Exploring the Relationship between Anticipatory Pushing of Information and Teammate Trust

by

Shawaiz Bhatti

A Thesis Presented in Partial Fulfillment
of the Requirements for the Degree
Master of Science

Approved July 2021 by the
Graduate Supervisory Committee:

Nancy Cooke, Chair
Erin K. Chiou
Robert Gutzwiller

ARIZONA STATE UNIVERSITY

August 2021

ABSTRACT

The prevalence of autonomous technology is advancing at a rapid rate and is becoming more sophisticated. As this technology becomes more advanced, humans and autonomy may work together as teammates in various settings. A crucial component of teaming is trust, but to date, researchers are limited in assessing trust calibration dynamically in human-autonomy teams. Traditional methods of measuring trust (e.g., Likert scale questionnaires) capture trust after the fact or at a specific time. However, trust fluctuates, and determining what causes this might give machine designers insight into how machines can be improved upon so that operator's trust towards the machines is more properly calibrated. This thesis aimed to assess the validity of an interaction-based metric of trust: anticipatory pushing of information. Anticipatory pushing of information refers to teammate A anticipating the needs of teammate B and pushing that information to teammate B. It was hypothesized there would be a positive relationship between the frequency of anticipatory pushing and self-reported trust scores. To test this hypothesis, text chat data and self-reported trust scores were analyzed in a previously conducted study in two different sessions (routine and degraded). Findings indicate that the anticipatory pushing of information and the self-reported trust scores between the human-human pairs in the degraded sessions were higher than the routine sessions. In degraded sessions, the anticipatory pushing of information between the human-human pairs was associated with human-human trust.

ACKNOWLEDGMENTS

The completion of this document would have not been possible without the help I received from so many gracious and wonderful people. I would like to acknowledge first my advisor, Dr. Nancy Cooke, who suggested and supported this idea from the very beginning. She has been a great mentor who generously shared her ideas with me and also mentored me throughout what was possibly my most difficult academic journey thus far. Next, I would like to thank Dr. Erin Chiou and Dr. Robert Gutzwiller for also supporting this project and sharing their ideas on how to move forward with it. I would also like to thank them for agreeing to be a part of my committee for my thesis. A special thank you is in order to Dr. Mustafa Demir who has guided and mentored me in all aspects of writing this document and conducting statistical analyses. His professional expertise was vital in the production of this document for if it were not for his patience, professionalism, and mentoring I would not have gotten this far. I would like to acknowledge all of the friends I made during my time as a student in the HSE program. They have supported me and carried me through the finish line and at times pulled me out of the dark void of self-doubt and fear of failure. I will be forever grateful to them. And last, but certainly not least, I would like to acknowledge my family: my sister, Shaigan Bhatti, for always being my biggest supporter in life and my father, Saeed Bhatti, for always being a shining beacon of strength and perseverance. Their support and love gave me clarity and guidance, and my gratitude towards them cannot be put into words.

In this thesis, some portions of Chapters 2, 3, and 4 are based on the following submitted report:

Bhatti, S., Demir, M., Cooke, N., & Johnson, C. (2021, September 15). Assessing Communication and Trust in an AI Teammate in a Dynamic Task Environment. *Human-Centered Systems for Our Digital World*. The 2021 IEEE International Conference on Human-Machine Systems. Virtual. Germany.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Figure Page

CHAPTER 1

INTRODUCTION

Technology is advancing at a rapid rate. Much of this advancement can be seen in the field of machine learning and artificial intelligence (AI) as highly autonomous technology (e.g., AI, robots, and synthetic agents) continues to permeate nearly all aspects of everyday life. It is not a stretch to say that autonomous technology is everywhere. There are many examples of how autonomous technology advances in high-risk environments, such as the new Mars Perseverance Rover. This new autonomous technology differs from its predecessor, Mars Curiosity Rover, in that it has the independence to cover ground without consulting human operators on Earth. It also has planning features that allow it to shift its daily activities around to be more efficient with openings in its daily schedule. The Mars Perseverance and Curiosity Rover are examples of advanced autonomous technology that provide opportunities for studying how these advanced technologies might assist, collaborate, and even team with humans.

A team can be defined as a sociotechnical system that contains two or more heterogeneous and interdependent team members who interact with each other to complete a common goal or task (Cannon-Bowers, Salas, & Converse, 1990). This definition is given for human-human teams, but there are also other types of mixed-teams such as human-canine teams (Ferworn et al., 2006). In this study, the mixed-teaming concept called human-machine teaming (HMT) is considered. An HMT is a sociotechnical system in which two or more heterogeneous and interdependent team members (either humans or autonomous technology) interact with one another to accomplish a common goal or task (Demir et al., 2017).

Consequently, the main focus of the current study is trust in a human and autonomous teammate in an HMT context. The current study aims to assess whether anticipatory pushing of information is a valid metric for measuring trust in a teammate using interactions as the unit of measurement. The specific interactions being used as units of measurement are interactions in which the pushing of information based on anticipated needs occurs. It is hypothesized that as a teammate anticipates another teammate's needs and pushes information to that teammate based on anticipated needs, there will be increased trust towards the teammate who pushed the information. This will lead to higher levels of interpersonal trust towards that teammate.

CHAPTER 2

BACKGROUND

Human-Autonomy Teaming

Automation vs. autonomy. In order to understand how people might team with autonomous technology and how trust might be an important cognitive construct to consider when studying HMT, it is important to understand what autonomous technology is and how a machine can be classified as automation or autonomy. A machine is a "device, having a unique purpose, that augments or replaces human or animal effort for the accomplishment of physical tasks" (Encyclopedia Britannica). Within the context of the machine, Sheridan (2002) underlines a three-part definition of what automation is: "(1) the mechanization and integration of the sensing of environmental variables (by artificial sensors); (2) data processing and decision making (by computers); and (3) mechanical action (by motors or devices that apply forces on the environment)" (p.9). On the other hand, autonomy can be thought of as more advanced and sophisticated automation that can carry out tasks independently or in conjunction with human input and oversight (McNeese et al., 2018). It is important to note, however, that though machines may have some autonomous capabilities and functions, some functions of the machine may not be autonomous. This may be because in the context of teaming, it may be of interest to have the machine interact independently, but also interdependently with other team members, therefore, the concept of a fully autonomous machine is not aligned with a machine as a teammate.

Beyond definitions, though, the difference between automation and autonomy can be thought of as a spectrum with automation being on the low end in which the technology is not autonomous and requires human oversight and intervention, and autonomy on the high end, in which the technology is independent of human input and oversight (Endsley & Kaber, 1999; Endsley & Kiris, 1995; Parasuraman, Sheridan, & Wickens, 2000; Sheridan & Verplanck, 1978). Accordingly, the overlap with all of these classifications seems to be that: (1) on the low end, the human does everything; (2) in the middle, the technology carries out a task or informs the human of certain variables to help the human make a decision; and (3) in the higher levels the autonomous technology is mostly (but still only partially) autonomous in the sense that it has some autonomous capabilities but not all and can work with humans in a team-like setting.

Autonomy as a team member. Autonomous technology is becoming more sophisticated, and thus, closer to teaming with humans in various professional spheres. Teaming with humans indicates that autonomy will have to work with humans as a teammate and an independent entity fulfilling a role not completed by any other teammate(s) on the team (O'Neill et al., 2020). This is important, especially in the context of trust, because in a team, team members have "heterogeneous roles," meaning that each team member has a specific role that determines his or her primary responsibilities pertaining to their tasks (Cooke & Gorman, 2009). Team members need to be able to carry out their responsibilities interdependently so that the team can achieve its overall goal.

Furthermore, autonomy must be "interdependent" with the team to achieve the team's overall task (Lyons et al., 2019; Lyons et al., 2018; Brill et al., 2018; O'Neill et al., 2020; Wynne and Lyons, 2019; Haimson et al., 2019). Research has indicated that interdependence with an autonomous agent helps human teammates perceive the autonomous agent (technology) as more cooperative, friendlier, and as if the technology provided the human teammate with high-quality information (Nass et al., 1996; O'Neill et al., 2020). And although these outcomes might seem beneficial in the sense that they will make the human trust the autonomy more, they do not necessarily help humans have better-calibrated trust toward the autonomy. Nevertheless, teammate interdependence is still a necessary aspect for trust development, as explained by Johnson and colleagues (2012). The researchers posit that though there might be a consensus that as technology becomes more autonomous, the better it will be for people. This is not the case when it comes to HMT settings. Johnson and colleagues (2012) conducted a study that showed that to the extent that autonomous agents carried out tasks perfectly and independently, it was more difficult for the human teammates to understand what was happening and what behaviors the agent would act out. Not being aware of teammates' actions and intentions is referred to as opacity which means the inability of team members to realize the current state of other team members to maintain effective team performance (Johnson et al., 2012). Opacity, therefore, is an outcome of teammates not having a sense of interdependence towards each other but rather an exaggerated sense of independence. Indeed, interdependence of teammates is necessary for effective team performance and is connected to benevolence (Johnson & Bradshaw, 2021).

