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Developing agent-based simulation models of task performance of cognitively diverse teams

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DEVELOPING AGENT-BASED SIMULATION MODELS OF TASK PERFORMANCE OF COGNITIVELY DIVERSE TEAMS

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of

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by

Megan Marie Nyre

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For my parents

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ABSTRACT

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Team-oriented work dominates industry, government, and academic areas with the goal of solving increasingly complex problems. However, the scope and external validity of traditional human factors research is inherently limited by the time and resources required to conduct laboratory studies. The model described in this thesis integrates simulation with human factors by providing an operationalized model that incorporates cognitive diversity and domain expertise. Convergence and functionality of the model have been established through a series of analyses, and a clear path for future research has been identified. By integrating simulation methods into human factors subject areas, researchers may be able to gain understanding of a more diverse set of teams, team dynamics, and group performance in a fraction of the time and resources required for traditional methods.

CHAPTER 1. INTRODUCTION

Work in organizations is often team-oriented. Simply put, a team is a group of people working towards the same goal, not merely a collection of individuals working on the same task or project. Teams are often formed to complete large, complex projects that require the effort and expertise of more than one individual. Successful completion of these tasks requires the team members working together and managing interpersonal dynamics, often called *teamwork* (as opposed to *taskwork*, or activities to complete the task). Team-oriented work is extremely common in a wide range of industries, such as academic, medical, and industrial (Bowers, Salas, & Jentsch, 2006).

Team-oriented work is gaining popularity and, thanks to the Digital Age, is now commonly distributed across technology channels. This poses some challenges for productivity, as it is now a network of individuals trying to work towards a single goal, sometimes from different locations, in different time zones, with different resources and technologies. As this distribution of resources continues to expand in terms of knowledge, time, and space, information alignment becomes increasingly critical to maintain performance and safety (Caldwell, Palmer, & Cuevas, 2008).

Information alignment has been identified by industry sources as a key component to success, especially in industries like healthcare (Ruhstaller, Roe, Thurlimann, & Nicoll, 2006). In relation to communication, Caldwell and colleagues (Caldwell, 1994) adopt the three levels of communication problems originally defined by Shannon & Weaver (1949). These levels include technical problems, semantic problems, and effectiveness problems (Shannon & Weaver, 1949). *Technical* problems refer to message transmission with respect to accuracy and noise. Shannon & Weaver (1949) studied technical problems in the context of the telephone, modeling a pairwise interaction between a sender and receiver, with noise affecting the amount of information received. *Semantic* problems describe those caused by message interpretation; such as if the message sent was the same as how it was received. *Effectiveness* problems connect the technical problem of transmission and the semantic problem of interpretation to desired outcomes. Essentially, effectiveness problems examine if the message resulted in the desired behavior. Wiener (1948) explores effectiveness problems in depth within the field of cybernetics, and describes message content and complexity with respect to sender, receiver, and result of the intercommunication between the two (Wiener, 1948).

Information alignment incorporates all three levels of communication problems. As defined in this thesis, information alignment is the activity of coordinating flows of information between people in a team. One factor of information alignment explored in this thesis is described by semantic problems, and represents how individuals receive and process information.

Cognitive diversity can be defined as “differences in the cognitive processes that people employ to accomplish their tasks” (Kurtzberg, 2005, p. 53; Mello & Rentsch, 2015). Research supports the idea that a range of backgrounds and perspectives positively affects team performance (Martins, Schilpzand, Kirkman, Ivanaj, & Ivanaj, 2013). However, while cognitive diversity represents potential for more organizational innovation, it can also pose challenges for information alignment.

Communication can be affected by a number of factors, including environmental factors and personality (Duggan, 2016). Differences in thinking associated with disciplinary training can obstruct communication with people from different disciplinary backgrounds (Deering, Johnston, & Colacchio, 2016). Furthermore, the language used in diverse disciplines is often a barrier in multidisciplinary communication (Haymaker, 2006; Sheehan, Robertson, & Ormond, 2007). These aspects have the potential to exacerbate information uncertainty or coordination losses, creating opportunity for incomplete, inefficient, or inadequate communication between members of a team.

One aspect of information alignment is communication effectiveness. How well do members of the team (human or automated) communicate with each other? Communication effectiveness attempts to measure this not in the form of “how often” or “which channel”, but in the message itself and how it is communicated. Information sharing literature proposes explicit, implicit and tacit modes of communication and coordination (Caldwell, 1997; Guinery, 2011). Situations that draw upon communication effectiveness as a key factor might include a lawyer meeting with a client from another country, a taxpayer using filing software, or a child interacting with an autistic family member (Grandin & Scariano, 1986).

Every year, billions of dollars are lost due to poor communication in areas such as productivity, sales, and even safety (Grossman, 2011; Leonard, Graham, & Bonacum, 2004; SIS International Research, 2009; Solari Communication, 2014). Moreover, this problem is not isolated to a specific business, culture or industry (Groysberg & Slind, 2012).

Articles and media commonly highlight the impact of information alignment in various industries and organizations. Areas such as law, teaching and academic advising have stressed the importance of understanding “cognitive diversity” and its role in collaboration with clients and mentoring of students (Collier, 2014; Uhlik, 2014). Business development and other types of consulting firms recognize the power of understanding differences in communication between members of a team, and commonly offer workshops or assessments in all industries to help businesses overcome information alignment problems (Leimbach, 2016). NASA even goes as far as building teams based on individual communication preferences to help increase cognitive diversity on project teams (Pellerin, 2009). Harvard Business Publishing and the Association for Psychological Science have both published videos and articles in this field to educate readers on the background and consequences of cognitive differences (Bonchek & Steele, 2015; Kozhevnikov, 2014).

This problem, if not solved, can cost time, productivity, and satisfaction. Furthermore, failures in communication can pose high risk to safety critical areas, such as healthcare (Leonard et al., 2004). Based on the number of consulting firms, articles, and educational materials available in this area, the problem is far-reaching and non-discriminatory.

The concept of a “hybrid human (or system)”, which consists of a collaborative communication relationship between humans or between humans and technology, draw attention to the need and powerful implications of expanding general understanding of the information alignment process (Bradshaw, 2015; Reijers, 2015). Multi-agent learning takes this a step further into a realm where agents in a system are omnipresent through each other, working in sync with constant real-time shared situation awareness and knowledge (Panait & Luke, 2005).

However, the reality of human performance in any system, with or without technology, is that humans are inherently different from each other and from any system with which they interact. Thus, assuming perfect information exchange or knowledge coordination via communication of a human with another entity or being is an unrealistic assumption.

The research in this thesis takes a step in the direction of modeling information alignment between humans (or agents with humanistic attributes, such as a mode of thinking). With the development of technology and increased speed in simulation, digital modeling and simulation provide ample opportunity to expand the range and magnitude of what can be learned about teams without some of the time and resource constraints of traditional laboratory settings. However, to be a successful and useful contribution, the attributes of modeled agents must be developed and run in a realistic way.

This thesis provides a different approach to addressing gaps in analysis of team communication processes and methods of improvement. The goal is to increase understanding of team dynamics, especially the link between communication and performance, by creating a new way to study it. More specifically, this thesis provides a proof of concept of a new method of simulation-based human factors research in team coordination. If this method can reduce the amount of time, cost and pain involved with improving team performance, organizations may be able to increase utilization of human assets, productivity and satisfaction of individuals. Additionally, teams may find alternative methods for drawing on and maximizing the strengths of cognitive diversity.

CHAPTER 2. BACKGROUND

This paper approaches the scientific study of teamwork by taking previous research and expanding upon the original framework to include mechanisms and processes under individual components. This section delivers a brief overview of literature that touches on group dynamics research.

2.1 Teams and Systems

2.1.1 Definition of "Team"

A more complete definition of a team is "a distinguishable set of two or more people who interact dynamically, interdependently, and adaptively toward a common and valued goal/objective/mission, who have each been assigned specific roles or functions to perform, and who have a limited life-span membership" (Paris, Salas, & Cannon-Bowers, 2000; Salas, Dickinson, Converse, & Tannenbaum, 1992, p. 4). To support the amount, scope, and complexity of work, teams are assembled to perform the needed tasks in an environment in which members can share knowledge and task load through communication and coordination, resulting in *teamwork*.

Examples of team-oriented work are in nearly every industry. Indeed, the teamwork emphasis exists as a large body of literature that extends from interdisciplinary to cross-cultural focus, from leadership to membership, and so on. Research and industry alike have identified the need to study teamwork in industries and environments in which the team functions are highly critical in terms of safety and performance, such as healthcare and space exploration (Baker, Day, & Salas, 2006; Onken & Caldwell, 2011; Orchard, Curran, & Kabene, 2009). Harnessing salient aspects of successful teams has become a main initiative for competitive businesses, which want to understand not only how to form successful teams, but also how to balance the team components, determine effective work methods, and lead them towards increased performance (Ferrazzi, 2012; Slocum, 2014).

2.1.2 Teams as Systems

The dictionary defines a system as "a group of components that move or work together"("System," 2015). Though many definitions can be found for the word 'system', the main theme is that there are two or more *components* that are *coordinated* toward a *purpose,* that are *more than the sum of the parts* (DeGreene, 1970; Meadows, 2008). This nicely parallels the definition of team.

An easily recognizable example of a team is a group of undergraduate students working on a course project. Inputs are tasks within the scope of the project, proposed problems, course objectives, or the semester project in general. These inputs are fed to the process, which is the problem-solving activity performed by the student team. The team then produces outputs, such as deliverables, presentations, or solutions. Feedback may include performance measurement and information alignment. In the case of the undergraduate team, the students might receive incremental feedback from teaching assistants or instructors, and receive a final grade at the end of the term. The goal of this system is to complete the project with acceptable performance in meeting the team's (and the instructor's) objectives: finishing a project on time, within budget, and with a finite and feasible solution. Figure 1 depicts the conceptual team-system model, which was created as part of this study.

Some other real-world examples of this type of system may include interdisciplinary research at university, NASA Mission Control Centers, or even an academic team completing a capstone project. In each of these cases, a team of individuals receives inputs of tasks (which can also be individual), executes the task, and produces corresponding deliverables. The feedback provided to the teams above would, respectively, include peer or ‘customer' responses to addressing gaps in a research area, resolved or unresolved problems during NASA missions, or grades and comments from instructors.

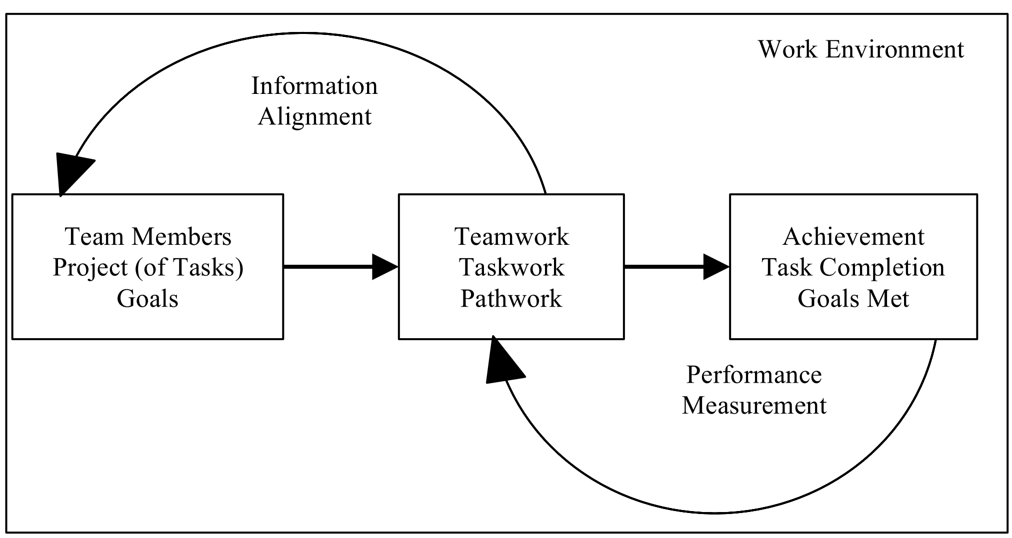


Figure 1. Team-System Conceptual Model

2.2 Teamwork, Taskwork and Pathwork

Teamwork, defined above, is distinctly different from taskwork and pathwork. Where teamwork is managing the process of interaction in order to support the work being performed, taskwork is the coordination of knowledge and information toward task execution (Crawford & Lepine, 2013; Kozlowski, Watola, Jensen, Kim, & Botero, 2009; Salas, Cannon-Bowers, & Johnston, 1997). Pathwork refers to how information is passed among team members, which is relevant especially in geographically and temporally distributed teams (Caldwell, 2005b). These aspects of group dynamics provide the structural basis for this thesis.

