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Tracing the Development of Trust in Automation/Autonomy in a Multitasking Environment

Tetsuya Sato
Old Dominion University, sato.tetsuya1996@gmail.com

TRACING THE DEVELOPMENT OF TRUST IN AUTOMATION/AUTONOMY IN A MULTITASKING ENVIRONMENT

by

Tetsuya Sato
B.S., May 2018, Old Dominion University
M.S., December 2020, Old Dominion University

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Approved by:

Yusuke Yamani (Director)

Xiao Yang (Member)

Sampath Jayarathna (Member)

Eric Chancey (Member)

ABSTRACT

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Tetsuya Sato
Old Dominion University, 2024
Director: Dr. Yusuke Yamani

Future Advanced Air Mobility (AAM) operations will likely involve autonomous systems that exceed the capabilities of a typical automation. However, human operators could use such systems counterproductively by either misusing unreliable systems or disusing reliable systems. One determinant for inappropriate use of autonomous systems is trust. Human factors theorists proposed numerous ways to characterize trust such as the tripartite model of trust that describes the bases of trust in automation (i.e., performance, process, and purpose; Lee & See, 2004). Previous works have indicated that participants rated lower performance- and process-based trust toward the automation when the tracking task required more frequent input in the Multi-Attribute Task Battery (MATB-II) paradigm (i.e., high task load condition). Yet, it is unclear how trust in automation and trust in autonomy develops over time in attention demanding environments. Specifically, my dissertation employed a 4 (agent characteristics) × 2 (task load) × 3 (time epoch) split-plot design. Participants completed three experimental trials that required participants to concurrently perform the tracking task and the system monitoring task. The system monitoring task was supported by a 70% reliable signaling system. Task load was manipulated between groups by altering the tracking difficulty. Agent characteristics were manipulated by administering one of four vignettes that describe the aid prior to the experimental session. Results demonstrated a temporal effect where participants supplied less attentional resources for performing the system monitoring task and rated high trust over time. Furthermore, the trajectory of trust development was inconsistent with previous findings whereby trust developed from dependability to faith. Finally, an exploratory analysis indicated that the progression of trust development varied across agent characteristics. These findings offer insights for understanding the dynamic nature of trust and developing interventions for mitigating counterproductive use of autonomous systems.

This dissertation is dedicated to my family, friends, faculty, and staff at Old Dominion University.

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This is not the end of my academic journey. It is merely the beginning of another academic journey. Not as a student, but as a faculty and as a research scholar. As I embark on this new journey, I look forward to meeting with all of them again in the near future.

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CHAPTER I

INTRODUCTION

Advanced Air Mobility (AAM) is an emerging form of aerial transportation that enables mobility of goods and people in both rural and urban areas (National Academics of Sciences, Engineering, and Medicine, 2020). In recent years, National Aeronautics and Space Administration (NASA) has launched the AAM National Campaign which aims to promote the safety of AAM to the public and raise awareness of the emerging AAM concept. To achieve the goals of the AAM National Campaign, NASA collaborated with different industry partners to test the vehicles involved in AAM (A. P. Cohen et al., 2021). For example, NASA tested an electric vertical takeoff and landing (eVTOL) aircraft with Joby Aviation in September 2021 (National Aeronautics and Space Administration, 2021). The eVTOL aircraft involves an autonomous system that operates the aircraft without pilot intervention. Many of the vehicles used for AAM will likely be supported by autonomous systems that perform a wide range of activities such as operating and navigating aircrafts (Chancey et al., 2021). The implementation of autonomous systems in AAM shifts the pilot's role to a passive monitor, calling for more research on the pilot's cognitive mechanisms that regulate their interactions with AAM in a highly autonomous environment. Particularly, it is essential to understand the pilot's trust toward autonomous systems as a determinant of human-autonomy teaming and how trust in human-autonomy teaming evolves over time. However, previous works examined the development of human-automation trust in a pasteurization plant task (Lee et al., 2021; Long et al., 2022; Muir & Moray, 1996) but not in modern professional environment involving highly automated systems. My dissertation follows Muir and Moray's (1996) seminal work to explore the dynamic nature of trust in automation and trust in autonomy in a flight simulation environment.

ADVANCED AIR MOBILITY (AAM)

AAM is characterized as the technological advancement of air transportation systems including electric propulsion, computer system, sensor, positioning system, and automated systems (National Academics of Sciences, Engineering, and Medicine, 2020). The technological advancement of these systems allows air vehicles to ensure safe, reliable, and noiseless operation. Thus, the emergence of AAM is expected to improve the logistics and air traffic management in the U.S. AAM involves air vehicles that are manned or unmanned, autonomous or non-autonomous. The subset of AAM include, but not limited to, Unmanned Air Vehicles (UAV), small Unmanned Aircraft Systems (sUAS), and Unmanned Air Mobility (UAM; A. P. Cohen, et al., 2021). UAM is visualized as having safe, efficient, accessible, and highly autonomous air mobility of passengers, goods, and services within urban areas. sUAS allow delivery of consumer goods, mapping, and surveillance. Unlike sUAS, UAV is not only limited to the transportation of goods, but it also carries passengers without pilots on-board. Several factors should be considered for the application of AAM operation such as safety (i.e., demonstration of safe AAM operation), security (i.e., management for potential cybersecurity hazards), and social acceptance (i.e., gaining public trust). Additionally, the success of AAM operation will likely require increasingly autonomous systems (Chancey et al., 2021).

THE ROLE OF AUTOMATION

Defining Automation

Automation refers to a system or device that performs the human operator's task or a task that cannot be accomplished by the human operator (Bainbridge, 1983; Parasuraman & Riley, 1997). Automation is often incorporated in professional attention-demanding environments to compensate for the human operator's attentional limits. According to the human-information processing (HIP) model, human operators have limited attentional resources that can be allocated to each task (Kahneman, 1973; Wickens et al., 2015). Task performance is determined by the correspondence between the number of attentional resources supplied and the amount of attentional demand imposed by the task. Specifically, human operators will successfully perform the task when the attentional resources exceed the attentional demand. Alternatively, human operators will fail to perform the task when the attentional demand exceeds the attentional resources. Later, Yamani and Horrey (2018) adapted the HIP model (Wickens et al., 2015) to propose a theoretical model that conceptualizes human-automation interaction involving automated driving. According to the theoretical model, human-automation interaction involves a closed-loop mechanism whereby the operators evaluate human-automation performance and adjust the allocation policy, altering the distribution of attentional resources to varying stages of the HIP model. Within AAM environments, human operators will likely be tasked to allocate attentional resources to monitor multiple air vehicles, degrading their monitoring performance because their resources were divided between the multiple air vehicles. AAM operation will involve highly autonomous systems that may supplant the human operator's task to monitor multiple air vehicles. A critical question for implementing automation in AAM operations are the level of automation required for successful AAM operation.

Levels of Automation

Several researchers have conceptualized that the level of automation is not dichotomous (i.e., all-or-none), but it involves a spectrum of levels at varying stages of the HIP model (Billings, 1991; Endsley & Kiris, 1995; Sheridan & Verplank, 1978; Wiener & Curry, 1980). For example, Sheridan and Verplank (1978) described ten levels of automation at the decision making and action implementation stage, ranging from manual control to full automation (see Table 1). Alternatively, Endsley and Kiris (1995) described five levels of automation based on Wiener and Curry (1980) and Billings' (1991) work.

Table 1

Sheridan and Verplank's (1978) classification of the levels of automation of decision and action selection.

HIGH	10. The computer decides everything, acts autonomously, ignoring the human
	9. Informs the human only if it, the computer, decides to
	8. Informs the human only if asked, or
	7. Executes automatically, then necessarily informs the human, and
	6. Allows the human a restricted time to veto before automatic execution, or
	5. Executes that suggestion if the human approves, or
	4. Suggest one alternative
	3. Narrows the selection down to a few, or
	2. The computer offers a complete set of decison/action alternatives, or
LOW	1. The computer offers no assistance: human must take all decisions and actions

The levels of automation in a system can be determined by referring to Parasuraman et al.'s (2000) guideline for designing automation. According to Parasuraman et al.'s (2000) framework, system designers need to determine whether automation should be implemented in one or more stages of the HIP model including sensory processing, perception and working memory, decision making, and action selection. The levels of automation for the corresponding stages of the HIP model could be determined by applying the primary evaluative criteria and the secondary evaluative criteria. The primary evaluative criteria examine human performance consequences by considering factors including workload, situation awareness, complacency, and skill degradation. The secondary evaluative criteria examine human performance consequences by considering system related factors including the automation's reliability and the cost of error made by the human operator. Although implementing automation can facilitate flight operation in AAM environments, joint human-automation performance could potentially be constrained by misuse and disuse of automation.