The concept of “benevolence” in an autonomous teammate as a necessary characteristic has been discussed by many researchers recently (e.g., Brill et al., 2018; Lyons et al., 2018; O’Neill et al., 2020; Panganiban et al., 2020; Lyons et al., 2019; Wynne and Lyons, 2019). From a teaming point of view, benevolence can be thought of as having teammates having each other’s best interest in mind and providing support when necessary (Lyons et al., 2019). It can also be thought of in terms of how teammates act such that benevolent teammates help each other so that the team can accomplish its goal(s) (Brill et al., 2018). Benevolence can lead to the fostering of trust between teammates, which would be crucial if teammates found themselves in high-risk and highly uncertain situations (Panganiban et al., 2020).

Trust in Human-Machine Teaming

Trust as a cognitive construct has been studied for a long period of time in many different fields including economics, political science, management, organizational psychology, and human factors. Although the origins of trust research can trace back to the 50’s when Albert Tucker popularized the prisoner’s dilemma (Tucker, 1950) to more recent work done in the human factors sphere (Lee & See, 2004; Hoff & Bashir, 2015), one major problem that still remains is that scholars differ on how to define and measure trust (Rousseau, Sitkin, Burt, and Camerer, 1998; Lee and See, 2004; Sheridan, 2019) which creates issues for conceptualizing and understanding what type of trust is being measured. Regardless, there have been some definitions that have been more widely accepted than others.

In general, trust can be defined as, “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party” (Mayer, Davis, & Schoorman, 1995, p. 712). McKnight and Cummings’ (1998) define trust as, “to mean that one believes in, and is willing to depend on, another party,” (McKnight & Cummings, 1998, p. 474). Das and Teng (1998) define trust as, “the degree to which the trustor holds a positive attitude toward the trustee’s goodwill and reliability in a risky exchange situation” (Das & Teng, 1998, p. 494). Whereas these seminal articles have provided definitions that have been widely used, definitions alone do not capture the essence of what trust is. To fully understand trust as a cognitive construct, it is important to understand the structural elements of trust. Depending on what type of trust is being discussed (e.g., interpersonal trust or trust in automation), it may be necessary to assume that different types of trust contain different structural elements.

Interpersonal trust. Interpersonal trust is the “generalized expectancy held by an individual that the word, promise, oral or written statement of another individual or group can be relied on” (Rotter, 1967, p. 651; Rotter, 1980). One important structural element crucial to understanding interpersonal trust is risk. Rousseau and colleagues (1998) argue that uncertainty is the source of risk, and only when there is risk can one trust. When one chooses to trust, they then engage in risk-taking behavior. This aligns with Mayer et al. (1995), who differentiate between risk and risk-taking behaviors as the two relate to trust. The authors assert that to trust is not to take a risk, but rather it is a willingness to take a risk. In other words, the willingness to take a risk (trust) precedes the actual taking of risk (trusting behavior) as trust (or trusting) is not a behavior but leads to behaviors. Trust leading to behaviors was summarized well by Lewis and Weigert (1985), who stated that to trust is to act as if you know how others will act even though you do not, and the behavioral component of trust that follows is a course of action that is in line with the belief that you know how others are going to act. The concept of risk as it pertains to a willingness to depend on others and be vulnerable also relates to another structural element of trust which is control.

Control is an important structural element of trust because to understand what trust is, it is important to understand what it is not. Past research has argued that controlling is not trusting (Rousseau et al., 1998; Das & Teng, 1998) and that control appears when there is a lack of trust (Rousseau et al., 1998). When control mechanisms are put in place, they can hinder progress towards the formation of trust because there will not be any perceived risk by any party (Schoorman, Mayer, & Davis, 2007). Furthermore, control mechanisms can lead to the false sense that parties trust each other. As Mayer et al. (1995) point out, control mechanisms (e.g., punishment for deceitful behavior) can bring about cooperative behaviors that make it seem like two parties trust each other. However, these behaviors might only respond to the control mechanism, not actual trust between two parties. Therefore, for one party to truly trust another party, the other party must be seen as trustworthy. It is, however, important to note that control mechanisms help people have shared experiences which may help foster trust (Chiou and

Lee, 2021). And in the case of autonomy, it may be important to have certain control mechanisms in high-risk situations when rapid adapting is required (Chiou & Lee, 2021).

Trustworthiness is another important structural element of trust. Mayer et al. (1995) put forth three factors that they believe explain trustworthiness: ability, benevolence, and integrity. For someone to be considered trustworthy, they have to be seen as competent (ability), well-intentioned towards the trustor (benevolent), and having beliefs and values that are deemed acceptable by the trustor (integrity). Trustworthiness is also related to interpersonal trust. Interpersonal trust is the belief that someone will do what they say they will do (Rotter, 1967). Interpersonal trust, therefore, not only serves as a foundation for being perceived as trustworthy initially, but also for being perceived as trustworthy in the future. Indeed, trustworthiness is history-based. For example, one's reputation is based on actions and behaviors one has done in the past. If those actions and behaviors lead to one having a positive reputation, they will be perceived as trustworthy. This perceived trustworthiness based on a person's reputation will lead to nonspecific others initially having high interpersonal trust towards that person even though they may not have previously interacted with that person (McKnight, Cummings, & Chervany, 1998).

Although risk, control (or lack thereof), and trustworthiness are indeed structural elements that can explain the nature of trust, they are limited in their capacity to define it for the current study. One reason for this is that trust, as defined in the organizational psychology literature, has been defined in human-human contexts. This is limiting because the broad context of the current study is trust in a teammate. Teammates do not necessarily have to be human. Therefore, and because the focus of this study is HMT and human-machine trust, a review of the human factors literature on trust in automation is needed.

Trust in a machine. The concept of modern-day machines can be divided into two categories, automation (e.g., automated driving system or autopilot) and autonomy (e.g., AI, robots, synthetic agents), which are separately defined above. In the following section, these two categories are separately discussed in terms of trust in the machine. However, only a machine with autonomous functions is considered as a team member because of the team definition and the recent trend in the literature.

Trust in automation. Although a tremendous amount of research conducted in human factors pertaining to trust has been produced since the late 80's, researchers in the human factors field differ on a definition of trust in automation (Hoff & Bashir, 2015; Sheridan, 2019; Schaefer et al., 2021). The most widely used definition comes from Lee and See's (2004) seminal article in which trust is defined as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Lee & See, 2004, p. 51). This definition is similar to the one provided by Mayer et al. (1995) as it mentions how a trustor (in Lee and See's case, the individual) relies on the action of the trustee (in Lee and See's case, the agent) and believes that the trustee will act in a way that benefits, rather than hurts, the trustor. However, the difference is that in Mayer et al.'s (1995) definition, the vulnerability of the trustor is with the actions of the trustee whereas, in Lee and See's (2004) definition, vulnerability is in relation to the situation, not the trustor or the trustee. Lee and See's (2004) definition captures the essence of trust in most human-automation dyads, and they define it as an agent that can be either automation or another human that interacts with the environment on behalf of the person. However, this does not necessarily mean that an agent is a teammate.

The distinction between machine as an agent and machine as a teammate is important. A machine might help a human counterpart achieve a goal but a machine that is a teammate will work with that person or multiple people to achieve a shared goal too big or complex for any one person to achieve. Furthermore, though teammates (whether human or autonomy) may step in for each other to reduce cognitive or physical workload, they will also have their own heterogenous roles with corresponding responsibilities.

Trust in autonomy. Autonomy as a teammate has been heavily researched and discussed in the studies published by the Cognitive Engineering and Research on Team Task (CERTT) lab and with the collaborators (Demir et al., 2021; Grimm et al., 2018; Huang et al., 2021; Johnson et al., 2021; McNeese et al., 2018; McNeese et al., 2021; Tenhundfeld and Demir, 2020; Tenhundfeld et al., 2021). In those studies, a specific team was defined by considering heterogeneous and interdependent task roles with a common goal in a specific task context (e.g., Cooke and Shope (2004); Cooke et al. (2021)). Then, trust in autonomy was measured by subjective (i.e., self-reports) and objective (i.e., behavioral and physiological) measures. To understand the difference between trust in automation versus trust in a teammate, the current research discussing the trust differences between human-automation (agent; again, not autonomy) dyads (trust in automation) versus human-human (teammate) dyads (interpersonal trust) can be reviewed. What are the different attributes of human-autonomy trust and human-human trust, and how does trust differ in its development in human-autonomy dyads versus human-human dyads?

