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AUTOMATED INTELLIGENT AGENTS: ARE THEY TRUSTED MEMBERS OF MILITARY TEAMS?

by

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Technological advances and increased operational challenges have led to the introduction of automated agents into military teams. Although these new combined teams have many advantages, it is possible that the interactions between members of these new human - automation teams may adversely impact mission accomplishment. This study investigates the similarities and differences between human – human teams and human – automation teams with respect to team communications, efficacy, and trust. Thirty-six participants were formed into twelve three-person teams. A confederate served as the fourth member for all twelve teams. In the human – human team condition, the confederate was present in the same room as the other three team members. In the human – automation team condition, the confederate was located in a separate room and the other three team members were told that their fourth team member was an automated intelligent agent. All teams played a computer-based team firefighting game (C3Fire). The order of presentation of the two trials (human – human vs. human – automation) was counterbalanced. The results of this study indicate there is a significant difference in the nature of the communication between these two types of teams. Additionally, the presence of an automated agent changes the nature of trust and team efficacy. These findings demonstrate the need to consider the unintended impact of including automated agents on team dynamics in military environments and other complex and dynamic systems.

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AUTOMATED INTELLIGENT AGENTS: ARE THEY TRUSTED MEMBERS OF MILITARY TEAMS?

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ABSTRACT

Technological advances and increased operational challenges have led to the introduction of automated agents into military teams. Although these new combined teams have many advantages, it is possible that the interactions between members of these new human - automation teams may adversely impact mission accomplishment. This study investigates the similarities and differences between human – human teams and human – automation teams with respect to team communications, efficacy, and trust. Thirty-six participants were formed into twelve three-person teams. A confederate served as the fourth member for all twelve teams. In the human – human team condition, the confederate was present in the same room as the other three team members. In the human – automation team condition, the confederate was located in a separate room and the other three team members were told that their fourth team member was an automated intelligent agent. All teams played a computer-based team firefighting game (C3Fire). The order of presentation of the two trials (human – human vs. human – automation) was counterbalanced. The results of this study indicate there is a significant difference in the nature of the communication between these two types of teams. Additionally, the presence of an automated agent changes the nature of trust and team efficacy. These findings demonstrate the need to consider the unintended impact of including automated agents on team dynamics in military environments and other complex and dynamic systems.

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EXECUTIVE SUMMARY

The technological advancements in the latter part of the last century led to an unprecedented proliferation of complex systems. Automated systems have become ubiquitous to the point that they are now being introduced into teams that were previously composed exclusively of humans. While the addition of automated agents may increase some aspects of mission effectiveness, the nature of the interactions between human - human teams and these new human – automation teams needs to be studied carefully. Technology is often thought of as the answer to many problems associated with increasing operational demands in a resource-constrained environment. However, the new challenges that emerge when automated systems are introduced are often not fully considered. These challenges can be mere inconveniences in some cases but catastrophic in other cases. This study investigates the differences in the interactions of human - human teams and human-automation teams through an analysis of team communications, efficacy, and trust.

Thirty-six participants were formed into twelve three-person teams. A confederate served as the fourth member for all twelve teams. In the human – human team condition, the confederate was present in the same room as the other three team members. In the human – automation team condition, the confederate was located in a separate room and the other three team members were told that their fourth team member was an automated intelligent agent. All teams played a computer-based team firefighting game (C3Fire). The order of presentation of the two trials (human – human vs. human – automation) was counterbalanced.

Results of this study reveal compelling evidence that the addition of an automated agent to a human team changes the nature of communications amongst team members, impacts team efficacy, and alters the task distribution of the team. Statistical analysis showed that even though the total number of communications amongst both group types was equivalent, the type of communication was different. In human - human teams, information was more likely to be shared to aid in decision-making, while on human-automation teams, communications were more likely to be directive in nature. While the presence of an automated agent did not affect overall team performance, it did affect trust, efficacy, and task distribution of the team. Statistical analysis indicated that human team members had greater confidence in another human team member compared to the automated agent. Analysis also showed that the human team members trusted the automated agent less, which directly affected task distribution. The results of this study suggest that there is are important differences in the interactions of human – human teams compared to human-automation teams and demonstrate the need to consider the unintended impact of including automated agents as team members in military environments and other complex and dynamic systems.

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I. INTRODUCTION

A. PROBLEM STATEMENT

The last century led to an unprecedented level of technological development and implementation. This explosion in the use of automation requires humans and machines to work together to effectively perform required tasks. The ability of a combined team to perform effectively in the face of difficult problem solving situations requires proper coordination, collaboration, integration and trust between all team members. For the military, these fundamental changes in technology and automation have altered the very nature of warfare. No longer do riflemen stand in a field, aim at the opponent and shoot at each other. Now, warfighting methods include computers, unmanned aerial vehicles (UAVs) and robotic agents. This fundamental change in the nature of warfare has transformed the normal team composition from teams consisting of entirely human members to teams consisting of humans and automated agents. This thesis seeks to investigate the possible differences between the nature in which humans interact with other humans as compared to their interaction with automated agents.

As the nature of warfare has changed, the resulting task complexity has led to an increased use of more sophisticated technological systems. These advances in technology have introduced intelligent agents (IAs) into military teams. While there is no universal definition for IAs, Wooldridge defines an IA as one capable of flexible autonomous action in order to meet its design objectives

(Richards, 2003). In this definition, flexibility means the IA is able to perceive and react to the environment, is able to take initiative to satisfy its design objectives, and is capable of interacting effectively with other agents, including human beings.

These advances in automation can significantly reduce manning levels, while increasing mission effectiveness, but they are not a panacea. One approach used in the past has been to automate the functions that are easiest to design and leave the rest to the human operators. This approach may not reduce the number of tasks assigned to the human, but merely change their nature. According to Sheridan (2002), this type of design may lead to ineffective automation because the remaining human tasks become more complex and less understood, resulting in the overall degradation of system performance.

While there is a large amount of research regarding team performance (Salas and Fiore, 2004; Patrashkova-Voldoska, McComb, Green, & Compton, 2003; Cook, Salas, Cannon-Bowers & Stout, 2000), some researchers suggest little is known about what is important in an effective human-intelligent agent team. Fiore, Jentsch, Becerra-Fernandez, Salas, & Finklestein (2005) argue that it is unclear what information human-agent teams use in order to effectively perform a given task, and how the presence of non-human team members alters what have been the traditional requirements of effective teams. Additionally the degree of automation required on each team for a defined task is uncertain. Other researchers have suggested that effective human-automated teams begin with a system design that incorporates two fundamental characteristics: observability and directability (Christoffersen & Woods, 2002). The design phase is followed by incorporating effective feedback mechanisms to share all information amongst team members.

Researchers have discovered that providing the right degree of automation for the proper function of a task can optimize overall team performance (Wright, 2005), but automation design and implementation is not an exact science. Since the military has limited resources, integrating automated agents into traditional human - only military teams remains challenging. This effort will require a proper understanding of how to effectively design and implement these teams. Additionally, human team members will require a proper understanding of the intelligent agents in order to maximize mission effectiveness. Because warfighting will become an activity in which humans and intelligent agents are even more interdependent than they are at present, it is critical that we understand the nature of interactions on these newly formed teams.

B. OBJECTIVES

The objective of this research effort is to compare the nature of the interactions between members of a purely human team and a team consisting of human members and an intelligent automated agent. The specific goals of this effort include:

- To analyze the difference in *frequency of communications* between human teams and human-automation teams;
- To analyze the *nature of the communication* to determine the differences in interaction between

members of a purely human team as compared to a team consisting of human and intelligent agents;

- To assess differences in team efficacy between human teams and human-automated teams

- To evaluate the results with respect to Human Systems Integration (HSI) and potential effects on the field of HSI

C. RESEARCH QUESTIONS

The specific research questions addressed in this study include:

- Are there differences in the nature of communication between human teams and teams that combine humans and an intelligent automated agent?
- If so, how do these differences affect team performance and team efficacy?
- What elements should designers consider in building future systems that partner humans with intelligent automated agents?

D. HUMAN SYSTEMS INTEGRATION (HSI)

HSI is less a process and more a field or discipline that recognizes that, in any complex system, humans play a vital role. According to Booher (2003, p.4), HSI is "primarily a technical and managerial concept, with specific emphasis on methods and technologies that can be utilized to apply the HSI concept to systems integration". According to the U.S. Navy, HSI is a multidisciplinary field of study consisting of eight basic areas or domains of study:

- Manpower
- Training
- Personnel

- Human Factors Engineering
- System Safety
- Personal Survivability
- Health Hazards
- Habitability

This thesis will focus on three of the eight HSI domains: personnel, training, and human factors engineering. The personnel domain focuses on the knowledge, skills, and abilities of the people that are required to operate, maintain, and support a system. This domain involves both the physical and cognitive attributes possessed by the individual (Archer, Headley, & Allender, 2003). The U.S. Department of Defense, and specifically the U.S. Navy, has been reducing manning levels significantly in order to reduce manpower costs, often utilizing technology and automation in an attempt to maintain mission effectiveness. Determining the correct personnel to fill the billets that require humans to interact with automation has proven to be challenging because the skill sets required for these billets are often unknown. This thesis will provide some insight into the nature of interaction between combined military teams, which should aid in determining critical factors when assigning these billets.

The training domain focuses on ensuring that the training requirements and programs will allow the personnel to properly operate, maintain and support the system (Archer et al., 2003). This domain will certainly need to change as the reliance on automation increases. In order for human-agent teams to be effectively utilized, the conditions under which training needs to be tailored and delivered requires further investigation (Fiore et al., 2005). The results of this thesis will provide insight into the nature of training requirements for future military teams.

Human factors engineering (HFE) is “the integration of human characteristics, into systems definition, design, development, and evaluation to optimize human-machine performance under operational conditions” (Lockett & Powers, 2003, p.463). Some of these characteristics, such as physical size of the human population may seem rather obvious, but other factors such as human cognition and trust in automation are not quite so apparent. This thesis will explore some of these human characteristics in an effort to gain a better understanding of how they relate to the effectiveness of future combined military teams.

E. THESIS ORGANIZATION

In Chapter II, literature regarding team performance, communication, trust and team efficacy is discussed. Chapter III outlines the methods used to conduct the experiment and describes C3fire, a microworld used to assess team performance and evaluate communication metrics. Chapters IV and V present the results of the experiment, a discussion of these results, conclusions, and follow-on research recommendations.

II. LITERATURE REVIEW

This literature review is divided into four sections. The first section focuses on team performance. The second section discusses communication techniques and communication frequency among members of a team. The third section examines the factors involved in trust among team members. The final section discusses the factors involved with team efficacy.

A. TEAM PERFORMANCE

A team is a mature grouping of individuals that generates synergistic effects through a coordination of its members' efforts (Robbins & Judge, 2007). A team may also be defined as "collectives who exist to perform organizationally relevant tasks, share one or more common goals, interact socially, exhibit task interdependencies, maintain and manage boundaries, and are embedded in an organizational context that sets boundaries, constrains the team, and influences exchanges with other units in the broader entity" (Mathieu, Maynard, Rapp, & Gilson, 2008, p. 411). The primary functions of teams, and a common reason for their formation, are to share information, develop strategies, make decisions, and accomplish tasks. If the difficulty of a task is too great for an individual's abilities, cognitive or otherwise, then the formation of a team may be necessary. But, according to Salas and Fiore (2004), it is a common misconception that the formation and implementation of a team will lead to success. Research indicates that in order for a team to be effective, it must develop a shared cognitive capability referred to as team cognition (Burnett, 2006). The end result of teamwork can be considered the result of the collaboration of individual cognition, behaviors and attitudes and it is important to understand the factors that affect team performance and effectiveness (Salas & Fiore, 2004).