2.2.1 Teamwork Research

There are different levels of analysis with which to study team performance. Many sources focus on tangible outputs, frequency of communication, information exchange, success versus failure, and more (Paris et al., 2000). Additional levels rooted in psychology promote shared mental models and team situation awareness as key factors in team performance measurement (Cohen & Levesque, 1991). Bales (1950) even went so far as to break down interactions into categorical elements, such as “shows tension” or “shows solidarity” to assist in analysis of such interactions (Bales, 1950). However, it is generally agreed that factors of team performance are not easily measured (Paris et al., 2000).

Besides the technical challenges of distributed teamwork, there are the social differences between team members that affect on an individual level how a person thinks and communicates. There are also differences in how well he or she can communicate with other people who may think differently. In relation to Garrett & Caldwell's six dimensions of expertise, flexibility in modes of communication can be categorized as *communication expertise* (Garrett, Caldwell, Harris, & Gonzalez, 2009). Communication expertise, like other types of expertise, can develop over time with education, exposure, and practice (Campbell, Maglio, Cozzi, & Dom, 2003; Scardamalia & Bereiter, 1991).

2.2.2 Taskwork Distinctions

Taskwork encompasses methods of carrying out teamwork, and includes strategies and technologies needed to complete a set of tasks (J. E. Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000). Consequently, taskwork is affected by the distribution of domain knowledge expertise on a team, as the amount of achievement the team can gain is dependent upon how well available information is shared between members on a team (Caldwell, 1997; Martins et al., 2013). Thus, taskwork has a strong relationship with expertise and knowledge sharing.

Tasks performed by a group, also called *group tasks*, can require different types of inputs from team members for different kinds of tasks. Steiner (1972) proposes three (3) types of tasks that utilize team members differently (Shaw, 1971; Steiner, 1972). *Additive* tasks produce results through a summation of constituents, or adding the inputs of each team member to product an output. *Disjunctive* tasks require only one constituent to have the necessary skills. *Conjunctive* tasks require every team member to have the necessary skills. These task types provide mathematical operations for rules and performance measurement.

2.2.3 Pathwork

Teams can work in a variety of environments, and can also be geographically, technologically and temporally distributed, which affects how the team members interact. Asynchronous communication through different channels describes how pathwork could be impacted. Thus, the goal of improving pathwork is understanding available communication paths to minimize negative effects on teamwork and taskwork. Pathwork describes constraints and possible future considerations for additional factors affecting team performance.

2.3 Expertise

Expertise is a topic of scientific research that has been pursued with several approaches, ranging from correlating intelligence to performance to analyzing specific abilities (Ericsson & Smith, 1991). All approaches similarly seek to assess expertise in controlled laboratory settings using standardized tasks. One approach defined by Ericsson & Smith (1991) with strong connection to this thesis is the analysis of task performance, which evaluates domain- or task-specific knowledge. While individual expertise is not assessed within the scope of this research, constructs that support future collection of input data should be considered. Ericsson & Smith (1991) present an *expertise approach*, capable of collecting expertise data compatible with the assumptions of this thesis.

There are a variety of domains or dimensions of expertise to consider in this system. Garrett et al. (2009) describe expertise using a multi-dimensional model to combine different concepts of expertise to integrate with the analysis of group performance in more complex task environments (Garrett et al., 2009). The six dimensions include subject matter, situational context, interface tools, expert identification, communication skills, and information flow path expertise, none of which is mutually exclusive with another.

Skills in teamwork are different dimensions of expertise than those in taskwork. However, most teams need to be adept on both areas because of the relationship between teamwork and taskwork (Fisher, 2014). Communication effectiveness, or the measure of how well communication is understood with respect to both sender (message sent) and receiver (message interpreted) ultimately will impact teamwork. Previous efforts in modeling these interactions portray these particular aspects as black box processes in how information is shared (Onken, 2012). The scope of this thesis encompasses the communication element of teamwork, under the term *information alignment*, and its relationship with taskwork.

With respect to task performance, expertise plays a pivotal role in a team's ability to complete a task. For instance, if a team is assigned a task that requires more expertise than available on the team, the task will not be completed to an ideal level, if at all. Another possibility is that the team has a single expert in a given area around which a task is focused. This person becomes the fulcrum between success and failure.

As demonstrated in the above scenarios, representation of domain expertise is a relevant and necessary aspect of studying taskwork and teamwork in group environments. Consequently, the model presented in this thesis includes distributions of domain expertise, implications of task attributes on expertise evaluation, and the effects on task performance. Domain expertise is represented as abstract areas, with the respective amount of expertise in each domain on an ordinal scale. In addition to expertise, Caldwell (2009) identifies other factors that relate to task performance, which could be incorporated into future expansion of this research (Caldwell, 2009).

2.4 Information Sharing and Knowledge Sharing

Coordinated information flow represents the consequences of taskwork. Information and knowledge sharing is a vast area of literature that discusses everything from shared mental models between team members to environmental factors that affect motivations and opportunities to share information between team members (Wang & Noe, 2010). Some studies of information sharing even use a cybernetics approach by operationalizing communication transactions between team members in complex mathematical models (Rothenburg, 2015; Wiener, 1948). Others use probabilistic approaches to accommodate for social aspects of information alignment (Ghosh & Caldwell, 2006).

The approach used in this thesis focuses mainly on flow of information with the understanding that knowledge can be shared along the channels that information normally flows within a given organization. Using this framing, similar factors and constraints can be considered while maintaining a 'systems' perspective on the team coordination (Caldwell, 1997). Within the framework proposed by Caldwell (2005a), there are four possible modules for simulating information alignment in teams, which include *asking, sharing, solving,* and *learning* (Caldwell, 2005a). Attempts have been made to focus specifically on the *sharing* module simulation, using data collected from knowledge sharing domains, such as chat rooms, to supplement research in this area

(Ghosh & Caldwell, 2006). More limited attention has been devoted to development of *solving* modules, which focus on models of teams addressing particular task challenges with an eye to an engineering solution (Onken & Caldwell, 2011; Onken, 2012).

McInerney & Koenig (2011) describe three types of information as it relates to flow. *Implicit* information is that which is implied, but not clearly stated. *Explicit* information is in tangible form, overcoming the possibility of confusion. *Tacit* information is that which is very difficult to transform into a tangible form, such as kinesthetic information (McInerney & Koenig, 2011, p. 45). A relevant metaphor proposed by Caldwell, Palmer and Cuevas (2008) describes an 'information clutch', which is used to control information flow between team members to adjust for relevance, priority and availability of each person (Caldwell et al., 2008). The 'information clutch' is then an important tool used by experts, managers, and leaders in organizations to improve team performance, though it may not be an actively studied process.

This thesis recognizes the importance of the 'information clutch', which draws on an individual's ability to gauge other team members, their availability, needs and strengths. Though there is no specific mechanism or equation in the model at this stage of development, information clutch could be represented in the same variable that quantifies efficiency of communication. Future versions of the model should further develop this aspect of information alignment, and could be incorporated into efficiency of expertise, environmental factors, and pathwork.

2.5 Cognitive Diversity and Thinking Modes

2.5.1 Origins of Style Differences in Cognition and Communication

Formal theories surrounding differences in behavior and communication style have been around since ancient Greece (Chapman, 2009; Wille, 2004). Most of these theories use terms associated with personality such as thinking style, learning style, and communication style (Coffield, Moseley, Hall, & Ecclestone, 2004). These terms have common roots in that a person's character is defined by their temperament, disposition, attributes, which are all factors in how that person thinks, organizes information, and expresses himself or herself (Wille, 2004).

This thesis emphasizes the aspects of the prioritization, organization, and presentation or communication of information between team members, as a combination of context, individual difference, and expertise factors. Thus, while some of the conceptual organization of terminology refers to personality and style, the focus of this thesis is on the effects of ranges of individual variations and capabilities on information alignment to support effective acquisition, sharing, and use of information in team performance settings.

2.5.2 Style versus Mode

Relevant literature presents two main terms for defining the differences in how people think: style and mode. While both are commonly used, sometimes interchangeably, the term 'mode' was adopted for this research. 'Style' suggests unique individual expression or personality, and is used with terms like 'assertive', 'aggressive', or ‘passive’. ‘Mode’ connects to a method to thinking, organizing, prioritizing and presenting information, which could be shared or common. Thus, this research distinguishes that between the two terms, ‘mode’ more accurately reflects the variable of interest regarding information alignment.

Consistent with modern models, many of the older theories regarding cognitive styles or modes propose that different types of behaviors align with a specific mode of thinking and communicating. While each model has its own taxonomy, there is a clear trend in that they propose four or more distinct behavior modes, which can be assigned to a person based on results of a binary response assessment of preferences and avoidances. Two commonly used instruments that assess preferred thinking modes, based on classic theories of communication and interpersonal interactions, include the DISC® Model and the Herrmann Brain Dominance Instrument (HBDI™) (Herrmann, 1991; Keirsey & Bates, 1984; Sugerman, 2009). Factor analysis of the HBDI™ instrument determined four factors, representing the four behavior modes (Coffield et al., 2004; Sundstrom, de Meuse, & Futrell, 1990).

The purpose of distinguishing between thinking modes is not to label or limit individuals. On the contrary, some models, including Herrmann’s, generally accept that these modes are flexible, and that tools such as HBDI™ should be used to encourage growth (Coffield et al., 2004). Some organizational psychologists have found that this concept of *cognitive style* is a central aspect of organizational behavior (Kozhevnikov, 2007). Cognitive diversity, or a difference in problem-solving style, is referenced in recent business articles as a typical challenge in teams, but also beneficial if understood by leaders and team members (Browning, 2013; Collier, 2014; Siverson, 2013). One article even stressed the importance of this particular aspect of teamwork for the next generation of professionals (Dishman, 2015).

Instruments that determine communication mode are used commercially in business, management, education, and coaching to help bridge gaps in understanding differences in preferred modes of thinking and communicating to increase effectiveness. Effectiveness here is loosely defined, and is dependent upon the process that is being analyzed and measured. Examples of successful education and use of these tools provide a large pool of anecdotal evidence that support the validity of the underlying theories. From increased sales, to higher student performance, users of these tools claim that the knowledge gained from the theories not only increase effectiveness in the respective domains, but also general satisfaction of communication in team environments (Herrmann International, n.d.; PeopleKeys, n.d.). Formal studies in psychology also contribute to the pool of evidence from the education domain (Bawaneh et al, 2011; Lumsdaine & Lumsdaine, 1995).

In general, the author accepts the general theory that there are different thinking modes, and that these thinking modes affect communication interactions; the purpose of this thesis is not to specifically test or validate these models (singularly or in direct comparison to each other). Though thinking mode tools are commonly used in business, studies that support and build on the impacts of their use are largely missing from the research community. Additionally, communication continues to be a critical and expensive problem in general areas of human-human or human-systems interactions.

Every year, billions of dollars are lost due to poor communication in areas such as productivity, sales, and even safety (Grossman, 2011; Leonard et al, 2004; SIS International Research, 2009; Solari Communication, 2014). Moreover, this problem is not isolated to a specific business, culture or industry (Groysberg & Slind, 2012).

Though some data are available, scientific support of the benefits of instruments such as HBDI™ is generally absent (Coffield et al., 2004). Lack of quantitative evidence and systematic study contribute to this gap, despite indications that thinking mode tools may be beneficial in other applications. Traditional research in team performance focuses on observed behaviors and subjective data to include relationships and dynamics in teams. Examples of studies that explore the effects of cognitive styles or modes range include effects on visual and verbal information processing (Sojka & Giese, 2001; Thomas, 1987) and education (McCloughlin, 1999).

However, a more recent review of literature in team effectiveness recommends considering different, more dynamic research approaches to reflect the complex team environments of the modern world (Mathieu et al, 2008). To address the identified gap, this paper will take this recommendation by using simulation to assess the impact of differences in thinking modes on productivity and emergent behavior in expert teams.

2.6 Team Performance Measurement

Group performance research suggests many different methods of measuring and understanding how well a team is performing. Many studies resort to quantitative methods, such as surveys, questionnaires, lab experiments with measurable outcomes

(Eden, 1985; Srivastava, Bartol, & Locke, 2006). Other qualitative methods, such as interviews and conceptual methods, can also be used to gain general understanding (Cooke, Salas, Cannon-Bowers, & Stout, 2000), but are difficult to translate into measurement.

2.6.1 Linking Outputs to Inputs

Many organizations interested in improving team performance want to see measurable improvement, starting with a baseline and comparing to an after-treatment value. Some areas of research, including industrial engineering, adopt this approach, using key performance indicators appropriate for the process or industry to measure productivity (Lynn & Reilly, 2000; National Research Council Staff & Harris, 1994). While quantitative approaches are widely used, certain aspects of team performance can be lost in the process of simplifying factors into measurable variables. Some common issues with performance measurement using productivity are the adequacy of the measures themselves, the intrusiveness of the measurement process, and complexity of linkages between individual and organizational productivity (National Research Council Staff & Harris, 1994; Zigon, 1998).