Challenges in Implementing Automation

Inappropriate use of automation is a major challenge in human-automation interaction (Parasuraman & Riley, 1997). Parasuraman and Riley (1997) suggested that implementing automation can lead human operators to use the automation counterproductively by either misusing unreliable automation or disusing reliable automation. In the context of aviation, the National Transportation Safety Board (NTSB) documented the detrimental effect of these counterproductive behaviors. For example, the NTSB (2017) reported that a pilot disused automation by disconnecting the Terrain Awareness and Warning System (TAWS). Consequently, disengaging the system could have impeded the pilot's ability to identify potential hazards, potentially resulting in a plane crash. One potential factor that influenced these counterproductive behaviors is trust in automation (Parasuraman & Riley, 1997). Particularly, human operators misuse reliable automation when they overtrust the automation whereas human operators disuse unreliable automation when they distrust the automation. In AAM environments, trust is expected to play a significant role in the use of automation (Chancey et al., 2021). To facilitate AAM operations, the challenges involving highly autonomous systems postulate the need to understand the psychological mechanisms of trust.

HUMAN-AUTOMATION TRUST

Defining Human-Automation Trust

Many researchers have emphasized that trust is a critical factor that influences human-automation interaction (Bailey & Scerbo, 2007; Bliss & Dunn, 2000; Chancey et al., 2017; Chancey et al., 2021; Hoff & Bashir, 2015; Karpinsky et al., 2018; Lee et al., 2021; Lee & See, 2004; Muir, 1994; Muir & Moray, 1996; Sato et al., 2020; Yamani et al., 2020). Trust is considered as a multidimensional construct and has multiple definitions. For example, Rotter (1967) defined trust as an expectation regarding the presence of an outcome or behavior, whereas Meyer (2001) conceptualized trust as a behavioral outcome. Within the realm of human-automation interaction, Lee and See (2004) characterized trust based on several works on interpersonal relationship (Barber, 1983; Rempel et al., 1985; Mayer et al., 1995; Kramer, 1999). Trust can be defined within Ajzen and Fishbein's (1980) framework. According to Ajzen and Fishbein's (1980) framework, an attitude, which is determined by the human's belief and the information source from the external environment, influences intention that leads to behavior. Within this framework, Lee and See (2004) defined trust as "an attitude that an agent will help achieve an individual's goal in a situation characterized by uncertainty and vulnerability" (Lee &

See, 2004, pp. 51). Lee and See (2004) thus characterized trust as an attitude toward automation because trust is developed based on the information sources characterizing the automation.

Models of Human-Automation Trust

Research on human-automation trust originated from theoretical frameworks of interpersonal trust (Barber, 1983; Rempel et al., 1985). Muir's (1994) earliest theoretical framework conceptualized the dynamics of human-automation trust by integrating Barber (1983) and Rempel et al.'s (1985) theoretical framework. Specifically, Muir (1994) proposed that the dynamics of human-automation trust is based on three expectations toward the automation including persistence, technical competence, and fiduciary responsibility. Persistence refers to the human operator's expectation that the natural and moral law will persevere. Technical competence refers to the human operator's expectation that the automation possesses the capability to perform a task. Fiduciary responsibility refers to the human operator's expectation that the automation has the obligation to accomplish a task. Additionally, Muir (1994) proposed that the basis of human-automation trust evolves similarly to interpersonal trust. Specifically, human-automation trust is initially determined by the extent to which the human operator can anticipate the automation's behavior (i.e., predictability). Then, human-automation trust is determined by the human operator's dependence on automation (i.e., dependability). Finally, human-automation trust is determined by the human operator's certainty toward the automation's future state (i.e., faith).

Muir and Moray (1996) adapted Muir's (1994) framework by conducting a simulation-based experiment that asked participants to perform a supervisory control task. The task required participants to control a semi-automated pump and heating system in a simulated pasteurizer. Trust toward the pump was measured by administering a subjective questionnaire which reflects the different dimensions of human-automation trust. Muir and Moray's (1996) findings confirmed that human-automation trust is based on the technical competence and fiduciary responsibility. Additionally, the dynamics of human-automation trust is determined by predictability, dependability, and faith. However, the dynamics of human-automation trust progressed in the order opposite of their expectation (i.e., faith, then dependability, followed by predictability).

Lee and See (2004) proposed a conceptual model which explains the basis of trust, the appropriateness of trust, the contextual factors that influence human-automation trust, and the different levels of processing involved in human-automation trust. According to Lee and See (2004), human-automation trust is based on three information sources – performance, process, and purpose. Performance-based trust is developed by accumulating information on the automation's behavior (i.e., what is the automation doing?). Process-based trust is developed by accumulating information on the automation's mechanism (i.e., how does the automation work?). Purpose-based trust is developed by accumulating information on the system designer's intention for developing the automation (i.e., why was the automation developed?). Additionally, Lee and See (2004) proposed that the appropriateness of human-automation trust is determined by the calibration, resolution, and specificity. Calibration refers to the degree to which the human operator's trust reflects the automation's capability. Resolution refers to the degree to which the changes in the human operator's trust represent the changes in the automation's capability. Specificity refers to the degree to which the human operator's trust is associated with a certain component of the automation.

Lee and See (2004) further suggested that the dynamics of human-automation trust is influenced by contextual factors including the individual context, the organizational context, and the cultural context. The individual context describes the human operator's previous experience interacting with the automation. The organizational context describes the interaction between the human operators within the organization that inform the automation's trustworthiness. The cultural context describes the human operator's expectation and the societal norms. Finally, Lee and See (2004) proposed that the information sources are accumulated by three different ways including analytic processing, analogical processing, and affective processing. Analytic processing involves the use of mental representation of the automation to evaluate the trustworthiness of the automation. Analogical processing accumulates information on the automation's characteristics to evaluate trust toward automation. Affective processing evaluates the automation's trustworthiness based on the human operator's affective response toward the automation's behavior. Within Lee and See's (2004) theoretical model, the interaction of these concepts (i.e., basis of trust, appropriateness of trust, contextual factors of trust, and processing levels involved in trust) explain the dynamic process involving human-automation trust.

In recent years, Hoff and Bashir (2015) proposed a theoretical model that describes the variability of human-automation trust. According to Hoff and Bashir's (2015) theoretical model, the variability of trust is determined by three different sources including dispositional trust, situational trust, and learned trust. Dispositional trust describes the human operator's propensity to evaluate the trustworthiness of the automation. Several factors influence dispositional trust including culture, age, gender, and personality trait. Situational trust describes that the external (e.g., complexity of automation and difficulty of task) and internal factors (e.g., personality and mood) influence the variability of trust. Learned trust describes that the variability of trust is determined by the human operator's past experience interacting with the automation. Similar to Lee and See's (2004) theoretical model, Hoff and Bashir (2015) identified pertinent factors that explain the variability of human-automation trust based on extensive review of the literature. Hoff and Bashir (2015) extended Lee and See's (2004) theoretical model by introducing three-layers of trust (i.e., dispositional, situational, and learned) that influences reliance behavior. Yet, Hoff and Bashir's (2015) theoretical framework does not provide an in-depth conceptualization of the underlying processes involved in trust formation. On the other hand, Lee and See's (2004) theoretical framework describes how human operators develop trust in automation by characterizing the different basis of trust (i.e., performance, process, and purpose) and cognitive processes (i.e., analogic, analytic, and affective). To sum, theoretical models of trust in automation (Hoff & Bashir, 2014; Lee & See, 2004; Muir & Moray, 1996) characterizes different sets of factors that influence human-automation trust and serve as a guide for future research.

Trust in Attention Demanding Environment

Several studies examined human-automation trust in attention demanding environment by controlling task load which is operationally defined as the difficulty of the primary task (Karpinsky et al., 2018; Sato et al., 2020; Sato et al., 2023c; Sato et al., 2024). For example, Karpinsky et al. (2018) examined the effect of task load on the human operator's subjective trust ratings and eye movement behavior by administering the Multi-Attribute Task Battery (MATB; Santiago-Espada et al., 2011). The MATB required participants to concurrently perform multiple simulation tasks including the compensatory tracking task and the system monitoring task. The compensatory tracking task required participants to maintain the moving circular target within a dotted square. Specifically, participants used the joystick to keep the moving circular target from going outside of the dotted square. The moving circular target represents the trajectory of the aircraft while the dotted square represents the target destination. The system monitoring task required participants to monitor the system's engine with the assistance of an automated aid. The system monitoring task consisted of four vertical gauges that depicted the aircraft's engine. Within each vertical gauge, a yellow pointer vertically fluctuates between the center of the vertical gauge. When the aircraft's engine malfunction, the yellow pointer touches either the upper or lower extremity of the vertical gauge. In this case, participants corrected the corresponding vertical gauge. The system monitoring task was assisted by an automated signaling system which indicated whether the yellow pointer hit either extremity of the vertical gauge. The reliability of the signaling system was set to 70% by controlling the frequency of Hit and false alarm (FA) events. Hit events occur when the signaling system accurately detected engine malfunction while FA events occur when the signaling system indicates engine malfunction even though the engine is in normal state. Task load was manipulated by altering the difficulty of the compensatory tracking task. Specifically, the difficulty of the compensatory tracking task was determined by frequency of the force function. Trust was measured using Chancey et al.'s (2017) trust questionnaire and Jian et al.'s (2000) trust scale. Results demonstrated that participants reported lower levels of performance- and process-based trust in the high than low task load condition. Karpinsky et al. (2018) demonstrated that human-automation trust is based on the automation's behavior (performance) and mechanism (process), but not the system designer's intention for developing the automation (purpose) in an attention-demanding environment that required the participants to interact with an unfamiliar automated system. Later, other studies examined different factors that influence the effect of task load on human-automation trust (Sato et al., 2020; Sato et al., 2023c; Sato et al., 2024).