Salas and Fiore (2004) define team cognition as the cognitive development that results when members in a team are engaged in complex and dynamic task accomplishment. Cannon-Bowers & Salas (2001) suggest that shared cognition can be a useful concept in describing team performance in several ways. First, shared cognition has value to explain how members of a team interact with one another. When highly effective teams are observed, they often coordinate their behavior without the need for verbal communication. In these effective teams, members have similar or compatible knowledge that guides their coordinated behavior. Additionally, the concept of shared cognition may have the potential to predict the likely effectiveness of the team. This predictive power may be able to identify potential problems and provide some insight into possible solutions. When team members have similar thoughts, knowledge, and experiences and utilize these attributes to coordinate their efforts, this shared cognition can be a good predictor of team effectiveness (Cannon-Bowers & Salas, 2001).

In completing assigned tasks, team members develop mental models that directly affect decision-making processes and team performance. In essence, mental models are organized knowledge structures that allow individuals to interact with the environment around them, explain and predict the behavior in their environment, and recognize and remember relationships in order to predict what is likely to occur next (Mathieu et al., 2000). Other researchers state “mental models are the mechanisms whereby humans are able to generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions (or expectations) of future system states” (Rouse, Cannon-Bowers & Salas, 1992, p. 1300). Figure 1 describes these three functions of mental models: description, explanation, and prediction.

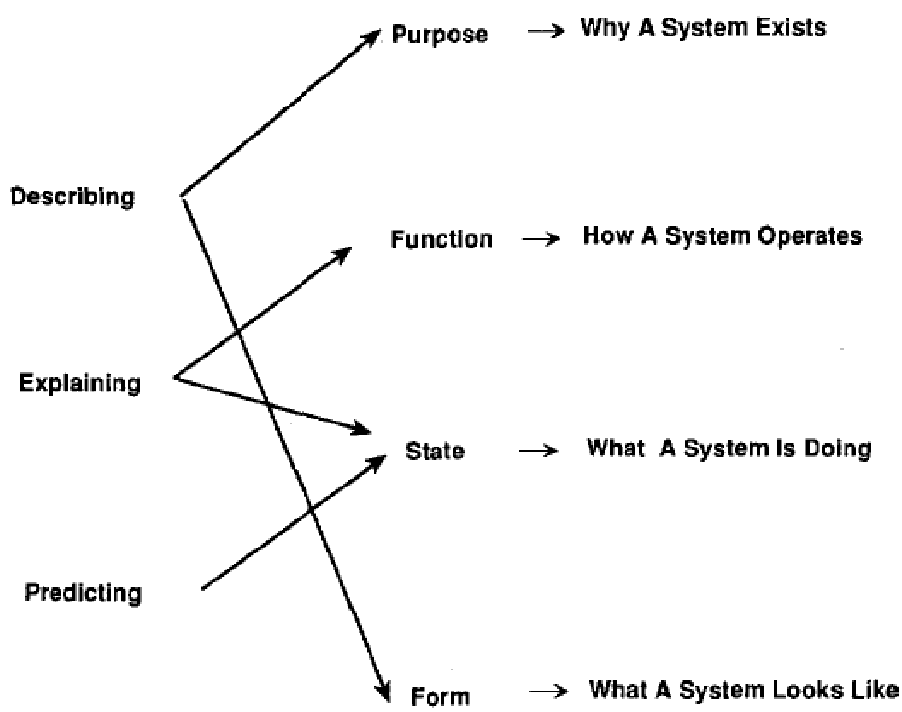

Figure 1. Nature of Mental Models (From: The Role of Mental Models in Team Performance in Complex Systems, 1992, p. 1300)

The description function involves knowledge of why a system exists and what it looks like. The explanation function describes how a system operates and interprets what the system is currently doing. The prediction function enables formation of expectations about future events involving the system. Of course, it stands to reason that the explanatory and predictive functions interact; the explanation of how a system functions has an impact on predicting future states.

Rouse, Cannon-Bowers and Salas (1992) assert that technology has allowed the development of increasingly sophisticated systems throughout all walks of life. This sophistication increases the complexity of activities for operators, maintainers, and managers of these systems. Furthermore, automation serves an increasingly fundamental role. The nature of the decision making process in these complex systems can be turbulent and often requires the coordinated efforts of multiple team members, whether humans or automation. Team dynamics, performance, and ability to integrate effectively become increasingly important for the success of these teams.

The following list from Rouse, Cannon-Bowers, and Salas (1992) indicates some of the characteristics of decision making in these complex environments that present themselves as challenges in highly sophisticated human and automated systems.

- The environment is highly dynamic and sometimes hostile; as a result, situations and rules can change quickly and risks abound.

- Goals vary in time and not infrequently conflict; shifting objectives and priorities, as well as the impossibility of satisfying all goals, result in no “best” decision and perhaps many “acceptable” decisions.

- Information is typically incomplete, uncertain, and ambiguous; consequently, it may not be clear what can or cannot be assumed, as well as what is known or unknown.

- Typically multiperson teams are involved; thus, overall performance depends on more than just individual performance.

- Members of teams have differing roles and responsibilities; consequently communication and coordination are central issues.

- Decision making is embedded in an organizational context; therefore, team performance must be consistent with objectives and constraints external to the team.

Some research suggests that not all team members may share the same mental model. Klimoski and Mohammed (1994, p. 432) state “there can be (and probably would be) multiple mental models co-existing among team members at a given point in time” that would include models of task and technology, response routines, and processes of team work. But it has been hypothesized that the greater the overlap or commonality among team member’s mental models, the greater the likelihood that members will predict the needs of the team and the task, be able to adapt to changing environments, and coordinate with one another (Cannon-Bowers & Salas, 1991). Additionally, a shared mental model allows team members to draw upon team - based knowledge to determine the best courses of action that are consistent and coordinated with the actions of their teammates. Furthermore, sharing mental models allows team members to predict the behavior and resources required by the other team members more accurately. In human-automated teams the building of an accurate shared mental model may present new challenges to team effectiveness.

B. COMMUNICATION

Teams do not perform in a vacuum; communication is necessary to share information, coordinate efforts and complete tasks. To function effectively, a team must act as a coordinated information processing unit, maintain situational awareness, and make collaborative decisions, all of which require some form of communication. Because communication requires time, effort and cognitive resources, there is an 'overhead' associated with its use. Christoffersen & Woods (2002) suggest that knowledge derived from communications in human systems is often derived at relatively low cost. In human-to-human cooperative work, people continually work to build and maintain a common understanding in order to support the coordinated problem solving efforts. Mutual knowledge of each others' actions and abilities supports efficient and effective efforts.

Another manner in which human to human interaction can be relatively low cost is in open work environments where individual team members can just observe the actions of others. The open nature of the environment allows team members to make intelligent judgments about what actions have been taken, what actions are necessary and when they should be taken without any explicit communication. However, when it comes to automated team members, this information no longer comes at low cost because automation often lacks intentionality. Human team members are often unaware of what the automation is doing, intends to do, and whether or not the tasks are conducted in a correct and efficient manner. In order to lower these communication costs, the automation must specifically be designed to generate the shared understanding needed to support cooperative work.

Sycara and Lewis (2004, p. 204) suggest that “the greatest impediment to assisting human users lies in communicating user intent to an agent and making the agent’s results intelligible to the human”. In today’s cases, the limiting factor in human-agent interaction is the users’ ability or willingness to communicate, organize, and interpret the machine’s response to satisfy them. Monitoring and evaluating is also more difficult because of increased flexibility and autonomy of the automation. The degree of this difficulty changes with the agent’s role. According to Sycara and Lewis (2004), there are three possible roles for automated agents in human teams. The first is to support the team members in completion of their own tasks. The second is to assume the role of an equivalent team member by performing the reasoning and tasks of that human teammate. In this role, issues associated with communication and coordination are very relevant because not only does the automation have to perform its own tasks, but also must communicate to share information about its actions, goals, and progress. The third possible role is to support the team as a whole by facilitating communication, allocation of tasks, and coordination among team members.

The measurement and analysis of communication frequency and type has been an ongoing area of team research because of the critical role that communication plays in team effectiveness. Some researchers have developed and validated rating scales for assessing such communications. Macmillan, Entin, and Serfaty (2004) have developed and used several measures that explicitly link the team's knowledge about each other and the shared tasks with the frequency and type of their communication. Their measures are based upon the theory that a shared mental model and shared awareness of information amongst team members results in the ability to coordinate implicitly, resulting in more efficient (lower overhead) communication. One such method proposed is the anticipation ratio, a measure of communication efficiency that has proven to be effective for several different types of teams (MacMillian, Entin, & Serfaty, 2004). Their method calculates the ratio of the number of communications transferring information to the number of communications requesting information. Values greater than one indicate that communications were 'pushed' (information was sent) among team members more frequently than requests for information were received indicating that the team was able to anticipate the need for information of the other team members. Values less than one indicate that information was 'pulled' (requested) more frequently than it was sent. Miller and Shattuck (2003) have suggested another set of criteria for measuring communication between team members. They proposed 13 categories of communication: perception, comprehension, projection, pull, response to pull, push, decision/tasking, decision request, coordination, coordination request, coordination transfer, and acknowledgement. These different categories can also be used to compare and contrast team communication frequency and type. Comparing communication types and frequency in human-automated teams increases the complexity of the analysis because the automation often uses a unique language and its true intentions are often unknown.

C. TRUST

"Trust refers to the expectation of, or confidence in, another and is based on the probability that one party attaches to co-operative or favorable behavior by other parties" (Madhavan & Wiegmann, 2007, p. 290). Review of the trust literature suggests that trust is a multidimensional factor that generally follows patterns established by sociologists. Barber (1983) explains trust as a compromise between persistence of natural and moral laws, technical competence, and fiduciary responsibility. Regarding the integration of humans with automation, research has shown that these concepts could be associated with the reliability, predictability, and competency of the automation (Dassonville, 1996). Another sociologist, Rempel (1985), explains trust in three dimensions: predictability, dependability, and faith. Predictability is the most concrete component of trust and depends on the stability of performance over time (Madhavan & Wiegmann, 2007). Dependability is based on the characteristics of the human in the system and is reflected in the level of confidence one has with the automation. Faith is based on beliefs about the future behavior or perceived accuracy of the automation and may be reflected in the person's willingness to continue to use the automation.

Sheridan (2002) modifies the concept of trust in regards to human-automation interaction. He distinguishes between trust as an ‘effect’ of operators or outcome of certain automated characteristics and trust as a ‘cause’ of the human’s behavior when utilizing automation (Madhavan & Wiegmann, 2007). This concept may dictate whether the automation is used and the method of employment. Trust in the context of automation was identified by Lee and See (2004) on three general bases: performance, process, and purpose. Performance describes ‘what’ the automation does and refers to the operation of the automation. More specifically it refers to the competency as demonstrated by its ability to achieve the operator’s goals. It includes such characteristics such as reliability and predictability.

Process describes ‘how’ the automation operates; it is the degree to which the automation actions are appropriate for the situation. Process as a basis of trust tends to reflect qualities and characteristics attributed to the automation that will lead to a concept similar to Sheridan’s (1992) statement that operators will tend to trust automation that can be understood and is likely to achieve the operator’s goals (Lee and See, 2004).

Purpose refers to the degree to which the automation is used as compared to the intent of the designer. It describes ‘why’ the automation was developed and corresponds to the faith and benevolence of the operator. Lee and See’s first two bases of trust (i.e., process and performance) tend to correspond to Rempel’s (1985) assertions of predictability and dependability and their third dimension (purpose) roughly corresponds to the component of faith and benevolence described in the Rempel model (Madhavan & Wiegmann, 2007).

Although past research has generally supported the concept that machine reliability predicts trust in automation, Merritt and Ilgen (2008) contend that the user’s personality and perceptions of automation also play a vital role in determining automation utilization decisions. They imply that an individual with a greater disposition towards trusting other people tends to display greater levels of trust when interacting with automation. Studies such as Reeves and Nash (2006) show that humans respond socially to technology, and reactions to computers and automation tend to be similar to human collaborators (Lee & See, 2004). Merritt and Ilgen (2008) use this concept to suggest that since extroverts tend to be more sociable than introverts, they tend to trust automation more frequently; so biases in social behavior may have an effect on reliance of automation. Their study involved an X-Ray screening task and showed significant results to support their assertion.