2.6.2 Measuring Communication

Shannon and Weaver (1949) devised a mathematical approach based in information theory to describe communication as signals passed between nodes (Shannon & Weaver, 1949). The model includes concepts such as feedback and noise, which are relevant beyond the scope of Shannon & Weaver's original research: the telephone. Bales (1950) had a similar view of communication. Instead of electrical signal transmissions, he focused on social cues as feedback to verify if a message was understood and accepted (Bales, 1950). His research breaks down communication transactions into visible responses for analysis. Wiener (1948) incorporated communication in terms of consequential observable behaviors within the field of cybernetics, connecting the original goal of message to the outcomes associated with it (Wiener, 1948).

All of these approaches can provide insight regarding how well communication is happening between two or more people. However, the gap between the methods is in the verification that a message was received and understood based on the content and the person sending and the person receiving. The first two approaches are transactional in nature, and do not include other socio-technical factors, such as how the information is presented and how the receiver interprets it. While the grain sizes of these analyses are too small for the system described here, the connection of messages sent, received and decoded between two or more entities is central to how communication is described in this model.

2.7 Methods for Researching Teamwork

2.7.1 Human Subjects Experiments

Traditional experimentation using human subjects is the most prominent method in collecting data regarding group dynamics. Research designs commonly employ a variety of methods that rely on direct access to real teams, such as objective testing, laboratory and field experiments, longitudinal studies, and interviews (Kerlinger & Lee, 2000).

These methods, while supporting validity of the research, require large amounts of time and money, as well as wide ranges of available participants. Research designs associated with these methods also introduce purposeful controls and inadvertent confounds, such as demographics of participants (Colquitt, Hollenbeck, Ilgen, LePine, & Sheppard, 2002). These design implications can reduce the amount of data that can be collected (Joshi & Roh, 2009) as well as the generalizability of the experiment (Acuna, Gomez, & Juristo, 2009; Day et al., 2004). In summary, inherent limitations exist in traditional group research methods.

2.7.2 Observation and Survey Research

Much of the work done in team research has been based on methods such as observation and surveys. Some authors focus their social science efforts on how to design surveys to collect information from organizations (Bauer & Bauer, 2005). Though both observational and survey methods provide data and insight regarding team performance, both leave large gaps in quantifying and understanding the communication between team members and how this relates to the team's performance, especially considering the subjective nature of each. Surveys are subjective, using only the participant's perspective, and represents a single viewpoint on the team and its performance. Observation studies do not provide visibility or access to internal factors, such as thinking mode or information alignment. Neither method provides opportunity for both holistic and individual levels of analysis.

2.7.3 Simulation

Simulation and computational modeling have recently gained popularity in social sciences, including areas such as team effectiveness. Advances in technology and computational resources now allow researchers to develop models quickly and at low cost, greatly increasing the incentive to engage in this method. Simulation, in comparison to traditional methods, is inexpensive and may take a fraction of the time to obtain potentially useful information. Researchers also have the ability to change treatments and increase trial numbers on identical teams with minimal time and cost implications. McGrath (1984) presents a variety of simulation possibilities for studying "concocted groups" doing tasks, wherein the groups can be manipulated in addition to the tasks (McGrath, 1984). For these reasons, simulation is growing in popularity within human factors and social science research (Gaylord & D'Andria, 1998; Ghosh & Caldwell, 2006).

Agent-based modeling is especially fitting for research in human systems, as it allows for the individual, non-linear behavior observed in humans (Bonabeau, 2002). Studies range from actual neurological modeling of thought, to full-scale team dynamics and knowledge sharing (Acquisti et al, 2002; Marsell et al, 2004; Wang & Noe, 2010). The goal of agent-based models in this context is prediction of real-world behavior as well as theory development (Gilbert & Terna, 2000), with the focus of this thesis on the latter.

One simulation study that concerns team problem-solving in Mission Control at NASA provides solid contextual basis for this work by presenting a team with diverse skill sets that is required to resolve anomalies in different problem domains (Onken & Caldwell, 2011). Onken's model accounts for communication, though in a simplified manner, using a 'black box' description of how communication happens, and how different levels of communication expertise affects team-level communication.

Operationalizing thinking modes, demonstrated in this thesis, provides a more robust module to discern team communication dynamics, but also quantifies the traditionally subjective results of using a thinking mode tool. The goal of this addition is to reveal significant effects or emergent behavior of team productivity based on differences in thinking modes within a diverse team of individuals, such as those experts in NASA Mission Control.

This thesis presents a revised model, which may be able to assist in forming hypotheses surrounding team effectiveness and revealing the mechanisms that drive specific behaviors. Further research using human subjects can be done to test the hypotheses and validate specific scenarios. Knowledge gained from this research could help leaders, team members, and researchers devise new approaches to improvement of team formation, management, and performance measurement.

CHAPTER 3. METHODOLOGY

3.1 Framework

The model described in this thesis is a proof of concept for exploring how different sizes of teams may or may not complete a set of tasks (called here a "project") based on diversity of thinking modes and expertise available on the team. An example of this can be found in the NASA Systems Engineering Handbook (2007), which describes the role of systems engineers in a diverse team of experts who need to complete a complex set of tasks. Tools for scheduling, tracking task performance, and reporting (communication) are all discussed as core components of a project (*NASA Systems Engineering Handbook*, 2007). The team is comprised of *agents,* which each have attributes, such as a thinking mode and expertise. The team is then assigned tasks, which have types that define how expertise needs to be applied to complete the task. Achievement of each task is determined by measuring how well the team was able to communicate, if the team had the expertise required by the task, and a roll for performance. These will all be defined below.

A helpful analogy in describing this model is in relation to team sports. Team sports require the contributions of each member to succeed. Some team sports, such as golf, add individual scores to get the team score, requiring each individual to perform well during his round. Track teams doing relay races rely not only on individual performance, but also the handoff from one player to the next. This setting builds upon the first, with the addition of the crossover from one player to the next during the handoff. Volleyball teams rely on all specialized positions, each with distinct skills, to perform well as individuals and together during a game in order to succeed.

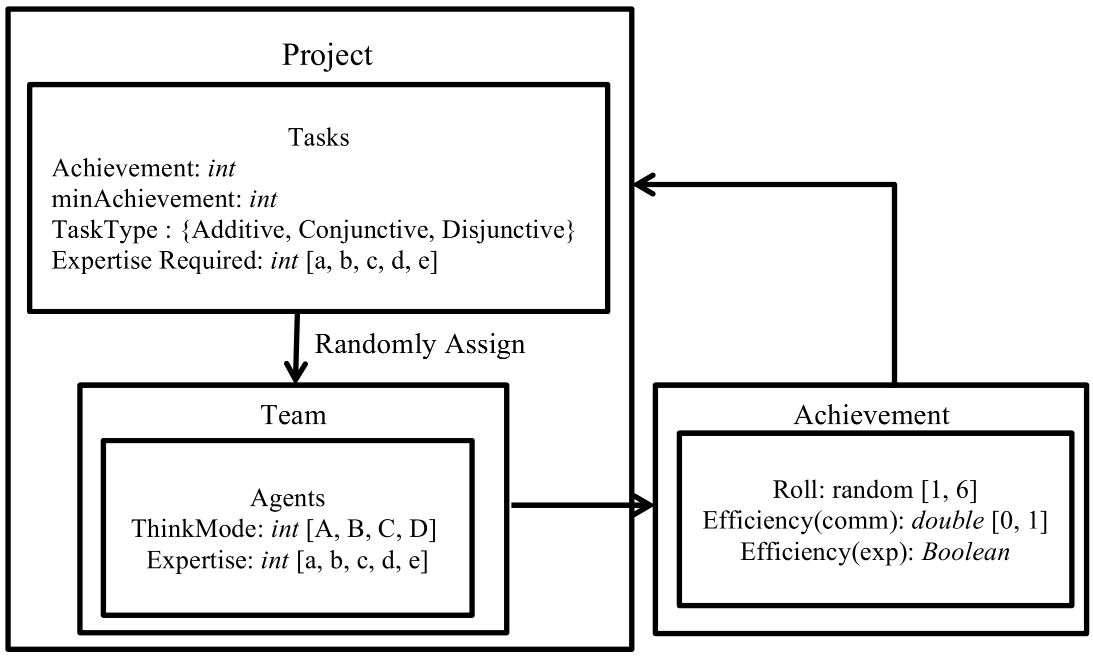


Figure 2. Model Framework

In the last sports example, communication between team members is especially important in coordinating offense and defense, as well as overcoming mistakes and rallying. Many team sports now recognize the importance of choosing team members not only for their skills, but also their ability to act in a team setting in a way that benefits the whole (May, 2014). A key aspect of this analogy is the importance of communication in teams, no matter if these teams are in industry, academia, or sports.

3.1.1 Agent-Based Modeling

Agent-based modeling (ABM) is a modeling and simulation paradigm that defines individual components, called *agents,* that can act independently in an environment (Macal & North, 2010). Salient aspects of the agents include individual attributes, such as memory and goals, which interact with the environment and other agents during the simulation. Thus, ABM is appropriate for organizational simulation in that it can provide qualitative insights into complex systems, including human systems (Bonabeau, 2002; Macal & North, 2005, 2010). ABM techniques are acknowledged in social sciences as relevant ways to study emergent behavior and develop theories (Gilbert & Terna, 2000).

3.1.2 Teams and Agents

The model described in this thesis includes a team composed of some predetermined number of agents. This number can easily be changed to reflect a specific team, but was largely determined by estimating the range of people on a productive team (Fried, 1991). The assumptions governing agent behavior in this simulation include aspects of real-world team assembly and functioning.

- The team is assigned a series of work-related tasks to complete.
- Team members do not choose their teammates.
- Team members have different roles with different associated skills.
- The team is working towards a common goal.

Consistent with ABM, the members of the team each have a set of attributes that influence how each member is able to collaborate with other members to achieve the goal. These attributes include thinking mode and expertise.

To represent communication, this model employs example results from a popular four-mode model as one possible way to help categorize different thinking modes in a population (Herrmann, 1996).This study does not assume the nature of the modes or the underlying theory of the four-mode model to be correct, only that there are multiple modes representing different ways of thinking.

Within the model, agents each have a *thinking mode profile* comprised of four (4) values that represent different modes of thinking, denoted by *l*. To simplify what these modes may represent, they will be called S, R, Y, and U, which denote four distinct ways people think. To add context, these modes might be thought of as *social, structural, analytical* and *conceptual.*

Each agent *A* has a magnitude of strength in each of the modes, resulting in a vector of values. It should be noted that an agent could have a high magnitude in *all* modes, consistent with some thinking mode models (Herrmann, 1996). The magnitude, denoted by *m,* represents the strength of the individual's preferences in employing that particular mode, which is an important distinction when understanding how a person might prefer to work in certain environments. For instance, how an individual prefers to operate at home may be different than what mode she prefers to work in while at her place of employment. The key point here is that these magnitudes are *preferences* that are *flexible* based on the time, environment, task context, and the individual himself.

Additionally, agents have *expertise profiles,* represented by *e*. These profiles are meant to represent the different domains in which an individual may have expertise, such as a subject area. For the purpose of this research, a profile consists of five (5) values, each a descriptor of a person's expertise in the particular area. This number can easily be changed for future applications of this model, but is meant to include a reasonable variety of areas that a team might need to draw on in order to complete a diverse set of tasks.

Each agent has a certain amount of expertise in each of those areas, ranging from 1 to 10. A simple video game analogy for this is a level of a particular skill in a domain of performance (known as 'player stats) (Caldwell, 2009). The dimensions are like different skill areas, such as strength or magic. The level, denoted by *k,* represents how much experience the individual has in that particular skill. A magnitude of 1 reflects absolutely no expertise in a particular area, such as a novice introduced to a system for the first time. A magnitude of 10 reflects immense experience and knowledge in a particular area, and can be thought of as representing a mastery of a trade.

The j-th agent assigned to a team is thus defined by a 9-tuple indicating the agent's strengths in each communication mode and domain of expertise:

$$A_j = \langle e_k, m_l \rangle \quad k = a, b, c, d, e \ \ and \ l = S, R, Y, U$$

$e \ \in [0, 10]$ where *e* is an integer

$m \ \in [1, 150]$ where *m* is an integer

The model randomly selects team members for a group *G* from a pool, which can be thought of as an organization. The selection process employs a Fisher-Yates shuffle, which produces results that are uniformly distributed. The agent pool is then rearranged based on the shuffle, and the first *n* elements of the array are then selected as the new team. The number of agents, *n,* needed for the experiment is defined in code by the researcher.

$$G = \{A_j | j \in 1, 2, \dots, n\}$$

where *n* is the number of members needed for the group

The model defines the size of the pool as twice the size of the largest team in the experimental design, allowing for the possibility of two distinct teams to be selected for an identical project. Additionally, the pool is static, and members within the pool maintain their respective attributes. Each time a project is run, a team is selected randomly from the pool. Thus, the team members change, but the individuals' attributes and the organization do not.

