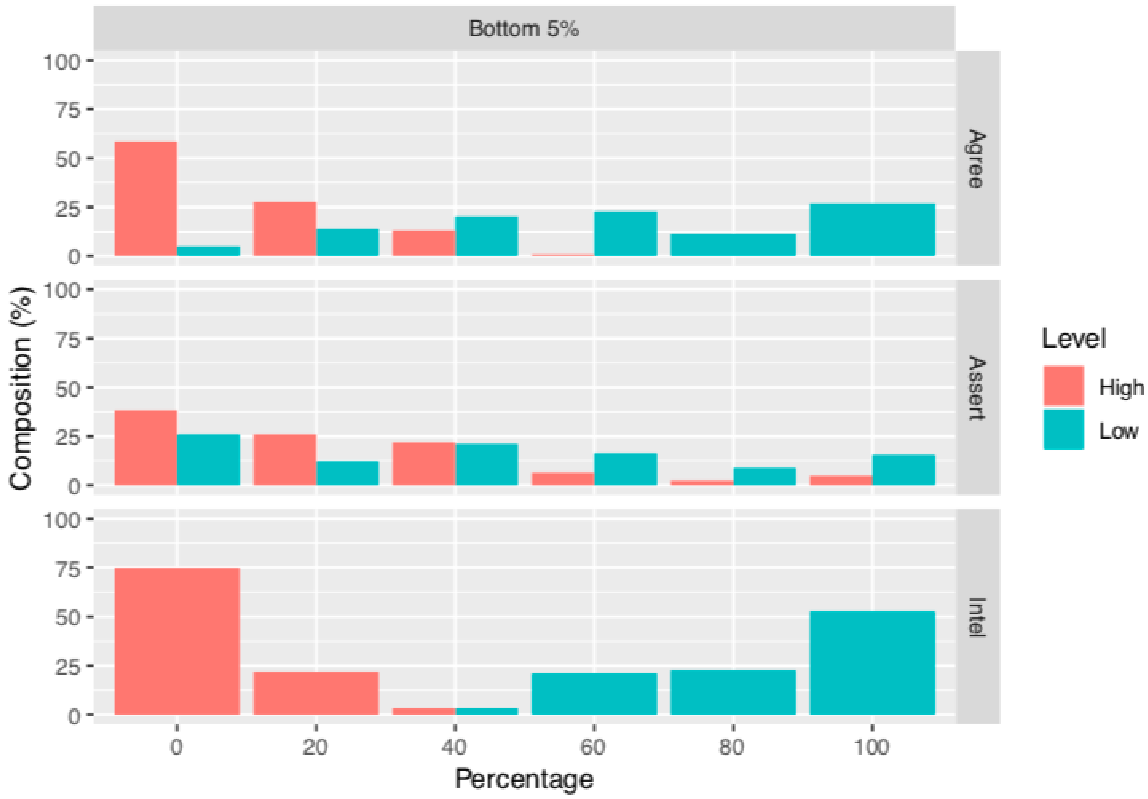


Figure 15. Team Composition Distributions for Bottom 5% Teams: TMM Mean Accuracy

Note: Agree = Agreeableness; Assert = Assertiveness; Intel = Intelligence; colors distinguish between high and low levels of each personality characteristic; x-axis represents percentage of members in a team with a personality characteristic; y-axis represents the percentage of simulated teams in the sample that match the percentage of each characteristic; moderate levels of each characteristic are excluded.

Teams were generally composed such that agents high in assertiveness were the minority. 38.21% of teams in this sample contained no agents high in assertiveness. Teams composed on 20% of members comprised 26.02% of the sample and 21.95% of teams were composed of 40% members high in assertiveness. Highly assertive agents were in the majority in a total of 13.77% of compositions. Compositions of 60% highly assertive agents were 6.50% of the sample; 80% were 2.44% of the sample; and 100% highly assertive teams were 4.88% of the samples.

Low assertive agents were more distributed across composition levels. 26.02% of team contained no agents low in assertiveness and 12.20% of teams were composed of 20% low agreeable team members. Teams composed of 40% members low in assertiveness comprised 21.14% of the sample, slightly higher than 16.26% of teams composed of 60% low assertiveness agents. Finally, teams composed of 80% low assertive members comprised 8.94% of the sample while 15.45% of teams were completely composed of low assertive agents.

Highly intelligent agent composition never exceeded 40% for teams in the bottom 5% of TMM average accuracy. In fact, 74.80% of teams did not include any member high in intelligence. Only 21.95% of teams were composed at 20% of highly intelligent agents. Finally, teams composed at a level of 40% of highly intelligent members composed only 3.25% of samples.

Opposite patterns emerged for low intelligence agents. Low intelligence agents were the majority of compositions for the bottom 5% of teams. 52.85% of teams were completely composed of low intelligence agents. This was followed by 22.76% of teams being composed of 80% low intelligence agents. A similar, 21.14% of teams were composed 60% of low intelligence agents. Finally, teams composed of 40% low intelligence agents composed 3.25% of the sample of least accurate teams.

Chapter 5: Discussion, Limitations, and Future Directions

Discussion

Research on TMM has a rich and fruitful history, spanning decades, within which numerous applications were discovered to aid teams perform better. The timing was crucial as TMM research emerged when teams were increasingly the most prevalent work unit in organizations (Devine, Clayford, Phillips, Dumford, Melner, 2001). As research has emerged to challenge the foundational ideas of this established paradigm, the goal of this dissertation was to create a platform by which theories could be pitted against one another. Additionally, a goal was to establish a framework that could be built upon to explore new interventions or ways of working that could help accelerate innovation in the improvement of team functioning. Although the model will need to be calibrated, using the current model output, some notable points are suggested.

Summarizing Key Findings

TMM Similarity. The model suggests that teams increase in TMM similarity over time, albeit at different rates. At no point in time did teams become less similar from one another. This aligns with the general consensus of research and reviews (DeChurch & Mesmer-Magnus, 2010; Mohammed et al., 2010; Resick et al., 2014). However, some teams did increase TMM similarity at negligible rates. Assuming that the model conceptually represents reality well, then reproducing both outcomes, notably both sides of a potential research debate, is promising. This could explain the findings from Levesque and colleagues (2001), who were pioneers in suggesting that shared cognition may be an unfeasible goal.

The idea that similarity increased monotonically throughout all simulations is promising but a variety of questions are raised. First, on what information are team members similar? Second, dyadically, which members are likely to become more similar to one another? Finally, what explains the differences in similarity across dyads and teams?

Considering the informational aspects of TMM similarity, there are some aspects of TMM on which teams are more or less similar to one another. Members enter a team with certain amounts of confidence in information which will impact both what they share and what they will change their mind about. Although not a part of the analysis here, a reanalysis of the model could reveal how information distribution, confidence in information, and agent qualities impact what specific aspects of TMM may be shared or unshared.

Affinities may also emerge between agents with particular characteristics. Within teams, dyads may become more or less similar to one another given informational aspects and individual differences. One study conducted by Edwards and colleagues, examined dyads in particular and found that dyads with high cognitive ability were able to more efficiently establish similar and accurate TMMs (2006). The computational model may replicate these findings and be able to expand upon the individual characteristics that also contribute to this effect. Already, the model replicates that higher ability teams as a whole more efficiently develop TMM.

Finally, the model demonstrates that differences exist between teams in levels of similarity that are easily attributed to team composition characteristics. The literature has demonstrated that information uniqueness is a contributing factor to the degree teams develop cognition (DeChurch & Mesmer-Magnus, 2009). This model does not refute this claim, but, given the degree of overlap with which agents were created, the model highlights the individual and relational characteristics that may be at play to impact cognition outcomes. More extensive analysis of the model will explicate how unique information impacts TMM development.

TMM Accuracy. On the surface, the model states that accuracy increases and decreases over the course of simulation. Instead of an interpersonal contextual feature that explains these results, it is one of measurement. TMM total accuracy, which represents if the correct information is anywhere within the mind of team members, even just one, was found to decrease over time.

The decreasing effect was conceptualized in the past (Hinsz, et al., 1997). In earlier work, teams were conceptualized as information processing systems but were emergent and composed of individuals. As individuals pass information between one another, errors could occur in encoding, retrieval, or communication of information. Thus, even though all team members may think or know the same information (i.e. share the information), the information would be incorrect.

The effect of inadvertent decreases in accuracy emerged in this model as well. Team members share information with one another that may convince otherwise an agent who, in fact, had the correct answer beforehand. In this case, agents became more similar but at the expense of having a lower limit on potential accuracy. TMM similarity at the expense of accuracy is an underexamined concept, but, from these results, warrant attention.