Trust in a Machine as a Teammate. Trust in a machine can be seen as a fundamental construct in the trust literature but considering trust in a machine teammate might be considered distinct. Demir et al. (2021) discuss this multidimensional perspective in the context of taskwork and teamwork, rather than considering trust in the machine. In their study there were three team members who interacted with each other to complete a dynamic team task. One of the team members is an AI team member played by a confederate experimenter. The results of their study were mixed in that the researchers found that stable team interactions were negatively associated with trust development, but beyond an inflection point, they were positively associated with trust development. Results also showed that recovery from machine failures was related to a moderate amount of trust, but too little or too much trust led to poorer recovery of the human teammates from machine failures. These results indicate that trusting a machine teammate is linked to team interactions and recovery from failures of the machine.

Other researchers have looked at additional factors that influence trust in an autonomous teammate. For example, Chen and Barnes (2014) describe multiple factors that influence trust in autonomous teammates, such as having a shared cognitive architecture; so that the humans and the autonomy's beliefs, desires, and intentions are compatible. The authors further state that an automated system's performance is linked to trust more so than how it may be perceived (i.e., its personality or human-like characteristics).

Trust Assessments

Trust in the fields of psychology and management has been measured using various metrics, such as questionnaires and surveys which only capture trust at certain instances (or even only at one instance) in time depending on how often they are administered. These methods use a Likert scale to measure people's trust towards automation using, for example, a score of 1 to indicate low trust or a score of 7 to indicate high trust (Gutzwiller et al., 2019). Popular examples of questionnaires used to assess trust are Rotter's (1967) scale that has been used to measure interpersonal trust, Mayer and Davis's (1995) scale to measure managerial/organizational trust, and Jian and colleagues' (1998) scale to measure trust in automated systems.

Although using questionnaires and scales continues to be popular methods of measuring trust, a few issues are worth noting when using scales to measure trust. Suppose a trust scale is administered in the middle of a task. In that case, this interruption might only be able to capture how a user feels about the automation at the current moment, but not in the moments before the interruption or afterward. This is certainly problematic as automation researchers should want to know what actions of the automation (and by extension what quality or feature of the automation designed by the designers of said automation) lead to trust increase or decrease. Another issue of trust scales is that depending on the linguistic valence of the questions used, the scale might skew results negatively or positively, as was discovered by evaluating the Jian, Bisantz, and Drury (2000) scale by Gutzwiller and colleagues (2019). And finally, the current scales that are used in the human factors field are used to measure trust towards automation as an agent in a dyad, not as a teammate in a team of three or more teammates. A machine that is a teammate would be expected to have more autonomous functions, but even more important is that it would be interdependent with other teammates. Therefore, the current study aims to validate a novel way of measuring trust in a teammate (human or machine) in real-time such that it can capture when trust increases or decreases and in a way that is not obtrusive but is observable.

A real-time metric for measuring trust in a teammate may have several benefits for human-automation and human-robot researchers as well as automation and robot designers and engineers. The first would be that a real-time trust metric would allow researchers and designers to observe when trust towards the autonomous teammate changes (Demir et al., 2021). This observable change in trust could be insightful as it may elucidate what quality or feature of the automation led to that change. Secondly, and related to the first point, because a real-time trust metric would not be interruptive, researchers and designers would observe the fluctuating of trust from the beginning through until the end of a task with greater granularity (Huang et al., 2021). Again, this is vitally important as observing when trust fluctuates might elucidate what qualities or features of the autonomous teammate cause the fluctuations (Tenhundfeld, Demir, & de Visser, 2021). As was mentioned earlier, the current study aims to validate a proposed real-time trust metric in a teammate that uses interactions as the unit of measure. This is discussed further in the next section.

Communication and coordination in Human-Machine Teaming

As it is indicated in the previous section, real-time objective measures are more informative to examine HMT trust. Behavioral and physiological measures play an important role in assessing trust from a dynamic perspective. Several studies (Demir et al., 2021; Huang et al., 2021; and Tenhundfeld et al., 2021) indicate that team interaction based on communication and coordination can give a bigger picture of trust in the light of the theory of interactive team cognition (ITC; Cooke et al., 2013). Thus, in the following section, first, the importance of ITC is discussed and then talked about the team communication and coordination and their connection with trust.

Interactive-team cognition theory. ITC theory focuses on team interaction between the team members (Cooke, Gorman, Myers, & Duran, 2013): from human to human and human to technology. ITC is a theory that posits that team cognition is team interaction and has three premises: (1) team cognition is a cognitive process, (2) team cognition should be measured at the team level, and (3) team cognition is context-dependent (Cooke et al., 2013). ITC differs from another team cognition theory called "Shared Cognition," which defines the sum of "individual knowledge" as team cognition. However, ITC does not use the aggregation of the knowledge of team members as a means for producing a team mental model; instead, it analyzes the team cognition at a team level using interactions as the unit of analysis, rather than individual team member knowledge. Furthermore, as Cooke et al. (2013) point out, there may be other contexts in which the shared cognition perspective is more appropriate, such as in smaller teams in which the roles of team members are more homogenous or in team planning and design tasks.

ITC posits that team cognition is team interaction, and because of this, one could logically assume that interactions are important to teams. Indeed, this is the case, and historical examples can be cited about what can happen if teammates do not interact effectively. For example, groupthink is a psychological phenomenon that encourages group members to think collectively rather than individually. This type of thinking can be catastrophic, as was demonstrated by the "Challenger Space Shuttle" explosion in 1986 (Schwartz, 1987; Vaughan, 1990). The explosion was caused by a lack of expansion of O-Rings due to below-freezing temperatures causing a leak. Although engineers voiced their concerns, the risks were deemed appropriate for launching. Another example of groupthink is the failed Bay of Pigs invasion in which Cuban exiles were expecting help from U.S. forces against the Cuban army. However, the support never came because of miscommunication from President Kennedy's advisors and a lack of speaking up about the dangers of launching an attack. In the end, 200 Cuban exiles were killed, and 1200 were taken prisoner (Raven, 1998). Clearly, it is not a stretch to say that lack of interaction with teammates can lead to death.

In the previous studies, team communication and coordination in HAT are considered the predictors of team trust, which were briefly discussed above. However, the focus of this study is to validate a specific type of communication (anticipatory pushing of information) in a team and how it may relate to trust in a team member(s) (either from human to human or human to autonomy).

Team Communication in human-autonomy teaming. Interactions are vital to team success and performance. Because of this, Cooke and colleagues (2010) developed metrics based on communication and coordination of team members to assess team cognition. These measures will be discussed here briefly. The event-data analysis is a measurement that explains the behavioral stream that sets up a chain of events. This measurement uses keystrokes, eye/head movements, social interactions, think-aloud protocols, and other observable events to explain a series of events. Communication analysis looks at who is talking to whom, what is being said, and communication flow to reflect interactions within a team. Team situation awareness is a measurement that aims to assess the situational awareness of teams by introducing perturbations in a task and then seeing how long it takes team members to overcome that perturbation. Cooke and colleagues termed their measurement of team situation awareness CAST (Coordinated Awareness of Situations by Teams) which is based on the idea that team situation awareness is a dynamic process characterized by getting the right information, to the right person, at the right time. (Cooke & Gorman, 2009; Gorman, Cooke, & Winner, 2006).

Using interactions to measure team cognition is not an entirely new concept. In fact, it stems from research done by Cannon-Bowers and colleagues (e.g., Cannon-Bowers, Salas, & Converse, 1990; Rouse, Cannon-Bowers, & Salas, 1992; Cannon-Bowers, Salas, & Converse, 1993; Cannon-Bowers & Salas, 2001) regarding shared mental models (SMM). SMM can be thought of as shared understanding among teammates about their current situation (i.e., the environment, other team members, nonspecific others within the shared environment, equipment status, etc.). It is also conceptualized as what each team member's role and task responsibilities are (Entin & Serfaty, 1999). SMM requires team members to be aware of each other's roles and responsibilities as well as what information they require. It is hypothesized that a good SMM helps teammates to communicate with each other what resources and information they need facilitating good team cohesion and performance (Stout, Cannon-Bowers, Salas, & Milanovich, 1999).