Another operator personality characteristic - self-confidence - may also be related to automation use as described by Lee and See (2004). Self-confidence is a critical factor in decision making and has effects on trust. They suggest that as operator confidence increases, use of automation decreases. The opposite is also true: low self-confidence directly relates to increased reliance on automated functions.

Even though trust between human team members and trust between human and automated team members has many similarities, some studies suggest that there are important differences between them. Trust between people is generally part of a social exchange relationship resulting from repeated interactions between people. There is a symmetrical relationship to this interpersonal trust as each party is aware of the other’s behaviors, intentions, and trust (Lee and See, 2004). But since automation often does not explicitly state its intentions, there is no symmetry in the relationship; therefore, people tend to trust automation through a different process.

Another research study (Lewandowsky, S., Mundy, M., & Tan, G., 2000) found that delegation to automation was different than delegation to human counterparts. They found that delegation to other humans, but not automation, was based on people’s assessment of how others perceive them. If people perceive their own trustworthiness to be low among other people, they are more likely to delegate tasks. Additionally they found that in delegation to automation, rather than humans, the degree of trust played a more critical role. One possible explanation is that in human to human partnerships, the ultimate responsibility is perceived as being shared as compared to the perception of ultimate responsibility resting with the operator in a human-automation partnership (Lewandowsky, S., Mundy, M., & Tan, G., 2000).

The final difference between interpersonal trust and trust in automation deals with the attribution process. Interpersonal trust tends to evolve in accordance with some of the previously discussed models. Initially, trust is based on performance (reliability). Eventually, trust is based on dependability or process. Ultimately trust is based on purpose or faith. Trust in automation generally follows the opposite progression in which faith is paramount early, followed by dependability, and ending with predictability (Lee & See, 2004). Substantial evidence exists to support the conclusion that trust in automation is meaningful and useful in understanding reliance on automation, but the lack of a symmetrical relationship, lack of intentionality, and differences in progression of trust indicate that caution must be exercised when attempting to extrapolate results from human-human trust to the human-automation trust relationship.

D. TEAM EFFICACY

In 1986, Bandura defined self-efficacy as “people’s judgments of their capabilities to organize and execute courses of action required in attaining designated types of performances” (Karrasch, 2003). Later Bandura (1997) suggested that self-efficacy reflects an individual’s belief is his own capabilities to pursue a course of action to meet given situational demands. There are three important characteristics of self-efficacy according to Gist & Mitchell (1992). Self-efficacy:

- involves a judgment or comprehensive review of the perceived capabilities of the individual performing the task
- has a motivational component

- is dynamic and changes over time in response to new experiences and information.

Self-efficacy also has a powerful effect on task performance (Durham, Knight, & Locke, 1997). There is clear evidence that efficacy has an effect on performance and is not simply a matter of past performance being correlated with future performance. Since people with higher self-efficacy tend to believe they can accomplish more, they tend to set higher goals. Accomplishment of higher goals tends to build self-confidence, which leads to greater efficacy. Finally Woods and Bandura (1989) suggest that higher self-efficacy leads to the use of more effective strategies, which tend to be more successful, thereby increasing effectiveness, which in turn increases self-confidence, that results in an even greater level of efficacy.

The role of efficacy on performance may shift slightly when transitioning from individual performance to group performance. Therefore, collective efficacy at the group level has been suggested as a construct parallel to self efficacy at the individual level (Durham, Knight, & Locke, 1997). Bandura has argued that perceived collective efficacy is an emergent group-level property, not just the sum of the efficacy beliefs of the individual members (Karrasch, 2003). Collective efficacy may reflect the shared beliefs of the group's members in their ability to accomplish the task at hand. Bandura (1997) argued that collective efficacy influences the level of persistence, the effort, and the actions taken by group members in an effort to accomplish group tasks. Durham, Knight and Locke (1997) state that efficacy can be expanded to teams to the extent that individual team members agree that their team can perform successfully at any given task. This leads to group efficacy which Gibson (1999) defines as the extent to which a group believes it can accomplish a task through concentrated and coordinated effort. Since efficacy tends to affect team dynamics as a team develops and gains confidence, it tends to affect group performance in a positive fashion. Indeed, researchers have established that group efficacy is a meaningful and measurable group attribute and is positively correlated to group effectiveness (Tyran & Gibson, 2008). Bandura (1997) suggested that group efficacy is often related to the level of effort a group expends because it relates to what the group thinks it can accomplish. Therefore group efficacy tends to also affect group motivation and confidence. This type of positive group efficacy may be more difficult to establish in human-automated teams because the human players are often not as familiar with the competency of the automation.

E. SUMMARY

Many factors must be considered in the formation of successful teams. Team communication type and frequency, trust between team members, team shared cognition and team efficacy are just a few of the factors that may affect team performance.

Research suggests that team performance among mixed human and automated teams may not be driven in the same methodology as teams consisting of only human members. In fact, (Fiore et al., 2005) argue that it is not clear what information human-agent teams use in order to effectively perform a given task, and how the presence of non-human team members alters what has traditionally been considered to be the requirements of effective teams.

Based on previous research, this thesis hypothesizes that teams consisting of only human members will communicate in a different fashion than human-automated teams. The literature suggests that the nature of communication between automation and humans is not the same as how humans communicate with each other. The second hypothesis asserted is that team efficacy will be higher for the teams without the automated agent. Team efficacy involves trust and the ability to understand the nature of each team member's actions and intentions. Most automation lacks the ability to fully express intentionality, which often results in a loss of confidence among the human team members. The third hypothesis is that the level of trust will be higher in the teams consisting of only human members. The literature suggests that trust between a human and automation, especially new automation, is not the same as trust between humans.

III. EXPERIMENTAL METHOD

Measuring the nature of interactions between team members and overall team performance in combined human and automated teams can be challenging. Trust also becomes a major factor in performance, especially with partially automated teams. Some experiments have focused on the types of information shared; some have concentrated on the level of trust amongst team members, while others have been more concerned about the actual achievement of desired objectives. For the purpose of this study, team performance was examined as a function of mission completion, communication and team efficacy. A computer-based microworld, C3Fire, was utilized as a tool to measure team performance in a controlled environment.

C3Fire was developed in 1993 as a research project in a collaborative effort between Rego Granlund and Henrik Artman at Linköping University in Sweden. C3Fire supports training and team research in a controlled environment (*Overview*. Retrieved October 22, 2008, from: http://www.c3fire.org/c3fire/overview/overview.en.shtml).
In the C3Fire microworld, a firefighting scenario is generated on a 40 x 40 matrix of cells. Participants control three types of trucks (i.e., firefighting, water, and fuel) in a collaborative effort to extinguish the fire. The firefighting trucks extinguish the fire, the water trucks provide water to the fire trucks, and the fuel trucks provide fuel to all trucks. Participants need to manage their own water and fuel states throughout the scenario.

Other parts of the interface for the participants include a chat system, a unit information panel, a unit property panel, clock, and a map legend (see Figure 2).

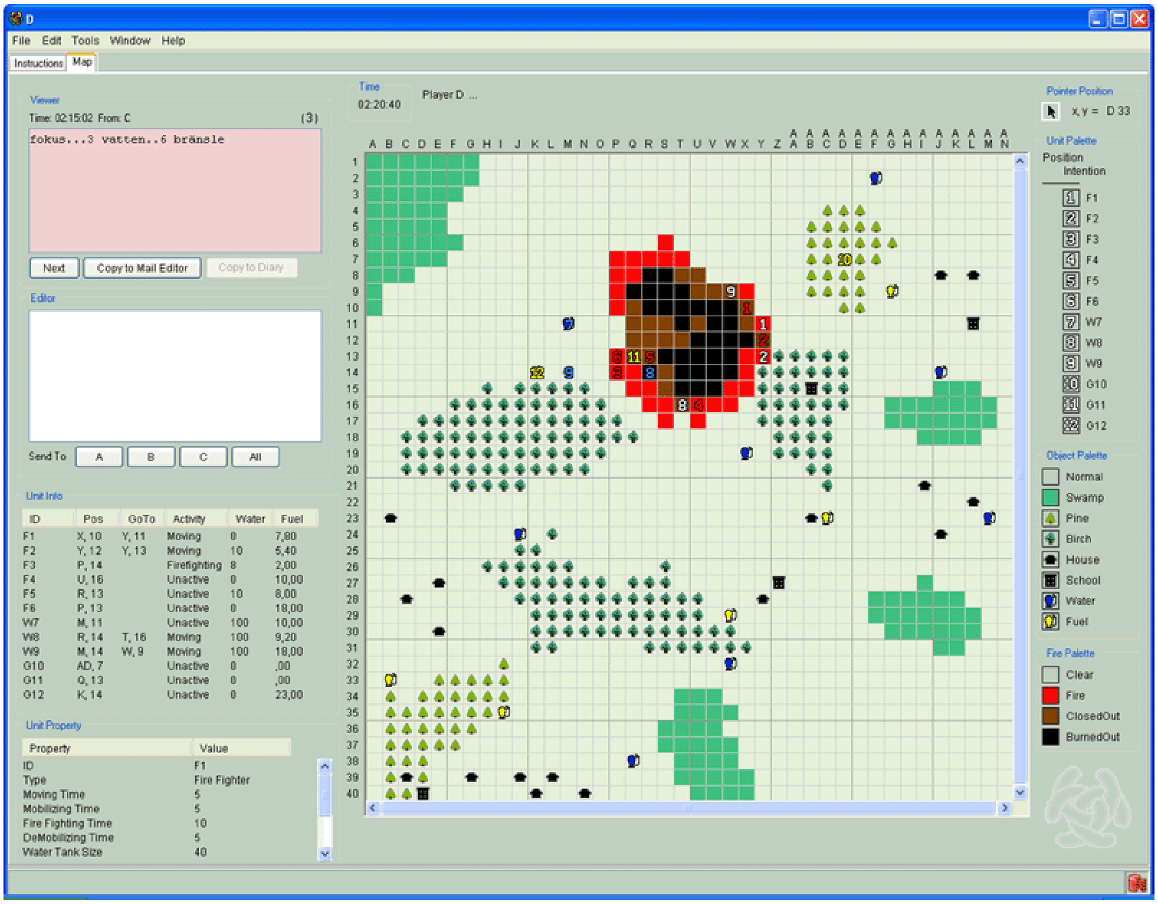

Figure 2. C3Fire User Interface. (From: www.c3fire.org)

A. PARTICIPANTS

For this study, all of the participants were U.S. military officers at the Naval Postgraduate School. The confederate member was a research associate employed at the Naval Postgraduate School.

Thirty-six participants (average age = 31.86, *SD*= 4.08) were assigned to twelve teams. Each team consisted of four members, three participants and a confederate. The confederate was designated as the gas truck operator in every group. The participants consisted of 28 male members and 8 female members ranging in age from 24 – 39 years old. The participants included five Lieutenant Junior Grades, eighteen Lieutenants, five Captains, four Lieutenant Commanders, and four Majors. Four participants were in the U.S. Army, four were in the U.S. Air Force, 27 were in the U.S. Navy, and one was in the U.S. Marine Corp. Six teams were all male and the other six teams were of mixed gender. Table 1 shows team composition.