Early inclusion of TMMs in the organizational literature focused on similarity (Cannon-Bowers et al., 1993; Klimoski & Mohammed, 1994). Researchers suggested that having teams share conceptualizations was paramount as it facilitated future team functioning and performance in a variety of ways. Over time, it was understood that similarity only told part of the story, requiring a predictor that could better explain or predict the type of cognitions that will directly lead to performance (Edwards et al., 2006; Mathieu et al., 2005). Hence accuracy was integrated into the team cognition literature as a direct influencer of team performance. It is not just if teams conceptualize the team context similarly, it is if they do it well as experts would.

This short digression was to highlight the emergent finding here from the computational model. While accuracy emerged as a TMM construct through the obvious connection to performance, the model demonstrated another reason why accuracy is important to note in conjunction with similarity: similar teams could be very wrong. The model yielded similar curves for both accuracy and similarity, suggesting teams increase in both over time. However, there were strong negative relationships between mean TMM accuracy and total TMM accuracy.

Mean TMM accuracy could only increase as agents learned information from others that was correct. Converging on the same information definitely increases similarity and, to the extent the information is correct, mean accuracy. TMM total accuracy, in contrast, apexed at the beginning of the simulation. The teams represented here were in a closed system: the only information that could enter the mental models of individual agents came from the mental models of other agents. Thus, in closed systems, the model suggests that there is a likely tradeoff between similarity and accuracy.

A new research question emerges from this model prediction concerning characteristics of teams that can increase similarity while maintaining total accuracy. Such a team would be able to converge only on the correct information. Thus, the ideal team would show increases in similarity and mean accuracy, without any decrements in team total accuracy. This idea is discussed further in future directions.

Additionally, TMM mean accuracy increases over the course of all simulations as well. While some teams did not increase by much, teams all increased in TMM accuracy. It would appear that in this scenario and simulated context, average accuracy follows a similar pattern to similarity. This effect may already extend to empirical data on teams. As team members share information they truly believe and others evaluate the information for its credibility before incorporating it into their own mental models, it would be expected that TMM mean accuracy increases over time, likely coevolving with similarity.

Finally, team personality compositions from the model were illuminating. Intelligence as represented here suggested large potential benefits for teams. Increases in agents with higher levels of intelligence was associated with increases in TMM similarity and TMM mean accuracy. Except for total accuracy, intelligence was an apparently indispensable factor for teams. This aligns with current empirical knowledge which finds that intelligence is associated with increases in both TMM mean accuracy and similarity (Edwards et al., 2005; Resick et al., 2014).

In this simulation, intelligence represented how much information agents could both communicate and consume each round of the simulation. One could perceive the amount of information that could flow between team members as a channel. The higher the intelligence of all members, the more information can flow between members. It is then understandable that the more potential flow in information, the higher the rates of change for TMM outcomes.

Intelligence in this simulation, however, can be a demonstrable curse. The flow of more information does not suggest the flow of correct information. Teams composed of high-intelligence members may be able to communicate more information, however, if members are communicating and agreeing upon information that is incorrect, the team's rate of accuracy will be similarly precipitous.

The is demonstrated in the model where total accuracy declines over the span of the simulation for all teams. Teams higher in intelligence lost the highest levels of total accuracy. What this suggests is that as teams converge and become more similar, they inadvertently converge on some of the wrong information. Once agents are all similar on a topic, even if it is discussed again, all agents will agree and will not change their mental models. This occurs whether or not the information is correct. The more information that can be communicated, the more the wrong information can be converged upon. Since agents have no way of learning from the environment or changing their minds outside of communicating with others, once total accuracy is lost, it cannot be reestablished.

Model Contributions

This research first reviewed the TMM literature to describe the behavioral processes by which TMM develop and the individual difference factors that influence those processes. TMM literature has focused on overarching team processes and individual differences that affect these processes, but theorists have urged for a true examination of process in the dynamic sense to explore how individuals impact TMM development at a micro level (Kozlowski et al., 2013). Additionally, debates concerning whether TMM can develop have arisen in the literature. Researchers question if searching for predictors of similarity is a worthwhile area of development given instances where TMM similarity has not occurred. A key conclusion from the literature is that the need for understanding microdynamics of teams is immense and may provide insight into not only how TMM develop, but also whether this stream of research is indeed fruitful.

The computational model developed in this dissertation provides a framework for modeling and comparing different team compositions and team processes in the aim of understanding how teams develop shared cognition. The simulation results predict that overall, teams become more similar over time in their understanding of the surrounding context. There are certain compositions and contextual circumstances that may influence this situation. Individuals that are highly assertive and untrusting of others may be of utility to a team, if they are correct in their information. Alternatively, teams that are all untrusting of others can develop negative feedback cycles that hinder development of shared cognition.

The model also offers methodological contributions. First it provides a general framework for modeling team processes. Although the aggregate team processes are observable, they are directly attributable to team member interactions and team member behaviors. Researchers can use such a model to explore and test interventions that may prove useful to influence TMM development. Additionally, this model could be used to test alternative relationships between processes, additional agent behaviors, additional agent characteristics, or explore additional contextual features that may impact team interactions and TMM development.

Model Utility

This research provides credence to the idea that computational models can be an effective investigation in studying TMM, especially in areas of complex systems such as teams. The interactions among components and agents towards TMM development is complex and dependent on myriad institutional and environmental factors (such as goals). There is no simple answer to the nature of how quickly, effectively, nor through which manner teams will integrate knowledge and come to shared conceptualizations. The proposed model here can be used flexibly to address most cognitive questions on teams.

The model is agnostic such that content could be built into the team situation. Thus, instead of sharing random information or information to which no meaning is ascribed, teams share information in a value-based way. This could include aspects of meta-thinking on part of agents that could be easily included.

The model is also context unspecific. Agents are simulating communication processes but are not able to learn from their environment or interact with anything other than one another. In this case, some of the findings discussed earlier may have been unintentionally built in. Without a context, agents have no choice but to listen and evaluate the information coming from the speaker. Additionally, this is why teams are limited by the loss of total accuracy: without a manner by which to learn from the environment, learn new knowledge, or refresh and verify knowledge, agents were constrained by past actions (e.g. incorporating information and removing personally held correct information).

In all areas that the model is agnostic, specificity may be built in. Details on how the model may specifically be adapted are discussed below. However, parsimony is suggested. Adapting the model increases model complexity and may decrease model interpretability.

The model is an architecture and therefore useful for a variety of purposes. First, the model as is, is a theoretical tool for exploring how TMM develop under various team compositions. Exploring the model as it stands, various parameters may be changed to examine the robustness of model predictions. For example, the amount of information agents begin with may influence TMM development dynamics. Teams beginning with more overlapping information may show different patterns than teams beginning with less overlap. Alternatively, the amount of confidence agents have in information could prove interesting. As agents are increasingly confident in their information, the amount of TMM change could be dramatically impacted. These and other questions expose the variety of manners in which the model can be currently used to explore TMM development.

Limitations

The model interpretations suggest increases in similarity and average accuracy across all simulated teams. However, this could be due to a number of limitations in the model, discussed below. Although the model attempts to explore teams as a complex system with multiple interacting features of the context, there were fixed effects of the model that may have detracted from a desirable level of realism. Fixed effects include: the variables used to represent the system, the impact of variables (e.g. coded relationships between variables), the communication processes modeled, the fact that agents had to attend to chosen speaker, and the context.

Agents

Non-speaking agents were always listening to the agent who was sharing information. Thus, each round that occurred, agents had the opportunity to evaluate the information and update mental models based on the speaker. This is a generous assumption in many organizational contexts. Team members may not receive all incoming communications from all other members. Team members with a poor history may also actively avoid or intentionally refuse to integrate information from particular others. Although the reputation of credible and discreditable information was modeled to address this, the examination of generative sufficiency suggests that more factors may be at play or that parameter settings should be adjusted to better represent the features of reputation and network effects in teams.

Agents are represented as agnostic interactants in the current model. Thus, agents have no goal of communication other than expressing the knowledge they feel confident sharing. In reality, team members will have goals that drive communication. These goals may be shared by other group members in cases where discussion is directly solely towards achieving group goals. However, agent goals could also be in competition with the goals of other team members such as when information may be withheld by members or information is used strategically.

Variable Selection

To maintain parsimony, variables considered in this research may not include all relevant variables for exploring the development of TMM. The degree to which variables interact and the impact of variables over time may also be areas of fruitful development. Additional variables that could be implemented include alternate individual difference variables, additional communication behaviors, and physical context demands.

The five-factor personality model, as used here is frequently used to explore personality impacts on teams. However, a large variety of individual differences exist and have been proposed to impact team development particularly in areas of team cognition. Potentially useful individual difference variables include values, goal-orientation, collectivism, or specialized expertise to name a few. For example, goal-orientation can impact how people react to receiving information from others, whether or not someone will ask questions to clarify, or how a person would handle disagreements (Payne, Youngcourt, & Beaubien, 2007).