Expertise is distributed throughout the organization such that no one person is an expert in everything, and each person has at least some expertise in at least one area. Team expertise was generated from a discretized triangular distribution in each dimension, with $N = 24$, $a = 0$, $b = 10$, and $k = 3$ to represent the mathematical mode expertise in a given subject area. The resulting profiles for agent expertise are shown in Table 2. The expertise data used in the simulation was not adopted from actual profiles of humans. Should the distribution of expertise be determined in a particular organization through skills assessments or other tools, the model can be easily and quickly modified to reflect this.

Thinking mode represents cognitive diversity in the organization. Thinking mode profiles for each member of the organization were generated in the same manner as expertise. This method used a discretized triangular distribution in each thinking mode with $N = 24$, $a = 1$, $b = 155$, and $k = 45$, representing a mathematical mode preference that is ranked neutral in the magnitude scale. Thinking mode profiles of the organization are shown in Table 3.

3.1.3 Projects and Tasks

The team of agents is assigned a project, comprised of some number of tasks. While this is an arbitrary number of tasks, it is meant to represent the range of subdivisions of work within a single project.

Each task has an expertise profile, much like the agents. However, this expertise profile represents how much expertise is required in any given dimension for the team to perform the task. For instance, the task might require a minimum of level 8 expertise in dimension *b,* level 2 expertise in dimension *c*, level 5 expertise in *a* and *e,* and no expertise required in *d.*

$$T_i = \langle e_k \rangle$$

Tasks also have a type assigned. Recalling the conjunctive, disjunctive, and additive task types defined in Chapter 2, the task type assigned dictates how much expertise is need based on the rules of the task. Does everyone need to have this expertise? Can the combined expertise of the team meet the requirements? Or is this a one-expert-required task? The output of this comparison is the *efficiency of expertise,* $I_t(G, T_i)$, which is a binary variable indicating whether or not the team can complete the task based on the expertise available on the team, the expertise required by the task, and the task type. The three equations below define the efficiency of expertise by task type.

$$I_{Additive}(G,T_i) = \begin{cases} 1 & if \displaystyle\sum_{A \in G} e_k \geq t_k \quad \forall k \\ 0 & else \end{cases}$$

$$I_{Conjunctive}(G,T_i) = \begin{cases} 1 & if \min\limits_{A \in G} e_k \geq t_k \quad \forall k \\ 0 & else \end{cases}$$

$$I_{Disjunctive}(G,T_i) = \begin{cases} 1 & if \max\limits_{A \in G} e_k \geq t_k \quad \forall k \\ 0 & else \end{cases}$$

Other attributes defining a project include the number of allowed iterations and measures of task and project progress. *Iterations* are attempts at completing a task. Each iteration has an associated probability of success, or *roll for performance,* that can be thought of as a roll of a die. The roll for performance mimics a die roll, and is based on a discrete uniform distribution between 1 and 6. Each iteration results in *achievement*, or 'how much' the team accomplished during the attempt. This measurement was purposely kept ambiguous, as teams measure achievement, success, and progress in many different ways. Achievement is meant to represent forward movement, such as places on a board in a board game.

Achievement is cumulative during a project. That is, each iteration produces incremental achievement, which is added over the course of the project. A task is complete when the cumulative achievement of a task is greater than or equal to the *minimum achievement* defined by the task. After a task is 'complete', it is removed from the list of tasks the team can work on within the project. Minimum achievement values can be found in Table 4, listed with the respective task.

3.2 Research Questions

The research questions for this thesis are meant to answer the underlying question of whether or not this type of method is feasible for studying group dynamics.

i. Do any distinctive patterns arise regarding performance using different methods for quantifying cognitive diversity?

ii. How does the interaction of distribution of expertise and task type affect productivity of a team?

iii. How does the team size affect the group dynamics and performance?

3.3 Actions to Gather Research Data

3.3.1 Simulation Program using Java

The method used for this study was a simulation programmed in the Java language. Java was an attractive choice for several reasons. First, Java is a free program with many resources and few restrictions (costs). Second, Java is compatible with other simulation programs that might build on this framework, such as AnyLogic. Lastly, Java is an Object-Oriented (OO) language, which suits agent-based models (Macal & North, 2010). The OO class structure allows for simple construction of teams of agents and projects with tasks.

3.3.2 Simulation Program using Java

The model described above attempts to operationalize certain aspects of team behavior, such as thinking mode and efficiency of communication, in order to quantify probability of success.

Each agent has a thinking mode profile, which is compared to other team members to understand differences in thinking mode. In reality, a large difference between two profiles typically manifests itself as conflict, as the two modes represent high preference for very different approaches. An example of this would be a meeting in which two individuals need to come to consensus. One individual strongly prefers the *structural* thinking mode, wanting structured information, schedules, and controlled movement in a project. The other individual strongly prefers the *conceptual* thinking mode, using creativity and abstraction to produce big ideas.

These two modes naturally conflict. The person dominant in the *structural* mode will naturally push for details and structure, and the person dominant in the *conceptual* mode will naturally avoid it. This situation will be represented in this model as efficiency of communication (eff_{com}), which is a measure of how well a team of individuals is able to communicate based on differences in thinking modes.

Each thinking mode can be described as a dimension. Thus, each agent's profile, comprised of four numbers, can be considered a point in four-dimensional space. This point can be compared to another point in space. Multiple points, representing a team of agents can be averaged, resulting in a centroid that represents the mean profile of the team. This point, like a singular profile, can be compared to another point (centroid or individual) using two mathematical methods: Euclidean distance and angle.

Previous research has used both correlation and Euclidean distance to determine different kinds aspects of similarity within a group (Aldenderfer & Blashfield, 1984; Skinner, 1978). In this research, efficiency of communication is calculated in three (3) different ways. The first is based on the Euclidean distance between the centroid of the thinking mode profiles of a team of agents and the centroid of the thinking mode profiles of every team member *except* the member farthest from the total team centroid. The second method uses the angle θ between the centroid of all member profiles and the centroid of all member profiles except the outlier member. The last is similar to the first, but instead of comparing just centroids, it measures the Euclidean distance between the centroid of the thinking mode profiles of every team member except the farthest member and the point represented by the thinking mode profile of the individual member.

The scale per thinking mode dimension was assumed to be between 0 and 150, which is just an example of the range that could be used to quantify strength of preference in a particular mode. This scale could be adjusted based on the scale of the instrument used to measure thinking mode preference.

Algorithm 1: eff_{com} is determined by Euclidean distance between the centroid of the team profiles and the centroid of the team profile *without* the farthest member.

$$Team\ Centroid\ (TC) = (\bar{A}, \bar{B}, \bar{C}, \bar{D})$$

$$Team\ Centroid\ without\ Outlier\ (TCO) = (\bar{A}, \bar{B}, \bar{C}, \bar{D})$$

Assuming a scale of [0,150] in four (4) dimensions, the maximum distance between these points can be determined as follows:

$$\max distance = \sqrt{(150)^2 + \ (150)^2 + (150)^2 + (150)^2} = 300$$

$$distance = \sqrt{(TC(\bar{A}) - TCO(\bar{A}))^2 + \ (TC(\bar{B}) - TCO(\bar{B}))^2 + \ (TC(\bar{C}) - TCO(\bar{C}))^2 + \ (TC(\bar{D}) - TCO(\bar{D}))^2}$$

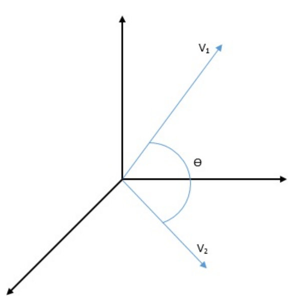
$$eff_{comm} = 1 - \frac{distance}{\max distance}$$

Algorithm 2: eff_{com} is determined by angle between the vector from (0,0,0,0) to centroid $(\bar{A}, \bar{B}, \bar{C}, \bar{D})$ of the team profiles and vector from (0,0,0,0) to the centroid of the team profile without the farthest member $(\bar{A}, \bar{B}, \bar{C}, \bar{D})$.

$$Team\ Centroid\ (TC) = (\bar{A}, \bar{B}, \bar{C}, \bar{D})$$

$$Team\ Centroid\ without\ Outlier\ (TCO) = (\bar{A}, \bar{B}, \bar{C}, \bar{D})$$

Assuming a scale of [0,150] in four (4) dimensions, the angle can be determined using the cosine formula:



$$\cos\theta = \frac{\vec{x} \cdot \vec{y}}{\|\vec{x}\|\|\vec{y}\|}$$

$$\overrightarrow{TC} \cdot \overrightarrow{TCO} = \left(TC(\bar{A}) * TOC(\bar{A})\right) + \left(TC(\bar{B}) * TOC(\bar{B})\right) + \ \left(TC(\bar{C}) * TOC(\bar{C})\right) + \left(TC(\bar{D}) * TOC(\bar{D})\right)$$

$$\|\overrightarrow{TC}\| = \sqrt{TC(\bar{A})^2 + \ TC(\bar{B})^2 + \ TC(\bar{C})^2 + \ TC(\bar{D})^2}$$

$$\|\overrightarrow{TCO}\| = \sqrt{TOC(\bar{A})^2 + \ TOC(\bar{B})^2 + \ TOC(\bar{C})^2 + \ TOC(\bar{D})^2}$$

$$eff_{comm} = \cos^{-1}\left(\frac{\overrightarrow{TC} \cdot \overrightarrow{TCO}}{\|\overrightarrow{TC}\|\|\overrightarrow{TCO}\|}\right) * \frac{180}{\pi}$$

Algorithm 3: eff_{com} is determined by Euclidean distance between the centroid of the team profiles and the singular profile of the farthest member.

$$Team\ Centroid\ (TC) = (\bar{A}, \bar{B}, \bar{C}, \bar{D})$$

$$Outlier\ Person\ (OP) = (A, B, C, D)$$

Assuming a scale of [0,150] in four (4) dimensions, the maximum distance between these points can be determined as follows:

$$\max distance = \sqrt{(150)^2 + (150)^2 + (150)^2 + (150)^2} = 300$$

$$distance = \sqrt{(TC(\bar{A}) - OP(A))^2 + (TC(\bar{B}) - OP(B))^2 + (TC(\bar{C}) - OP(C))^2 + (TC(\bar{D}) - OP(D))^2}$$

$$eff_{comm} = 1 - \frac{distance}{\max distance}$$

3.3.3 Experimental Design

As this model is a proof of concept, the experimental design is meant to test different levels of independent variables to see if there are distinguishable differences in the dependent variables. The design is not meant to be exhaustive in determining the response surfaces of all possible inputs or combinations.

However, the design does aim to allow for enough trials to reach distributional convergence for a particular combination of parameters. With an average run time of 59.0 seconds for 200 trials of a single project configuration, data collection time is insignificant and allows for a reasonable amount of trials to establish convergence. Each trial has a unique output per project run, as well as play-by-play output for each task iteration.

Table 1. Experimental Design

	Projects					
	3 Task Project		6 Task Project		9 Task Project	
Agents	AAD	ACA	ACCCAA	DCACAD	CDAADCCAA	AADCAAADD
3 Agents	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1
	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2
	Alg 3	Alg 3	Alg 3	Alg 3	Alg 3	Alg 3
6 Agents	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1
	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2
	Alg 3	Alg 3	Alg 3	Alg 3	Alg 3	Alg 3
9 Agents	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1
	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2
	Alg 3	Alg 3	Alg 3	Alg 3	Alg 3	Alg 3
12 Agents	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1
	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2
	Alg 3	Alg 3	Alg 3	Alg 3	Alg 3	Alg 3

The full experimental design, shown in Table 1, denotes all treatments explored during the preliminary testing phase. This includes multiple levels of team size, project size, project configuration, and algorithm for calculating eff_{comm}.

The independent variables include *team size, project size* (number of tasks), and *task type*. The experimenter controls team size, though the team is randomly selected from a pool. Task type and project size are both integrated into the code as separate projects with a designated set of tasks. Task order is not controlled once the project is initiated.