	Composition		**Composition**
Human First Teams	**Age, Sex, Rank**	**Automation First Teams**	**Age, Sex, Rank**
(1)	29, M, O-3	(2)	32, M, O-3
	37, M, O-4		35, M, O-4
	31, F, O-3		32, M, O-3
(3)	25, F, O-2	(4)	35, M, O-4
	33, M, O-3		37, M, O-4
	30, M, O-2		35, M, O-3
(5)	26, M, O-3	(6)	35, M, O-3
	26, F, O-2		36, F, O-3
	24, M, O-2		31, F, O-3
(7)	29, M, O-3	(8)	31, M, O-3
	33, M, O-3		28, M, O-3
	39, M, O-4		36, M, O-3
(9)	37, M, O-3	(10)	26, M, O-2
	28, M, O-3		28, M, O-3
	29, M, O-3		34, F, O-3
(11)	38, M, O-4	(12)	30, M, O-3
	37, M, O-4		31, F, O-3
	31, M, O-3		32, F, O-4

Table 1. Team Composition

In order to control for prior knowledge of other team members, it would be desirable to form groups whose members had never met, but some individual team members were known to each other. The Naval Postgraduate School student body consists of approximately 1,900 students making it virtually impossible to form groups of students who had not served with each other previously or taken classes together.

The experimental procedures were screened and approved by the Naval Postgraduate School Institutional Review Board (IRB), thereby meeting both the Department of the Navy and the American Psychological Association (APA) standards. All participants signed an informed consent form, which notified them of their rights as a participant in the experiment, and an exit debrief, form which informed them that intentional deception was necessary to complete the experiment.

B. PARTICIPANTS

1. C3Fire

The C3Fire program requires approximately 250 MB of free disk space and was run on a desktop personal computer server. All computers used by the participants and the confederate were identical.

a. Server Specifications

- 24” Dell monitor
- Dell Optiplex 745 desktop computer

  Windows XP O/S

  Intel Core 2 CPU, 2.66 GHz, 3.0 GB RAM

  Broadcom NetXtreme 57xx Gigabit Network Controller
- Netgear DS108 10/100 Mbs Dual Speed Hub

b. Participants' Computer

- 20” Dell monitor
- Dell Optiplex 745 desktop computer
    - Windows XP O/S
    - Intel Core 2 CPU, 2.66 GHz, 3.0 GB RAM
    - Broadcom NetXtreme 57xx Gigabit Network Controller
    - Netgear DS108 10/100 Mbs Dual Speed Hub

C. VARIABLES

1. Independent Variables

- Group Composition – A team consisted of four human members or a team with three human members and one ‘automated’ agent.

2. Dependent Variables

- The number of messages sent per minute between team members during the scenario.
- The type of messages sent between team members during the scenario.
- The responses to the Team Efficacy Questionnaire.
- C3fire task performance (the number of cells in the 40 x 40 grid that are burned, have been extinguished, or remain on fire at the conclusion of the scenario).
- The number of commands issued to a truck by a team member who was assigned a different role.

D. PROCEDURE

Participants were solicited through various methods and assembled into teams of three based on their availability. The experiment was conducted in an enclosed lab space in the Human Systems Integrations Laboratory (HSIL) at the Naval Postgraduate School. The lab space contained the C3Fire server and four client computers. The fifth client computer, used by the confederate, was located in a separate private lab area and was unknown to the participants.

The participants and the confederate arrived at the HSIL independently and were allowed to socialize until the experiment started. All members were given consent forms to sign followed by PowerPoint training on the C3Fire program and the parameters of the experiment. The experimenter explained that two scenarios would be run, one with four human players and the other with three human players and an intelligent automated agent playing the role of the gas truck operator. The methodology for communicating with the automated agent was also explained. Next, all four participants picked a computer station at random and a training scenario was conducted using the C3Fire program. Information to provide clarity among team member roles and communication instructions for the automated agent was provided at each client station. Figure 3 shows the C3Fire client computer setup.

Figure 3. C3Fire Client Computer Station.

Since actual roles had not been assigned at this point, all members were allowed to practice all four possible roles on the team. At the completion of the training, each participant was randomly assigned a permanent role on the team. The confederate was always assigned the role of the gas truck operator. The participants were told the role of each of the other team members.

At this point, the group was notified which team composition would be utilized for their first scenario: either four human team members or three members and the automated agent. Next all team members completed an electronic Team Efficacy Questionnaire (TEQ). The TEQ was generated after consultation with a Professor of Management from the University of Nebraska-Lincoln, Dr. Bruce Avolio. He suggested appropriate questions for the TEQ, which were then modified to align with the C3Fire scenario (see Appendix A).

For the condition with four human members, the first scenario was then started. The scenario lasted until either the fire was extinguished or twenty minutes had elapsed. Another TEQ (see Appendix B) was completed and the confederate was dismissed to go back to work. In reality, the confederate left the enclosed lab area and went to the fifth C3Fire client computer located in a separate lab space. The second scenario was then conducted utilizing the confederate as the automated agent followed by another TEQ. The experiment was counter balanced such that half the groups started with four human team members in scenario one and the other half started with the automated agent. Both scenarios were similar and the behavior of the confederate was scripted to be the same for both scenarios.

Following the two scenarios all team members met face-to-face for a recorded exit debriefing. At the conclusion of the verbal debriefing, the true role of the confederate was revealed and the participants signed forms indicating they had been informed of the intentional deception.

IV. RESULTS

A. TEAM COMMUNICATIONS

1. Communication Density

Communication density was analyzed by examining the number of messages sent by each team during each scenario. C3Fire provides a chat box tool, similar to instant messaging, that was the sole form of communication between the participants. During scenarios in which the confederate was playing as the intelligent agent gas truck operator, he did not generate any messages. During scenarios in which he was acting as the human gas truck operator, he sent a few messages to maintain his credibility. None of the confederate’s messages were included in the analysis of the communication density data. The reason they were removed is because this analysis was conducted to determine whether the participants interacted differently with one another in the two conditions (i.e., confederate acting as human or intelligent agent). Figure 4 shows the average number of messages sent between team members per minute for each team type. The human team type sent an average of 2.51 (*SD*=.78) messages per minute while the automated teams sent an average number of 2.49 (*SD*=.92) messages per minute. A t-test was conducted to determine if the average number of messages per minute was the same across both team types. The difference in the number of messages sent by team type was not statistically significant ($t_{(11)}$=.09, *p*=.93).

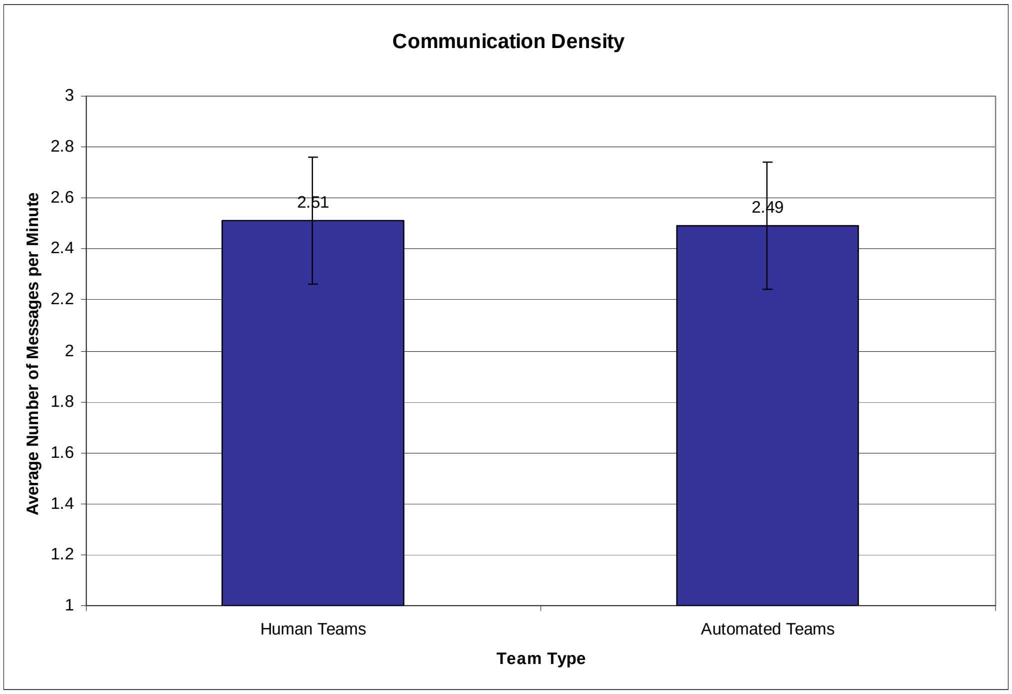

Figure 4. Communication Density for each Team Type.

Communication density was then analyzed based on the number of messages sent to the human confederate per minute versus the number of messages sent to the automated confederate per minute. Figure 5 shows the average number of messages sent to each type of confederate per minute. The human confederate received an average of 0.88(*SD*=0.39) messages per minute while the automated confederate received an average of 0.97(*SD*=0.54) messages per minute. A t-test was conducted to determine if the average number of messages sent per minute to the human confederate was the same as the average number of messages sent to the automated confederate. Again, no statistical significance was found for the average number of messages sent per minute based on the type of confederate ($t_{(11)}$=1.22, p=.25).

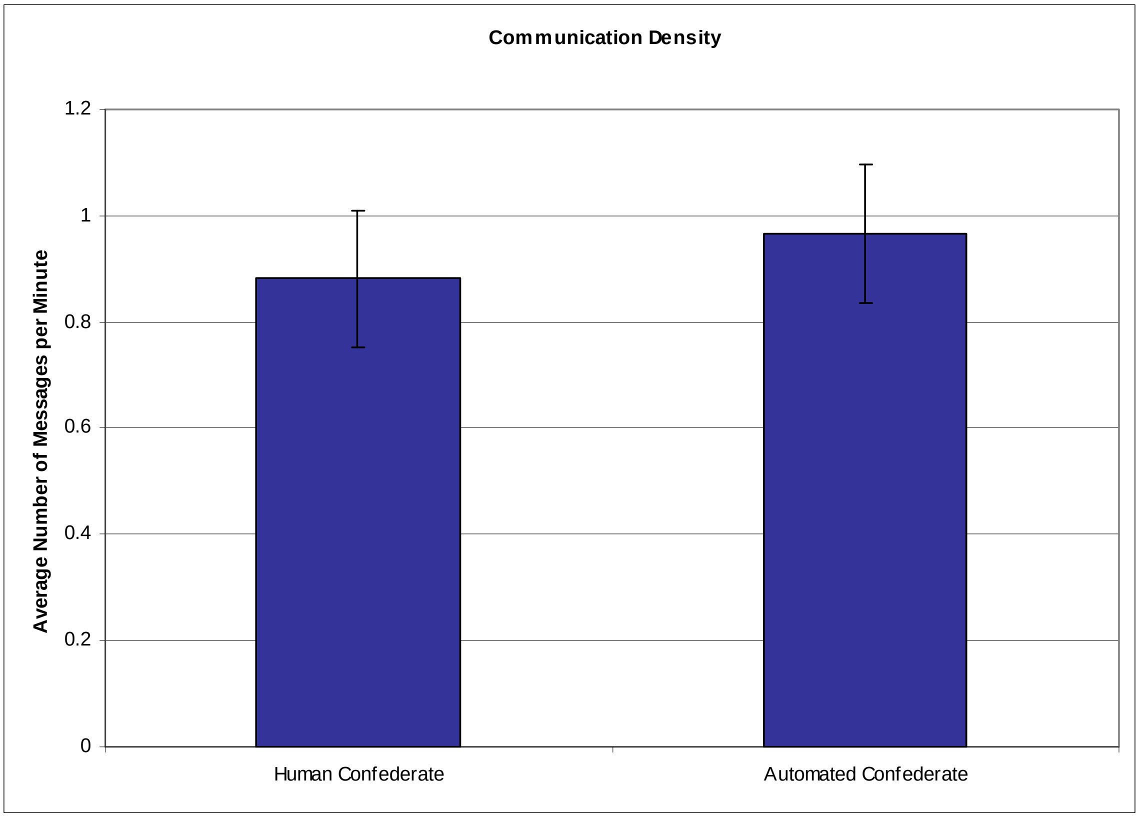

Figure 5. Communication Density to the Confederate.