Process Selection

For team processes, the team communication pattern is a potentially robust method for understanding how information may flow within a team and eventually change the knowledge composition of team members. However, teams are no longer confined to a board room and communication may happen in a variety of contexts, through a variety of modalities (e.g. face to face, virtual). Given the dynamic nature of communication, the model could be adapted to explore how different types of communication may impact TMM development and whether the communication process used in the model is sufficient to represent the dynamics of team communication.

Types of processes may have additional bearing on TMM development. Communication processes here describe constant discussion of what could be conceptualized as a single topic. Additional communication processes include reflecting on previous discussions and actions, nonverbal communication, or selectivity of communication partners. Also, communication processes are not the only way in which TMM information may be obtained or changed. TMM development is analogous to learning and, thus are likely subject to factors that influence learning. For example, observing and learning from the behaviors of others is vicarious learning and may prove useful in explaining how similarity arises (Bandura & Locke, 2004).

Context

Currently, the model does not represent a particular team context and lacks many contextual features. This was an intentional decision so that model interpretations could apply to teams in general. However, lack of context increases the difficulty of application. Without an understanding of an observable situation to which the suggestions of models can be applied, the model is limited in its readiness to be used for workplace decisions.

The only context inherent in the model are agents and their history of interaction. While this serves the purpose of the model, contextual features such as task type, mode of communication, resources, organizational culture, or competing goals are absent. These contextual features are of great use to the prediction and understanding of individual and team behavior and could be helpful additions to the model. Including them could provide a degree of specificity necessary to base potential workplace decisions.

Future Directions

Validation

Currently, multiple aspects of the model are uninformed by data. The model was constructed from examinations of empirical literature but not using the empirical literature to directly inform the estimates as many of the estimates (e.g. probability of speaking given an individual's personality) are not currently available in the TMM literature. Generative sufficiency of the model was promising, and the model has great utility in understanding predicted outcomes conceptually, but practitioners may find a model more useful if estimates could be translated to familiar metrics or if metrics were more directly informed by raw data. For example, model interpretability will be increased if a round of interaction in the model were translated to interpretable units of time (e.g. hours, days, etc.).

In addition to time, stochastic relationships between individual behavior and individual differences could be further explicated. In the current form, the model apparently overemphasizes the impact of individual differences, according to the comparison of correlations between variables found in the model and in empirical studies. Educated estimates based on the literature were made to understand probabilities of behavior. Conceptually helpful in this case, future directions for these relationships may be drawn from distributions instead of fixed probabilities of behavior.

Validation could occur using human subjects to commiserate modeled data outputs. Decision making paradigms where team members share information to come to the correct answer is a useful and straightforward way to test the predictions of the model. By manipulating information team members bring to the team discussion, the closed system modeled here is easily recreated in a laboratory setting.

A researcher could measure many of the aspects modeled in this dissertation. Team members could provide ratings of confidence in the information they hold after being provided with their sample of information. Personality variables could be collected and correlated with who speaks, how often, and the quality of the information presented. At the end of a study, teams could be given a test that could capture their knowledge and be used to measure total accuracy, mean accuracy, and similarity among respondents. Building on such a validation, contextual changes could then be modeled both computationally and in a laboratory environment.

Alternative validation procedures would include adapting the model to fit a particular context. Team cognition is necessary in many tasks that teams perform, especially as teams perform over time. For example, consulting teams use TMMs to understand the needs of one another to know how each member can contribute to addressing client needs. The outcome could be a creative presentation or solution for the client. However, consulting teams also work on multiple project simultaneously or in rapid succession. The model framework could add a contextual layer that demonstrates how knowledge is applied, acquired, and shared across contexts (e.g. projects) and contributes to expected work products. This model could then be compared to data produced by real teams.

Virtual Experimentation

This simulation is designed to be expanded upon and used for virtual experimentation to augment human subject data collection. Virtual experimentation could include creating particular contextual features that augment or hinder TMM development. For example, one could simulate how TMM would develop if agents could reference past materials or were granted external cognitive resources with which to share information. Such an intervention could potentially help lower ability agents process more information more quickly.

Virtual experimentation could, effectively, model how various interventions could impact all aspects of the team system. Exploring different combinations of variable interactions or functions provide a glimpse into what could be the outcome of a system. An excellent example of this is the work completed by Scullen, Bergey, and Smith (2005), which explored the interactions between selection ratios, turnover, and firing practices. Through modeling complete organizations, these authors were able to explore the range of possible outcomes by varying the estimates of their included variables.

Agents

A major next step for the model is to represent goal-directed agents. Currently, agents do not actively reflect on the situation at hand other than remembering the interaction history with other agents. Agents could be programmed to observe the situation at hand, follow conversations and pieces of information, and have ulterior motives that direct behavior.

The fields of individual differences and motivation are an excellent area to start (Driskell et al., 2005; Deshon & Gillespie, 2005). Through understanding the active processes that impact immediate behavior or general trends in behavior, agents could come to represent realistic individuals. Realistic agents would again add to the variety of situations that could be examined under this architecture.

Process Selection

Alternative processes could explore different models of team interaction than orientation, differentiation, and integration. This model is designed for team communication and describes, holistically, the processes teams engage in that facilitate cognition changes. Myriad alternative communication models exist, however, positioning different aspects of the communication process as a focal aspect (Stamp, 1999). For researchers so inclined to model the diverse microdynamics of interpersonal communication, explicated aspects of the model could include nonverbal communication, the impact of various message types, or structure or mode of communication.

Context

Future iterations of the model may explore a variety of contextual features to capture the complexity of the social system. The types of processes modeled may include reflective processes where teams have directed discussions over disagreements in information to model a collective evaluation of information. This is in contrast to the current model whereby each agent individually evaluated incoming information. Collective evaluation of information is a better representation of reality because teams may not randomly jump from one topic to the next without further discussion or elaboration.

Conclusion

The present study was designed to provide insight into the influence of individual differences on the emergence of TMM. Through a process-oriented theory translated into a computational model, a critical examination of TMM development in a variety of metrics were explored. Assessment of these outcomes suggest that intelligence, in this case a proxy for the amount of information that can be processed or communicated in a team, serves equally as an advantage and liability for teams. This suggestion challenges the notion of strictly linear relationships between team intelligence and performance. The liabilities of team ability to communicate and process information is a fruitful area for new research.

Model results are debatable and will remain so until the model is calibrated to more accurately describe the process and context or until the model is calibrated against human subject data. Overall, the theoretical framework offers a general point of departure to explore the future of TMM research. Future research that adapts this framework to adapt wider varieties of tasks, contexts, or agent characteristics could have substantial positive impact on this area of research.

References

Baddeley, A. (2003). Working memory and language: An overview. *Journal of Communication Disorders*, *36*(3), 189-208.

Bartunek, J. M., Gordon, J. R., & Weathersby, R. P. (1983). Developing “complicated” understanding in administrators. *Academy of Management Review*, *8*(2), 273-284.

Bell, S. T. (2007). Deep-level composition variables as predictors of team performance: A meta-analysis. *Journal of Applied Psychology*, *92*(3), 595.

Bell, S. T., Brown, S. G., Colaneri, A., & Outland, N. (2018). Team composition and the ABCs of teamwork. *American Psychologist*, *73*(4), 349.

Bettenhausen, K., & Murnighan, J. K. (1985). The emergence of norms in competitive decision-making groups. *Administrative Science Quarterly*, 350-372.

Burke, C. S., Stagl, K. C., Salas, E., Pierce, L., & Kendall, D. (2006). Understanding team adaptation: A conceptual analysis and model. *Journal of Applied Psychology*, *91*(6), 1189.

Calori, R., Johnson, G., & Sarnin, P. (1994). CEOs' cognitive maps and the scope of the organization. *Strategic Management Journal*, *15*(6), 437-457.

Cannon-Bowers, J. A., & Salas, E. (2001). Reflections on shared cognition. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior*, *22*(2), 195-202.

Cannon-Bowers, J. A., Salas, E., & Converse, S. A. (1993). Shared mental models in expert team decision making. In N. J. Castellan, Jr. (Ed.), Current issues in individual and group decision making (pp. 221-246). Hillsdale, NJ: Erlbaum.

Cannon-Bowers, J. A., Tannenbaum, S. I., Salas, E., & Volpe, C. E. (1995). Defining team competencies and establishing team training requirements. In R. Guzzo & E. Salas (Eds.), *Team effectiveness and decision making in organizations* (pp. 333-380). San Francisco: Jossey-Bass.

Conant, R. C., & Ashby, R. W. (1970). Every good regulator of a system must be a model of that system. *International Journal of Systems Science*, *1*(2), 89-97.

Cooke, N. J., Kiekel, P. A., & Helm, E. E. (2001). Measuring team knowledge during skill acquisition of a complex task. *International Journal of Cognitive Ergonomics*, *5*(3), 297-315.

Curşeu, P. L., & Rus, D. (2005). The cognitive complexity of groups: A critical look at team cognition research. *Cognitie, Creier, Comportament* , *9*(4), 681-710.