For example, Sato et al. (2020) extended Karpinsky et al.'s (2018) work to examine whether the effect of task load on human-automation trust was due to the absence of risk which is a critical factor that influences human-automation trust (Chancey et al., 2017; He et al., 2022;

Hoesterey & Onnasch, 2023; Hoff & Bashir, 2015; Lee & See, 2004; Mayer et al., 1995; Sato et al., 2020; Stuck et al., 2022). Risk is defined as "the extent to which there is uncertainty about whether potentially significant and/or disappointing outcomes of decisions will be realized" (Sitkin & Pablo, 1992, p. 10). In Sato et al.'s (2020) work, participants in the high-risk condition were instructed that poor performance will result them to redo the trial while participants in the low-risk condition did not receive such instructions (e.g., Chancey et al., 2017). Results indicated that performance-based trust elevated under high task load condition when participants perceived high risk. Human-automation trust did not differ between risk conditions, but there were measurable differences in human-automation trust when risk interacted with task load. Sato et al.'s (2020) findings were consistent with Mayer et al.'s (1995) theoretical model which characterizes trust as the willingness to be in vulnerable state.

Later, Sato et al. (2023c) examined whether the effect of task load on human-automation trust was modulated by task priority which is commonly defined as the value of a task (Gutwiller & Sitzman, 2017; Gutzwiller et al., 2014; Wickens et al., 2016). Task priority was manipulated by instructing participants to aim for a certain target value in the tracking task during the experimental session. Participants aimed for the target value across task load conditions by either equally prioritizing all tasks (i.e., equal priority condition) or prioritizing the tracking task (i.e., tracking priority condition). Results indicated that participant's performance-based trust degraded when they equally prioritized all tasks under high task load condition. Following Sato and his colleagues' (2020; 2023c; 2024), my dissertation extends Karpinsky et al.'s (2018) work by examining other factors that modulate the effect of task load including time and agent characteristics.

Measures of Human-Automation Trust

Previous work has employed several techniques to gauge human-automation trust such as administering subjective questionnaires (Karpinsky et al., 2018; Sato et al., 2020; Sato et al., 2023a; Sato et al., 2023c; Sato et al., 2024), assessing behavioral responses (Meyer 2001; Rice, 2009), and recording physiological responses (Lu & Sarter, 2019). Subjective questionnaires are commonly used to measure human-automation trust because they can be easily administered. Karpinsky et al. (2018) examined human-automation trust by administering two different questionnaires including Chancey et al.'s (2017) trust questionnaire and Jian et al.'s (2000) trust scale. Jian et al.'s (2000) trust scale is an empirically driven questionnaire which consists of 12 items. These items reflected the human operator's trust and distrust toward the automation. Chancey et al.'s (2017) theory-driven questionnaire includes 15 items that are adapted from Madsen and Gregor's (2000) human-computer trust scale. These items reflected the three basis of human-automation trust including performance, process, and purpose (Lee & See, 2004). A few works have demonstrated discrepancies between results using these two subjective questionnaires (Sato et al., 2020; Sato et al., 2023a; Sato et al., 2023c; Sato et al., 2024). For example, Sato et al. (2020) demonstrated a main effect of task load on human-automation trust using Chancey et al.'s (2017) trust questionnaire, but not from Jian et al.'s (2000) trust scale. Additionally, Yamani et al.'s (2024) multi-level confirmatory factor analysis (CFA) showed that these two questionnaires are unlikely to measure the same construct.

The behavioral effects of human-automation trust have been explored by measuring the human operator's compliance and reliance toward the automation. For example, Chancey et al. (2017) asked participants to concurrently perform the compensatory tracking task and resource management tasks within the MATB as well as a detection task. The detection task involved an automated aid that informed the presence of a target stimuli (i.e., the tank). Compliance toward the automated aid was assessed by counting the number of times the participants agreed with the automated aid when it alerted for the presence of a tank. Reliance toward the automation was assessed by counting the number of times the participants agreed with the automated aid when it did not alert for the presence of a tank. Compliance and reliance are robust measures that reflect the extent to which operators are willing to take risk or place themselves in vulnerable state (Kohn et al., 2021). Although these behavioral measures are robust and unobtrusive, operators can exhibit reliance toward the automation even though they distrust the automation under high workload condition. Thus, Kohn et al. (2021) suggested to use behavioral measures in conjunction with subjective measures.

Physiological measures have been used alternatively to examine human-automation trust such as eye movement behavior (Lu & Sarter, 2019). Lu and Sarter (2019) examined the dynamics of human-automation trust by recording participant's eye movement when performing a target identification task with the assistance of an automated aid. The metrics of eye movement include fixation duration, saccade amplitude, backtrack rate, transition rate, length of scan path, fixation count, and transition count. Eye movement data were correlated with subjective ratings and behavioral responses. Results indicated that most eye movement measures were negatively correlated with subjective trust ratings except for saccade amplitude, proposing eye movement behavior as a measure of human-automation trust. Specifically, participants rated lower trust ratings when frequently monitoring a low reliable automation (i.e., 50%). Indeed, Sato et al.'s (2023b) meta-analytic study indicated that eye movement behavior was negatively correlated with human-automation trust whereby participants rated high performance-based trust when they fixated the automation less frequently. Although behavioral and physiological measures predict human-automation trust, human operators could exhibit trust behaviors even though they do not trust the automation (Bolton, 2022). For example, human operators can visually sample the automation more frequently because of social pressure or the rules of the authority. Thus, my dissertation measured trust by employing subjective trust scales (Chancey et al., 2017; Jian et al., 2020; Muir & Moray, 1996).

CURRENT STUDY

Previous works on human-automation trust suggested that performance- and process-based trust fluctuates under varying levels of workload depending on the human operator's eye movement patterns (Karpinsky et al., 2018; Sato et al., 2020; Sato et al., 2024). However, there are several caveats that need to be addressed to understand human-automation trust in AAM operation. First, the dynamic nature of Lee and See's (2004) trust dimensions in attention demanding environment is still uncertain. In my dissertation, the dynamic nature of human-automation trust refers to the change in the operator's trust toward the automation over time. Several studies explored the dynamic nature of trust in automation (Dikmen & Burns, 2017; Ebinger et al., 2023; Gold et al., 2015; Wilson et al., 2020). For example, Dikmen and Burns (2015) conducted a survey study to examine the dynamic nature of trust toward Tesla's automated systems (i.e., AutoPilot and Summon). In the survey, participants were asked to rate their initial trust and current trust toward the two automated systems. Results indicated that the participants reported higher current trust than initial trust toward both automated systems. Furthermore, they suggested several factors that determine human-automation trust including ease of learning, usefulness, and knowledge about the automation. Wilson et al. (2020) asked participants to rate their trust toward a partially automated vehicle before and after driving on a public highway. Results indicated that trust was higher after driving a partially automated vehicle than before. Overall, these studies indicated that human operators rate high levels of trust after they interact with an automation. Yet, it is uncertain whether the development of Lee and See's (2004) trust dimensions follow previous findings (Dikmen & Burns, 2017; Ebinger et al., 2023; Gold et al., 2015; Wilson et al., 2020).

Second, it is uncertain whether the development of human-automation trust follows the pattern of the development shown in Muir and Moray's (1996) work. Muir and Moray (1996) conducted a simple linear regression to examine predictors of overall trust in each session (i.e., first training session, last training session, and last experimental session). Results indicated that faith predicted overall trust during the beginning of the training session, dependability predicted overall trust during the end of training session, and predictability predicted overall trust during last experimental session. Thus, human-automation trust initially develops from faith followed by dependability and predictability. Muir and Moray's (1996) findings contrasted from Rempel et al.'s (1985) theoretical framework of interpersonal trust. Specifically, Rempel et al.'s (1985) theoretical framework postulated that trust develops in the opposite order from predictability, to dependability, and to faith. Recent works showed mixed findings on the development of human-automation trust (Lee et al., 2021; Long et al., 2022). For example, Lee et al.'s (2021) replication study indicated that dependability predicted overall trust in all three sessions. The author suggested that the difference could be attributed by cohort difference between participants in Lee et al.'s (2021) study and participants in Muir and Moray's (1996) study. That is, automation has become presumably more prevalent and frequently used by participants in Lee et al.'s (2021) study than participants in Muir and Moray's (1996) study. Additionally, the difficulty of the pump control task could have lowered self-confidence, resulting participants to rely on the automation. Alternatively, Long et al.'s (2022) replication study indicated that dependability predicted initial trust, followed by predictability and lastly faith. Only these studies (Lee et al., 2021; Long et al., 2022) recently re-examined the development of human-automation trust in a pasteurizer plant task, but not in a flight simulated environment.