2. Communication Type

The messages between team members were then categorized into six of the thirteen types identified by Miller and Shattuck (2003): projection, push, decision/tasking, coordination, acknowledgment, and pull. A seventh category, chatter, was added to account for communications that were not relevant to the scenario. Table 2 shows the average number of each type of message sent per minute by team type and to each type of confederate. Further analysis was conducted by applying t-tests to compare the means for each type of message for all team members. Another set of t-tests was conducted on just those messages sent to the confederate. The t-tests revealed one significant result.

The number of messages pushing information was different between the two types of confederates ($t_{(11)}$=2.55, p=.03). The human confederate received an average of .18(*SD*=.03) messages per minute, while the automated confederate received and average of .07(*SD*=.01) messages per minute. Table 3 shows the p values for the t-tests for each communication type between all team members and to the confederate.

Type of Message	Total Human Team	Total Automated Team	To Human Confederate	To Automated Confederate
Projection	0.09	0.11	0	0
Push	0.62	0.78	0.18	0.07
Decision/Tasking	1.1	0.8	0.38	0.67
Coordination	0.56	0.56	0.32	0.21
Acknowledgement	0.01	0.08	0	0
Chatter	0.09	0.12	0	0
Pull	0.04	0.04	0	0.01

Table 2. Average Number of Communication by Type per Minute.

Type of Message	All Team Members	Confederate Only
Projection	0.75	Insufficient Data
Push	0.19	0.03
Decision/Tasking	0.07	0.1
Coordination	0.99	0.21
Acknowledgement	0.19	0.34
Chatter	0.07	Insufficient Data
Pull	0.37	0.34

Table 3. *p* Values for t-tests by Communication Type.

3. Participants' Comments

During the face to face debrief, and before the identity of the confederate was revealed, participants were asked to discuss their experience participating in this study. The researcher did not direct the debrief, or specifically address any topic; the participants were allowed to discuss any aspect of the study they desired. The confederate was also present at the debrief, but did not reveal his identity or provide any comments that would influence the discussion of the participants. The exit debriefs were recorded and later analyzed for any comments specifically related to the automated agent. The comments related to the automated agent were overwhelmingly negative; twenty-one comments (84%, CI:69.7-98.3%) indicated a negative perception of the automated agent, while only four (16%, CI:1.6-30.4%) indicated a positive experience with the automation. A typical comment was 'I did not trust the automated gas trucks.' See Appendix C for all comments referencing the automated agent.

B. TEAM EFFICACY QUESTIONNAIRE

Question number five from the TEQ, (*I had confidence in the gas truck operator's ability to properly perform the role)*, was analyzed from three different aspects. First, an order effect (human or automation first) was evaluated. Next, a team type effect (human or automated confederate) was investigated. Finally, an effect based on transitioning from one type of team to the other (human to automation versus automation to human) was evaluated. In addition to those three, an analysis of the transition effect from pre TEQ to post TEQ was also conducted for question number five.

1. Order Effect

In this study, the order of presentation of the scenarios and the role played by the confederate were counterbalanced. Using question 5 from the TEQ, *(I had confidence in the gas truck operator's ability to properly perform the role)*, a two-tailed Sign test was conducted to determine if the participants' confidence levels of the gas truck operator's ability was influenced by the order of the scenarios. Figure 6 shows the average response to question 5 based on the order of the scenarios. The teams that completed the human scenario first and the automated scenario second had an average score of 3.69(SD=1.01). The teams that completed the automated scenario first and the human scenario second had an average score of 3.67(SD=1.31). A two-tailed Sign test was conducted and no significant difference was found for confidence in the gas truck operator's ability (z=0.00, p=1.00).

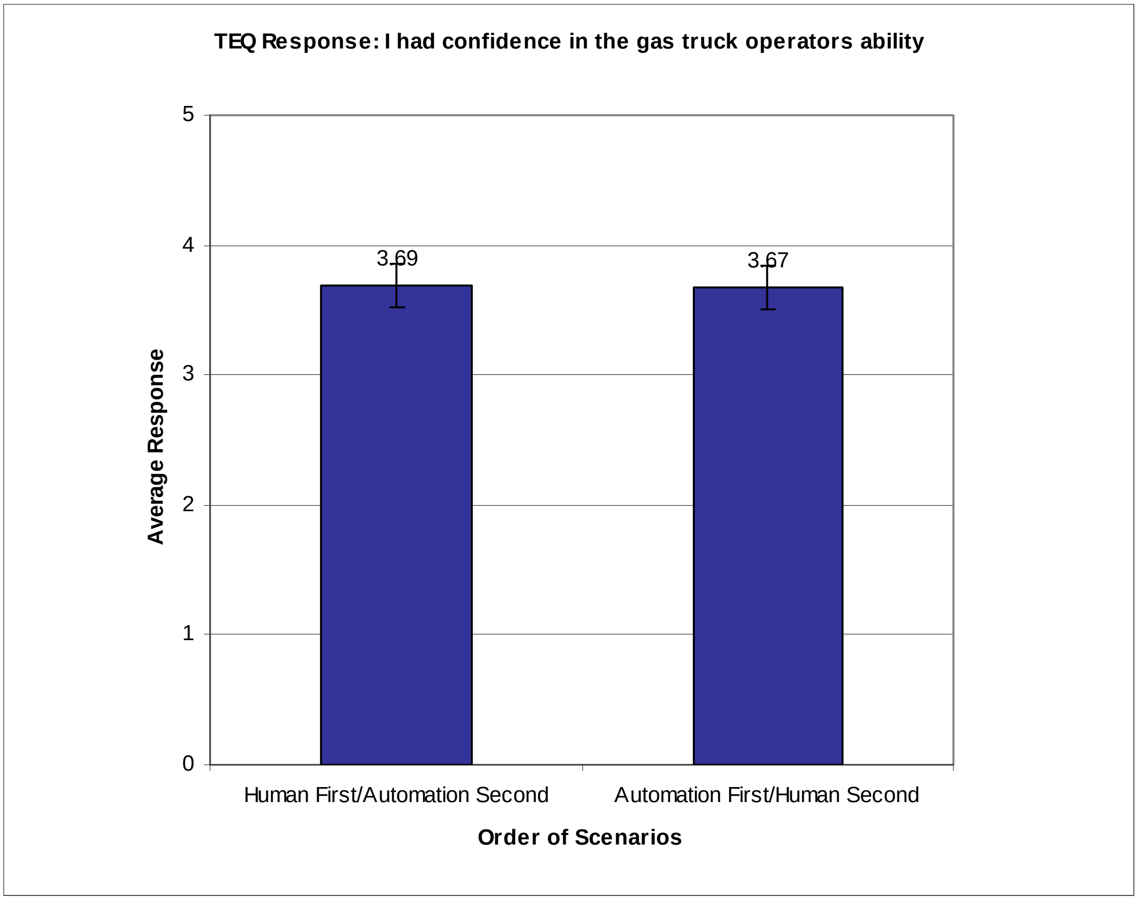

Figure 6. Average Response by Order of Scenario.

2. Team Type

In this study there were two different types of teams. The first type of team consisted of three participants and the confederate, who played the role of another human participant. The confederate was assigned as the gas truck operator in every team. The second type of team consisted of the same three participants and an 'automated agent.' The 'automated agent' was actually the confederate who was assigned the role of the gas truck operator and played the C3Fire game from a remote location. A two-tailed Sign test was conducted on responses to question 5 of the TEQ, (*I had* *confidence in the gas truck operator's ability to properly perform the role*) to determine if there was an effect of perceived team composition on confidence level in the gas truck operator's ability. Figure 7 shows the average response to question 5 for each type of team. The human teams had an average score of 4.17 (*SD*=0.74), while the perceived automated teams had an average score of 3.19 (*SD*=1.31). A significant difference was found in the confidence level of the gas truck operator's ability based on team composition (*z*=3.14, *p*=0.0025).

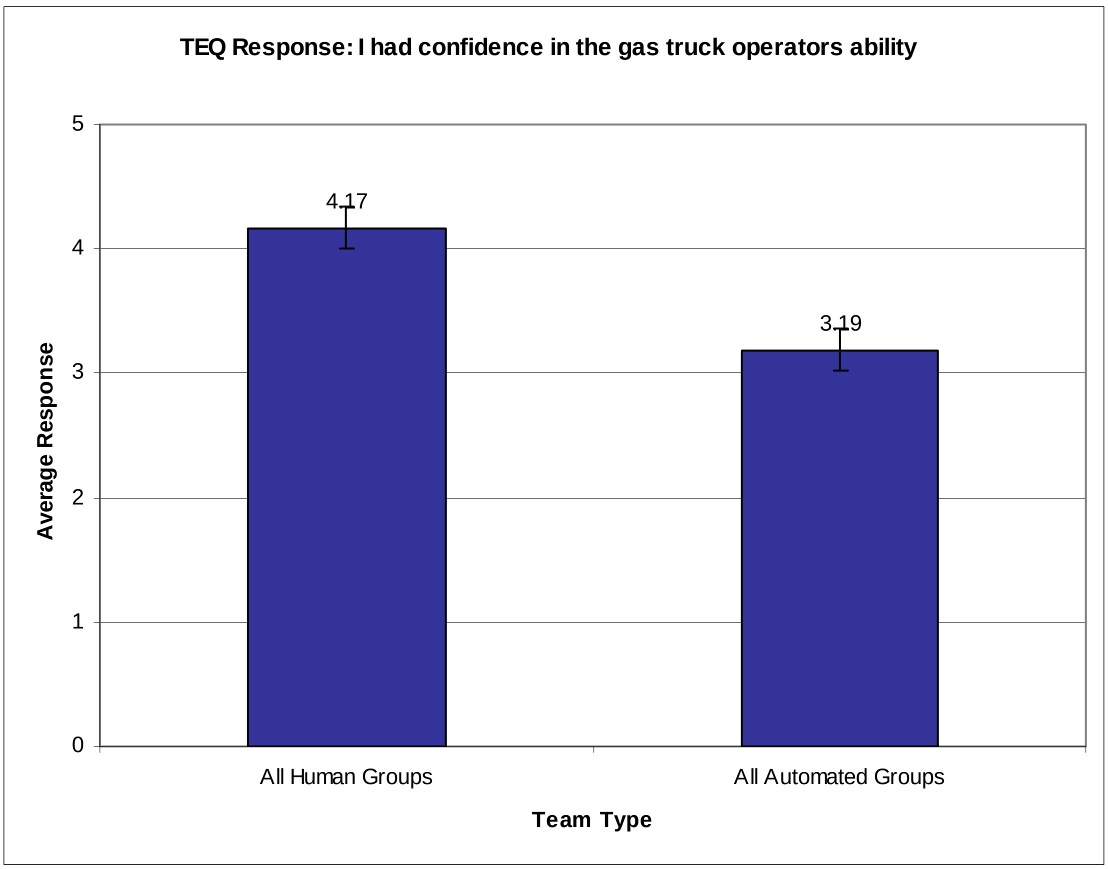

Figure 7. Average Response by Group Type.

3. Transition Effects

In this study the participants were told either their first scenario would be conducted with a human participant or with the automated agent. Prior to playing with this team composition, the participants were asked to take a pre-scenario TEQ (Attachment A). Immediately after the scenario ended the participants were asked to take the post scenario TEQ (Attachment B). The teams that played in the human condition first had an average score for question 5 of 3.94 for the pre-scenario TEQ and an average score of 4.06 for the post scenario TEQ, resulting in an average increase in confidence in the gas truck operator’s ability of .12. A two-tailed Sign test indicated no significant difference (z=.32,p=.625) The teams that played in the automated condition first had an average pre-scenario TEQ score for question 5 of 3.72 and an average score of 3.06 for the post scenario TEQ, resulting in an average decrease in confidence of the gas truck operator’s ability of .66. A two-tailed Sign test revealed a significant difference (z=2.66, p=.0039). Table 4 summarizes the results.