Day, E. A., Arthur Jr, W., & Gettman, D. (2001). Knowledge structures and the acquisition of a complex skill. *Journal of Applied Psychology*, *86*(5), 1022.

Dayan, P. (2003). Levels of analysis in neural modeling. In: L. Nadel (Ed.), Encyclopedia of Cognitive Science. Macmillan, London.

DeChurch, L. A., & Mesmer-Magnus, J. R. (2010a). The cognitive underpinnings of effective teamwork: A meta-analysis. *Journal of Applied Psychology*, *95*(1), 32.

DeChurch, L. A., & Mesmer-Magnus, J. R. (2010b). Measuring shared team mental models: A meta-analysis. *Group Dynamics: Theory, Research, and Practice*, *14*(1), 1.

Devine, D. J., Clayton, L. D., Philips, J. L., Dunford, B. B., & Melner, S. B. (1999). Teams in organizations: Prevalence, characteristics, and effectiveness. *Small Group Research, 30,* 678–711. http://dx.doi.org/10 .1177/104649649903000602

Dionne, S. D., Sayama, H., Hao, C., & Bush, B. J. (2010). The role of leadership in shared mental model convergence and team performance improvement: An agent-based computational model. *The Leadership Quarterly*, *21*(6), 1035-1049.

Driskell, J. E., Goodwin, G. F., Salas, E., & O'shea, P. G. (2006). What makes a good team player? Personality and team effectiveness. *Group Dynamics: Theory, Research, and Practice*, *10*(4), 249.

Edmondson, A. C., & Lei, Z. (2014). Psychological safety: The history, renaissance, and future of an interpersonal construct. *Annual Review of Organizational Psychology and Organizational Behavior*, *1*(1), 23-43.

Edwards, B. D., Day, E. A., Arthur Jr, W., & Bell, S. T. (2006). Relationships among team ability composition, team mental models, and team performance. *Journal of Applied Psychology*, *91*(3), 727.

Epstein, J. M. (1999). Agent-based computational models and generative social science. *Complexity*, *4*(5), 41-60.

Epstein, J. M. (2006). Remarks on the foundations of agent-based generative social science. *Handbook of Computational Economics*, *2*, 1585-1604.

Fisher, D. M., Bell, S. T., Dierdorff, E. C., & Belohlav, J. A. (2012). Facet personality and surface-level diversity as team mental model antecedents: Implications for implicit coordination. *Journal of Applied Psychology*, *97*(4), 825.

Fussell, S. R., & Krauss, R. M. (1989). The effects of intended audience on message production and comprehension: Reference in a common ground framework. *Journal of Experimental Social Psychology*, *25*, 203-19.

Gary, M. S., & Wood, R. E. (2011). Mental models, decision rules, and performance heterogeneity. *Strategic Management Journal*, *32*(6), 569-594.

Gersick, C. J., & Hackman, J. R. (1990). Habitual routines in task-performing groups. *Organizational Behavior and Human Decision Processes*, *47*(1), 65-97.

Grand, J. A., Braun, M. T., Kuljanin, G., Kozlowski, S. W., & Chao, G. T. (2016). The dynamics of team cognition: A process-oriented theory of knowledge emergence in teams. *Journal of Applied Psychology*, *101*(10), 1353.

Gruenfeld, D. H., & Hollingshead, A. B. (1993). Sociocognition in work groups: The evolution of group integrative complexity and its relation to task performance. *Small Group Research*, *24*(3), 383-405.

Harrison, J. R., Lin, Z., Carroll, G. R., & Carley, K. M. (2007). Simulation modeling in organizational and management research. *Academy of Management Review*, *32*(4), 1229-1245.

Hill, R. C., & Levenhagen, M. (1995). Metaphors and mental models: Sensemaking and sensegiving in innovative and entrepreneurial activities. *Journal of Management*, *21*(6), 1057-1074.

Hinsz, V. B., Tindale, R. S., & Vollrath, D. A. (1997). The emerging conceptualization of groups as information processors. *Psychological Bulletin*, *121*(1), 43.

(Holyoak, 1984) Bower, G. H., Anderson, J. R., & Kosslyn, S. M. (1984). *Tutorials in learning and memory: Essays in honor of Gordon Bower*. San Francisco: W.H. Freeman.

Humphrey, S. E., & Aime, F. (2014). Team microdynamics: Toward an organizing approach to teamwork. *The Academy of Management Annals*, *8*(1), 443-503.

Jackson, C. L., Colquitt, J. A., Wesson, M. J., & Zapata-Phelan, C. P. (2006). Psychological collectivism: A measurement validation and linkage to group member performance. *Journal of Applied Psychology*, *91*(4), 884.

Klimoski, R., & Mohammed, S. (1994). Team mental model: Construct or metaphor?. *Journal of Management*, *20*(2), 403-437.

Kozlowski, S. W. J., & Bell, B. S. (2013). Work groups and teams in organizations. In N. W. Schmitt, S. Highhouse, & I. B. Weiner (Eds.), *Handbook of psychology: Industrial and organizational psychology* (pp. 412-469). Hoboken, NJ, US: John Wiley & Sons Inc.

Kozlowski, S. W., & Chao, G. T. (2012). The dynamics of emergence: Cognition and cohesion in work teams. *Managerial and Decision Economics*, *33*(5-6), 335-354.

Kozlowski, S. W., Chao, G. T., Grand, J. A., Braun, M. T., & Kuljanin, G. (2013). Advancing multilevel research design: Capturing the dynamics of emergence. *Organizational Research Methods*, *16*(4), 581-615.

Kozlowski, S. W., Chao, G. T., Grand, J. A., Braun, M. T., & Kuljanin, G. (2016). Capturing the multilevel dynamics of emergence: Computational modeling, simulation, and virtual experimentation. *Organizational Psychology Review*, *6*(1), 3-33.

Kozlowski, S. W. J., & Klein, K. J. (2000). A multilevel approach to theory and research in organizations: Contextual, temporal, and emergent processes. In K. J. Klein & S. W. J. Kozlowski (Eds.), *Multilevel theory, research, and methods in organizations: Foundations, extensions, and new directions* (pp. 3-90). San Francisco, CA, US: Jossey-Bass.

Klayman, J. (1995). Varieties of confirmation bias. In J. Busemeyer, R. Hastie, & D. L. Medin (Eds.), *Decision making from a cognitive perspective* (Psychology of Learning and Motivation, vol. 32), pp. 365-418. New York: Academic Press

Krauss, R. M., & Fussell, S. R. (1991). Constructing shared communicative environments. In L. B. Resnick, J. M. Levine, & S. D. Teasley (Eds.), *Perspectives on socially shared cognition* (pp. 172-200). Washington, DC: American Psychological Association.

Leonard, N. H., Beauvais, L. L., & Scholl, R. W. (2005). A multi-level model of group cognitive style in strategic decision making. *Journal of Managerial Issues*, 119-138.

LePine, J. A., Piccolo, R. F., Jackson, C. L., Mathieu, J. E., & Saul, J. R. (2008). A meta-analysis of teamwork processes: Tests of a multidimensional model and relationships with team effectiveness criteria. *Personnel Psychology*, *61*(2), 273-307.

Li, J., & Roe, R. A. (2012). Introducing an intrateam longitudinal approach to the study of team process dynamics. *European Journal of Work and Organizational Psychology*, *21*(5), 718-748.

Lim, B. C., & Klein, K. J. (2006). Team mental models and team performance: A field study of the effects of team mental model similarity and accuracy. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior*, *27*(4), 403-418.

Lucassen, T., & Schraagen, J. M. (2012). Propensity to trust and the influence of source and medium cues in credibility evaluation. *Journal of Information Science*, *38*(6), 566-577.

Marks, M. A., Mathieu, J. E., & Zaccaro, S. J. (2001). A temporally based framework and taxonomy of team processes. *Academy of Management Review*, *26*(3), 356-376.

Marks, M. A., Sabella, M. J., Burke, C. S., & Zaccaro, S. J. (2002). The impact of cross-training on team effectiveness. *Journal of Applied Psychology*, *87*(1), 3.

Marks, M. A., Zaccaro, S. J., & Mathieu, J. E. (2000). Performance implications of leader briefings and team-interaction training for team adaptation to novel environments. *Journal of Applied Psychology*, *85*(6), 971.

Mathieu, J. E., Heffner, T. S., Goodwin, G. F., Cannon-Bowers, J. A., & Salas, E. (2005). Scaling the quality of teammates' mental models: Equifinality and normative comparisons. *Journal of Organizational Behavior: The International Journal of*

Industrial, Occupational and Organizational Psychology and Behavior, *26*(1), 37-56.

Mathieu, J. E., Heffner, T. S., Goodwin, G. F., Salas, E., & Cannon-Bowers, J. A. (2000). The influence of shared mental models on team process and performance. *Journal of Applied Psychology*, *85*(2), 273.