Third, it is unclear whether previous findings on human-automation trust generalize to AAM operations. AAM operations heavily focus on human-autonomy teaming whereby autonomous systems are implemented instead of traditional automation. Autonomous systems are machines that surpass the capability of traditional automation (Chancey et al., 2021). Specifically, autonomous systems are expected to achieve “full autonomy” whereby the machine requires minimal human intervention (Wings et al., 2020). There has been growing research in human-autonomy teaming (Demir et al., 2021; Graham et al., 2022; M. C. Cohen et al., 2021) due to the emergence of cognitive modeling techniques and AI (McNeese et al., 2019; McNeese et al., 2021). For example, Demir et al. (2021) employed the Wizard of Oz paradigm to examine trust and team performance across different system failures (i.e., system failure related to automation, system failure related to autonomy, and cyber-attack). Specifically, two participants worked together to complete a flight simulated task while interacting with an experimenter who acted as an autonomous agent. Findings revealed a decline in the trust of human operators over time when the autonomous pilot supplied inaccurate information or executed incorrect actions (i.e., system failure related to autonomy). Yet, there are scarce work that directly compared trust in automation and trust in autonomy (Sato et al., 2023a). One explanation was that the functional difference between these agents were unclear, complicating researchers to distinguish autonomy from automation. Recently, Sato et al. (2023a) conducted a survey study that compared trust in automation and trust in autonomy using Kaber’s (2018) conceptual framework. According to Kaber (2018), a machine achieves “full autonomy” when it possesses the highest level of all three dimensions including viability (i.e., the machine's ability to perform basic function in the environment), independence (i.e., the machine's ability to perform a task without human intervention), and self-governance (i.e., the machine's ability to develop strategic plans). Sato et al. (2023a) used Kaber's (2018) conceptual framework to generate different vignettes that each describe different agent characteristics including an autonomous agent, an automated agent without viability, an automated agent without independence, and an automated agent without self-governance. Participants read each vignette and completed a series of trust questionnaire (Chancey et al., 2017; Jian et al., 2020) for each agent characteristics. Results indicated that trust varied across different agent characteristics. Specifically, participants rated higher trust towards an autonomous agent and an automated agent without independence compared to automated agent without viability and an automated without self-governance. Furthermore, results indicated similar data pattern when analyzing performance-based trust. Interestingly, participants rated higher purpose-based trust towards an automated agent without independence compared to an automated agent without viability and an automated agent without self-governance. These results indicated that using an automated agent that requires human input will not impede trust. However, it is unclear how trust in autonomy develop over time.

My dissertation extends Karpinsky et al.'s (2018) work by investigating the development of trust across varying agent characteristics in attention demanding environment. Specifically, participants completed three 20-minute experimental sessions. In each session, participants concurrently performed the tracking task and the system monitoring task. The system monitoring task was aided by an imperfect signaling system (i.e., 70%). Prior to the beginning of the experimental session, participants read one of the four vignette that described a signaling system that is either an autonomous agent (i.e., possesses all three dimensions of autonomy) or an automated agent (i.e., does not possess one of the three dimensions of autonomy). In addition, the difficulty of the tracking task varied across task load conditions. After each experimental session, participants completed a series of questionnaires that assessed trust (Chancey et al., 2017; Jian et al., 2000; Muir & Moray, 1996) and workload (Hart & Staveland, 1988). My dissertation manipulated task load by changing the difficulty of the tracking task (Karpinsky et al., 2018). Thus, I anticipated that the effect of task load will be similar to Karpinsky et al.'s (2018) work. Specifically, I hypothesized that:

1. Participants will rate higher subjective workload when more attentional resources are required to perform the tracking task (i.e., high task load condition).
2. Participant's tracking performance will improve when less attentional resources are required to perform the tracking task (i.e., low task load condition).
3. Participants will visually sample the system monitoring display less frequently and the tracking display more frequently under the high task load condition than the low task load condition.
4. Participants will rate lower Jian et al.'s (2000) trust towards the signaling system under high task load condition compared to the low task load condition.
5. Participants assigned to the high task load condition will rate lower performance- and process-based trust compared to those assigned to the low task load condition, but purpose-based trust ratings will be comparable between task load conditions.

I anticipate that the present findings will be consistent with Sato et al.'s (2023a) finding whereby participants exhibited varying trust ratings across different agent characteristics. Therefore, I hypothesized that:

6. Jian et al.'s (2000) trust rating will be greater with an autonomous agent than with an automated agent without viability or an automated aid without self-governance.
7. Jian et al.'s (2000) trust rating will be greater with an automated agent without independence than with an automated agent without viability or an automated agent without self-governance.
8. Participants will rate higher performance-based trust towards an autonomous agent than an automated agent without viability or an automated aid without self-governance, but not on the process- and purpose-level of attributional abstraction.
9. Participants will rate higher performance-based trust towards an automated agent without independence than an automated agent without viability or an automated agent without self-governance, but not on the process- and purpose-level of attributional abstraction.

Although Sato et al. (2023a) did not examine how attention allocation varied across different agent characteristics, Sato et al.'s (2023b) meta-analysis indicated a negative correlation between human-automation trust and attention allocation. That is, participants spent less time fixating the automation when they displayed higher trust towards the automation. Based on Sato et al.'s (2023b) finding, I hypothesized that:

10. Participants will fixate on the system monitoring display less frequently when they assume that the signaling system is an autonomous agent compared to when they assume that the signaling system is an automated agent without viability or an automated agent without self-governance.
11. Participants will fixate on the system monitoring display less frequently when they assume that the signaling system is an automated agent without independence

compared to when they assume that the signaling system is an automated agent without viability or an automated agent without self-governance.

12. Participants will fixate on the tracking display more frequently when they assume that the signaling system is an autonomous agent compared to when they assume that the signaling system is an automated agent without viability or an automated agent without self-governance.
13. Participants will fixate on the tracking display more frequently when they assume that the signaling system is an automated agent without independence compared to when they assume that the signaling system is an automated agent without viability or an automated agent without self-governance.

As indicated in my previous hypotheses, participants could reallocate attentional resources depending on the agent characteristics. Based on the general HIP model, I speculated that reallocating attentional resources between the tracking task and the system monitoring task could alter task performance in both tasks. Specifically, I hypothesized that:

14. Tracking performance should degrade while system monitoring performance should improve when participants assume that the signaling system is an autonomous agent compared to when participants assume that the signaling system is an automated agent without viability or an automated agent without self-governance.
15. Tracking performance should degrade while system monitoring performance should improve when participants assume that the signaling system is an automated agent without independence compared to when participants assume that the signaling system is an automated agent without viability or an automated agent without self-governance.

Previous work (Dikmen and Burns, 2017; Ebinger et al., 2023; Gold et al., 2015; Wilson et al., 2020) showed that trust towards an automation evolved over time. I anticipate that the present findings will be consistent with previous findings on the development of trust (Dikmen & Burns, 2017; Ebinger et al., 2023; Gold et al., 2015; Wilson et al., 2020). Thus, it was hypothesized that:

16. Jian et al.'s (2000) trust and Chancey et al.'s (2017) trust dimensions will increase over time.

Sato et al. (2023b) demonstrated a negative correlation between trust in automation and visual scanning behavior. Thus, I hypothesized that the findings would be consistent with Sato et al.'s (2023b) finding whereby:

17. Participants will visually sample the system monitoring display less frequently while visually sampling the tracking display more frequently over time.

Furthermore, Haga et al. (2002) demonstrated an effect of time on task performance whereby participant's tracking task and memory search task degraded over time. However, they did not find a main effect of time on task on subjective workload. Therefore, I hypothesized that:

18. Participant's tracking task performance and system monitoring performance will degrade over time.
19. Participant's subjective workload will not vary across experimental sessions.

Sato et al.'s (2023b) work indicated that trust in automation is a dynamic construct that can develop over time while Dikmen and Burns' (2017) work indicated that trust elevated when engaging with an autonomous vehicle that possesses all three dimensions of autonomy. These works indicated that trust elevated over time regardless of the agent characteristics. Therefore, I speculated no interaction effect between time and agent characteristics on trust. Specifically, it was hypothesized that:

20. Jian et al.'s (2000) trust and Chancey et al.'s (2017) trust dimensions will elevate over time regardless of agent characteristics.