Pretest Human Average Score	Post Test Average Score for Human Scenario First	Net Change
3.94	4.06	0.12
Pretest Automation Average Score	Post Test Average Score for Automation Scenario First	Net Change
3.72	3.06	-0.66

Table 4. Transition Effect from Pre scenario to Post scenario.

After each team type finished their first scenario, the other team type was utilized to complete the second scenario. Immediately upon completion, another post scenario TEQ was completed. The teams that transitioned from a human player to the automated agent scored an average of 3.33 for question 5 on the post scenario TEQ, resulting in an average decrease in confidence in the gas truck operator’s ability of .73. A two-tailed Sign test revealed a significant difference (z=2.88, p=.002) The teams that transitioned from an automated agent to a human player scored an average of 4.28 for question 5 on the post scenario, resulting in an average increase in confidence in the gas truck operator’s ability of 1.22. A two-tailed Sign test revealed a significant difference (z=3.89, p=.0001) Table 5 summarizes the results.

Post Test Average Score for Human Scenario First	Post test Average Score for Automation Scenario Second	Net Change
4.06	3.33	-0.73
Post Test Average Score for Automation Scenario First	Post test Average Score for Human Scenario Second	Net Change
3.06	4.28	1.22

Table 5. Transition Effect of Changing Team Type.

C. TEAM PERFORMANCE

1. C3Fire Cell Status

At the conclusion of each scenario, the cells on the C3Fire matrix that caught on fire at any time during the scenario could be in one of three states: still on fire, extinguished, or burned out. Still on fire indicated the team never attempted to fight the fire in that cell or time expired prior to that cell being extinguished, extinguished meant that the team successfully used the trucks to put the fire out; and burned out meant that the team did not successfully extinguish the fire, but the cell had been on fire for a long enough period of time to stop burning. Human teams had an average of 18.00 (*SD*=27.52) cells still on fire, an average of 27.33 (*SD*=8.56) cells extinguished, and an average of 106.33 (*SD*=102.80) cells that had burned out at the conclusion of the scenario. Automated teams had an average of 24.67 (*SD*=27.82) cells still on fire, an average of 33.67 (*SD*=12.56) cells extinguished, and an average of 148.08 (*SD*=120.42) cells that had burned out at the conclusion of the scenario. Figure 8 shows the average final cell status for each type of team. A two-tailed Sign test was conducted to determine if team type had an effect on the cell status at the end of the scenario. No statistical significance was found for number of cells on fire (p=.45), number of cells extinguished (p=1.0), or number of cells burned out (p=.15).

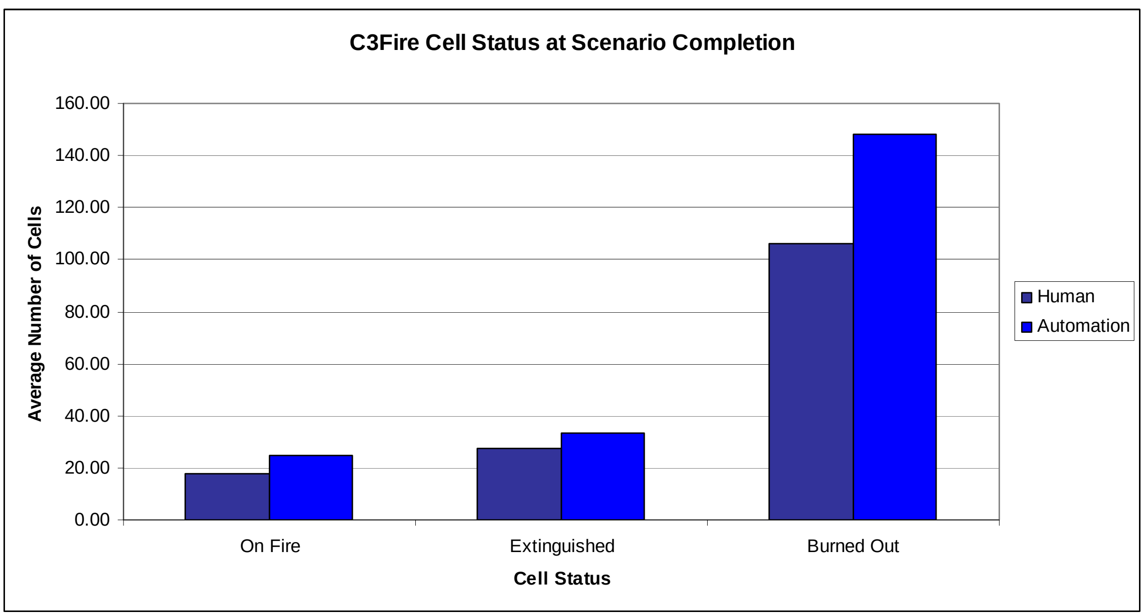

Figure 8. Average C3Fire Cell Status at Scenario Completion.

2. Team Success Rate in Completely Extinguishing the Fire

The C3Fire scenario used for this study produced a fire that could be extinguished by an effective and coordinated team. Fourteen of the twenty-four (58.3%) sessions ended prior to the twenty minute time limit because the fire had been completely extinguished. Figure 9 shows the number of teams able to successfully extinguish the fire by team type and order.

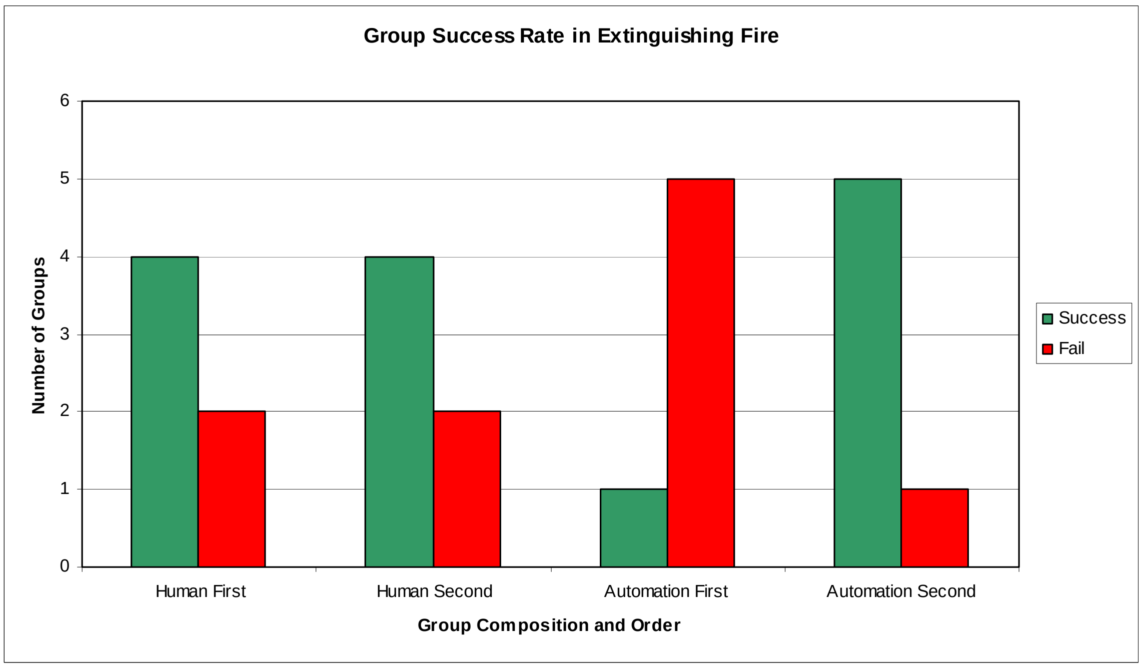

Figure 9. Team Success in Extinguishing Fire.

3. Scenario Length

The C3Fire session ended either at the artificial twenty minute time limit or when the team successfully extinguished the entire fire. Ten of the twenty-four (41.7%) sessions lasted the entire twenty minutes. Table 6 shows the length of each session by team type and order.

Team Type and Order	Team 1	Team 2	Team 3	Team 4	Team 5	Team 6
Human First	20	20	7.95	7.72	8.1	11.83
Human Second	8.55	7.2	8.15	20	20	8.52
Automation First	20	10.52	20	20	20	20
Automation Second	8.17	8.52	8.3	20	14.35	8.12

Table 6. Session Lengths in Minutes.

The average scenario length for human teams was 12.34 minutes (*SD*=5.77), while the average scenario length for automated teams was 14.83 minutes (*SD*=5.65). Figure 10 shows the average scenario length by type of team. A t-test was conducted to determine if the average scenario length was different for each team type; no statistically significant results were found ($t(11)=1.07$, $p=.30$).

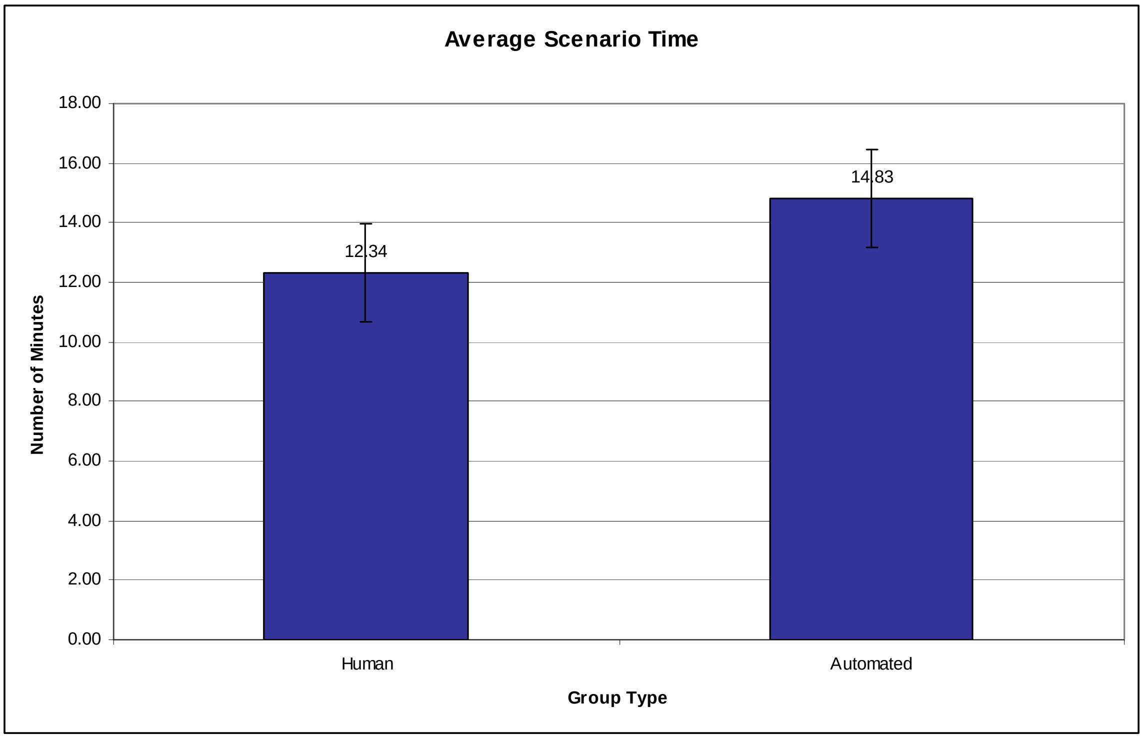

Figure 10. Average Scenario Length by Team Type.

D. TASKING NON-ASSIGNED UNITS

During the C3Fire training process, participants were instructed to move only the units assigned to their role, unless there was a compelling reason to task other participant's units. C3Fire is able to determine which participant tasked which units, thereby enabling researchers to determine the number of times a unit was tasked by a participant other than the one with the primary responsibility for that resource. Table 7 shows the total number of taskings to other player's assets by player role and team type. A paired t-test was conducted on the total number tasks issued to units by a player other than the designated player. The results were statistically significant ($t(11)=2.58$, $p=.03$) indicating that the number of tasks issued to non-assigned units was different between the two types of teams.