This anticipation of teammates' needs regarding information is the independent variable of this study. The current study aims to analyze if there exists a correlation between anticipatory pushing of information and teammate trust. Anticipatory pushing of information is defined as, for the current study, the pushing of information from teammate A to teammate B based on teammate A's anticipation of information that teammate B requires. It is hypothesized that the anticipation of information for a teammate stems from a good SMM among teammates leading to implicit coordination (i.e., coordination that is not preplanned but rather rises out of necessity for a given situation). Anticipatory pushing of information can be thought of as an example of implicit coordination because one team member is helping another teammate adjust to a change, but (1) notifying them of the change in the situation, and (2) possibly recommending an action that addresses the change in the situation (McNeese, Demir, Cooke, & Myers, 2018).

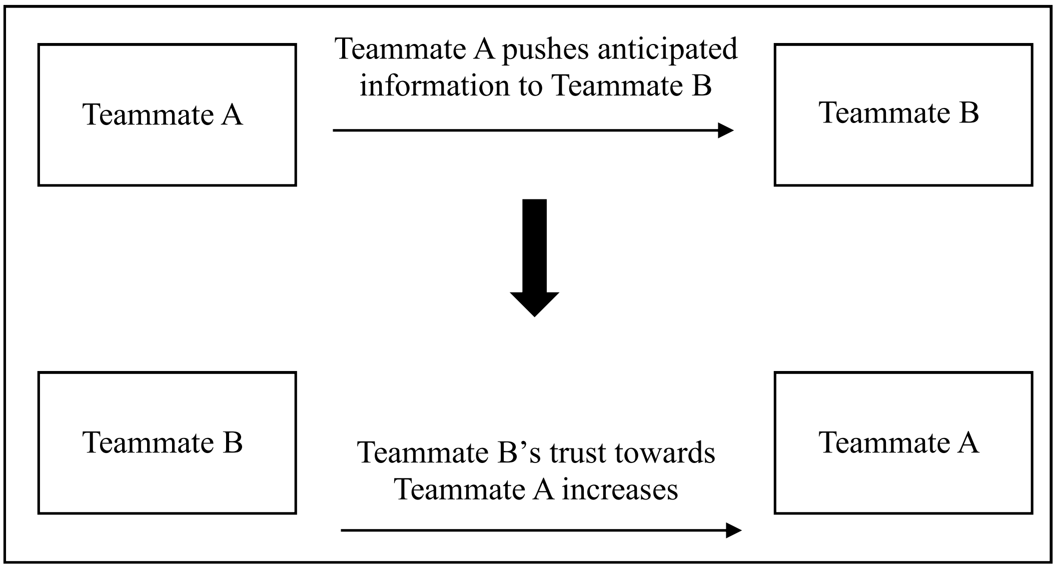
Overall, this leads to a better understanding of trust by considering the anticipatory pushing of information between the team members. Therefore, the following novel definition of trust in a teammate is proposed for the following study in the context of action-oriented teams (e.g., command and control): trust in a teammate is the expectation that teammates will share anticipated and needed information with each other such that the sharing of information facilitates goal accomplishment, safety, and task continuation and completion. In a dynamic task environment, it is crucial that teammates communicate and coordinate with one another to accomplish the overarching goal(s). Teammates in a dynamic task environment need to keep each other safe, not only physically but also mentally and emotionally. Sharing information based on anticipated needs certainly can help with keeping teammates safe. And finally, information sharing is necessary for task continuation as task continuation and completion help the team as a whole accomplish its goal(s). And because the current study is focused on information sharing as the means by which trust is formed, maintained, and calibrated, a corresponding measure of trust has to be implemented.

CHAPTER 3

CURRENT STUDY

The aim of this thesis is to address the research question, can anticipatory pushing be used as a proxy measure for trust during routine and degraded conditions? Traditional methods of measuring trust are static, interruptive, and cannot capture fluctuating levels of trust in real-time. The experiment discussed later in the methods section in further detail mimics a remotely piloted aerial system in a synthetic task environment (RPAS-STE) to study team communication and other cognitive processes, such as trust in a HAT context (Cooke & Shope, 2004). Frequencies of anticipatory pushing captured through text-chat in the RPAS-STE are compared against self-reported trust scores. These measures are discussed in detail in the data analysis and preliminary results section. The hypothesis for this thesis is that higher levels of anticipatory pushing by a teammate will positively correlate with a higher level of self-reported trust in that teammate (Weber & Aha, 2003).

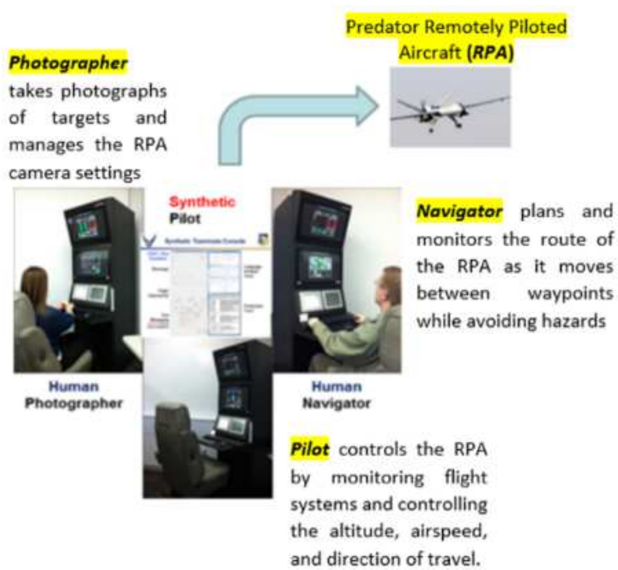
Figure 1. Hypothesis Diagram. Diagram depicting hypothesis that Teammate A pushes anticipated information to Teammate B, Teammate B's trust towards Teammate A will increase.



Simulated Testbed and Task Roles

The Johnson et al. (2020) study was completed using ground stations in the RPAS-STE (Cooke and Shope, 2004). This environment is used to support the roles of three heterogenous teammates who have different roles, responsibilities, and have access to varied information: (1) a *pilot* is the synthetic teammate played by a confederate experimenter following a script, who is responsible for flying the simulated remotely piloted drone (RPA) via monitoring of flight systems and controlling altitude, airspeed, and direction of travel; (2) a *navigator* who is responsible for monitoring and planning the route the RPA travels along via waypoints and targets while additionally avoiding hazard zones; and (3) the *photographer* who is responsible for taking good photos of targets and monitoring the camera settings. The goal for all three teammates is to work together by communicating with each other in a coordinated manner to take good photos of targets similar to a real-life reconnaissance mission that involves using an RPA. In this experiment, the wizard of oz paradigm (WoZ) methodology was applied. Accordingly, the synthetic teammate in each condition was a trained confederate experimenter, meaning that the beliefs of the navigator and photographer about the pilot was the synthetic agent and not human. In this case, one synthetic teammate (pilot) communicated and coordinated with two human team members in order to achieve the team task. Thus, the synthetic teammate was able to communicate via text chat using a limited vocabulary. The synthetic teammate followed a script pertaining to behaviors, such as piloting the drone and verbal comprehension (Johnson, 2021).

Figure 2. The Ground Station Consoles in RPAS-STE. Each of the three-team members communicated via a touch-screen text-chat interface.



Design

There were three conditions (i.e., between-subjects) and five missions (within-subjects) in this study. The conditions are *coordination training, calibration training,* and *control training*. The difference in these conditions is associated with the differences in the pre-mission training which is not the focus of this thesis; rather, within-subjects manipulation is the main focus of the study The pre-mission training differed in three ways: differences in the training slideshow, which provided the participants with information regarding the different roles and their respective responsibilities; differences in the experimenter's behavior during a hands-on training mission in which the experimenter would use different scripts; and changes in the experimenter playing the role of the synthetic teammate (pilot) using the WoZ technique also during the hands-on training mission. These differences between the conditions are (Johnson et al., 2020):

- *Coordination Training*: The aim of the coordination training condition was to train the participants to push information to other teammates in a timely manner. Participants were informed about what information they had at their disposal and what information the other teammates had during the hands-on training mission and the training slideshow. This was the only condition in which the participants were informed that the other teammates had access to heterogeneous information which means that the three teammates did not have access to the same information, so they were reliant on each other to get and provide the information that was needed in a timely manner. During the training mission, the synthetic teammate (WoZ confederate) would push important information onto a teammate earlier than he/she would in other missions and the synthetic teammate would ask for information from teammates repeatedly if they failed to deliver it in a timely manner. It was believed that this pushing and pulling of information behavior exhibited by the synthetic teammate would lead to good coordination because previous research (Demir, McNeese, & Cooke, 2017) has indicated that when the synthetic teammate stops pushing information, so do the human teammates.