Based on Sato et al.'s (2023b) study, I hypothesized that there will be no interaction effect between time and the agent characteristics on attention allocation whereby:

21. Participants will visually sample the system monitoring display less frequently while visually fixating the tracking display more frequently over time regardless of the agent characteristics.

Muir and Moray's (1996) study indicated that trust was developed from faith, to dependability, and to faith. However, a few works failed to replicate Muir and Moray's (1996) findings perhaps due to cohort effect (Lee et al., 2021; Long et al., 2022). Therefore, I speculate that the development of trust should align with recent findings on the development of trust (Long et al., 2022). That is, I hypothesized that:

22. Trust will develop from dependability, to predictability, and to faith.

CHAPTER II

METHOD

PARTICIPANTS

The present study recruited 75 participants (21 males and 54 females; M_{age} = 23.28, SD_{age} = 7.69) from Old Dominion University through the SONA system. Participants were screened for normal or corrected-to-normal vision and normal color perception using the Ishihara Color Blindness test (Ishihara, 2014). The cutoff score for nearsighted eye examination was 20/30. Credits were awarded for participation through the SONA system.

APPARATUS

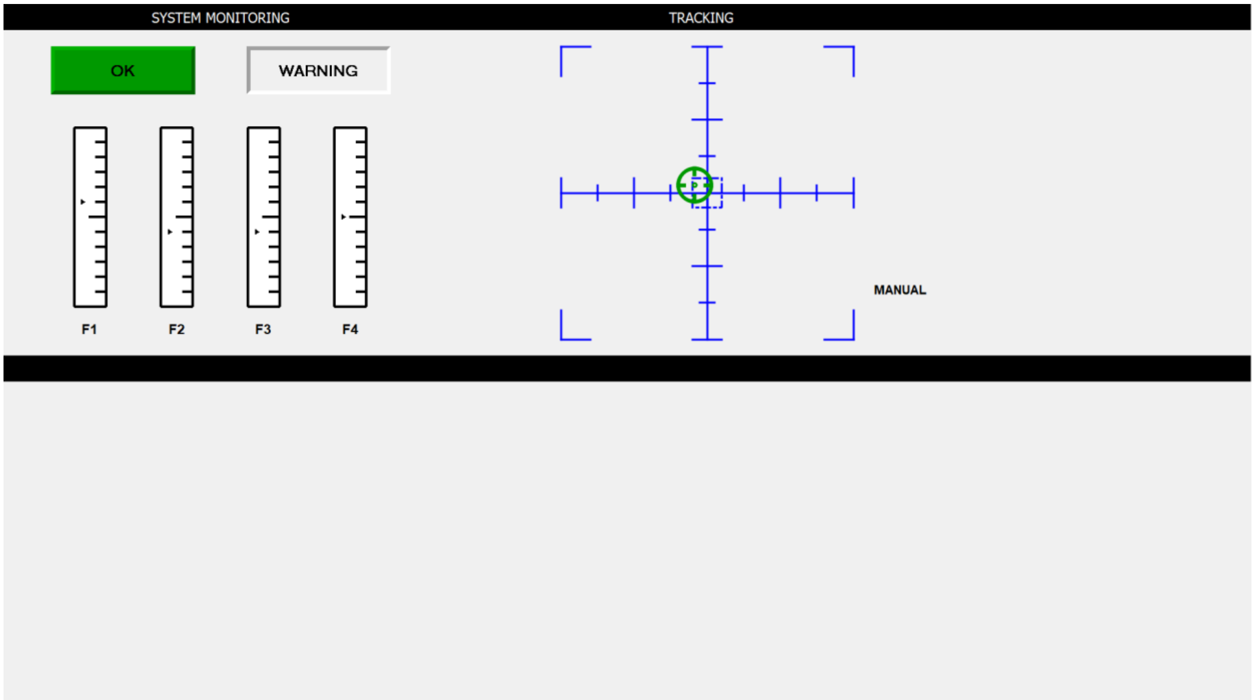
Stimuli was presented on a Samsung T24C550 23.6” LED monitor (1920 x 1080 pixel) with a frame rate of 60 Hz. Dell Precision 3460 was used to run the OpenMATB (Cegarra et al., 2020) which is a computer-based simulated software that assesses the participant’s multitasking performance. Tobii Nano eye tracker was used to record the participant’s eye movement with a sampling rate of 60 Hz. The experiment was conducted in a quiet room with dim light.

FLIGHT SIMULATION TASKS

The present study employed the OpenMATB software (Cegarra et al., 2020) which enables participants to concurrently perform tasks while being supported by an automated signaling system. Specifically, participants concurrently performed the system monitoring task and the tracking task. Following previous works (Karpinsky et al., 2018; Sato et al., 2020; Sato et al., 2023c; Sato et al., 2024), an automated signaling system was implemented in the system monitoring task with a reliability of 70%. Figure 1 presents the OpenMATB display.

Figure 1

Sample display of the OpenMATB.



Note. The system monitoring task is located on the top left, whereas the tracking task is located on the top middle.

System Monitoring Task

The system monitoring task consisted of four vertical gauges that represent the aircraft's engine (i.e., labeled as F1, F2, F3, and F4). Participants were asked to monitor the fluctuating pointer within the vertical gauge. Furthermore, participants were asked to correct the fluctuating pointer when the pointer hits either the top or bottom extremity of the vertical gauge (i.e., indicating system error) by pressing the corresponding keys (i.e., F1, F2, F3, or F4). The two boxes, located above the four vertical gauges (i.e., labeled as OK and WARNING), informed whether any system error was detected by the automated signaling system. A red rectangular box indicated the presence of system error in one aircraft's engine while a green rectangular box indicated that the aircraft's engine is in normal state. When the signaling system notified a system error, the red rectangular box illuminated for 10 seconds. While the red rectangular box illuminated, participants were required to check for any system errors and correct the system error when present. In each experimental session, the system monitoring task consisted of 28 Hit events and 12 false alarm (FA) events. Hit events occur when the signaling system correctly detects system error in one of the aircraft's engines. In this case, participants responded to the signaling system by correcting the system error. FA events occur when the signaling system detects system error even though there are no system errors in any of the aircraft's engine. In this case, participants were instructed to ignore the signaling system's notification. The present study did not incorporate miss events because previous work showed that trust did not differ between FA and miss events (Karpinsky et al., 2018).

Tracking Task

The tracking task required participants to control a joystick to keep the moving circular target from deviating away from the center of the dotted square. The difficulty of the tracking task was determined by the frequency of the force function. In each experimental session, the frequency of force function was set to 0.12 Hz (i.e., high tracking difficulty) for the high task load condition and 0.06 Hz (i.e., low tracking difficulty) for the low task load condition. However, the frequency of force function was set to 0.09 Hz (i.e., medium tracking difficulty) during the training session in order to avoid carryover effect.

PROCEDURES

Prior to the training session, participants completed an informed consent and a demographics form, followed by a visual screening test (i.e., visual acuity test and color blindness test). Participants were randomly assigned to either the low or high task load condition. Then, participants were trained to perform each task separately for 3 minutes (i.e., system monitoring task and tracking task) and all tasks simultaneously for 3 minutes (i.e., total of 9 minutes) following the part-task training procedure. After training, participants read a vignette that described an autonomous signaling system (i.e., possess all three dimensions of autonomy), a signaling system without viability, a signaling system without Independence, or a signaling system without self-governance (See Table 2 for description of each type of signaling system). Then participants completed three 20-minute experimental sessions while being recorded by an eye tracker. Prior to each experimental session, a standard 9-dot calibration system was used to calibrate the eye tracker. Upon completion of each experimental session, participants completed a series of questionnaire (Chancey et al., 2017; Hart & Staveland, 1988; Jian et al., 2000; Muir & Moray, 1996; See Dependent Measures section below for the four instruments).

Table 2

Description of each agent characteristics.

Agent Characteristics	Description
Autonomous Agent	• The signaling system can accurately detect system malfunction in stormy weather conditions. • The signaling system does not require someone to monitor the operations while performing the tracking task. • The signaling system can program a strategy for searching system malfunction.
Automated Agent without Viability	• The signaling system cannot accurately detect system malfunction during stormy weather conditions. * • The signaling system does not require someone to monitor the operations while performing the tracking task. • The signaling system can program a strategy for searching system malfunction.
Automated Agent without Independence	• The signaling system can accurately detect system malfunction in stormy weather conditions. • The signaling system requires someone to monitor the operations while performing the tracking task. * • The signaling system can program a strategy for searching system malfunction.

Table 2

Continued

Agent Characteristics	Description
Automated Agent without Self-governance	• The signaling system can accurately detect system malfunction in stormy weather conditions. • The signaling system does not require someone to monitor the operations while performing the tracking task. • The signaling system cannot program a strategy for searching system malfunction. *

Note. A statement with an asterisk indicates a violation in one of the three dimensions of autonomy.