Table 2. Expertise Profiles of Organization

	Expertise Area				
Agent	***a***	***b***	***c***	***d***	***e***
1	2	2	3	9	3
2	1	4	2	5	2
3	1	4	3	3	7
4	3	5	1	4	4
5	9	2	2	6	3
6	7	1	2	2	4
7	3	6	2	7	1
8	4	9	3	4	5
9	8	5	5	5	6
10	2	1	2	3	2
11	5	8	2	2	4
12	3	4	1	3	2
13	5	8	2	3	2
14	3	7	3	4	4
15	4	9	6	6	5
16	5	3	6	2	5
17	6	2	8	8	7
18	5	3	6	4	3
19	9	3	6	6	4
20	2	4	3	8	5
21	4	0	4	7	4
22	7	5	5	3	4
23	6	2	2	5	4
24	9	3	2	5	2

Table 3. Thinking Mode Profiles of Organization

	Thinking Mode Profile			
Agent	***S***	***R***	***Y***	***U***
1	54	69	126	24
2	4	78	63	32
3	55	66	90	136
4	72	79	62	55
5	61	17	101	112
6	22	74	61	75
7	34	110	127	55
8	38	102	87	67
9	61	88	42	68
10	120	16	62	47
11	108	22	129	42
12	116	22	45	92
13	20	97	58	74
14	67	122	29	78
15	91	29	94	58
16	42	60	47	79
17	41	60	130	91
18	99	82	75	129
19	68	33	43	11
20	97	27	47	67
21	104	141	44	25
22	71	80	25	102
23	64	11	113	58
24	113	103	43	118

Much like the team data, task data inputs were determined using a random number generator based on a discretized triangular distribution. However, instead of distributing required expertise over each expertise dimension, the task requirements were determined by task. Thus, the distribution can be described as $N = 5$, $a = 0$, $b = 10$, and $k = 4$. The task type was determined using a random number generator that selects a number between 1 and 3, with each number corresponding to a task type (*additive, conjunctive,* and *disjunctive*). Task types and requirements for each project are shown in Table 4.

Table 4. Task Profiles by Project

Project 1: 3 Tasks								
	Expertise Required					Task Type		
Task Number	*a*	*b*	*c*	*d*	*e*	*P1.1*	*P1.2*	Min Ach
1	2	4	4	9	5	A	A	10
2	7	7	3	5	2	A	C	30
3	6	8	9	7	6	D	A	30
Project 2: 6 Tasks								
	Expertise Required					Task Type		
Task Number	*a*	*b*	*c*	*d*	*e*	*P2.1*	*P2.2*	Min Ach
1	4	6	5	6	5	A	D	10
2	5	7	6	6	7	C	C	30
3	4	4	4	3	2	C	A	30
4	4	4	4	6	2	*C*	*C*	50
5	4	7	7	2	7	A	A	10
6	2	3	0	6	9	A	D	15
Project 3: 9 Tasks								
	Expertise Required					Task Type		
Task Number	*a*	*b*	*c*	*d*	*e*	*P3.1*	*P3.2*	Min Ach
1	5	2	4	4	7	C	A	10
2	4	2	8	3	6	D	A	30
3	5	3	2	8	8	A	D	30
4	7	5	4	3	5	*A*	*C*	50
5	6	7	7	4	7	D	A	10
6	3	3	4	7	2	C	A	15
7	4	2	4	5	9	C	A	20
8	8	1	5	4	2	A	D	40
9	9	2	1	5	3	A	D	5

Dependent variables include *achievement* and *iterations to solution*. Both are cumulative for an entire project. These represent variables not directly controlled by the experimenter for these studies, but can be empirically and quantitatively assessed for any given set of projects. Other variables include team cognitive diversity, task complexity, and project integration demand (relative requirements for conjunctive vs. additive or disjunctive tasks). It is intended that future research can investigate any of these variables separately or in combination.

3.4 Testing Phases

Three (3) separate phases of testing were completed as part of this research. The purpose of the preliminary phase was to test the functionality of the model by exercising all treatment combinations at n = 600 trials. The intent was to flush out any bugs or discrepancies in the code itself, as well as to do some preliminary data analysis. This number of trials was chosen for two reasons. First, the Strong Law of Large Numbers states that a large n improves the likelihood that the data will converge (Graham & Talay, 2013). Second, the time and resources required to run 600 trials was manageable.

The purpose of the intermediate phase was to test convergence of the model, testing whether or not the variance reaches a finite range as the number of trials increases. While there is no specific number of trials required to established convergence, the acceptable range for evaluating starts in the 100's and extends upwards. Experiments using n = 10,000 have shown acceptable precision and consistent outputs (Farrance & Frenkel, 2014), providing a starting point for this study. Thus, the convergence phase ran to n = 10,000 trials.

The final (or secondary) phase was to produce data for hypothesis testing, using the convergence data as an estimate for number of trials needed. The final testing phase used n = 3,000, which was the first point of approximated convergence in the intermediate test results. Fewer scenarios were run for hypothesis testing, but the number of trials increased by a factor of 5. This will be further discussed in Chapter 4.

3.5 Limitations and Implications

The limitations of this research include a variety of areas, which were expected considering the goal as a feasibility project. First, this model is not prescriptive or exhaustive, but meant to provide descriptive and exploratory insight into how some of the included factors might affect overall group performance. This model is a proof of concept for a method that could help reduce the time, money and resources for group performance research, but it is still a partial product. Thus, the model proposed is merely a demonstration of feasibility.

Another limitation is that the thinking mode profile data for individuals are synthetic. In other words, the team in the model is not based on a real team in which thinking modes were measured. Additionally, the underlying theories of thinking modes, and the instruments considered to be consistent with these theories, were not the focus of the research. However, the model could easily be adapted for different instruments with different numerical outputs.

Next, expertise and task requirements are simplified, and assume a known amount of expertise per individual on a team, as well as a known amount of area expertise required per task. Individual expertise might be realistically estimated in organizations through skills assessments, but was not determined this way in the proposed model.

Furthermore, the model does not yet account for other social dynamics and environmental pressures or factors, such as deadlines, roles or hierarchies, and organizational strategy. However, the model can be adopted if these can be appropriately quantified. Additionally, the model does not include adaptive behaviors at this point in development. These adaptive behaviors would allow agents to change over time, increasing the rate of unexpected interactions or developments within agent teams or between teams and environments. Adaptive agent attributes allow for emergent behavior, one of the key outcomes of agent-based modeling. Future stages of development for this model will introduce some of these adaptive attributes, justifying the need to produce an agent-based model for this particular system.

Agent-based modeling introduces additional limitations. According to Macal & North (2010), one limitation is the idea that there is not a single correct way to build or execute a model. This includes methods, tools, and modeling attributes, such as population size, agent attributes, or agent interactions. Agent-based modeling usually involves a portfolio of tools that are developed over time (Macal & North, 2010). Thus, this research represents demonstration of feasibility and functionality, not optimality, of a particular agent-based approach to investigate realistic team coordination and task performance processes in a software simulation (*in silica*) environment.

CHAPTER 4. RESULTS

The model itself allows for variation in several dimensions. The independent variables include the size of the team and the tasks in a project (including the expertise requirements, achievement level, and task type). The researcher can also control the pool of agents from which the team is selected. The model introduces probability in the selection of team members, the order of the tasks in a project and the performance roll for each attempt at completing a task.

The primary dependent variable of interest is *iterations to solution*, or the number of attempts needed by a team to complete a set of tasks. The discussions below compare iterations to solution for different areas of the experimental design. *Efficiency of communication* is also a dependent variable determined by the random selection of team members from a known pool of agents and calculated by one of three methods. This dependent variable strongly influences iterations to solution, as it is a main input for determining incremental achievement. Thus, this variable is only explored to compare the three methods used for calculating it.

4.1 Functionality Test (600-trial run)

The simulation explored the full experimental design during the preliminary phase of data collection. Each scenario was run for 600 trials, (n = 600) in which a different team assembled from the pool of agents for every trial. Project independent variables, such as how many tasks and which tasks of a particular type, were held constant for each scenario, with a total of 72 scenarios explored during this phase. Findings from the 600-trial runs, discussed in this section, informed the secondary phase of data collection.

Each project (3-, 6-, and 9-task) is depicted in the following sections, which compare average iterations to solution for each configuration of team and communication algorithm. One major finding consistent in all experimental configurations was the probability of success for conjunctive tasks. Recalling the definition of conjunctive, this type of task would require every agent on the team to have the level of expertise required by the task in each dimension.

4.1.1 3-Task Project

The preliminary phase included two task type configurations for all project sizes. Results from the 600-trial of Additive-Conjunctive-Additive (ACA) and Additive-Additive-Disjunctive (AAD) projects are shown in Figure 3, which shows the average number of iterations to solution by task type, communication efficiency algorithm, and team size. Note the secondary vertical axis (additive tasks) is scaled differently than the primary axis (disjunctive and conjunctive tasks).

One finding from this set of experiments is that no team (in any size) was able to complete the conjunctive or disjunctive tasks from the 3-task project. Zero achievement is the result of *efficiency of expertise = 0,* or a lack of required expertise available on the selected team. Referring to the expertise required by the tasks in the 3-task project, the expertise required by both the conjunctive and disjunctive tasks were very high compared to the expertise of the organization. Thus, any team configuration for this project may have difficulty gaining achievement, as the likelihood of randomly selecting a team of capable agents is low. Additionally, based on the high average of iterations to solution, the 3-agent team had difficulty finishing even additive tasks. Finally, there are visible differences in the effects of the algorithm used to calculate efficiency of communication of a team, likely due to the differences in scale that each algorithm produces.

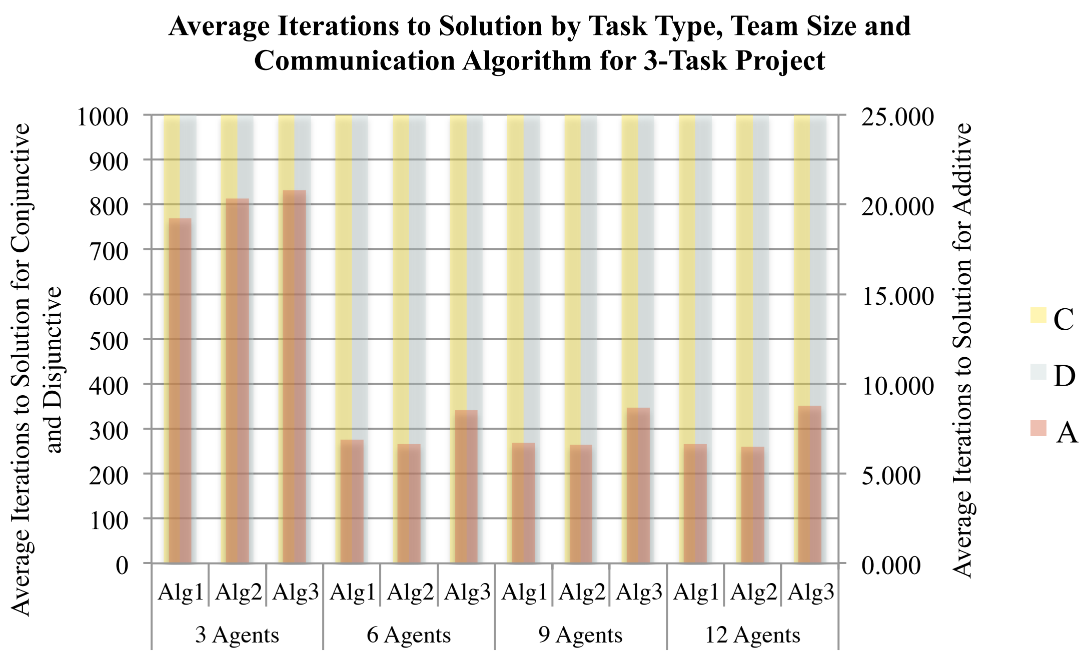


Figure 3. 600-trial Results for 3-Task Project

4.1.2 6-Task Project

The two task type configurations used for the 6-task project experiments were ACCCAA and DCACAD. Figure 4 below depicts the average iterations to solution for each task type by communication efficiency algorithm and team size, and the vertical axes employ different scales to adjust for differences in range per task type.

Despite this scale difference, the same pattern is seen between additive and disjunctive tasks based on a 3-agent team size and the second algorithm used to calculate efficiency of communication. A similar pattern is also seen in the 12-agent team size using the third algorithm. According to the following chart, 6-agent teams were still unable to complete conjunctive tasks because none of the teams modeled satisfied the tasks' expertise requirements.