Mathieu, J. E., Tannenbaum, S. I., Donsbach, J. S., & Alliger, G. M. (2014). A review and integration of team composition models: Moving toward a dynamic and temporal framework. *Journal of Management*, *40*(1), 130-160.

McComb, S. A. (2007). Mental model convergence: The shift from being an individual to being a team member. In *Multi-level issues in organizations and time* (pp. 95-147). Emerald Group Publishing Limited.

Mesmer-Magnus, J. R., & DeChurch, L. A. (2009). Information sharing and team performance: A meta-analysis. *Journal of Applied Psychology*, *94*(2), 535.

Mohammed, S., Ferzandi, L., & Hamilton, K. (2010). Metaphor no more: A 15-year review of the team mental model construct. *Journal of Management*, *36*(4), 876-910.

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, *63*(2), 81.

Newell, A. (1994). *Unified theories of cognition*. Harvard University Press.

Nisbett, R. E., Aronson, J., Blair, C., Dickens, W., Flynn, J., Halpern, D. F., & Turkheimer, E. (2012). Intelligence: New findings and theoretical developments. *American Psychologist*, *67*(2), 130.

Ones, D. S., Dilchert, S., Viswesvaran, C., & Judge, T. A. (2007). In support of personality assessment in organizational settings. *Personnel Psychology*, *60*(4), 995-1027.

Ostroff, C., & Kozlowski, S. W. (1992). Organizational socialization as a learning process: The role of information acquisition. *Personnel Psychology*, *45*(4), 849-874.

Parker, K. C. (1988). Speaking turns in small group interaction: A context-sensitive event sequence model. *Journal of Personality and Social Psychology*, *54*(6), 965.

Payne, S. C., Youngcourt, S. S., & Beaubien, J. M. (2007). A meta-analytic examination of the goal orientation nomological net. *Journal of Applied Psychology*, *92*(1), 128.

Peterson, D. K., & Pitz, G. F. (1988). Confidence, uncertainty, and the use of information. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(1), 85.

Randall, K. R., Resick, C. J., & DeChurch, L. A. (2011). Building team adaptive capacity: The roles of sensegiving and team composition. *Journal of Applied Psychology*, *96*(3), 525.

Ree, M. J., Carretta, T. R., & Teachout, M. S. (1995). Role of ability and prior knowledge in complex training performance. *Journal of Applied Psychology*, *80*(6), 721.

Rentsch, J. R., & Klimoski, R. J. (2001). Why do 'great minds' think alike?: Antecedents of team member schema agreement. *Journal of Organizational Behavior: The*

International Journal of Industrial, Occupational and Organizational Psychology and Behavior, *22*(2), 107-120.

Rentsch, J. R., & Woehr, D. J. (2004). Quantifying congruence in cognition: Social relations modeling and team member schema similarity. In E. Salas & S. M. Fiore (Eds.), *Team cognition: Understanding the factors that drive process and performance* (pp. 11-31). Washington, DC, US: American Psychological Association.

Resick, C. J., Murase, T., Randall, K. R., & DeChurch, L. A. (2014). Information elaboration and team performance: Examining the psychological origins and environmental contingencies. *Organizational Behavior and Human Decision Processes*, *124*(2), 165-176.

Rico, R., Sánchez-Manzanares, M., Gil, F., & Gibson, C. (2008). Team implicit coordination processes: A team knowledge–based approach. *Academy of Management Review*, *33*(1), 163-184.

Robert, L. P., Denis, A. R., & Hung, Y. T. C. (2009). Individual swift trust and knowledge-based trust in face-to-face and virtual team members. *Journal of Management Information Systems*, *26*(2), 241-279.

Rouse, W. B., & Morris, N. M. (1986). On looking into the black box: Prospects and limits in the search for mental models. *Psychological Bulletin*, *100*(3), 349.

Schmidtke, J. M., & Cummings, A. (2017). The effects of virtualness on teamwork behavioral components: The role of shared mental models. *Human Resource Management Review*, *27*(4), 660-677.

Schneider, S. C., & Angelmar, R. (1993). Cognition in organizational analysis: Who's minding the store?. *Organization Studies*, *14*(3), 347-374.

Schroder, H., Driver, M., & Streufert, S. (1967). *Human information processing*. New York: Holt, Rinehart, & Winston.

Scullen, S. E., Bergey, P. K., & AIMAN-SMITH, L. Y. N. D. A. (2005). Forced distribution rating systems and the improvement of workforce potential: A baseline simulation. *Personnel Psychology*, *58*(1), 1-32.

Siemsen, E., Roth, A. V., Balasubramanian, S., & Anand, G. (2009). The influence of psychological safety and confidence in knowledge on employee knowledge sharing. *Manufacturing & Service Operations Management*, *11*(3), 429-447.

Smith-Jentsch, K. A., Kraiger, K., Cannon-Bowers, J. A., & Salas, E. (2009). Do familiar teammates request and accept more backup? Transactive memory in air traffic control. *Human Factors*, *51*(2), 181-192.

Stamp, G. H. (1999). A qualitatively constructed interpersonal communication model: A grounded theory analysis. *Human Communication Research*, *25*(4), 531-547.

Stasser, G., & Vaughan, S. I. (2014). Models of participation during face-to-face unstructured discussion. In E.H. Witte, & J.H. Davis (Eds.) *Understanding group behavior: Consensual action by small groups*, *1*, 165-192. Psychology Press.

Stasser, G., Vaughan, S. I., & Stewart, D. D. (2000). Pooling unshared information: The benefits of knowing how access to information is distributed among group members. *Organizational Behavior and Human Decision Processes*, *82*(1), 102-116.

Stasser, G., & Davis, J. H. (1981). Group decision making and social influence: A social interaction sequence model. *Psychological Review*, *88*(6), 523.

Stewart, D. D., & Stasser, G. (1995). Expert role assignment and information sampling during collective recall and decision making. *Journal of Personality and Social Psychology*, *69*(4), 619.

Stout, R. J., Cannon-Bowers, J. A., Salas, E., & Milanovich, D. M. (1999). Planning, shared mental models, and coordinated performance: An empirical link is established. *Human Factors*, *41*(1), 61-71.

Sun, R. (Ed.). (2006). *Cognition and multi-agent interaction: From cognitive modeling to social simulation*. Cambridge University Press.

Sun, R. (2009). Theoretical status of computational cognitive modeling. *Cognitive Systems Research*, *10*(2), 124-140.

Sun, R. (2008). Introduction to computational cognitive modeling. In R. Sun (Ed.), *The Cambridge handbook of computational psychology* (pp. 3-19). New York, NY, US: Cambridge University Press.

Sun, R., Coward, L. A., & Zenzen, M. J. (2005). On levels of cognitive modeling. *Philosophical Psychology*, *18*(5), 613-637.

Sun, R., & Naveh, I. (2004). Simulating organizational decision-making using a cognitively realistic agent model. *Journal of Artificial Societies and Social Simulation*, *7*(3).

Uitdewilligen, G. J. A. M. L., Waller, M. J., & Zijlstra, F. R. H. (2010). Team Cognition and Adaptability in Dynamic Settings: A review of Pertinent Work. In G.P.

Hodgkinson & J.K. Ford (Eds.), *International review of Industrial and Organizational Psychology*. UK: John Wiley & Sons.