- *Calibration Training*: The aim of the calibration training condition was to adjust the participant's trust levels towards the synthetic teammate such that the participant would not overtrust the synthetic teammate and would be persistent in correcting synthetic teammate failures. The approach during the hands-on training mission and the training slideshow was to tell the participant that the synthetic teammate was still in the development stage of production and therefore, would sometimes malfunction. Examples of malfunctions included delays in responding to inquiries made by the participant and completing tasks. During the training, if these malfunctions occurred, the experimenter would tell the participant to be persistent by, for example, resending the text to the synthetic teammate because the synthetic teammate might be undergoing a malfunction at that time. The researchers expected the participant to have a calibrated trust level towards the synthetic teammate after this training such that the participant would be able to identify malfunctions readily and easily in the synthetic teammate's behaviors. This condition is particularly relevant to the current study because in previous studies it was observed that human teammates over-trusted the synthetic teammate in the case of autonomy failures (Johnson et al, *in press*). In the current study it may be possible that when anticipatory pushes are not received, instead of decreasing trust in the synthetic teammate, it might be given a break and trust may not be adjusted.

- *Control Training*: The control training was the same training that was used in previous research conducted by Demir, McNeese, and Cooke (2019). This training included informing the participants of the roles and tasks via the interactive training slideshow and a single training mission. A standard script was used for the synthetic teammate. Whereas in the other two conditions, there were manipulations, there were no such manipulations for the control training condition.

This study consists of between-and within-subjects design manipulations (See Appendix A for descriptive statistics for between-subjects effects). However, we only consider the within-subjects design manipulations because of the main focus of the current study and page limit. There are three between-subjects design effects based on the pre-mission training, including coordination training, calibration training, and control training—all defined by manipulating pre-mission training Demir et., al. 2020). The within-subjects design includes routine conditions (i.e., missions with no technology failures) and degraded conditions (i.e., missions with technology failures; see Table I). Because the focus of this study was to identify the relationship between anticipatory pushing of information and trust under routine and degraded conditions in HMT, we combined all six types of technology failures together into one condition (see Table 1, Demir et., al. 2020). This allowed us to analyze the data more simply and match the dimension of the trust measure, which was obtained via questionnaire once following routine conditions and again following degraded conditions (as within-subjects design).

Table 1

Technological Failures Within the Degraded Condition (Demir et. al., 2020)

Type	***Description***
Automation	Prevented display of flight information such as airspeed, altitude, or heading to the photographer or pilot.
Automation	A one-way communication cut between photographer and pilot.
Automation	A gradual power-down and subsequence power-up of all six workstation screens, affecting all experimental positions.
Autonomy	Simulated a malfunction in the AI teammate's capacity for properly responding to messages from teammates.
Autonomy	Simulated a hijacking of the RPAS by moving it to an enemy waypoint while the AI agent provided deceptive responses.
Hybrid	A combination of both automation and autonomy failures into a single failure.

The current study focuses on trust in a teammate, regardless of whether a teammate is a human or machine, and how to measure trust. The goal is to assess whether a proposed trust metric is a valid metric for measuring trust in a teammate, using interactions as measurement units. The specific interactions being used as the units of measure are interactions where information pushing based on anticipated needs occurs. It is assumed that as a teammate anticipates another teammates' needs and pushes information to that teammate based on anticipated needs, there will be increased trust towards the teammate who pushed the information. This will lead to higher levels of interpersonal trust towards that teammate.

CHAPTER 4

METHOD

Participants

A total of 60 randomly selected participants from Arizona State University and surrounding areas completed an approximately 7-hour experiment. The age range of the participants was 18 to 33 ($M_{\text{age}} = 22.53$, $SD_{\text{age}} = 3.55$). The participants were randomly assigned into either navigator or photographer roles, and an experimenter played the role of the third team member or synthetic *pilot*. Each team participated in one session that lasted for seven hours, and ten teams each participated in one of three experimental training conditions: (1) *coordination,* (2) *calibration,* and (3) *control.*

Procedure

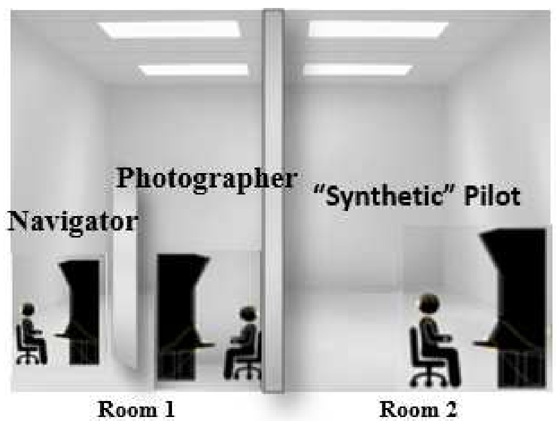
Upon arrival to the lab, participants were asked to complete a consent form. Afterward, the participants were taken to their workstations, and a partition was used to separate the participants. The role of the synthetic teammate (the pilot) was played by a trained confederate experimenter who was in a separate room. Next, depending on which condition the participants were assigned (calibration training, coordination training, or control training) the participants completed a training session which consisted of the interactive slideshow explaining the roles and tasks and a 40-minute hands-on training mission which helped participants become acquainted with the interface of the workstation, their roles, and how to communicate in the RPAS-STE. The experimenter used a script to facilitate the participants in their training. A checklist of tasks was also given to the participants so they could refer to it regarding their role and how to communicate with the synthetic teammate. To establish a baseline, the first mission did not expose the participants to any failures. There was a total of five missions and after the first and fifth mission participants were asked to complete questionnaires regarding subjective trust and workload. After the fifth mission, the participants were asked to complete a demographic questionnaire, they were briefed and monetarily compensated for their participation.

Figure 3. (a) Experimental procedure and (b) WoZ methodology location setting

(A)

Session Order	Failure I	Failure II
Training	–	–
Mission 1 **(Routine)**	No Failure	No Failure
Pre-Questionnaires (**Trust**, NASA-TLX Workload)		
Mission 2 **(Degraded)**	Automation	Autonomy
Mission 3 **(Degraded)**	Autonomy	Automation
Mission 4 **(Degraded)**	Hybrid	Automation
Mission 5 **(Degraded)**	Automation	Autonomy
Pre-Questionnaires (**Trust**, NASA-TLX Workload)		

(B)



Measures

There were several measures used in Johnson et al. (2020), including individual and team performance, number of failures overcome, communication flow patterns, team coordination, team process ratings, sensor-based metrics (electrocardiogram and facial expressions), NASA Task Load Index, task-level modified version of trust, and demographic questions. Only the following two measures are considered for this thesis:

- *The trust questionnaire* used by Johnson et al. (2020) was a modified version of Mayer, Davis, and Schoorman's (1995) and Mayer and Davis's (1999) questionnaire. The questionnaire used by Johnson et al. (2020) was an 18-item

(9-items per teammate) questionnaire that used a 1-5 scoring scale. To obtain the means of participants' reported trust score, 4 of the 18 items were reverse scored to align with the scale for the remaining 14 questions. These trust scores were compared with frequencies of anticipatory pushing of information done by each teammate.

- Another measure that is used in this study is the *anticipatory pushing of information*. Text-chat data was analyzed to determine how much anticipatory pushing of information teammates was doing. Anticipatory pushing of information, in this case, refers to text-chat data that shows the pushing of information from one teammate to another without it being explicitly asked for. As an example of what anticipatory pushing might look like, imagine two people moving a couch. The person walking backward might be close to running into a wall. The other person might say "Lookout! You're about to run into the wall on your right." The person walking backward did not ask, but the person walking forwards anticipated that the person walking backward would need to know that information to avoid injury; therefore, the person walking backward might have increased trust in the person walking backward. The hypothesis for this thesis is that teammates who exhibit higher frequencies of anticipatory pushing of information will have higher reported trust scores, given the nature of the task which requires frequent, timely communication to succeed. Two experimenters coded 10% of the communication behaviors. An interrater reliability test was applied to ensure there was reliability between the 10% data that the two experimenters coded. Fleiss' Kappa showed a good agreement between the experimenters' judgments, κ=0.869 (95% CI, 0.842 to 0.895), $p < 0.0001$. Therefore, only one experimenter coded the rest of the data.