Average Iterations to Solution by Task Type, Team Size and Communication Algorithm for 6-Task Project

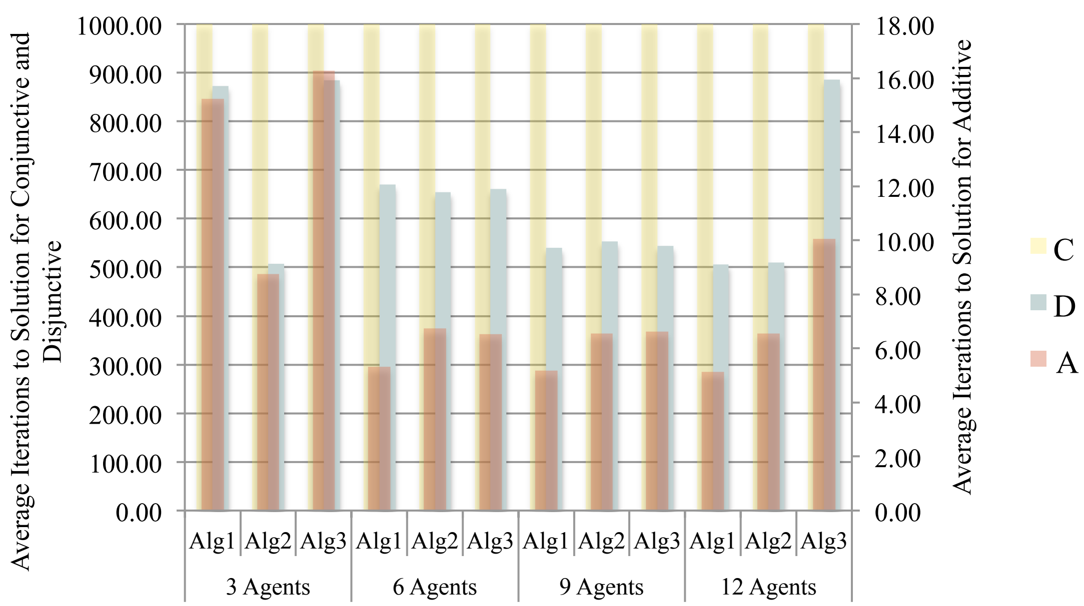


Figure 4. 600-trial Results for 6-Task Project

4.1.3 9-Task Project

The 9-task project was run using the two task type configurations CDAADCCAA and AADCAAADD. Consistent with the previous figures, Figure 5 depicts the average iterations to solution for each task type by communication efficiency algorithm and team size, and the vertical axes employ different scales to adjust for differences in range per task type.

The data show a noticeable parallel trend between disjunctive and additive tasks. Results of conjunctive tasks are consistent with the previous experiments, showing that these tasks were not able to be completed by any team configuration over 600 different project runs with different teams. This result is somewhat expected. As team size grows, the probability that the team can produce any achievement for a conjunctive task decreases. The likelihood of randomly drawing a large team with high minimum expertise in any given area decreases as team size increases. Conversely, the likelihood of a larger team producing achievement against a disjunctive task increases as team size increases due to the increase in likelihood of drawing at least one person with adequate expertise.

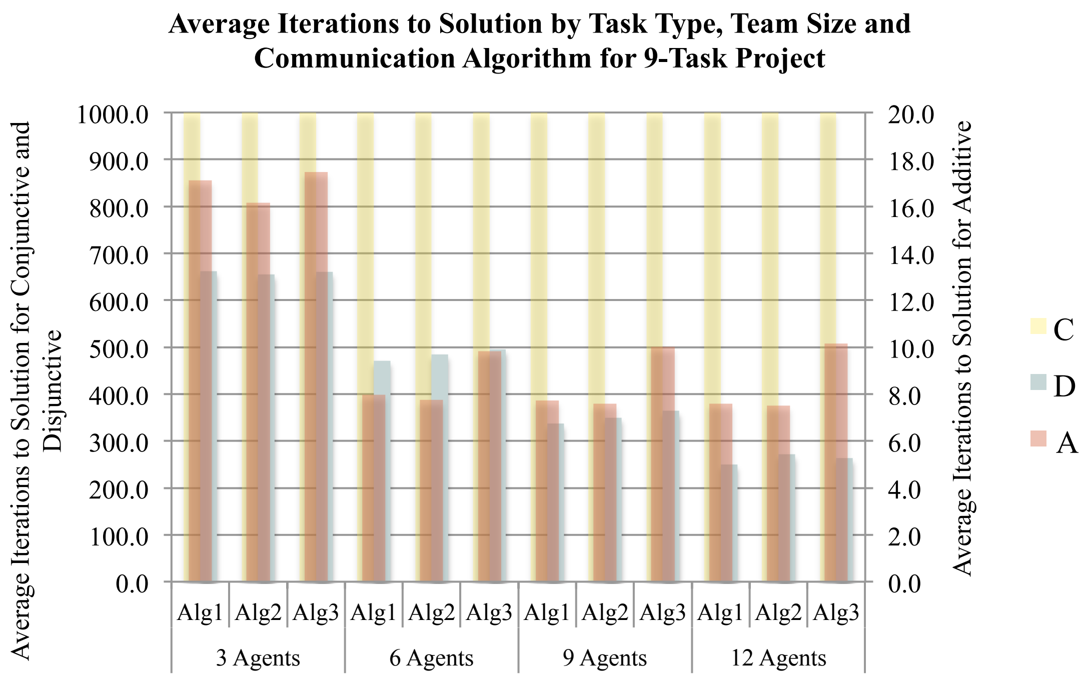


Figure 5. 600-trial Results for 9-Task Project

4.2 Convergence

The model developed in this thesis follows the traditional description of a Monte Carlo method. One aspect of determining robustness of a Monte Carlo simulation is to test for convergence of model results as a function of the number of trials used in the simulation. Convergence indicates that, over a number of trials, the model stabilizes, effectively increasing confidence of predictions. Variance and error are two key variables in Monte Carlo methods, with a goal of minimizing error within a band around the variance. Considering the time it takes to complete 200 trials, 10,000 trials was an achievable task in a reasonable amount of time to test for convergence.

Controlling all independent variables, the model visually shows some convergence around 3,000 trials. No official convergence test was performed on the data. Using a controlled set of six (6) agents completing six (6) additive tasks with different expertise requirements and equal minimum achievement, the simulation was run for 10,000 trials. The model outputs end achievement per task per project run, as well as the number of task iterations to reach the end achievement. Figure 6 below depicts the variance of iterations to solution for each task over 10,000 trials.

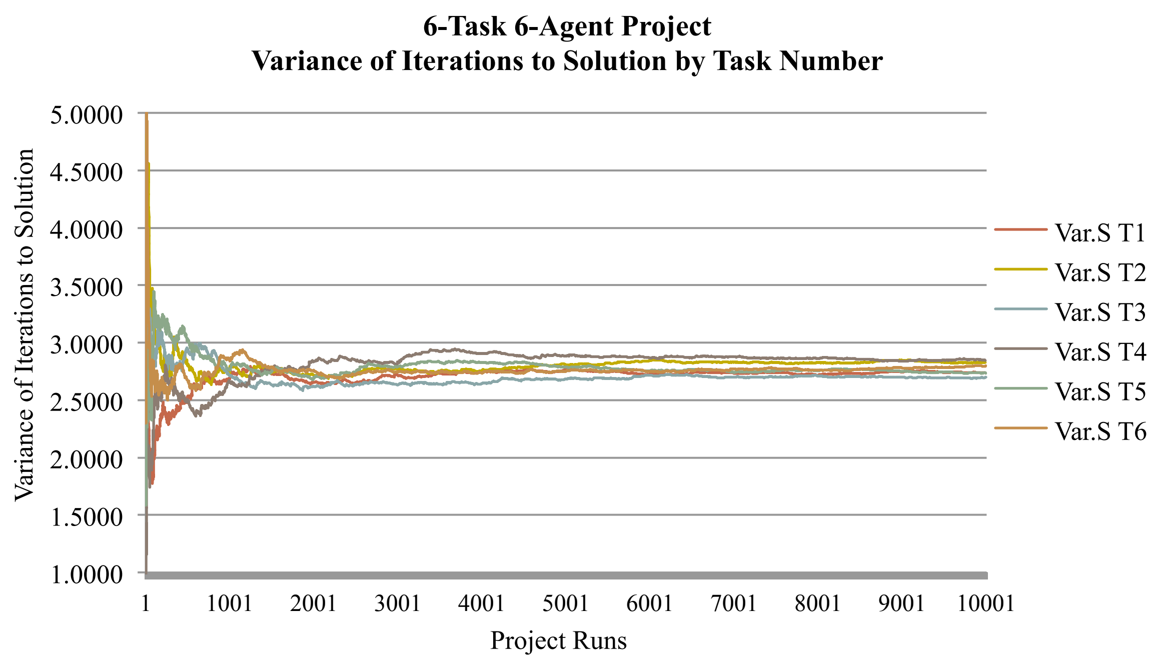


Figure 6. Convergence of Model

4.3 Hypothesis Testing (3000-trial Run)

Preliminary results using a 600-trial approach yielded insights regarding probability of success in doing certain types of tasks. Furthermore, performance based on project configuration (same task expertise requirement, different task type) was heavily influenced by task type. Thus, some decisions were made in the second phase of data collection to eliminate certain treatment configurations but preserve the diversity of data to be collected. Resulting test configurations are highlighted in Table 5.

Due to the lack of achievement for any conjunctive task in the functionality tests, treatments high in number of conjunctive tasks were removed from the pool for hypothesis testing. Additionally, differences between the first and second algorithms (Alg 1 and Alg 2 in table below) were less apparent in the preliminary results, leading to a decision of removing at least one algorithm within the same treatment block (e.g. for 6-task 12-agent block in DCACAD project, only one of the algorithms would be retested for hypothesis testing). This process continued until the experiments were reduced to at least one per team size, project size and algorithm used. Treatments that were not retested in the secondary phase are filled in with grey in Table 5, while the remaining treatments (shown in white with bold lettering) were rerun for 3,000 trials.

This secondary phase of data collection introduced variation in the same way as the preliminary phase: random dice roll, team randomization, and task order randomization. The probability of success is driven by the team member selection, the expertise of the selected team members, and the comparison of the team’s expertise to the requirement of the tasks.

Table 5. Plan for Additional Data Collection

	Projects					
	3 Task Project		6 Task Project		9 Task Project	
Agents	AAD	ACA	ACCCAA	DCACAD	CDAADCCAA	AADCAAADD
3 Agents	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1
	Alg 2	Alg 2	Alg 2	**Alg 2**	Alg 2	Alg 2
	Alg 3	**Alg 3**	Alg 3	Alg 3	Alg 3	Alg 3
6 Agents	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1
	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2
	Alg 3	Alg 3	Alg 3	Alg 3	Alg 3	**Alg 3**
9 Agents	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1	Alg 1
	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2
	Alg 3	Alg 3	Alg 3	Alg 3	Alg 3	**Alg 3**
12 Agents	Alg 1	Alg 1	Alg 1	**Alg 1**	Alg 1	Alg 1
	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2	Alg 2
	Alg 3	Alg 3	Alg 3	Alg 3	Alg 3	Alg 3

4.3.1 Probability of Success

After the initial analysis of average iterations to solution for each project size, probability of success became a point of interest. Table 6 shows the probability of completing a task based on task type and team size. Although there are some general trends regarding team size and probability of success, it is also apparent that expertise required by the task (the differences between each line item in the table) is a significant factor in determining whether or not a team will complete a task. For example, conjunctive tasks consistently have a probability of success of 0.00 for all tested team sizes and task expertise configurations. However, disjunctive tasks are less consistent, with probabilities of success ranging from 0.00 to 0.99 depending on the expertise required and the expertise available on the team.

Table 6. Probability of Success by Task Type and Team Size

Team Size	Task Type A	Task Type C	Task Type D
3	0.97	0.00	0.24
3	0.59	0.00	0.00
3	1.00	0.00	
3	0.80		

Team Size	Task Type A	Task Type C	Task Type D
6	1.00	0.00	0.00
6	1.00		0.65
6	1.00		0.60
6	1.00		
6	1.00		

Team Size	Task Type A	Task Type C	Task Type D
9	1.00	0.00	0.00
9	1.00		0.86
9	1.00		0.76
9	1.00		
9	1.00		

Team Size	Task Type A	Task Type C	Task Type D
12	1.00	0.00	0.99
12	1.00	0.00	0.00

4.3.2 Efficiency of Communication: Algorithm Comparison

As described in Chapter 3, three (3) different algorithms were developed to determine the measure of communication efficiency based on thinking mode profiles of each team member. The secondary phase of data collection spanned all three algorithms, with 3,000 trials for each condition. To test the differences between these algorithms, a Mood’s Median test was performed against two different independent variables: algorithm and team size.