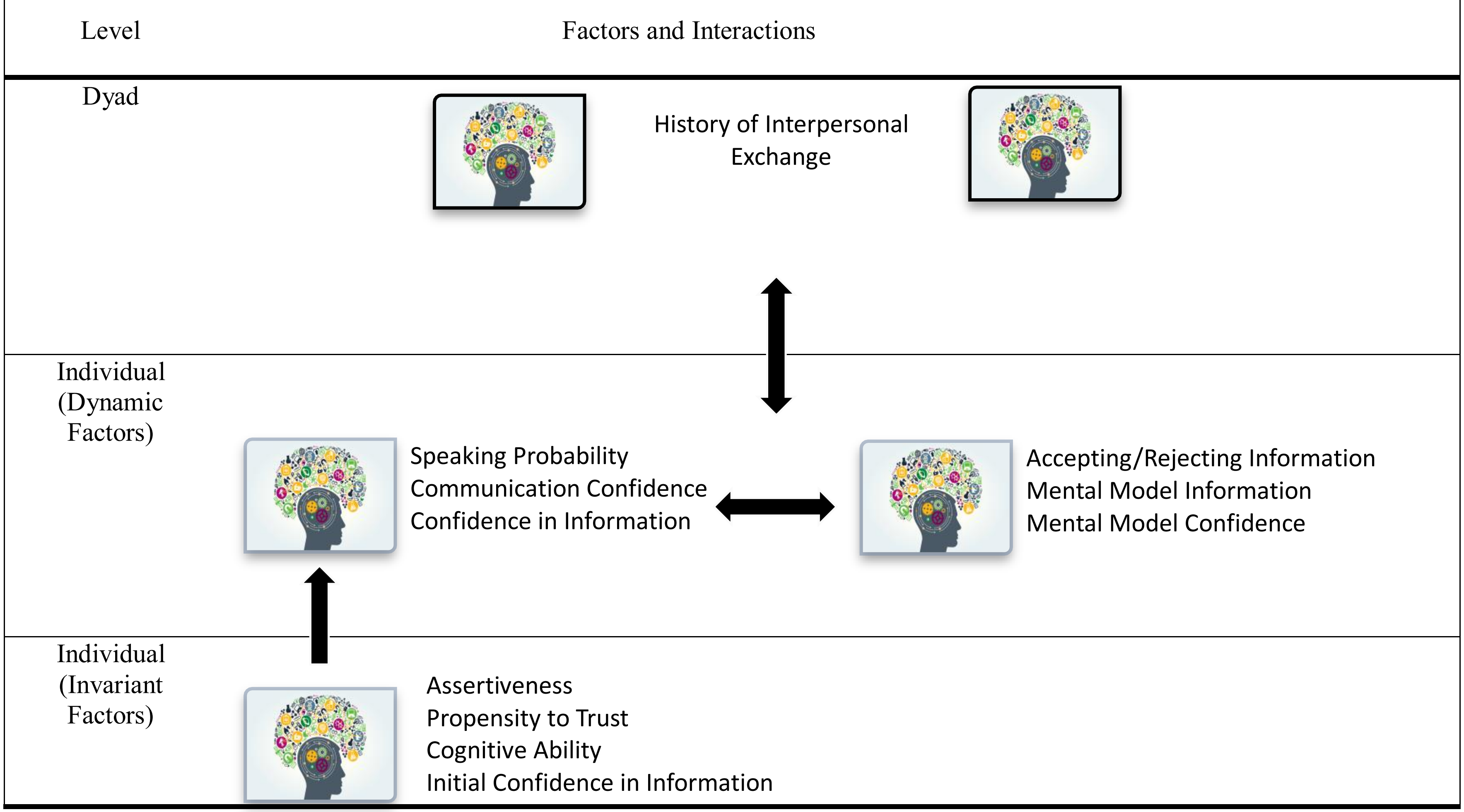
Webber, S. S., Chen, G., Payne, S. C., Marsh, S. M., & Zaccaro, S. J. (2000). Enhancing team mental model measurement with performance appraisal practices. *Organizational Research Methods*, *3*(4), 307-322.

Wenzel, L. H., & Kraiger, K. (1997). Conceptual development and empirical evaluation of measures of shared mental models as indicators of team effectiveness. In *Team performance assessment and measurement* (pp. 75-96). Psychology Press.

Zarnoth, P., & Sniezek, J. A. (1997). The social influence of confidence in group decision making. *Journal of Experimental Social Psychology*, *33*(4), 345-366.

Appendix A: Conceptual Relationships Among Factors

Figure 1. Multilevel Model of TMM Development Process



Appendix B

Table 28
Multilevel Factors Used in Computational Model

	Factor	Description	Representation in Computational Model
Independent Factors	Cognitive Ability	The amount of information agents can process and communicate in a round.	Low = 5 bits of information Moderate = 7 bits of information High = 9 bits of information
	Assertiveness	The drive agents have to further their own ideas.	Low = 30% base speaking drive Moderate = 50% base speaking drive High = 70% base speaking drive
	Propensity to Trust	The probability that information will be viewed as credible.	Low = 30% base information acceptance Moderate = 50% base information acceptance High = 70% base information acceptance
	Confidence in Information (Initial)	The confidence in each bit of information held in an agent's initial mental model.	Randomly sampled value between 1-100 to demonstrate amount of certainty in mental model structural linkage

Dependent Factors	Speaking Motivation	The motivation agents have to present their selected information in a round.	$\text{Speaking Motivation}_{ij} = \text{Confidence}_{ij} \times \text{Assertiveness}_{i}$
	Communicated Confidence	The confidence perceived by agents receiving information. Labeled “credibility”.	$\text{Communicated Confidence}_{ij} = Trust_i \times .99^{(1/Trust_i \, x \, Time j)} + Confidence_{pj} \times (\sum integrated - rejected)^{1/3}$
	Confidence in Information	The average confidence of all the information on a particular topic of information.	$\text{Confidence}_{ij} = \frac{1}{n}\sum x_i$ Note: n = number of content; x_i = confidence in piece of information; i ranges from 1 to number of content selected.
	Acceptance of Information	Information perceived as credible.	Agents probabilistically accept each bit of presented information based on credibility.

Mental Model Content	The topics an agent knows about.	Rows and columns of the matrix representing the agent's mental model.
Mental Model Structure	The linkage (1) or absence of a linkage (0) between topics.	For each cell of the mental model matrix, agents hold their beliefs of relationships between topics with 0 to represent absence of a relationship and 1 to represent presence of a relationship.
History of Interactions	The amount of accepted and rejected information between the speaking agent and receiving agent.	$\sum integrated - rejected$

Appendix C

Table 29
Operationalization of Core Concepts in Computational Architecture of Team Mental Model Emergence

Mechanism	Description	Representation in Model	Rationale
Information Selection	Agents select information to share with other team members. Amount of information depends on cognitive ability	Sample from mental model topics based on average confidence in information. Topics similar in confidence have similar probabilities of being selected.	Individuals communicate information they are confident in (Siemsen et al., 2009).
Information Sharing	Agent selected to speak presents information (content and structure) to other agents.	Non-speaking agents receive information presented by speaking agent.	Groups present information in a turn-taking style with one member presenting at a time (Stasser et al., 2000).
Information Processing	Agents process the amount of information possible based on cognitive ability.	If the amount of information presented exceeds an agent's cognitive limit, information is randomly selected from the	The ability to handle and process information depends on working

		presented information that meets the receiving agent's cognitive limits. If receiving agent's cognitive limits meets or exceeds the amount of information presented, all presented information is processed.	memory capacity (Nisbett et al., 2012).
Speaker Selection	Agents are probabilistically selected to speak based on desire to present information (i.e. "speaking motivation")	$\text{Speaking Motivation}_{ij} = \text{Confidence}_{ij}$ x Assertiveness_{i}	Assertive individuals are more likely to share their information with others and further their ideas (Driskell et al., 2006; Ellis, 2005). Confident members tend to influence decisions in groups (Zarnoth & Sniezek, 1997).

Credibility Calculation	Agents determine credibility of incoming information. Credibility influences probability to integrate information.	Communicated Confidence$_{ij}$ $= Trust_i$ x $.99^{(1/Trust_i \, x \, Time j)} + Confidence_{pj}$ x $(\sum integrated - rejected)^{1/3}$	As speaker confidence increases, the likelihood that the information is viewed as credible also increases (Zarnoth & Sniezek, 1997). Impact of propensity to trust on perceptions of trustworthiness decrease over time in non-linear pattern (van der Werff & Buckley, 2017). History of interaction between individuals predicts future trust between individuals (Azjen, 1991).

Differentiate Information	Agents distinguish new information from already held information before determining which information is agreed with, in conflict, or unknown.	Agents search current mental model and structure and categorize content and structure of presented information. Presented information is categorized as agreed, disagreed, and unknown information.	Individuals reconcile current mental models with incoming information (McComb, 2007).
Integrate Information	Agents integrate conflicting or unknown information based on the credibility of information. Integrated information will alter the agents' content and structure.	Agreed information will cause an agent to become more confident in the content and structure. Unknown and disagreed information that was accepted to be integrated will take the credibility level of the information as its confidence level.	Individuals update mental models through interaction with others (McComb, 2007).

Appendix D

Table 30

Potential Multilevel Factors to use in Computational Architecture

Level	Variable	Description	Citation
Organizational	Culture Structure Reward System Values Leadership	Variables describing organizational systems and rules that exert top-down influence on lower level variables.	
Team	Climate Structure Information Sharing Planning Collective-Efficacy Personality Familiarity Cognitive Ability	Team global and shared properties that are either compositional or compilational in nature.	Kozlowski & Klein, 2000
Dyad	Liking Trust Familiarity Similarity Exchange	Dyadic properties that specify types and strength of relationships between individuals.	Kilduff & Brass, 2010
Individual	Knowledge Personality Previous work experience Ability Skill Level Information seeking	Characteristics of individuals that influence and may be influenced by individual behavior. In some cases variables may be static (e.g. personality), while other variables may fluctuate over time (e.g. attitudes).	