DESIGN

The present study employed a mixed factorial design with task load and agent characteristics as a between-subjects factor and time epoch as a within-subjects factor. The dependent variables were subjective workload, trust, attention allocation, tracking performance, and system monitoring performance.

DEPENDENT VARIABLES

Subjective Workload

NASA-TLX (Hart & Staveland, 1988; Appendix C) was employed to measure the participant's subjective workload. The questionnaire consisted of 6 items on a 21-point gradient scale ranging from 1 (*very low*) to 21 (*very high*). Each items reflected the subscales of workload including mental demand, physical demand, temporal demand, performance, effort, and frustration. Subjective workload was computed by finding the sum of the 6 subscales (minimum score = 6, maximum score = 126). Previous works have shown concurrent validity (Rubio et al., 2004), convergent validity (Rubio et al., 2004), and test/retest reliability (Hart & Staveland, 1988).

Trust

Chancey et al.'s (2017; Appendix D and E) trust questionnaire was used to measure Lee and See's (2004) three trust dimensions. Chancey et al.'s (2017) trust scale is a modified version of Madsen and Gregor's (2000) trust questionnaire which consisted of 13 items on a 12-point Likert scale ranging from 1 (*not descriptive*) to 12 (*very descriptive*). These items were divided into three subscales of trust including performance-based trust (minimum score = 5, maximum score = 60), process-based trust (minimum score = 5, maximum score = 60), and purpose-based trust (minimum score = 3, maximum score = 36). Chancey et al.'s (2017) work demonstrated internal consistency for performance-based trust (α = .96), process-based trust (α = .91), and purpose-based trust (α = .93).

Jian et al.'s (2000; Appendix F) trust questionnaire was employed to measure overall trust. The trust questionnaire comprised of 12 items on a 7-point Likert scale ranging from 1 (*not at all*) to 12 (*extremely*). The items reflected either participant's trust or distrust toward the automation. Thus, items pertaining to distrust toward the automation were reverse-coded (minimum score = 12, maximum score = 84). Safar and Turner (2005) demonstrated internal consistency for Jian et al.'s (2000) trust questionnaire (α = .93).

Muir and Moray's (1996; Appendix G) trust questionnaire was employed to examine the development of trust. The trust questionnaire consisted of 9 items on a 100-mm scale ranging from 0 (*none at all*) to 100 (*extremely high*). A few questions were modified since participants will be asked to rate their trust toward the signaling system instead of the pump. Following Muir and Moray's (1996) work, the present study used four items to examine the development of trust including predictability, dependability, faith, and overall trust. Although researchers employed Muir and Moray's (1996) trust questionnaire (Lee et al., 2021; Long et al., 2022), the reliability and the validity of the trust questionnaire was unknown.

Attention Allocation

Participant's attention allocation was examined by measuring percentage dwell time (PDT) within each area of interest (AOI). PDT is defined as the proportion of time in which participants gazed on the tracking display and on the system monitoring display.

MATB Performance

Participant's tracking performance was measured by computing the root means squared deviation (RMSD) between the moving circular target and the center of the tracking task display.

Participant's system monitoring performance was measured by computing the error rate and reaction time (RT) during Hit and FA event. Error rate is defined as the ratio of events that participants made incorrect response over the total number of events. RT is defined as the time it takes the participant to make an initial response after the onset of an event.

STATISTICAL ANALYSIS

The present study employed a default Bayesian test (Rouder & Morey, 2012; Rouder et al., 2012; Rouder et al., 2009) instead of the traditional null hypothesis significance test (NHST). Bayesian test measures the strength of evidence for the effect of interest or the null effect which is denoted as bayes factor (B_{10}; Jeffreys, 1961). Bayes factor depicts the ratio of the likelihood of the effect of interest against the null effect. For example, a bayes factor of 5 indicates that the observed data is 5 times more likely to be arisen from the effect of interest than the null effect. The present study described each effect by following Jeffery's (1961) terminology (see Figure 2). That is, a bayes factor greater than 3 indicates that the observed data is in favor of the effect of interest while a bayes factor less than 1 indicates that the observed data is in favor of the null effect. Therefore, the present study employed a Bayesian analysis of variance (ANOVA), t-test, and regression. Statistical packages from R (R Core Team, 2018) was used to perform all statistical analysis.

Figure 2

Jeffreys' (1961) interpretation for each bayes factor.

B_{10}	Interpretation
>100	Decisive evidence for H1
30-100	Very strong evidence for H1
10-30	Strong evidence for H1
3-10	Substantial evidence for H1
1-3	Not worth more than a bare mention
1/3-1	Not worth more than a bare mention
1/10-1/3	Substantial evidence for H0
1/30-1/10	Strong evidence for H0
1/100-1/30	Very strong evidence for H0
<1/100	Decisive evidence for H0

CHAPTER III

RESULTS

The present study applied a 4 × 3 × 2 mixed Bayesian analysis of variance (ANOVA) with agent characteristics (an autonomous agent, an automated agent without viability, an automated agent without independence, and an automated without self-governance) and task load (high and low) as a between-subjects factor and time epoch (first experimental session, second experimental session, and third experimental session) as a within-subjects factor. I applied a Bayesian linear regression analysis and stepwise regression analysis to examine whether predictability, dependability, and faith predicted overall trust across the three experimental sessions for each agent characteristics. Additionally, I applied a Bayesian linear regression analysis and stepwise regression analysis to examine whether performance, process, and purpose predicted Muir and Moray's (1996) overall trust across the three experimental sessions for each agent characteristics. Prior to the analysis, I examined the internal consistency of each questionnaire. Results on Chancey et al.'s (2017) trust questionnaire indicated acceptable internal consistency for performance- ($\alpha = .92$), process- ($\alpha = .87$), and purpose-based trust ($\alpha = .85$). Furthermore, results indicated acceptable internal consistency for Jian et al.'s (2000) trust ($\alpha = .89$). Finally, results demonstrated acceptable internal consistency for NASA-TLX ($\alpha = .80$).

Three participant's data were excluded from the analysis. Of these participants, one was excluded from the analysis because the participant's system monitoring performance was below the inclusion criteria (i.e., 50%). One participant's data were excluded from the analysis due to technical issues with the eye tracker. Finally, one participant withdrew from the study due to headache and eye strain. Therefore, my dissertation analyzed data from 72 participants (20 males and 52 females; M_{age} = 23.33, SD_{age} = 7.78) that were equally assigned to 8 different groups with varying conditions of task load and agent characteristics (n = 9).

SUBJECTIVE WORKLOAD

Data gave no evidence for and against the effect of task load [$F < 1$, B_{10} = 1/1.68, η^2_G = 0.01] and agent characteristics [$F < 1$, B_{10} =1/2.40, η^2_G = 0.02]. Also, data provided no substantial evidence that subjective workload varied across experimental sessions [$F(2, 128) = 1.87$, B_{10} = 1/3.40, $\eta^2_G < 0.01$]. Furthermore, data provided strong evidence against the presence of an interaction between agent characteristics and time epoch [$F < 1$, B_{10} = 1/14.77, $\eta^2_G < 0.01$]. However, data provided no evidence that task load did not interact nor interact with agent characteristics [$F(3, 64) = 1.08$, B_{10} = 1/1.41, η^2_G = 0.04] and time epoch [$F(2, 128) = 2.42$, B_{10} = 1/1.20, $\eta^2_G < 0.01$]. Finally, data gave strong evidence against the presence of a three-way interaction effect [$F < 1$, B_{10} = 1/14.28, $\eta^2_G < 0.01$].