Preliminary results were tested for normality using an Anderson-Darling test, which resulted in a p-value < 0.001. Accordingly, nonparametric methods, executed in Minitab 17, were used for hypothesis testing of secondary results, specifically the efficiency of communication for each team assembled. The Mood’s Median test resulted in p-values of 0.000 and very high Chi-Square values, indicating that the samples are from different populations based on both team size and algorithm used. Minitab output is included below.

```
Mood Median Test: TeamEffComm versus Agent/Team

Mood median test for TeamEffComm
Chi-Square = 9792.14    DF = 3    P = 0.000

                                       Individual 95.0% CIs
Agent/Team    N≤    N>  Median  Q3-Q1  ---------+---------+---------+-------
 3          1624  4376   0.829  0.101                   *)
 6          2881   119   0.728  0.042     *
 9          2996     3   0.711  0.039  (*
12             0  3000   0.950  0.004                                     *
                                       ---------+---------+---------+-------
                                              0.770     0.840     0.910

Overall median = 0.781

Mood Median Test: TeamEffComm versus CommAlg

Mood median test for TeamEffComm
Chi-Square = 9904.82    DF = 2    P = 0.000

                                    Individual 95.0% CIs
CommAlg    N≤    N>  Median  Q3-Q1  --------+---------+---------+--------
       1    0  3000   0.950  0.004                                     *
       2   15  2985   0.875  0.056                         (*
       3 7486  1513   0.733  0.056   *
                                   --------+---------+---------+--------
                                         0.780     0.840     0.900

       Overall median = 0.781
```

4.4 Differences in Task Performance by Team Size, Project Size and Algorithm

The dependent variable '*iterations to solution'* was tested using a Mood's Median Test with a 95% confidence level. The goal was to understand potential differences in task performance based on team size. The dependent variable was separated by task type given the observable differences in preliminary testing. Tasks of the same type within the same project were then averaged per project trial. Results of Mood's Median tests on task performance (iterations to solution) are found in Table 7.

Table 7. Mood's Median Tests of Task Performance by Task Type

	Additive		**Disjunctive**		**Conjunctive**	
	Chi-Square	p-value	Chi-Square	p-value	Chi-Square	p-value
Team Size	1960.66	0.000	3169.56	0.000	*N/A*	*N/A*
Project	1880.66	0.000	243.68	0.000	*N/A*	*N/A*
Algorithm	1007.13	0.000	2891.52	0.000	*N/A*	*N/A*

Team size, evaluated at 3, 6, 9, and 12 agents resulted in a p-value of 0.000 for additive tasks and a p-value of 0.000 for disjunctive tasks, as well as high Chi-square values, indicating significant differences and distance between the medians. Project design for 3, 6, and 9 task projects resulted in a p-value of 0.000 for additive tasks and a p-value of 0.000 for disjunctive tasks. The Chi-square values were also high for project design, indicating large distances between sample medians. Algorithms used for calculating $eff_{comm,}$ called algorithm 1, 2 and 3, resulted in p-value of 0.000 for additive tasks and 0.000 for disjunctive tasks, again with high Chi-square values. These values indicate significant differences in the sample medians, as well as large distances between the medians.

CHAPTER 5. DISCUSSION

5.1 Effects of Task Type

Task type was a significant factor in a team's ability to complete a project. Specifically, conjunctive tasks were not completed in any team configuration, even in small teams. Recalling the definition of conjunctive, in order for the team to complete the task, each team member must have a minimum expertise greater than or equal to the expertise requirement of the task in each dimension.

Disjunctive tasks displayed high variance in iterations to solution, presumably due to the high variation in probability of success between tasks of the same type. That is, each task has different expertise requirements, which significantly impacts the team's probability of success, especially if the randomly selected team does not include an agent with sufficient expertise. Generalizing this point, if a task requires greater expertise than what is available in the organization, the efficiency of expertise will be 0, and the task will not be completed within the organization. When evaluated by task type, if the task requirements are less than or equal to the availability on the team, the probability of making progress is 1, and achievement will be gained. Additionally, tasks of the same type (additive, disjunctive and conjunctive) can have very different requirements. Thus, task type alone may not be an appropriate predictor of success, as it is completely dependent upon the expertise requirements of the task itself

An interesting point of discussion regarding expertise requirements is that, in real world settings, the level of expertise required by a task may not be what is actually delivered by the team. If the task is essential and achievement is forced, yet the team is not truly capable, then the level of performance, while not acceptable based on ideal standards, would be accepted. In other words, the standard of performance would be effectively lowered if the incapable team tried to perform a task above its expertise level, and the resulting performance was in some way labeled 'acceptable'. An extreme example of this would be the Hyatt Regency walkways collapse in 1981 ("The Hyatt Regency Walkway Collapse," 2007). The fabricator of the walkway apparatus simplified the design to meet his own capabilities, but he did not fully understand the consequences of the design change regarding load distribution. This modification resulted in an overloaded connector, the collapse of the system, and the deaths of 114 people.

5.2 Effects of Team Size & Selection

Team size was especially a factor, seen in the scenario of a 3-agent team performing additive tasks. The results show that the more agents on a team, the more likely the team will have the expertise to complete tasks that require some amount of expertise in a given set of dimensions. This finding has high ecological validity considering the probability of eventually finding the expertise needed by continually adding members to a team.

An additional finding related to additive tasks and team size, evident between Figure 5 and Figure 6 from Chapter 4, is that disjunctive tasks are harder to complete as the team size decreases. The smaller the team, the more important it is to have team members with high levels of expertise in multiple dimensions. This team recipe would ensure that a small group of individuals could complete a broad range of tasks. Essentially, the smaller the team, the more critical individual expertise becomes. The alternative scenario is when a small team (such as a small business) does not have the expertise needed to organize and manage information systems, so the task is contracted out to a consulting expert, who then fills the expertise gap (Premkumar, 2003).

5.3 Effects of Efficiency Algorithm

Three different algorithms, described in Chapter 3, were developed to operationalize the interaction of thinking modes in teams. All three algorithms were used for the functionality testing (600-trial) phase of data collection, and show differences in the dependent variable ‘iterations to solution’. Based on the mathematical equations used to develop these algorithms, differences were expected as each algorithm results in a different range of values. Though each algorithm produces a number between 0 and 1, none of them produce a value that could span the entire range, and the ranges of each are not the same. This is clearly shown in the figure below. Due to the inherent differences in range of values based on the calculation method, future model exploration should include normalizing the algorithms’ outcomes.

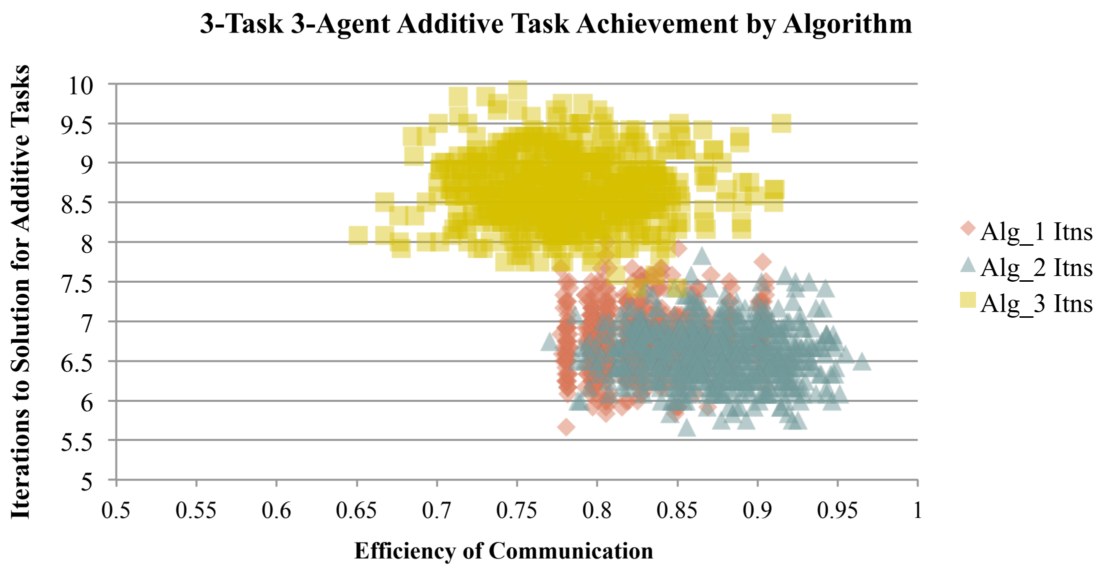


Figure 7. Iterations to Solution vs. Efficiency of Communication by Algorithm

Figure 7 above shows some of the differences observed in the data, focusing only on one type of task within a 3-agent team performing a 3-task project. Based on the figure above, Algorithm 3 increases the average iterations to solution for at least this size team and project. With respect to thinking mode, the model was successful in showing differences in task performance based on different individual thinking mode profiles and different algorithms to assess cognitive diversity.

5.4 Generating Questions

The model not only shows that it is functional as an agent-based simulation, but also that the model is capable of prompting research questions based on observed results. For instance, the model has the potential to directly output data in an analyzable format that would allow for studies of cognitive diversity and task performance. Additionally, other modifications, such as manipulating desired task achievement, task type, and team size, would allow for the study of what combinations of agents perform which projects best. The possibilities are extensive, and have the potential to grow the use and understanding of simulation methods within the field of human factors.

Learning and flexibility are two characteristics that could be incorporated into a simulation regarding group dynamics. *Flexibility* corresponds with the thinking mode profile of each agent, and refers to the individual's ability to adjust to other team members with different preferred modes of thinking. *Learning* speed corresponds with the expertise profile of each agent, and refers to how fast the individual gains expertise in a given area. These attributes would reflect individual changes in behavior and expertise seen in team activity. However, more information and measurement data are needed to adequately represent these in a simulation.

Further exploration of effects of thinking mode is possible using the simulation program created in this thesis. The independent variable *flexibility,* or *communication expertise* defined by Garrett et al (2008), was proposed but not used in this version of the model. Flexibility represents how well an individual is able to adjust to another individual's dominant thinking mode. This attribute may be of interest to researchers wanting to explore or understand the effects of flexible agents on the efficiency of communication and task performance of a team. For instance, should one agent on a team have a high amount of thinking mode flexibility, the centroid used to compare with an outlier agent may be able to move closer to the outlier, reducing the distance (and angle) between them, thus increasing the efficiency of communication. Alternatively, interactions between small (or zero) amounts of flexibility within a team may still increase efficiency of communication, but by a smaller margin that does not significantly impact the task performance.

In addition to flexibility, dynamic *learning* could be incorporated into future studies to understand how growth of expertise affects a team's ability to perform tasks over time. If teams are capable of gaining some amount of expertise during the course of taskwork, how could this change the overall results? Literature and current studies within human factors could supplement the framework of this variable to help support integration into the simulation. *Learning* is likely to significantly impact the probability of success over time, as agent teams can start with insufficient expertise to complete a task, but gain enough cumulative expertise over a number of attempts at a task to produce an acceptable outcome. Additionally, knowledge and information sharing literature introduces the idea of non-expert members of a team gaining expertise faster from an actual expert member of the team than simply trying to learn from the past attempts.

Despite the fact that this model was constructed as agent-based, the design and results of the presented design produced no emergent behavior. This was likely due to the fact that most agent-based models include adaptive behaviors on the part of the agents, allowing for unexpected interactions to occur between agents, or between agents and the environment. The phase of the model represented by this thesis was exploring feasibility of using simulation, thus it did not include the two adaptive attributes *learning* and *flexibility*. However, additional development of team systems executing taskwork in simulation environments will include these variables. For this reason, the model was developed as an ABM, as an agent-based platform will be necessary for further exploration of this area.

5.5 Improvements to the Model and Analysis Methods

While the model is capable of producing analyzable outputs, some modifications could be made to increase the efficiency of analysis in future studies. Additionally, further development of the framework, especially task types and expertise dimensions, may increase understanding, and exercise additional aspects of task performance. Lastly, some lessons learned from this process include the appropriate tools for statistical analysis to properly accommodate data format.

In order to be able to align efficiency of communication with the task performance more directly, some slight changes should be made to the code to print the efficiency on the same line as the final project achievement per task. Currently, the code produces three files per execution: one with final achievement data, one with incremental achievement data, and one with team data. Alignment of the dependent variables was tedious and difficult because of this separation. Additional formatting changes in data output may depend on what particular outputs are of value to the researchers performing the study, and should be carefully considered before running any additional testing.

One factor that greatly influenced the results was the task type for each task defined in a project. Mathematically, the task type dictated the way team expertise was evaluated, and assumed the same rules applied *to each dimension* of expertise. Considering this variable directly influenced the probability of success, additional research and development of task type and the connection to multi-dimensional expertise is highly encouraged. Further exploration of this area is recommended in future research to determine whether or not this is a valid and appropriate assumption.

Another challenge faced during this research was the statistical analysis of the data produced by the simulation. Though this point may seem trivial, the advantages of one analysis package over other will benefit and streamline the analysis phases in subsequent studies using this model, or other simulations used in human factors. Based on the volume and format of the output produced by the simulation, Minitab 17 is not an optimal package for analysis. Viable alternatives for statistical analysis and graphing include SAS or R. MATLAB is also capable of the visualization outputs used for analysis. MATLAB also has established protocols and code available specifically for Monte Carlo models, such as calculating convergence rate and error bounds. Thus, these packages should be considered for future data analysis.