Appendix E: R Code

```
#### Functions

#### Auxiliary functions ####

# Truncated normal distribution sampling

rtnorm <- function(n, mean = 0, sd = 1, min = 0, max = 1) {

  bounds <- pnorm(c(min, max), mean, sd)

  u <- runif(n, bounds[1], bounds[2])

  qnorm(u, mean, sd)

}

####


#### Simulation Setup Functions ####


# Function to create combinatorial grid of conditions for simulation

conditionsFunction <- function(teamSize){


  ##Composition Conditions

  # # 27 unique individual profiles

  characteristics <- c("Assertiveness","Agreeableness","Ability")

  levels <- c("low", "avg", "high")
```

```
    compositionTable <- cross3(levels,levels,levels) %>% map(., unlist) %>%
bind_cols()

    # Overall number of potential compositions based on team size

    profileTable <- compositionFunc(teamSize = teamSize, Long = F)

    teamCondition <- lapply(profileTable, function(x){

      profiles <- bind_cols(lapply(x, function(y){
        compositionTable[y]

      }))

    })
  }

  # True Mental Model Function
  # Creates True mental Model. Currently 25X25 matrix used in simulation (625
bits of information)
  modelCreate <- function(Info){
```

```
  if(missing(Info)){
    Info <- 100
  }
  # Naming the Information
  infoNames <- paste0("I",1:Info)

  accMat <- matrix(sample(c(0,1),length(infoNames)^2,replace = T),
                   nrow = Info, ncol = Info, dimnames = list(infoNames,infoNames))
  diag(accMat) <- 1
  accMat <- data_frame(rows=rownames(accMat)[row(accMat)],
                       vars = colnames(accMat)[col(accMat)], values = c(accMat))
  return(accMat)

}

# Team composition Function
# Generates all portential combinations of team compositions for the team size
# Written specifically for this simulation as the number of potential profiles is 27.
# Must change if potential individual personality make up changes.
compositionFunc <- function(teamSize, Long = F){

  profiles <- 1:27
```

```
  if(Long == F){
    teamSelec <- as_tibble(combinations(profiles, teamSize, replace = T) %>% t())
  }else{
    teamSelec <- as_tibble(combinations(profiles, teamSize, replace = T))
  }

  return(teamSelec)

}


## Change hard-coding levels... turn into distributions
#### Agent Creation Functions ####
# Agent Model Creation... samples true mental model for agent's mental model
agentMind <- function(MM, accuracy = accuracy, knowledge = knowledge,
                      confidence = knowledge, confDev = confDev){

  if(is.null(accuracy)){
    accuracy <- .75
  }
```

```
if(is.null(knowledge)){
  knowledge <- .75
}

if(is.null(confidence)){
  confidence <- .5
}

if(is.null(confDev)){
  confDev <- .25
}




# Sampling content based on knowledge level
indMM <- sample_frac(MM, knowledge)

# Correcting for accuracy level.
indMM <- indMM %>% mutate(values = abs(values - sample(0:1, n(), replace =
T, prob = c(accuracy, 1 - accuracy))))

# Calculating Confidence in information
```

```
  indMM <- indMM %>% mutate(conf = rtnorm(n(), mean = confidence, sd =
confDev))

  return(indMM)
}

# Agent Personality Functions
# Samples personality levels and specific factors based on level
personality.level <- function(intel, agree, assert){
  if(missing(intel)){
    intel <- sample(c("high","avg", "low"),1)
  }
  if(missing(agree)){
    agree <- sample(c("high", "avg", "low"),1)
  }
  if(missing(assert)){
    assert <- sample(c("high", "avg", "low"),1)
  }

  personality <- c(intel,agree,assert)
  names(personality) <- c("Intel","trustProp","Assert")
  return(personality)
```

```
}

personality.num <- function(x){
  intel.num <- if(x[1] == "high"){
    sample(8:10, 1)
  }else{if(x[1] == "avg"){
    sample(5:7, 1)
  }else{if(x[1] == "low"){
    sample(2:4, 1)
  }}
  }
  agree.num <- if(x[2] == "high"){
    runif(1, .6, .85)
  }else{if(x[2] == "avg"){
    runif(1, .35, .6)
  }else{if(x[2] == "low"){
    runif(1, .1, .35)
  }}
  }
  assert.num <- if(x[3] == "high"){
    runif(1, .6, .85)
  }else{if(x[3] == "avg"){
```

```
  runif(1, .35, .6)
 }else{if(x[3] == "low"){
  runif(1, .1, .35)
 }}
 }
 Output <- c(intel.num, agree.num, assert.num)
 names(Output) <- c("Intel", "trustProp", "Assert")
 return(Output)
}


# Agent Creation Function
# Combines agent personality and mental model functions
agentCreate <- function(mentalModel, accuracy, knowledge, confidence,
                        confDev, intel, agree, assert, teamsize){
 brain <- agentMind(MM = mentalModel, accuracy = accuracy, knowledge =
knowledge, confidence = confidence,
                    confDev = confDev)
 profile <- personality.level(intel = intel, agree = agree, assert = assert)
 persLevels <- personality.num(profile)
 Agent <- list(Info = brain,
               Profile = profile, Personality = persLevels,
               infoHistory = tibble(Agent = paste0("Agent",1:teamsize),
```

```
                    integInfo = 0,
                    rejInfo = 0))
  return(Agent)
}

# Team Creation Function
# applies agent creation to team composition profiles.
# Generates team based on team composition profiles.
# This matches the different conditions of the simulation
teamCreate <- function(teamProfile, compositionTable, mentalModel,
             accuracy, knowledge, confidence, confDev){

  teamsize <- length(teamProfile)

  team <- lapply(teamProfile, function(x){
    agentCreate(mentalModel = mentalModel,
        accuracy = accuracy,
        knowledge = knowledge,
        confidence = confidence,
        confDev = confDev,
        assert = x[1],
        agree = x[2],
```

```
             intel = x[3],
             teamsize = teamsize)
  })

  return(team)
}

#### Agent Interaction Functions ####
# Agent Information selection
infoSelect <- function(focalAgent){

  intelLevel <- focalAgent$Personality["Intel"]

  information <- sample_n(focalAgent$Info, intelLevel) %>%
    mutate(conf = conf^(-log(focalAgent$Personality["Assert"])))


  return(information)
}

# Speaker Function
speaker_Select <- function(agents, info){
```

```
  agents[info %>% map_df(~summarise_at(.x, "conf", mean)) %>%
rownames_to_column() %>%
      sample_n(., 1, weight = conf) %>% select(1) %>% as.numeric()]
}

# Agent Communication Function
communicate <- function(focalAgent, information){

  communication <- information %>% mutate(spoken = conf^(-
log(focalAgent$Personality["Assert"])))

  return(communication)
}


# Agent Information Processing Function
infoInteract <- function(presentedInformation, focalagent, infoImpact = .01,
speaker, simRounds = 200){


  trustProb <- focalagent[["Personality"]]["trustProp"]
```

```
prevInfoamt <- focalagent[["infoHistory"]] %>% filter(Agent == speaker) %>%
transmute(prev = integInfo + rejInfo)
prevInfotrust <- focalagent[["infoHistory"]] %>% filter(Agent == speaker) %>%
transmute(infoTrust = integInfo - rejInfo)
trustWeight <- (exp(1)^(-prevInfoamt/simRounds))

# Check for information processing ability
if(focalagent[["Personality"]]["Intel"] > nrow(presentedInformation)){
  heldInfo <- presentedInformation
}else{
  heldInfo <- sample_n(presentedInformation,
focalagent[["Personality"]]["Intel"], weight = conf)
}

indModel <- focalagent[["Info"]]

# Known and unknown information from focal agent perspective.
knownInfo <- semi_join(indModel, heldInfo, by = c("rows", "vars"))
unknownInfo <- anti_join(heldInfo, knownInfo, by = c("rows", "vars"))

## Split information into agreed, disagreed
# Agreed information modified. Finished
```

```
agreedInfo <- semi_join(indModel, heldInfo, by = c("rows","vars","values"))
%>% mutate(conf = conf + .05)

# Disagreed information
# Disagreed information is sampled with weights corresponding to confidence.
Finished.
disagreedInfo <- anti_join(heldInfo, agreedInfo, by = c("rows","vars", "values"))
%>%
  anti_join(.,unknownInfo, by = c("rows","vars"))

if(nrow(disagreedInfo) > 0){

  disagreedProcessed <- disagreedInfo %>%
    mutate(AcceptProb = unlist(map(.$conf, ~((trustWeight*trustProb) + (1-
trustWeight)*(.x + infoImpact*(prevInfotrust)))))) %>%
    mutate(AcceptProb = if_else(.$AcceptProb > 1, 1, .$AcceptProb)) %>%
mutate(AcceptProb = if_else(.$AcceptProb < 0, 0, .$AcceptProb)) %>% rowwise() %>%
    mutate(Accept = sample(0:1, 1, prob = c(1 - AcceptProb, AcceptProb )))
%>%
    filter(Accept == 1) %>% select(-Accept, -AcceptProb) %>%
full_join(.,semi_join(indModel,disagreedInfo, by = c("rows","vars"))) %>%
    group_by(rows, vars) %>% sample_n(1, weight = conf)
```

```
}else{
  disagreedProcessed <- disagreedInfo
}



#Unknown Information Processing
if(nrow(unknownInfo) > 0){

  unknownProcessed <- unknownInfo %>%
    mutate(AcceptProb = unlist(map(.$conf, ~((trustWeight*trustProb) + (1-
trustWeight)*(.x + infoImpact*(prevInfotrust)))))) %>%
    mutate(AcceptProb = if_else(.$AcceptProb > 1, 1, .$AcceptProb)) %>%
mutate(AcceptProb = if_else(.$AcceptProb < 0, 0, .$AcceptProb)) %>% rowwise() %>%
    mutate(Accept = sample(0:1, 1, prob = c(1 - AcceptProb, AcceptProb )))
%>%
    filter(Accept == 1) %>% select(-Accept, -AcceptProb)

}else{
```

```
    unknownProcessed <- unknownInfo

  }



  #Consolidating new MM information
  newInfo <- bind_rows(agreedInfo,disagreedProcessed,unknownProcessed)
  newMM <- anti_join(indModel,newInfo, by = c("rows","vars")) %>%
bind_rows(newInfo)


  #rewriting mental model
  focalagent[["Info"]] <- newMM

  # Updating information history
  infoUpdate <- tibble(
    Agent = speaker,
    integInfo = semi_join(newInfo, heldInfo, by = c("rows","vars","values")) %>%
summarise(n()) %>% as.numeric(),
    rejInfo = anti_join(heldInfo, newInfo, by = c("rows","vars","values")) %>%
summarise(n()) %>%
```

```
        as.numeric())



      focalagent[["infoHistory"]] <- focalagent[["infoHistory"]] %>% left_join(.,
infoUpdate, by = "Agent") %>%
        group_by(Agent) %>% transmute( integInfo = sum(integInfo.x,integInfo.y,
na.rm = T),
         rejInfo = sum(rejInfo.x, rejInfo.y, na.rm = T)) %>% ungroup()

      return(focalagent)

    }



    #### Calculation Functions ####
    # Calculating Team Accuracy
    tmAccuracyCalc <- function(mentalModel, team, round, indAccuracy){
      map(team, `[[`, "Info") %>% bind_rows() %>% semi_join(mentalModel,.,
                                    by = c("rows","vars","values")) %>%
        count() %>% transmute(TotalAccuracy = n/nrow(mentalModel),
                   AvgAccuracy = indAccuracy %>% summarise(mean(Accuracy))
%>% unlist(),
```

```
                    Round = round)
    }


    # Calculating Similarity between Dyads
    similarityCalc <- function(agents, team, round){
      cross2(agents,agents) %>% map(~semi_join(map(team, `[[`, "Info")[[.x[[1]]]],
                                      map(team, `[[`, "Info")[[.x[[2]]]],
                                      by = c("rows","vars","values")) %>% count) %>%
        bind_rows() %>% bind_cols(cross2(agents, agents) %>% map(bind_cols)
%>% bind_rows()) %>%
        rename(Overlap = n, Agent = V1, Comparison = V2) %>%
        left_join(., bind_rows(map(map(team, `[[`, "Info"), ~count(.x)), .id = "Agent"),
by = "Agent") %>%
        mutate(Similarity = Overlap/n) %>% add_column(Round = round)
    }


    # Individual Accuracy calculations
    indAccuracyCalc <- function(team, mentalModel, round){
      map(team, `[[`, "Info") %>% map(., ~semi_join(.x, mentalModel,
                                        by = c("rows","vars","values")) %>%
                                  count) %>% bind_rows(., .id = "id")  %>%
```

```
        transmute(id = id, Accuracy = n/nrow(mentalModel)) %>%
add_column(Round = round)
    }

    # Calculating valued networks of relationships between agents
    networksCalc <- function(team, agents, round){
      map(team, `[[`, "infoHistory") %>% map2(.,agents, ~mutate(.x, FocalAgent =
.y, Round = round)) %>%
        bind_rows()
    }

    # Simulation Function
    tmmSimulation <- function(simRounds = 200, teamProfile, accuracy, knowledge,
                              confidence, confDev, mentalModel){

      # team <- teamCreate(teamProfile = conditionsList$Composition, accuracy =
conditionsList$accuracy,
      #                    knowledge = conditionsList$knowledge, confidence =
conditionsList$confidenceX,
      #                    confDev = conditionsList$confDev, mentalModel =
conditionsList$Context)
```