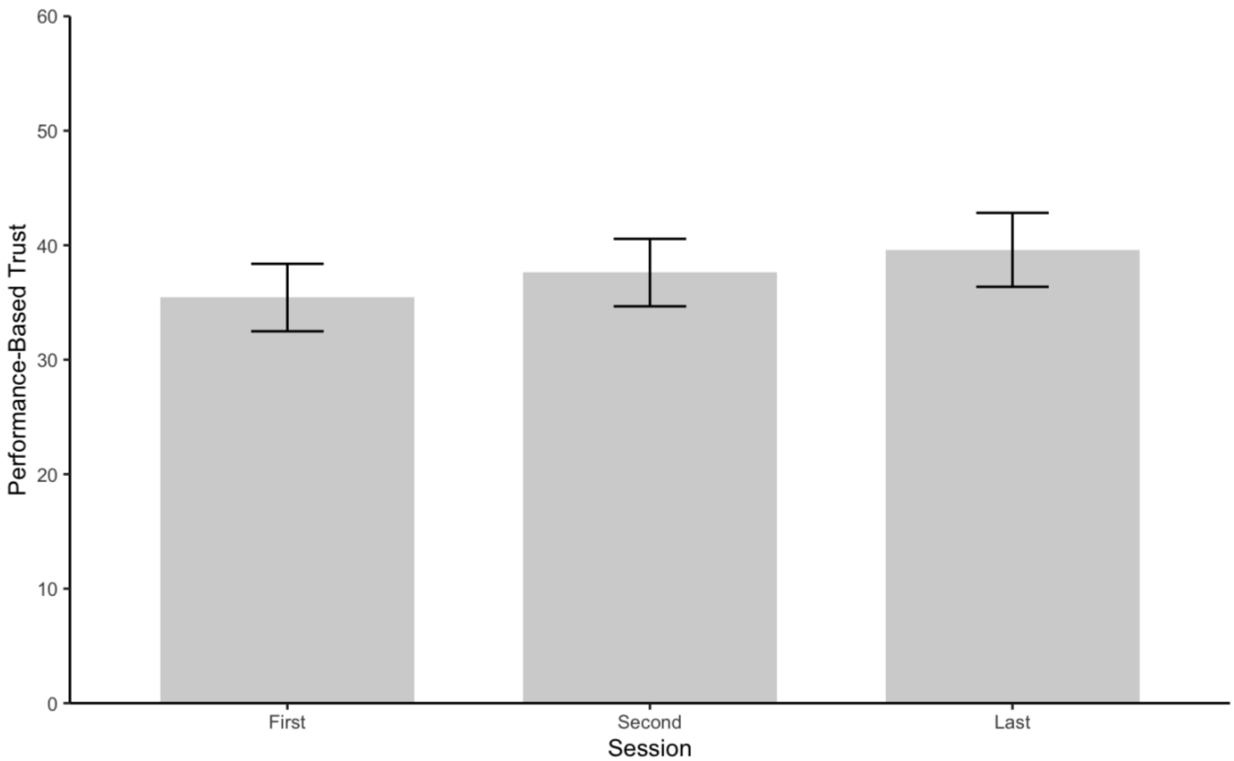
CHANCEY ET AL.'S (2017) TRUST

Performance-Based Trust

Data indicated strong evidence that performance-based trust varied across time epochs [$F(2, 128) = 6.74$, B_{10} = 21.34, η^2_G = 0.02]. Post-hoc t-test indicated very strong evidence that participants rated higher performance-based trust in the third experimental session compared to the first experimental session [M = 39.60 vs. 35.43, respectively; $t(71) = 3.70$, B_{10} = 55.00, d = 0.32]. However, data did not provide evidence on the presence and the absence of a difference when comparing the second experimental session from the first experimental session [$t(71)$ = 1.85, B_{10} = 0.65, d = 0.17] and from the third experimental session [$t(71) = 1.74$, B_{10} = 0.54, d = 0.15]. Figure 3 presents the mean ratings for performance-based trust across time epochs. Data provided substantial evidence that performance-based trust did not vary across different agent characteristics [$F < 1$, B_{10}=1/4.41, $\eta^2_G = 0.02$]. Also, there was no evidence for and against the main effect of task load [$F < 1$, B_{10}=1/2.83, $\eta^2_G < 0.01$]. Data indicated strong evidence against the interaction effect between agent characteristics and time epoch [$F < 1$, B_{10}= 1/11.55, $\eta^2_G =$ 0.01]. Furthermore, there was substantial evidence that task load did not interact with time epoch [$F(2, 128) = 1.54$, B_{10}= 1/3.90, $\eta^2_G < 0.01$]. However, data indicated no evidence for and against the interaction between task load and agent characteristics [$F(3, 64) =$, B_{10}= 2.70, $\eta^2_G = 0.09$]. Finally, data gave no reliable evidence for the presence and the absence of a three-way interaction effect [$F(6, 128) = 1.44$, B_{10}=1/2.63, $\eta^2_G = 0.01$].

Figure 3

Mean performance-based trust ratings across time epochs.



Note. Error bars represent 95% confidence intervals.

Process-Based Trust

Data provided strong evidence that process-based trust did not vary across time epochs [$F < 1$, $B_{10} = 1/17.58$, $\eta^2_G < 0.01$]. Also, data gave no evidence for the main effect of task load [$F < 1$, $B_{10} = 1/2.61$, $\eta^2_G < 0.01$] and agent characteristics [$F(3, 64) = 1.77$, $B_{10} = 1/1.28$, $\eta^2_G = 0.06$]. There was no substantial evidence that time epoch interacted with agent characteristics [$F(6, 128) = 1.36$, $B_{10} = 1/4.65$, $\eta^2_G = 0.01$] and task load [$F < 1$, $B_{10} = 1/7.98$, $\eta^2_G < 0.01$]. However, there was no evidence for and against the interaction effect between task load and the agent characteristics [$F(3, 64) = 2.28$, $B_{10} = 1.31$, $\eta^2_G = 0.08$]. Lastly, data provided no evidence for the presence and absence of a three-way interaction effect [$F(6, 128) = 1.67$, $B_{10} = 1/1.44$, $\eta^2_G = 0.02$].

Purpose-Based Trust

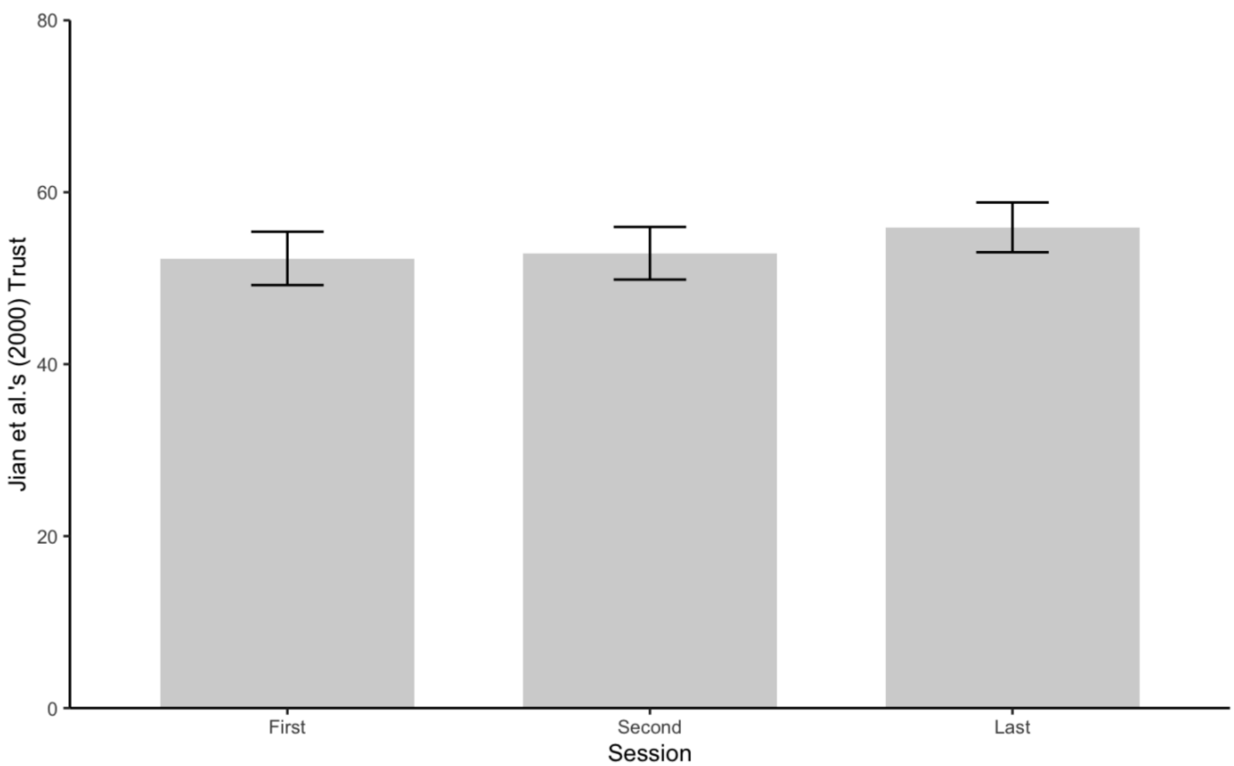
Data gave no evidence for and against the main effect of task load [$F < 1$, $B_{10} = 1/2.11$, $\eta^2_G < 0.01$], agent characteristics [$F < 1$, $B_{10} = 1/2.64$, $\eta^2_G = 0.03$], and time epoch [$F(2, 128) = 2.07$, $B_{10} = 1/2.93$, $\eta^2_G < 0.01$]. Also, there was no evidence that task load did not interact nor interact with time epoch [$F(2, 128) = 3.60$, $B_{10} = 2.07$, $\eta^2_G = 0.01$] and agent characteristics [$F(3, 64) = 1.89$, $B_{10} = 1.07$, $\eta^2_G = 0.07$]. However, data indicated substantial evidence against the interaction between agent characteristics and time epoch [$F(6, 128) = 1.44$, $B_{10} = 1/4.00$, $\eta^2_G = 0.01$]. Additionally, data provided substantial evidence against the presence of a three-way interaction effect [$F < 1$, $B_{10} = 1/6.98$, $\eta^2_G < 0.01$].