Table 2

Example of Anticipatory Pushing

Sender	**Message Text**	**Receiver**
Navigator	The next waypoint is M-STR after S-STR. It's a target waypoint. There is no speed restriction, altitude restriction is 2000-5000, effective radius is 5.	Pilot

CHAPTER 5

DATA ANALYTICS AND RESULTS

Pearson Correlation

A Pearson product-moment correlation coefficient was computed to assess the relationship between anticipatory pushing of information and self-reported trust scores in the human teammate pairs. From the navigator (DEMPC) to the photographer (PLO) role in the routine condition there was no statistical significance (r = - 0.018, n = 28, p = 0.928). Likewise, from the navigator to the photographer role in the degraded condition there was also no statistical significance (r = 0.056, n = 28, p = 0.775). Additionally, there was no statistical significance from the photographer to the navigator role in the degraded condition (r = 0.165, n = 28, p = 0.402). There was no anticipatory pushing of information from the photographer to the navigator in the routine condition thus, no correlation coefficient was calculated for this pair. Note, human-autonomy teammate pairs were not included in the correlation analysis because there was no anticipatory pushing of information from the synthetic teammate pilot to either of the human teammates; thus, no correlation coefficient was calculated for these pairs either. Based on these findings, the second alternative hypothesis, "as the frequency of anticipatory pushing increases from teammate A to teammate B, it will be correlated with an increase in trust levels of teammate B towards teammate A" is rejected, and the researcher of the current study failed to reject the second null hypothesis "as the frequency of anticipatory pushing increases from teammate A to teammate B, it will NOT be correlated with an increase in trust levels of teammate B towards teammate A". Pearson results show some inconsistencies regarding the relationship between anticipatory pushing and trust due to the limited modeling because the session was not included in the Pearson correlation. Therefore, a stepwise regression analysis was applied to see how the relationships between human-human anticipatory pushing of information and trust change across the two sessions.

Stepwise Regression

Stepwise regression was conducted to predict teammate trust (dependent variable) by anticipatory pushing of information (independent variable) in human-human teammate pairs under routine to degraded conditions? Stepwise regression with Akaike criteria (AIC) was used to determine which teammate pair would be used as a reference variable. AIC was chosen for the stepwise regression because it reduces the impact of larger models more heavily (e.g., as seen with overfitting data) and tends to prefer smaller models. Stepwise regression was chosen because it includes an additional predictor variable (i.e., forward selection) and eliminates a predictor variable (i.e., backward elimination) already in the model (Weisberg, 2005), thus eliminating the issue regarding the accuracy of any individual predictor variable. AIC was also chosen because our sample size was limited, and AIC places a moderate penalty on the number of predictor variables compared to Bayesian, which places a heavier penalty (Berk, 2008). This analysis was calculated in R (*R: The R Project for Statistical Computing*, n.d.), using the MASS packages for stepwise regression (Ripley, 2021) and lm-beta (Behrendt, 2014) for adding standardized regression coefficients.

In this study, pairs, sessions (degraded and routine), and their interaction with each other were used as a set of predictors from which the best subset was obtained for predicting a model of trust. Because there is no trust data collected from the "synthetic" pilot, only the human teammate pairs (one of our candidate variables) were re-coded using dummy variables with four pairs (i.e., the navigator to photographer and vice versa for both sessions). In this case, the pair, the *navigator to the photographer in Session 2*, was chosen as a reference group (coded zero, '0') because its mean of anticipatory pushing of information ($M = 3.54$) is the closest mean to the overall mean ($M = 3.48$, which was obtained without the pilot pairs). The closest mean strategy for dummy coding was chosen as the reference group because it allows for making statistical comparisons with high and low means simpler. Binary coding was used to classify the pairs with their respective dummy variables (See Table 3).

Table 3

Dummy Coding Sample

Participant	**Session**	**Anticipatory pushing**	**Navigator to the photographer in Session 1**	**Photographer to the navigator in Session 1**	**Navigator to photographer in Session 2 (*Reference*)**	**Photographer to the navigator in Session 2**	**Trust**
1	**1**	1	1	0	0	0	3.78
1	**1**	0	0	1	0	0	3.67
1	**2**	1	0	0	0	0	4.11
1	**2**	1	0	0	0	1	3.78

The model accounted for 10.9% of the variance, $F(4, 107) = 3.29$, $p = 0.013$. According to these findings, there was a marginal and negative association between anticipatory pushing of information from the navigator to the photographer and the photographer's trust towards the navigator in Session 1, see Table 5. In Session 2, a moderate level of anticipatory pushing of information from the navigator to the photographer was positively related to trust from the photographer to navigator (based on the model's significant linear and quadratic terms; 6).

The reason why there was an opposite association between the anticipatory pushing and trust in these two sessions is because of the degraded condition (Session 2) had technological failures (i.e., within-subjects effects). That is, Session 2 (i.e., degraded condition) had automation failures that required two human team members to interact with each other more in comparison to Session 1 to overcome the automation failures. Session 1 (i.e., routine condition), however, did not have these failures; thus, there was a lesser need for such interactions between the human team members.

The increase in interaction among the human team members in Session 2 was associated with an increase of trust towards the navigator from the photographer, as seen by the positive coefficient of the photographer's trust in the navigator in Session 2. However, it is important to note that just because these two factors were observed to be correlated with each other in Session 2, it cannot be said that there is a causal relationship between anticipatory pushing and trust.

Table 4

Stepwise Regression Results

Variable	Term	β	SE β	t	p
Anticipatory pushing from the navigator to photographer in Session 1	Linear	-0.22	0.13	-1.83	0.069
Anticipatory pushing from the navigator to photographer in Session 2	Linear	0.52	0.15	3.54	0.001
	Quadratic	-0.12	0.04	-3.19	0.002

The photographer's trust in the navigator in Session 2	Linear	0.01	0.12	0.07	0.945

CHAPTER 6

DISCUSSION AND LIMITATIONS

The primary research question of the current study was, can anticipatory pushing of information be used as a valid metric to assess trust in a teammate, whether that teammate is a human or a machine. This question was further explored by running statistical analyses that compared frequencies of anticipatory pushing to self-reported trust scores in two different conditions: routine and degraded. The data used for the statistical analyses comes from a previous study conducted by Johnson et al. (2020) in which the effect of three different training conditions on team communication behaviors was examined. Text-chat data from 28 teams across five missions in each team was coded to obtain the frequencies of anticipatory pushing of information for each teammate pair: the navigator to the photographer, photographer to navigator, photographer to pilot, and navigator to pilot. These frequencies of anticipatory pushing of information were then compared to self-reported trust scores in two different statistical analyses: Pearson product-moment correlation and stepwise regression. The hypothesis for this study was that higher levels of anticipatory pushing of information from a teammate would be positively correlated with higher levels of self-reported trust in a said teammate.

The Pearson product-moment correlation was conducted on just the human teammate pairs. The correlation analysis results showed no statistically significant relationship between anticipatory pushing of information and self-reported trust scores in any of the human-teammate pairs. However, in the correlation analysis, the effect of how the automation's failures in the degraded condition might change the relationship of the human teammate pairs was not taken into account. Therefore, a stepwise regression was conducted to assess that effect.

The stepwise regression results show a statistically significant positive correlation of anticipatory pushing of information from the navigator to the photographer and the photographer's trust towards the navigator in session two. The stepwise regression results also showed a marginally negative correlation of anticipatory pushing of information from the navigator to the photographer and the photographer's trust towards the navigator in session one. Overall, the findings from this study support the hypothesis that anticipatory pushing of information is positively associated with trust in human-human pairs but not human-autonomy pairs. Regarding human-autonomy teams, the possible reasons why anticipatory pushing of information might be a valid metric for trust might be because of differences in training (i.e., between-subjects effects) and lack of anticipation capability of the autonomous pilot. However, there are several limitations to consider moving forward with this research.

The first limitation to consider is that the data used for the current study came from a previous study that was not designed for anticipatory pushing. Although the previous study had pushed communications, only some pushes could be considered anticipatory. Future research should look at how varying anticipatory pushing levels from team members correlate with self-reported trust scores. The other limitation to consider is that the AI teammate did not do any anticipatory pushing of information because of its scripted role, nor did it contribute any trust-in-human scores. Because of this, it was not accounted for in this study. Therefore, it cannot be concluded if there is a difference if the anticipatory pushing of information comes from a human or an autonomous team member. Lastly, it is possible that anticipatory pushing of information can have a team-level effect. In other words, while teammate A might anticipate information that teammate B needs and push it to teammate B, teammates C and D might observe this and their trust towards teammate A might increase.