Player Role	Human Teams	Automated Teams
Command & Control	3	90
Fire Truck	19	62
Water Truck	33	34
Gas Truck	1	2
Total	56	188

Table 7. Number of Tasks Issued by Participants to Resources of Other Participants.

Further analysis was conducted for tasking of just the gas trucks by other participants. Table 8 shows the number of tasks issued by other participants to the Gas Trucks. A paired t-test was conducted on the total number tasks issued to the gas trucks by a player other than the gas truck operator. The results were statistically significant

($t_{(11)}$=2.41, p=.03), indicating that the number of tasks issued to the gas trucks by other participants was different between the two types of teams.

Player	Human Gas Truck	Automated Gas Truck
C+C	0	64
Fire	5	34
Water	7	5
Team	12	103

Table 8. Number of Tasks Issued by Other Participants to the Gas Trucks.

Figure 11 shows a combination chart of tasking of the gas truck operator by team type and the total number of team taskings by other than non-assigned participants by team type. The chart indicates the total number of times each role tasked the gas tuck operator in the human and automated condition, as well as how much each role tasked the other trucks.

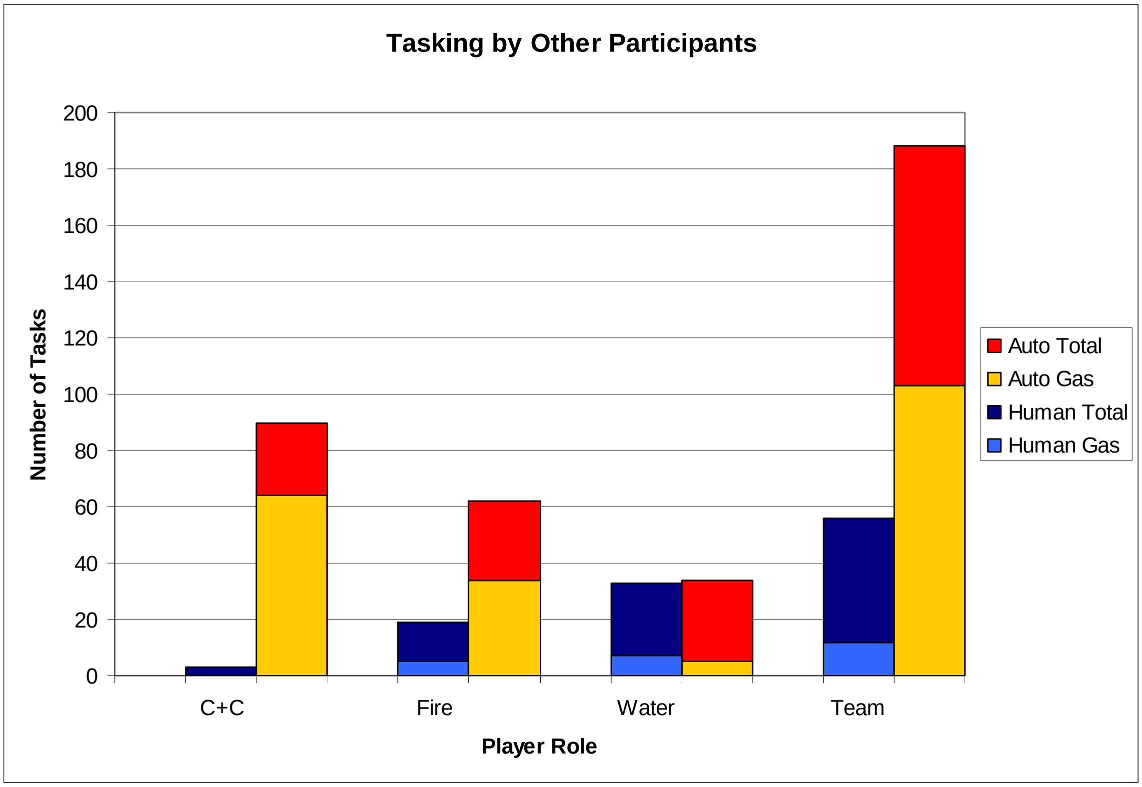

Figure 11. Non-Assigned Member's Number of Taskings to the Gas Truck and the Total Team by Team Type.

V. DISCUSSION

A. HYPOTHESIS ONE

The hypothesis that teams consisting of only human members will communicate in a different fashion than teams comprised of human members and an automated agent is partially supported by this research. The difference in the number of messages sent by team composition was not statistically significant. Furthermore, the number of messages sent to the confederate for each team type was not significantly different. One possible explanation why there were no differences found in the number of messages sent is the low number of messages actually sent. Since all players were able to view the entire map and the actions of the other players, the use of chat to communicate intent was often unnecessary. For example, when a player moved a truck to a new location on the map, an indication of the new intended location for that truck was displayed, thereby eliminating the need to inform the rest of the team.

Additionally, the messaging tool diverted participants' attention and required players to spend their time sending and reading messages rather than managing their assets. Given this configuration, messages were often overlooked when participants experienced a heavy workload. Finally, since all scenarios were not the same in duration (because some teams extinguished the fire more quickly than others), the number of messages sent were analyzed per unit of time. The resulting analysis did not yield a significant difference.

The next step in the analysis was to identify the types of communications utilized by each team type and how each type of team communicated to the confederate. No differences were found in the types of communications between each team type (i.e., projection, push, decision/tasking, coordination, acknowledgment, pull and chatter). Only one statistically significant difference was found in the analysis of the type of communications sent to the confederate. The number of messages 'pushed' to the human confederate was significantly greater than the number of messages 'pushed' to the automated confederate. A message labeled as 'push' is sent to a player without it being specifically requested. This information could then be utilized to build awareness or make decisions. The teams playing with the human confederate may have thought it appropriate to pass this type of information to a human player, while the teams playing with the automated confederate may have assumed that the automated player already had access to the information.

There were other examples of the automated player being treated differently than the human player. Participants attempting to coordinate with – or direct the actions of - a human player would allow a reasonable time lag for the human to process the information and take action, but when these same participants thought they were interacting with an automated agent, they desired an immediate response. When interacting with another human player it was also acceptable for the human to continue the current task and then address the new task, but when the participants interacted with the automation, they desired an immediate stop in the automation's current actions to address the new task. One possible suggestion is that the participants believed the automated agent could process in parallel, but the human could only process or perform one action at a time.

This research effort only partially supported the hypothesis that human-human teams communicate differently than human-automation teams. Christoffersen and Woods (2002) suggest that the 'overhead' associated with communication in a human system incurs a relatively low workload cost in open work environments, but utilizing automation in the same situation will increase the cost. The C3Fire microworld utilized in this study did not take advantage of an open work environment; the participants were not allowed to communicate through any method other than the chat box. This study was not able to determine the benefit of open work environments to human communication, but does support the concept that closed work environments drive up the cost for communicating with automated agents as compared to human agents.

The work of Sycara and Lewis (2004), which suggests communication is one of the biggest challenges in human-automation teams, is strongly supported by this study. Their belief that the users' ability and willingness to communicate with the automated agent is a limiting factor held true in this study. While under heavy workload, the participants appeared to put minimal effort into the task of communicating with the automated agent.

B. HYPOTHESIS TWO

The second hypothesis, that the human teams would have a higher team efficacy, was supported by this research. The Team Efficacy Questionnaire (See Appendix B) was analyzed for differences in confidence level for each team role. No significant differences were found for the roles of command and control, fire truck operator, or water truck operator. However, question number five, (*I had confidence in the gas truck operator's ability to properly perform the role*), provided significant results. When analyzed for an order effect, either human-human or human-automation team first, no significant results were found indicating that order had no effect on the perceived confidence level of the gas truck operator. When question number five was analyzed for the type of team, containing either a human or automated agent, significant differences were found with respect to the perceived confidence level of the gas truck operator. The participants rated the human confederate significantly higher than they rated the automated confederate.

The style of game play of the participants appears to be reflected in the TEQ. The participants were much more likely to override the actions of the perceived automation than the human. When the gas truck was under human control, there were only 12 instances (the fewest of any truck) where the participants chose to issue a command to the gas truck. When the gas truck was controlled by the perceived automated agent, there were 103 commands (the most of any truck) issued to the gas truck by the participants. The difference in number of commands issued suggests that the participants had more confidence in the human gas truck operator. Some participants also elected to ask the human gas truck operator for permission to move a gas truck, but no participant ever attempted to communicate with the automated agent prior to moving a gas truck.

Bandura‘s (1997) assertion that group efficacy may be more difficult in automated teams because the human players may not be familiar with the level of competence with the automation is supported by this research. Most of the participants were unsure of the level of competency of the automation and chose to monitor its actions very closely. Deviations from what the human player believed to be the best course of action often resulted in the participant interfering with the automation. This breakdown in roles and responsibilities affected group efficacy, and appears to be linked to the results of the TEQ.

Since team efficacy is often more difficult to establish and maintain in human-automation teams, those who design complex systems need to give due consideration to the method by which human and automated agents interact with one another. A possible area for improvement would be to provide the automated agent with an ability to communicate in a manner similar to human communication. The chances would be better that the automated agent would be understood and accepted as an equal team member.

C. HYPOTHESIS THREE

Based on the comments from the debriefs with the participants, such as ‘I did not trust the automated gas trucks’, it was quite apparent that the level of trust in the automated gas truck operator was considerably less than that of the human gas truck operator (See Appendix C). When the confederate played the role of the automated gas truck operator, there was a statistically significant increase in the number of commands sent to all trucks by participants not responsible for those assets. A likely reason this occurred is that once trust in the automation broke down, the team lost its sense of roles and responsibilities. The players then began to spend energy managing other assets, which left their own assets partially unattended. The second possible contributing factor is that the participants were heavily tasked. As participants began to compensate for the automated gas trucks, they were unable to properly fill their assigned role causing other team members to intervene.

Although not statistically significant, potentially due to the low number of messages, the teams playing with the automated confederate tended to send a greater number of decision/tasking messages to the confederate indicating the participants were making decisions and tasking the automation, not trying to provide information for the automation to make a decision.

According to literature cited earlier (Christoffersen & Woods, 2003), feedback is a crucial element to the success of a human-automation team. Feedback is crucial since the human team members often lack an understanding of the automation's intentions. As the complexity of the automation increases, the level of feedback needs to increase. In this study a feedback mechanism for the automation was in place, but may have been too cumbersome to useful. This resulted in a breakdown in trust between the human team members and the automation. Since the appropriate feedback mechanisms were not in place, most participants chose to strictly monitor the automation and intervene once the barrier of trust had been violated. Trust needs to be a top consideration in the design of any automated system that will interact with human team members. Once the bond of trust is broken between the automation and the human team members, the team will lose effectiveness.

This study expected a greater number of communications between the participants about the automated agent. Although most of the participants were concerned about the competency of the automated agent, they did not express that concern to the other participants. Additionally, the participants did not ask each other what their thoughts were about the automation. There were no collective efforts by the participants to evaluate the automated agent. One possible explanation is that the automated agent did perform at the same level as the human player, which did not warrant the need for any concern. Another possible explanation is that the participants were unsure of the automated agent’s abilities and chose to monitor it in an effort to gather more information to make a decision.

When the automated agent’s performance was adequate, there was no real reason to ask for the rest of the participant’s thoughts. But when the performance of the automated agent became substandard, instead of communicating with the other human team members, the participants choose to just deal with the automated agent at a personal level. At this point the roles and responsibilities of the team may have broken down to the point where the participants felt it necessary to concentrate on only their actions. Another possible explanation is that the degradation in performance of the automated agent was not significant enough to warrant concern.