5.6 Future Research

Some areas for future research that may add to the functionality and usefulness of this model include further development of existing variables, environmental factors, organizational factors, measurement or quantification of the aforementioned factors, and validation and verification of the model against real-world team performance. With a functional model on how teams perform tasks, researchers may be able to observe emergent behavior of projects, teams, or interactions during the problem-solving process.

Further development of *learning* and *flexibility* would allow for the agents in the model to be adaptive to the tasks and to the rest of the members of a team. The addition of these variables may provide additional insight and observable behaviors that would increase the ecological validity of the model. Methods for measuring these variables would need to be developed, and may possibly increase interest of other fields of research, such and human resources or management, by contributing methods to be used in actual team management.

Quantification, through measurement or estimation, is a key aspect of operationalizing the theory into executable scientific experiments. Though this thesis attempts to connect some measurement of an instrument into a simulation model, further quantification of factors is required should this product be transformed into a tool for analysis of living teams. The intent of building this model was not to guide predictive projects, but rather insight regarding task performance as a direct consequence of a team's attributes, including some that have not yet been used in simulation studies, such as thinking mode. Future research may include adding factors to the model to increase robustness of understanding of team dynamics, as well as methods for quantifying those factors.

Some of these factors may include environmental influences in team performance, such as culture or time pressures. Existing literature and simulations that attempt to quantify these may be of use to future development of the model and may provide groundwork that could be expanded upon in relation to taskwork. Organizational factors, such as management structures and hierarchies, may also be important to consider when modeling group dynamics. Leadership and roles have been identified in literature as influential in team performance and would be helpful in understanding emergent behavior.

Socio-technical factors in general could help integrate technology constraints that affect pathwork, and social factors that affect teamwork. For example, communication channels (email, phone, text message, or live chat) and the effects on message transmission rate are relevant considering the distributed nature of teams in modern settings. Overall, this model is not meant to be complete or comprehensive at the current stage, but it could help drive understanding of current gaps in research through simulation studies.

Validation and verification (V&V) are two important aspects of modeling and simulation that should be included in future research to help solidify the usefulness and validity of the model, as well as to provide merit and trust in the results. The functionality test described in Chapter 4 provides some verification for this model. Within the modeling and simulation community, V&V are considered requirements in order for models to be published and used. Though there is no universal approach to V&V, some literature exists that may help guide this process for the proposed model (Xiang, Kennedy, & Madey, 2005).

One way this model could be validated is to collect case studies of teams performing task work. The case studies should include some measures of performance, some information about the team, and some information about the tasks, such as what expertise might be required to perform them. The case study data could then be input into the model, and the outputs of the model could be compared to the actual outputs produced by the teams.

Some information about the team, such as thinking mode profiles, might be approximated using known connections between career paths and stereotypical thinking modes aligned with particular occupations. For instance, many engineers prefer to engage in structural thinking, employing strict organization and specification within daily tasks or projects. Conversely, a person who works in development might prefer conceptual thinking, using creativity and lack of structure to produce alternative solutions to a problem. While these generalizations about certain populations may not produce individual profiles with multiple preferred modes, the process may allow for some interactions between types of occupations.

Information about the tasks may also be generalized based on how the organization structures a project and assembles a team. For instance, tasks that are divided amongst individuals may be considered disjunctive, requiring only one individual to execute a task and report out results. Others, such a collaborative tasks, may require all team members to contribute for the task to be completed, which could be additive or conjunctive depending on the expertise requirements and task objectives.

With the above information, a comparison between model outputs and real-world task performance is possible. Differences between these can then be explored, explained or addressed to incorporate additional factors or calibrate the model accordingly

CHAPTER 6. CONCLUSION

Team-oriented work dominates industry, government, and academic areas with the goal of solving increasingly complex problems. Research seeks to understand the effects of interactions of factors within team, as well as the effects of new factors, such as technology. Deeper understanding of team dynamics through comprehensive and multidisciplinary research could positively influence organizational management, operations, and performance of teams worldwide.

Socio-technical factors affecting the performance and dynamics of teams are included in a deep and diverse set of literature that spans from psychology to engineering disciplines. Though the amount of research in this topic is vast, integration of research, methods and tools is limited. Traditional human factors methods have sought to study group dynamics in laboratory or field settings. However, the scope and external validity of this type of research is inherently limited based upon the time and resources required to conduct team-oriented laboratory studies.

The model described in this thesis provides a human factors simulation that incorporates at least two factors: cognitive diversity and domain expertise. The framework described allows for additional factors to be incorporated into existing code with relative ease. The model provides task performance data of teams of agents, selected from a defined organization of agents, performing a defined set of tasks. Based on domain expertise, cognitive diversity, and achievement probability, the model computes attempts (or task iterations) needed for a team to complete a task with known type and expertise requirements. The dependent variable of interest (iterations to solution) is compared based on task type, team size, project size, and method of calculating cognitive diversity.

Based on the outputs presented in Chapter 4, the model is functional and capable of producing testable results. Though only a limited number of treatments were collected in the secondary phase, the results suggest that additional work with this model could aid in mapping the surface of performance based on multiple factor dimensions, which can be expanded through additional development of the model. Additional focus on model convergence is recommended if additional factors or factor levels are incorporated, as the convergence analysis done in this thesis was both informal and limited based on the number of particular independent variable values.

Potential areas of future research include the addition of other relevant factors in task performance, such as roles within a team, work environment, and technological factors. Each of these has been known to affect a team's ability to perform, and would increase the merit and usefulness of this model. For those factors that cannot yet be assessed quantitatively, there is opportunity to develop measurement methods. Additional work in validation and verification of the model is recommended. With a functional model that shows effects of certain factors on task performance, researchers are able to generate research questions, which can then be tested using human factors methods, including the model itself.

This thesis expands the methods currently employed in human factors and incorporates an interdisciplinary approach to researching teams and task performance. Though limited in scope, this model is able to show some effects of team-task interactions, which are verified against real-world scenarios. Future research could expand this connection, allowing for scientists and organizations to gain a better understanding of how teams might operate in varying conditions, and what treatments might have a positive or negative impact on their performance. By integrating simulation methods into human factors subject areas, researchers may be able to gain understanding of a more diverse set of teams, team dynamics, and group performance in a fraction of the time and resources required for traditional methods.

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APPENDICES

Appendix A Code Sample

Project Class: Task Assignment

The following is a sample of code from the program that assigns the tasks to be completed in within the project. This includes the expertise requirements in each task, as well as a task type, a maximum number of iterations allowed for a team to attempt achievement, and the minimum achievement for each task.

```
{
…
// Populate Task List - TASK CONTEXT
// **TODO** User to change project list here to design
tasks in the project
     Expertise tmpTaskExp;
     tmpTaskExp = new Expertise(4, 6,   5,   6,   5);
     project.taskList[0] = new Task(tmpTaskExp, 1000,
TaskType.Disjunctive, 10);
     tmpTaskExp = new Expertise(5, 7,   6,   6,   7);
     project.taskList[1] = new Task(tmpTaskExp, 1,
TaskType.Conjunctive, 30);
     tmpTaskExp = new Expertise(4, 4,   4,   3,   2);
     project.taskList[2] = new Task(tmpTaskExp, 100,
TaskType.Additive, 30);
     tmpTaskExp = new Expertise(4, 4,   4,   6,   2);
     project.taskList[3] = new Task(tmpTaskExp, 1000,
TaskType.Conjunctive, 50);
     tmpTaskExp = new Expertise(4, 7,   7,   2,   7);
     project.taskList[4] = new Task(tmpTaskExp, 100,
TaskType.Additive, 10);
     tmpTaskExp = new Expertise(2, 3,   0,   6,   9);
     project.taskList[5] = new Task(tmpTaskExp, 1000,
TaskType.Disjunctive, 15);


     int numAgents = 12;
     // **TODO** This is a user input for # of agents
…
}
```

Task Class: Task Construction

The following is a sample of code from the program that dictates the component variables of a “task” within the program. This includes some of the variables that are assigned in the previous code. well as a task type and a max number of iterations allowed for a team to attempt achievement.

```
Task Class: Components of a Task

public class Task {
     public Expertise taskExp;
     public String taskStatus;
     public int iterationsCompleted;
     public int iterationsAllowed;
     public double taskAchievement;
     public double minAchievement;
     public TaskType taskType;

     public Task(Expertise taskExpInput, int
iterationsInput, TaskType taskTypeInput, double
minAchievementInput) {
     taskExp = taskExpInput; // Expertise required by the
Task
     iterationsCompleted = 0; // How many attempts it took
for the team to complete the task
     taskAchievement = 0; // How much the team has achieved
toward the task's  completion
     taskStatus = "Not Started";
     iterationsAllowed = iterationsInput; // Attempt
pressure
     taskType = taskTypeInput; // Additive, Conjunctive,
Disjunctive
     minAchievement = minAchievementInput; // How much
achievement is required for the task to be considered
"Complete"
…
}
```

Appendix B Profile Determination

Table 8. Example of Team Expertise Distribution

Agent	a	b	c	d	e	MAX	MIN
1	2	2	3	9	3	9	2
2	1	4	2	5	2	5	1
3	1	4	3	3	7	7	1
4	3	5	1	4	4	5	1
5	9	2	2	6	3	9	2
6	7	1	2	2	4	7	1
7	3	6	2	7	1	7	1
8	4	9	3	4	5	9	3
9	8	5	5	5	6	8	5
10	2	1	2	3	2	3	1
11	5	8	2	2	4	8	2
12	3	4	1	3	2	4	1
13	5	8	2	3	2	8	2
14	3	7	3	4	4	7	3
15	4	9	6	6	5	9	4
16	5	3	6	2	5	6	2
17	6	2	8	8	7	8	2
18	5	3	6	4	3	6	3
19	9	3	6	6	4	9	3
20	2	4	3	8	5	8	2
21	4	0	4	7	4	7	0
22	7	5	5	3	4	7	3
23	6	2	2	5	4	6	2
24	9	3	2	5	2	9	2

Each agent has an expertise that is randomly selected from a triangular distribution for each area of expertise

N	24
a	0
b	10
k	3
a+b/2	5
mean	4.33
mode	3
median	4.08
variance	4.39

Triangular Distribution Statistics

$$\text{mean} = \frac{a+b+k}{3}$$

$$\text{mode} = k$$

$$\text{median} = \begin{cases} a + \sqrt{\frac{(b-a)(k-a)}{2}} & \text{for } k \geq \frac{a+b}{2} \\ b - \sqrt{\frac{(b-a)(b-k)}{2}} & \text{for } k \leq \frac{a+b}{2} \end{cases}$$

$$\text{variance} = (a^2+b^2+k^2-ab-ak-bk)/18$$

$$\text{skew} = \frac{\sqrt{2}(a+b-2k)(a+k-2b)(2a-b-k)}{5(a^2+b^2+k^2-ab-ak-bk)^{1.5}}$$

Table 9. Example of Task Expertise Distribution

PROJECTS							
	REQUIRED EXP					TASK TYPE	
Task	a	b	c	d	e	TYPE1	TYPE2
1	2	4	4	9	5	A	A
2	7	7	3	5	2	A	C
3	6	8	9	7	6	D	A
Task	a	b	c	d	e	TYPE1	TYPE2
1	4	6	5	6	5	A	D
2	5	7	6	6	7	C	C
3	4	4	4	3	2	C	A
4	4	4	4	6	2	C	C
5	4	7	7	2	7	A	A
6	2	3	0	6	9	A	D
Task	a	b	c	d	e	TYPE1	TYPE2
1	5	2	4	4	7	C	A
2	4	2	8	3	6	D	A
3	5	3	2	8	8	A	D
4	7	5	4	3	5	A	C
5	6	7	7	4	7	D	A
6	3	3	4	7	2	C	A
7	4	2	4	5	9	C	A
8	8	1	5	4	2	A	D
9	9	2	1	5	3	A	D

Each task is randomly generated based on triangular distribution across different areas of expertise

N	5
a	0
b	10
k	4
a+b/2	5
mean	4.67
mode	4
median	4.52
variance	4.22

Random Numbers: Type

1	A
3	D
2	C
2	C
1	A
3	D
3	D
1	A
2	C

Triangular Distribution Statistics

$$\text{mean} = \frac{a+b+k}{3}$$

$$\text{mode} = k$$

$$\text{median} = \begin{cases} a + \sqrt{\frac{(b-a)(k-a)}{2}} & \text{for } k \geq \frac{a+b}{2} \\ b - \sqrt{\frac{(b-a)(b-k)}{2}} & \text{for } k \leq \frac{a+b}{2} \end{cases}$$

$$\text{variance} = (a^2+b^2+k^2-ab-ak-bk)/18$$

$$\text{skew} = \frac{\sqrt{2}(a+b-2k)(a+k-2b)(2a-b-k)}{5(a^2+b^2+k^2-ab-ak-bk)^{1.5}}$$