Hence, future research should dig further into how anticipatory pushing of information by one team member affects team trust as a whole. In particular, it would be interesting to see if anticipatory information pushing from an AI leads to higher trust levels in the AI and the other human teammates.

REFERENCES

Behrendt, S. (2014). *Add Standardized Regression Coefficients to lm-Objects [R package lm.beta version 1.5-1]*. Comprehensive R Archive Network (CRAN). https://CRAN.R-project.org/package=lm.beta

Berk, R. A. (2008). *Statistical Learning from a Regression Perspective*. Springer-Verlag. https://doi.org/10.1007/978-0-387-77501-2

Cannon-Bowers, J. A., & Salas, E. (2001). Reflections on shared cognition. *Journal of Organizational Behavior*, *22*(2), 195–202. https://doi.org/10.1002/job.82

Cannon-Bowers, J. A., Salas, E., & Converse, S. (1993). Shared mental models in expert team decision making. In *individual and group decision making: Current issues* (pp. 221–246). Lawrence Erlbaum Associates, Inc.

Cannon-Bowers, J. A., Salas, E. & Converse, S. A. (1990). Cognitive psychology and team training: Shared mental models in complex systems. Human Factors Bulletin, *33*: 1-4.

Chen, J. Y. C., & Barnes, M. J. (2014). Human–agent teaming for multirobot control: A review of human factors issues. *IEEE Transactions on Human-Machine Systems*, *44*(1), 13–29. https://doi.org/10.1109/THMS.2013.2293535

Christopher Brill, J., Cummings, M. L., Evans, A. W., Hancock, P. A., Lyons, J. B., & Oden, K. (2018). Navigating the advent of human-machine teaming. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *62*(1), 455–459. https://doi.org/10.1177/1541931218621104

Cohen, A. (1991). Dummy Variables in Stepwise Regression. *The American Statistician*, *45*(3), 226–228. https://doi.org/10.2307/2684296

Cooke, N. J., & Gorman, J. C. (2009). Interaction-based measures of cognitive systems. *Journal of Cognitive Engineering and Decision Making*, *3*(1), 27–46. https://doi.org/10.1518/155534309X433302

Cooke, N. J., Gorman, J. C., Myers, C. W., & Duran, J. L. (2013). Interactive team cognition. *Cognitive Science*, *37*(2), 255–285. https://doi.org/10.1111/cogs.12009

Cooke, N. J., & Shope, S. M. (2004). Designing a synthetic task environment. In S. G. Schiflett, L. R. Elliott, E.Salas, & M. D. Coovert (Eds.), Scaled worlds: Development, validation, and applicationn(pp. 263–278). Surrey, England: Ashgate.

Das, T. K., & Teng, B.-S. (1998). Between trust and control: Developing confidence in partner cooperation in alliances. *Academy of Management Review*, *23*(3), 491–512. https://doi.org/10.5465/amr.1998.926623

Demir, M., McNeese, N. J., & Cooke, N. J. (2018). Team synchrony in human-autonomy teaming. In J. Chen (Ed.), *Advances in Human Factors in Robots and Unmanned Systems* (Vol. 595, pp. 303–312). Springer International Publishing. https://doi.org/10.1007/978-3-319-60384-1_29

Demir, M., McNeese, N. J., Gorman, J. C., Cooke, N. J., Myers, C. W., & Grimm, D. (2021). Exploration of team trust and interaction dynamics in human-autonomy teaming. https://doi.org/10.13140/RG.2.2.27566.23366

Demir, M., McNeese, N. J., Johnson, C., Gorman, J. C., Grimm, D., and Cooke, N. J. (2019). "Effective team interaction for adaptive training and situation awareness in human-autonomy teaming," in 2019 IEEE COGSIMA, 2019. doi: 10.1109/COGSIMA. 2019.8724202.

Endsley, M. R., & Kaber, D. B. (1999). Level of automation effects on performance, situation awareness and workload in a dynamic control task. *Ergonomics*, *42*(3), 462–492. https://doi.org/10.1080/001401399185595

Endsley, M. R., & Kiris, E. O. (1995). The out-of-the-loop performance problem and level of control in automation. *Human Factors*, *37*(2), 381–394. https://doi.org/10.1518/001872095779064555

Entin, E. E., & Serfaty, D. (1999). Adaptive team coordination. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *41*(2), 312–325. https://doi.org/10.1518/001872099779591196

Ferworn, A., Sadeghian, A., Barnum, K., Rahnama, H., Huy Pham, Erickson, C., Ostrom, D., & Dell'Agnese, L. (2006). Urban search and rescue with canine augmentation technology. *2006 IEEE/SMC International Conference on System of Systems Engineering*, 309–313. https://doi.org/10.1109/SYSOSE.2006.1652317

Gorman, J. C., Cooke, N. J., & Winner, J. L. (2006). Measuring team situation awareness in decentralized command and control environments. *Ergonomics*, *49*(12–13), 1312–1325. https://doi.org/10.1080/00140130600612788

Grimm, D., Demir, M., Gorman, J. C., & Cooke, N. J. (2018). The complex dynamics of team situation awareness in human-autonomy teaming. *2018 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)*, 103–109. https://doi.org/10.1109/COGSIMA.2018.8423990

Gutzwiller, R. S., Chiou, E. K., Craig, S. D., Lewis, C. M., Lematta, G. J., & Hsiung, C.-P. (2019). Positive bias in the 'Trust in Automated Systems Survey'? An examination of the Jian et al. (2000) scale. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *63*(1), 217–221. https://doi.org/10.1177/1071181319631201

Haimson, O. L., Semaan, B., Dym, B., Hsiao, J. C.-Y., Herron, D., & Moncur, W. (2019). Life transitions and social technologies: Research and design for times of life change. *Conference Companion Publication of the 2019 on Computer Supported Cooperative Work and Social Computing*, 480–486. https://doi.org/10.1145/3311957.3359431

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *57*(3), 407–434. https://doi.org/10.1177/0018720814547570

Huang, L., Cooke, N. J., Gutzwiller, R. S., Berman, S., Chiou, E. K., Demir, M., & Zhang, W. (2021). Distributed dynamic team trust in human, artificial intelligence, and robot teaming. In *Trust in Human-Robot Interaction* (pp. 301–319). Elsevier. https://doi.org/10.1016/B978-0-12-819472-0.00013-7

Jian, J. Y., Bisantz, A. M., & Drury, C. G. (1998). Towards an empirically determined scale of trust in computerized systems: Distinguishing concepts and types of trust. *Proceedings of the Human Factors and Ergonomics Society 42nd Annual Meeting, Vols 1 and 2*, 501-505.

Jian, J. Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems. *International Journal of Cognitive Ergonomics*, *4*(1), 53–71. https://doi.org/10.1207/S15327566IJCE0401_04

Johnson, M., Bradshaw, J. M., Feltovich, P. J., Jonker, C., van Riemsdijk, B., & Sierhuis, M. (2012). Autonomy and interdependence in human-agent-robot teams. *IEEE Intelligent Systems*, *27*(2), 43–51. https://doi.org/10.1109/MIS.2012.1

Johnson, Matthew, & Bradshaw, J. M. (2021). The role of interdependence in trust. In *Trust in Human-Robot Interaction* (pp. 379–403). Elsevier. https://doi.org/10.1016/B978-0-12-819472-0.00016-2

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *46*(1), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392

Lewis, J. D., & Weigert, A. (1985). Trust as a social reality. *Social Forces*, *63*(4), 967. https://doi.org/10.2307/2578601

Lyons, J.B., Mahoney, S., Wynne, K.T., Roebke, M.A. Viewing machines a teammates: A qualitative study. AAAI Spring Symposium Series, pp. 166-170, Palo Alto, CA (2018).