team <- teamCreate(teamProfile = teamProfile, accuracy = accuracy, knowledge = knowledge,

confidence = confidence, confDev = confDev, mentalModel = mentalModel)

names(team) <- paste0("Agent", 1:length(teamProfile))

agents <- names(team)

PreSim Calculations

Accuracy Calculation

indAccuracy <- indAccuracyCalc(team = team, mentalModel = mentalModel, round = 0)

Similarity Calculation

Similarity <- similarityCalc(agents = agents, team = team, round = 0)

Team Accuracy

teamAccuracy <- tmAccuracyCalc(team = team, mentalModel = mentalModel, indAccuracy = indAccuracy, round = 0)

Data storage

```
mmInfo <- list(indAccuracy = indAccuracy, Similarity = Similarity,
teamAccuracy = teamAccuracy)
Networks <- networksCalc(team = team, agents = agents, round = 0)
Speakers <- data_frame(Speaker = NA, Round = 0)
#
# teamInfo <- map(team, `[`, "Info")




# Iterate
for(i in 1:simRounds){

  # Have agents all select information to present
  info <- map(team, infoSelect)

  # Select which agent will speak based on confidence
  speaker <- speaker_Select(agents = agents, info = info)

  # Have agents interact with information
  team[names(team) != speaker] <-  map(team[names(team) != speaker],
                                   ~infoInteract(presentedInformation = info[[speaker]],
                                                 focalagent = ., speaker = speaker))
```

```
#### Calculations
indAccuracy <- indAccuracyCalc(team = team, mentalModel = mentalModel,
round = i)
# Similarity Calculation
Similarity <- similarityCalc(agents = agents, team = team, round = i)

# Team Accuracy
teamAccuracy <- tmAccuracyCalc(mentalModel = mentalModel, team = team,
round = i, indAccuracy = indAccuracy)

mmInfoNew <- list(indAccuracy = indAccuracy, Similarity = Similarity,
teamAccuracy = teamAccuracy)
spoken <- data_frame(Speaker = speaker, Round = i)



NetworksNew <-  map(team, `[[`, "infoHistory") %>% map2(.,agents,
~mutate(.x, FocalAgent = .y, Round = i)) %>%
  bind_rows()

# Recording
```

```
    Networks <- bind_rows(Networks, NetworksNew)

    mmInfo <- map2(mmInfo, mmInfoNew, bind_rows)

    Speakers <- bind_rows(Speakers, spoken)

  }

  return(list(Networks = Networks, TMMinfo = mmInfo, Speakers = Speakers,
TeamInfo = team))

}
### End Dissertation Functions###
### Begin  Simulation Script###
# Libraries
library(tidyverse)
library(arrangements)
library(parallel)

# Source Simulation Functions
source("/Users/Neal/Documents/Dissertation/TMM Dissertation Functions 2.R")
```

```
# Create conditions
# simConditions <- conditionsFunction(teamSize = 5)
# save(simConditions, file = "Sim Coditions size 5.rdata")
# load("Sim Coditions size 5.rdata")
# Info <- 25
# accuracy <- .75
# knowledge <- .75
# confidenceX <- .5
# confDev <- .15
# infoImpact <- .01
# mm <- modelCreate(Info)
load("~/Downloads/Disser Environment 012119.RData")
# readRDS("~/Assertiveness_homogeneity_Sims.RDS")
Intel_sims_run <-
readRDS("/Users/Neal/Documents/Dissertation/Intelligence_homogeneity_Sims.RDS")
for(w in (c("avg","high","low"))){
  sims <- filter(Intel_sims_run, V1Intel == w) %>% pull(rowname)


  for(b in 1:3){
    if(b == 1){
      simNumbers <- sims[1:43]
```

```
    }
    if(b == 2){
      simNumbers <- sims[44:86]
    }
    if(b == 3){
      simNumbers <- sims[87:129]
    }

    output <- mclapply(simConditions[simNumbers], function(y){
      mclapply(1:100, function(x){
        tmmSimulation(accuracy = accuracy, confDev = confDev,
                      confidence = confidenceX, mentalModel = mm,
                      teamProfile = y, knowledge = knowledge)
      })
    })

    saveRDS(output, file = paste0("Intel_",w,"_batch_",b,"_75coverage.RDS"))
    rm(output)
  }
}

system.time(
```

```
mc169826_169850 <- mclapply(simConditions[169826:169850], function(y){
  mclapply(1:100, function(x){
    tmmSimulation(accuracy = accuracy, confDev = confDev,
                  confidence = confidenceX, mentalModel = mm,
                  teamProfile = y, knowledge = knowledge)
  })
})
)
```