VI. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSION

Given the importance of automation to the future of military operations, it is vital that new technology and automated systems are designed and utilized in the most effective manner possible. In a resource constrained environment, these new systems that require humans and automation to work together must take into account the differences in how combined teams function as compared to human teams. These differences need to be researched and better understood in order to maximize overall performance of these new teams.

The concept asserted by Sheridan (2002), that automated systems are designed based on automating the most basic functions, will not suffice in the future. Christoffersen and Woods (2002) suggest that the two critical characteristics that need to be present in a design from the beginning are observability and directability. The human users need to be able to see and understand what the automation is doing and intends to do, along with the ability to change the automation’s actions as necessary. Other suggestions include the need for better user interfaces and displays to increase coordination capabilities and the incorporation of better feedback channels to increase awareness and understanding. The key to effective design and implementation of human-automated teams is to understand the nature of the differences between human-human teams and human-automation teams and design to minimize their impact on performance.

In the present study, 36 participants were organized into four-member teams (three participants and a confederate) to participate in a team performance experiment. Each team participated in two C3Fire scenarios, one with the confederate acting as a human player and the other with the confederate acting as an automated agent playing the same role. Both scenarios were necessary in order to compare the nature of the interactions across both types of teams.

The original hypothesis, that the two team types would communicate differently, was only partially supported. The second hypothesis, that the human teams would have an overall higher team efficacy, was supported. The third hypothesis, that the trust among the team with the automated agent would be lower, was also supported.

The results of this study apply directly to the HSI domains of manpower, personnel, and human factors engineering. Manning requirements are driven by system design, but just adding automation without evaluating the effect on the overall system performance will not lead to proper manpower decisions. Additionally, these new automated systems may be utilized to reduce manpower, but if not properly designed and implemented may lead to less productivity. The type of personnel recruited to work on these new teams will also undoubtedly change. Working with these new human-automated teams will require personnel with aptitudes and skill sets related to advanced technologies. In order for these new systems to be operated, maintained, and supported, it will be necessary for designers to adjust system design while considering manpower and personnel implications. Additionally, the automation itself needs to be designed with consideration for the manpower and personnel who will be recruited to interact with the systems.

The design of these new systems must also be guided by the appropriate human factors engineering principles that take into account the variability of human skills and abilities, the limits of human cognition, and manner in which trust is established and eroded. New types of interfaces, displays, and information sharing devices need to be designed and utilized to maximize team cognition. Effective feedback mechanisms that allow humans to understand and communicate with automation in an effortless fashion need to be incorporated into the design.

B. RECOMMENDATIONS

The empirical findings of this study warrant the consideration of designers, engineers, and acquisition professionals. This study suggests that system designers should consider the differences in communication, team efficacy, and trust between human-human and human-automation teams and work to improve the manner in which human – automation teams perform. Appropriate communication protocols should be employed to facilitate efficient and complete transfer of information between all members of the team. The system must be designed so that the human users are aware of the automation's current state and intended actions. In order to increase team efficacy, the human users need to be able to understand how the automation functions. The ‘hide everything in the black box approach’ must be abandoned; the abilities and shortcomings of the automation need to be transparent to the human users.

With respect to trust, several design implications can be derived from this study. First, trust in automation is rapidly eroded when the automation does not perform as expected. One possible (but unrealistic) solution is to acquire automated systems that are completely reliable. A better solution is to provide users with cues that allow them to quickly and accurately calibrate their trust to the automation. Human team members need to know when to trust and when not to trust automated team members. Ignoring the performance differences due to team composition and continuing to design systems that do not account for such differences may have a profound impact on future military team capabilities.

C. FOLLOW-ON RESEARCH

Research in this area is still relatively new. There are many opportunities to advance our understanding of how to integrate automation and automated agents effectively into military teams. Further research is necessary to fully understand the differences in the interactions between members of human teams and human-automated teams. For example, one key improvement that could be made to the present study would be to standardize the scenarios for duration. The scenarios need to be designed so that all teams would play for the same amount of time under all conditions. This could be accomplished by generating multiple fires throughout the scenario that are not capable of being fully extinguished before time elapses. In order to reduce large variability in team performance, additional training time should be allocated. Multiple C3Fire sessions prior to conducting actual data collection would lead to more consistent performance among teams. The final suggestion would be to conduct another study that would look at a proximity factor. To what extent does proximity affect trust and efficacy? If the participants never met face to face, would their trust and efficacy still be higher in the human-human condition than the human-automation condition?

Research should also be conducted in the laboratory with other simulations, as well as in field settings. Research with actual autonomous agents and the actual user population needs to be conducted to ensure that the results of the present study are valid beyond the experimental setting reported herein.

Results of this study reveal compelling evidence that the addition of an automated agent to a human team changes the nature of communications amongst team members, impacts team efficacy, and alters the task distribution of the team. Statistical analysis showed that even though the total number of communications amongst both group types was equivalent, the type of communication was different. In human - human teams, information was more likely to be shared to aid in decision-making, while on human-automation teams, communications were more likely to be directive in nature. While the presence of an automated agent did not affect overall team performance, it did affect trust, efficacy, and task distribution of the team. Statistical analysis indicated that human team members had greater confidence in another human team member compared to the automated agent. Analysis also showed that the human team members trusted the automated agent less, which directly affected task distribution.

The results of this study suggest that there are important differences in the interactions of human – human teams compared to human-automation teams and demonstrate the need to consider the unintended impact of including automated agents as team members in military environments and other complex and dynamic systems. Proper design and implementation of future military systems will lead to new capabilities that will increase flexibility, adaptability, and overall mission effectiveness.

APPENDIX A. PRE TEAM EFFICACY QUESTIONNAIRE (TEQ)

1. Default Section

1. What is your assigned role on the team?

- ◯ Command and Control
- ◯ Fire Trucks
- ◯ Gas Trucks
- ◯ Water Trucks

2. Please answer the following questions about the team.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	N/A
My role is clear in helping to meet the team's objectives.	◯	◯	◯	◯	◯	◯
I am confident in my ability to properly perform this role.	◯	◯	◯	◯	◯	◯
I have confidence in the command and control operator's ability to properly perform the role.	◯	◯	◯	◯	◯	◯
I have confidence in the fire truck operator's ability to properly perform the role.	◯	◯	◯	◯	◯	◯
I have confidence in the gas truck operator's ability to properly perform the role.	◯	◯	◯	◯	◯	◯
I have confidence in the water truck operator's ability to properly perform the role.	◯	◯	◯	◯	◯	◯
All necessary roles on the team are being filled.	◯	◯	◯	◯	◯	◯
The proper operators are filling the correct roles on this team.	◯	◯	◯	◯	◯	◯
This team will be able to fulfill its responsibilities.	◯	◯	◯	◯	◯	◯
This team will work together to get the job done.	◯	◯	◯	◯	◯	◯

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APPENDIX B. POST TEAM EFFICACY QUESTIONNAIRE (TEQ)

1. Default Section

1. What was your assigned role on the team?

- ◯ Command and Control
- ◯ Fire Trucks
- ◯ Gas Trucks
- ◯ Water Trucks

2. Please answer the following questions about the team.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	N/A
My role was clear in helping to meet the team's objectives.	◯	◯	◯	◯	◯	◯
I was confident in my ability to properly perform this role.	◯	◯	◯	◯	◯	◯
I had confidence in the command and control operator's ability to properly perform the role.	◯	◯	◯	◯	◯	◯
I had confidence in the fire truck operator's ability to properly perform the role.	◯	◯	◯	◯	◯	◯
I had confidence in the gas truck operator's ability to properly perform the role.	◯	◯	◯	◯	◯	◯
I had confidence in the water truck operator's ability to properly perform the role.	◯	◯	◯	◯	◯	◯
All necessary roles on the team were being filled.	◯	◯	◯	◯	◯	◯
The proper operators were filling the correct roles on this team.	◯	◯	◯	◯	◯	◯
This team was able to fulfill its responsibilities.	◯	◯	◯	◯	◯	◯
This team worked together to get the job done.	◯	◯	◯	◯	◯	◯

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APPENDIX C. PARTICIPANT COMMENTS FROM DEBRIEFINGS

1. I think the gas truck AI sucks.
2. Yes it was a little confusing with the (automated) gas trucks.
3. It was difficult to type commands to the automation.
4. The (automated) gas trucks screwed us.
5. In the first scenario (human operator) I knew as the command and control guy that I knew that I was supposed to tell the gas trucks what to do if I did not like what they were doing, but I noticed one truck kept being inactive. I think it was G9, so I kept typing G9 refuel something and I think I typed it in four or five times before the thing finally moved. So either I wasn't doing it right or I think I finally put it in quotations so maybe it was the quotation marks it was looking for.
6. I did not trust (automated) gas trucks so I refueled myself initially.
7. I(Command and Control Operator) did not monitor the other trucks, just the (automated) gas trucks.
8. The automation needed more monitoring that the human.
9. Communication was more difficult (with the automation).
10. Sometimes he (the automation) did what I said, sometimes he did not, sometimes he seemed to do his own thing.
11. I did not think the automated gas trucks were as easy to work with. Towards the end it seemed like I was having to tell them what to do as if I was a gas truck guy. They weren't doing what I thought they should do. Toward the end they were not really going to where they needed to be, but when we actually had a person there they were going to where you would just guess they needed to go without me having to tell them.
12. I didn't like working with the computer (automation) very much. I did not want to think about any special commands. I just wanted to be able to type what I wanted to say. Like when you are working with a human you just say 'hey get over there'. It seemed like it was doing a good job initially, but there towards the end, it wasn't getting fuel to the fire trucks.

13. I thought among the people it was easier to coordinate than with the automation because we all generally had the idea to box the fire into that corner.

14. The change (between the scenarios) was the Intelligent Agent and it sucked ass ‘yeah it sucked’ (background).

15. The gas truck intelligent agent thing, well it sucks. It didn’t respond to the commands that I would send. I am the command and control and nothing that it is doing is making sense so I am typing furiously commands to it or then just trying to move the damn truck.

16. I am like refuel (to the automated agent) and then it doesn’t move so I try and move it and then it moves back.

17. The automated, yeah that was terrible because I could tell when a person was doing it.

18. Yes I did notice a difference in the two scenarios. In the second scenario (working with humans), we did not have as bad of time running out of fuel and water (as compared to working with the automation). I think the collaboration was a lot better. They knew what I was going to do and they were able to react to that.

19. Yeah it was definitely difficult to coordinate (with the automation). I was like, ‘what do I type?’

20. It was kinda hard to get my point across (with the automation) with the typing. I am used to voice chat.

21. I thought it was easier when the person moved the gas truck because the automation was overriding my commands.

22. I think the biggest thing that I noticed just from monitoring all the chat especially when you have an actual person as the gas truck I think in the chat box there needs to be some kind of line or something that says who this is actually from because you are getting all the commands from people and you don't know where they are coming from so you can't respond back that person without saying 'oh I assume Player B sent this so let me send it back to B'. You need some way to know who the chat is coming from. I thought it was definitely easier the second time (working *with* automation) when you don’t have a physical person sitting at a gas command and you don’t have another set of commands coming in, but that's just from lack of message traffic.

23. But the other thing is the umm. I wasn't looking at where the trucks actually were, the (automated) gas trucks in the second scenario, like if they actually went to a station to fill up, but it seemed like they were out of gas and then instantly they were refueling, so like they didn't… I don’t know if they went to a gas station to fill up, I never even looked. But it seemed like they refueled with their automated command a whole lot quicker than we could have refueled ourselves. It just seemed like I had no problems with (automated) gas. I didn’t look to see if I was out of gas or at a gas station or not, but all of the sudden everything… nothing ever ran out of gas. (Other team member) "Yeah I just quit checking the gas because I was so full for so long that I said I do not even need to look at it."

24. It appeared that the gas trucks refueled a whole lot quicker with the automated command.

25. I did not see any difference between the two scenarios. The automated thing did a good job. A couple of times it would not move through the fire, but it is not supposed to.

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