Lyons, J. B., Wynne, K. T., Mahoney, S., & Roebke, M. A. (2019). Trust and human-machine teaming: A qualitative study. In *Artificial Intelligence for the Internet of Everything* (pp. 101–116). Elsevier. https://doi.org/10.1016/B978-0-12-817636-8.00006-5

Mayer, R. C., & Davis, J. H. (1999). The effect of the performance appraisal system on trust for management: A field quasi-experiment. *Journal of Applied Psychology*, *84*(1), 123–136. https://doi.org/10.1037/0021-9010.84.1.123

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*(3), 709–734. https://doi.org/10.5465/amr.1995.9508080335

McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial trust formation in new organizational relationships. *Academy of Management Review*, *23*(3), 473–490. https://doi.org/10.5465/amr.1998.926622

McNeese, N. J., Demir, M., Chiou, E. K., & Cooke, N. J. (2021). Trust and team performance in human–autonomy teaming. *International Journal of Electronic Commerce*, *25*(1), 51–72. https://doi.org/10.1080/10864415.2021.1846854

McNeese, N. J., Demir, M., Cooke, N. J., & Myers, C. (2018). Teaming with a synthetic teammate: Insights into human-autonomy teaming. *Human Factors*, *60*(2), 262–273. https://doi.org/10.1177/0018720817743223

Nass, C., Fogg, B. J., & Moon, Y. (1996). Can computers be teammates? *International Journal of Human-Computer Studies*, *45*(6), 669–678. https://doi.org/10.1006/ijhc.1996.0073

O'Neill, T., McNeese, N., Barron, A., & Schelble, B. (2020). Human–autonomy teaming: A review and analysis of the empirical literature. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 001872082096086. https://doi.org/10.1177/0018720820960865

Panganiban, A. R., Matthews, G., & Long, M. D. (2020). Transparency in autonomous teammates: Intention to support as teaming information. *Journal of Cognitive Engineering and Decision Making*, *14*(2), 174–190. https://doi.org/10.1177/1555343419881563

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *30*(3), 286–297. https://doi.org/10.1109/3468.844354

Parasuraman, Raja, & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *39*(2), 230–253. https://doi.org/10.1518/001872097778543886

Parasuraman, Raja, Sheridan, T. B., & Wickens, C. D. (2008). Situation awareness, mental workload, and trust in automation: Viable, empirically supported cognitive engineering constructs. *Journal of Cognitive Engineering and Decision Making*, *2*(2), 140–160. https://doi.org/10.1518/155534308X284417

R: The R Project for Statistical Computing. (n.d.). Retrieved May 20, 2021, from https://www.r-project.org/

Raven, B. H. (1998). Groupthink, bay of pigs, and watergate reconsidered. *Organizational Behavior and Human Decision Processes*, *73*(2–3), 352–361. https://doi.org/10.1006/obhd.1998.2766

Ripley, B. (2021, May 3). *Support Functions and Datasets for Venables and Ripley's MASS [R package MASS version 7.3-54]*. Comprehensive R Archive Network (CRAN). https://CRAN.R-project.org/package=MASS

Rotter, J. B. (1967). A new scale for the measurement of interpersonal trust1. *Journal of Personality*, *35*(4), 651–665. https://doi.org/10.1111/j.1467-6494.1967.tb01454.x

Rotter, J. B. (1980). Interpersonal trust, trustworthiness, and gullibility. *American Psychologist*, *35*(1), 1–7. https://doi.org/10.1037/0003-066X.35.1.1

Rouse, W. B., Cannon-Bowers, J. A., & Salas, E. (1992). The role of mental models in team performance in complex systems. *IEEE Transactions on Systems, Man, and Cybernetics*, *22*(6), 1296–1308. https://doi.org/10.1109/21.199457

Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *Academy of Management Review*, *23*(3), 393–404. https://doi.org/10.5465/amr.1998.926617

Schaefer, K. E., Perelman, B. S., Gremillion, G. M., Marathe, A. R., & Metcalfe, J. S. (2021). A roadmap for developing team trust metrics for human-autonomy teams. In *Trust in Human-Robot Interaction* (pp. 261–300). Elsevier. https://doi.org/10.1016/B978-0-12-819472-0.00012-5

Schoorman, F. D., Mayer, R. C., & Davis, J. H. (2007). An integrative model of organizational trust: Past, present, and future. *Academy of Management Review*, *32*(2), 344–354. https://doi.org/10.5465/amr.2007.24348410

Schwartz, H. (1987). On the psychodynamics of organizational disaster: the case of the space shuttle Challenger. *The Columbia Journal of World Business*, *22*, 59–.

Sheridan, T. B. (2002). Humans and automation: System design and research issues (pp. xii, 264). *Human Factors and Ergonomics Society*.

Sheridan, T. B. (2019a). Individual differences in attributes of trust in automation: Measurement and application to system design. *Frontiers in Psychology*, *10*, 1117. https://doi.org/10.3389/fpsyg.2019.01117

Sheridan, T. B. (2019b). Extending three existing models to analysis of trust in automation: Signal detection, statistical parameter estimation, and model-based Control. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *61*(7), 1162–1170. https://doi.org/10.1177/0018720819829951

Sheridan, T. B., & Verplank, W. L. (1978). Human and computer control of undersea teleoperators. Massachusetts Inst of Tech Cambridge Man-Machine Systems Lab. https://apps.dtic.mil/sti/citations/ADA057655

Stout, R. J., Cannon-Bowers, J. A., Salas, E., & Milanovich, D. M. (1999). Planning, shared mental models, and coordinated performance: An empirical link is established. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *41*(1), 61–71. https://doi.org/10.1518/001872099779577273

Tenhundfeld, N., Demir, M., & de Visser, E. (2021). An argument for trust assessment in human-machine interaction: overview and call for integration [Preprint]. Open Science Framework. https://doi.org/10.31219/osf.io/j47df

Tucker, A. W. (I 950). 'A two-person dilemma.' Mimeo, Stanford University. Published under the heading on jargon: the prisoner’s dilemma. UMAP Journal, vol. I, 1980.

Vaughan, D. (1990). Autonomy, interdependence, and social control: NASA and the space shuttle challenger. *Administrative Science Quarterly*, *35*(2), 225. https://doi.org/10.2307/2393390

Weisberg, S. (2005). Variable Selection. In *Applied Linear Regression* (pp. 211–232). John Wiley & Sons, Ltd. https://doi.org/10.1002/0471704091.ch10

Wynne, K. T., & Lyons, J. B. (2018). An integrative model of autonomous agent teammate-likeness. *Theoretical Issues in Ergonomics Science*, *19*(3), 353–374. https://doi.org/10.1080/1463922X.2016.1260181

APPENDIX A

DESCRIPTIVE STATISTICS OF ANTICIPATORY PUSHING AND TRUST

Session	Pairs for Anticipatory Pushing	Condition	Mean	Std. Deviation	N
Session 1	From navigator to pilot	Control	1.0000	1.49071	10
		Calibration	.3333	.70711	9
		Coordination	2.1111	2.36878	9
	From navigator to photographer	Control	.6000	.69921	10
		Calibration	.6667	.86603	9
		Coordination	1.1111	1.26930	9
	From photographer to pilot	Control	.0000	.00000	10
		Calibration	.0000	.00000	9
		Coordination	.0000	.00000	9
	From photographer to navigator	Control	.0000	.00000	10
		Calibration	.0000	.00000	9
		Coordination	.0000	.00000	9
Session 2	From navigator to pilot	Control	2.1740	1.35098	10
		Calibration	1.9900	2.09253	9
		Coordination	4.6111	4.46009	9
	From navigator to photographer	Control	1.4500	1.01559	10
		Calibration	.7411	.79102	9
		Coordination	2.1667	2.13966	9
	From photographer to pilot	Control	.0910	.14813	10
		Calibration	.0556	.16667	9
		Coordination	.5278	.98777	9
	From photographer to navigator	Control	.5250	.47423	10
		Calibration	.0833	.25000	9
		Coordination	.5000	1.00000	9

Session	Pairs	Condition	Mean	Std. Deviation	N
Session 1	Trust from navigator toward pilot	Control	3.1890	.51434	10
		Calibration	3.3078	.45296	9
		Coordination	3.0478	.66537	9
	Trust from navigator toward photographer	Control	3.4180	.44507	10
		Calibration	3.2033	.47721	9
		Coordination	3.1411	.71420	9
	Trust from photographer toward pilot	Control	3.3970	.76120	10
		Calibration	3.2311	.42339	9
		Coordination	3.2467	.67980	9
	Trust from photographer toward navigator	Control	3.6000	.50638	10
		Calibration	3.4444	.34271	9
		Coordination	3.5711	.56070	9
Session 2	Trust from navigator toward pilot	Control	2.8220	.92025	10
		Calibration	3.3700	.22439	9
		Coordination	2.9511	.67369	9
	Trust from navigator toward photographer	Control	3.6330	.46524	10
		Calibration	3.4867	.36042	9
		Coordination	3.4900	.54072	9
	Trust from photographer toward pilot	Control	2.5580	.86285	10
		Calibration	3.2211	.38322	9
		Coordination	3.0633	.83105	9
	Trust from photographer toward navigator	Control	3.9230	.50897	10
		Calibration	3.1467	.73121	9
		Coordination	3.6289	.62641	9

46