Jian et al.'s (2000) Trust

Data on Jian et al.'s (2000) trust questionnaire gave substantial evidence that ratings varied across time epochs [$F(2, 128) = 5.68$, $B_{10} = 12.49$, $\eta^2_G = 0.02$]. Follow-up t-test indicated strong evidence that participants rated higher trust after completing the third experimental session then after completing the first experimental session [M = 55.92 vs. 52.31, respectively; $t(71) = 3.24$, $B_{10} = 14.72$, $d = 0.28$]. Also, there was substantial evidence that participants rated higher trust after completing the third experimental session then after completing the second experimental session [M = 55.92 vs. 52.90, respectively; $t(71) = 2.72$, $B_{10} = 3.86$, $d = 0.24$]. However, there was no substantial evidence that trust differed between the first experimental session and the second experimental session [$t(71) = 0.5$, $B_{10} = 1/6.84$, $d = 0.05$]. Figure 4 presents the mean ratings for Jian et al.'s (2000) trust across time epochs. Data gave no evidence for and against the main effect of task load [$F < 1$, $B_{10} = 1/2.36$, $\eta^2_G < 0.01$] and agent characteristics [$F(3, 64) = 2.23$, $B_{10} = 1.37$, $\eta^2_G = 0.08$]. Additionally, data gave strong evidence against the interaction between agent characteristics and time epoch [$F < 1$, $B_{10} = 1/13.96$, $\eta^2_G = 0.01$]. However, data provided no evidence that task load did not interact nor interact with agent characteristics [$F(3, 64) = 1.70$, $B_{10} = 1.05$, $\eta^2_G = 0.06$] and time epoch [$F(2, 128) = 1.77$, $B_{10} = 1/2.04$, $\eta^2_G = 0.01$]. Finally, data indicated substantial evidence for the absence of a three-way interaction effect [$F < 1$, $B_{10} = 1/5.80$, $\eta^2_G = 0.01$].

Figure 4

Mean ratings from Jian et al.'s (2000) trust questionnaire across time epochs.



Note. Error bars represent 95% confidence intervals.

MUIR AND MORAY'S (1996) OVERALL TRUST

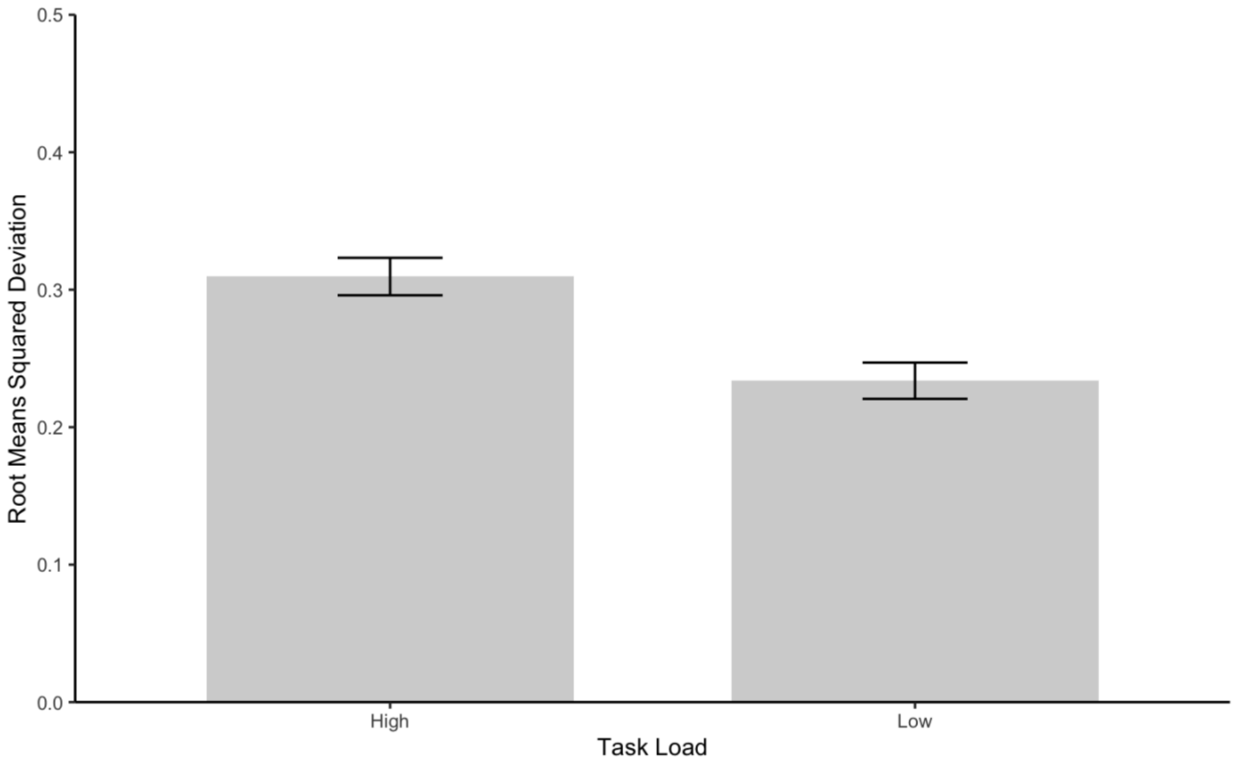
Data on Muir and Moray's (1996) overall trust indicated substantial evidence against the main effect of task load [$F < 1$, $B_{10} = 1/3.19$, $\eta^2_G < 0.01$] and time epoch [$F(2, 128) = 1.80$, $B_{10} = 1/3.80$, $\eta^2_G = 0.01$]. However, there was no evidence for and against the main effect of agent characteristics [$F(3, 64) = 3.20$, $B_{10} = 2.47$, $\eta^2_G = 0.10$]. Data gave substantial evidence against the interaction effect between agent characteristics and time epoch [$F(6, 128) = 1.18$, $B_{10} = 1/6.79$, $\eta^2_G = 0.02$]. Furthermore, data indicated no evidence that task load did not interact nor interact with agent characteristics [$F < 1$, $B_{10} = 1/2.56$, $\eta^2_G = 0.03$] and time epoch [$F(2, 128) = 3.79$, $B_{10} = 2.30$, $\eta^2_G = 0.02$]. Data on a three-way interaction indicated substantial evidence for the absence of the effect [$F < 1$, $B_{10} = 1/4.95$, $\eta^2_G = 0.01$].

TRACKING PERFORMANCE

Data gave decisive evidence for the main effect of task load whereby participants assigned in the low task load condition outperformed those assigned in the high task load condition [$M = 0.23$ vs 0.31, respectively; $F(1, 64) = 27.60$, $B_{10} = 8383.64$, $\eta^2_G = 0.26$]. Figure 5 presents mean RMSD between task load conditions. Also, data gave substantial evidence that tracking performance varied across agent characteristics [$F(3, 64) = 3.97$, $B_{10} = 5.62$, $\eta^2_G = 0.13$]. Post-hoc t-test indicated strong evidence that participants performed the tracking task worse when they assumed that the signaling system was an automated agent without viability compared to when they assumed that the signaling system was autonomous agent [M = 0.31 vs 0.25, respectively; $t(106) = 3.38$, $B_{10} = 28.70$, $d = 0.65$], an automated agent without independence [M = 0.31 vs 0.26, respectively; $t(106) = 3.21$, $B_{10} = 18.00$, $d = 0.62$], or an automated agent without self-governance [M = 0.31 vs 0.26, respectively; $t(106) = 3.08$, $B_{10} = 12.63$, $d = 0.59$]. However, there was no substantial evidence that participant's tracking performance was worse when they assumed that the signaling system was an autonomous agent compared to when the signaling system was an automated agent without independence [$t(106) = 0.36$, B_{10}=1/4.64, $d = 0.07$] or an automated agent without self-governance [$t(106) = 0.53$, B_{10}=1/4.33, $d = 0.10$]. Also, there was no substantial difference in tracking performance between a scenario involving a signaling system without independence and a scenario involving a signaling system without self-governance [$t(106) = 0.18$, B_{10}=1/4.83, $d = 0.04$]. Figure 6 presents mean RMSD across different agent characteristics. Data gave strong evidence against the main effect of time epoch [$F < 1$, B_{10}= 1/18.18, $\eta^2_G < 1$]. Additionally, data gave substantial evidence that agent characteristics did not interact with time epoch [$F < 1$, B_{10}= 1/10.44, $\eta^2_G < 1$] and task load [$F < 1$, B_{10}= 1/3.96, $\eta^2_G < 1$]. However, there was no evidence for and against the interaction between task load and time epoch [$F(2, 128) = 2.67$, B_{10}= 1/1.17, $\eta^2_G = 0.01$]. Finally, data gave no evidence for and against a three-way interaction effect [$F(6, 128) = 1.32$, B_{10}=1/2.84, $\eta^2_G = 0.01$].

Figure 5

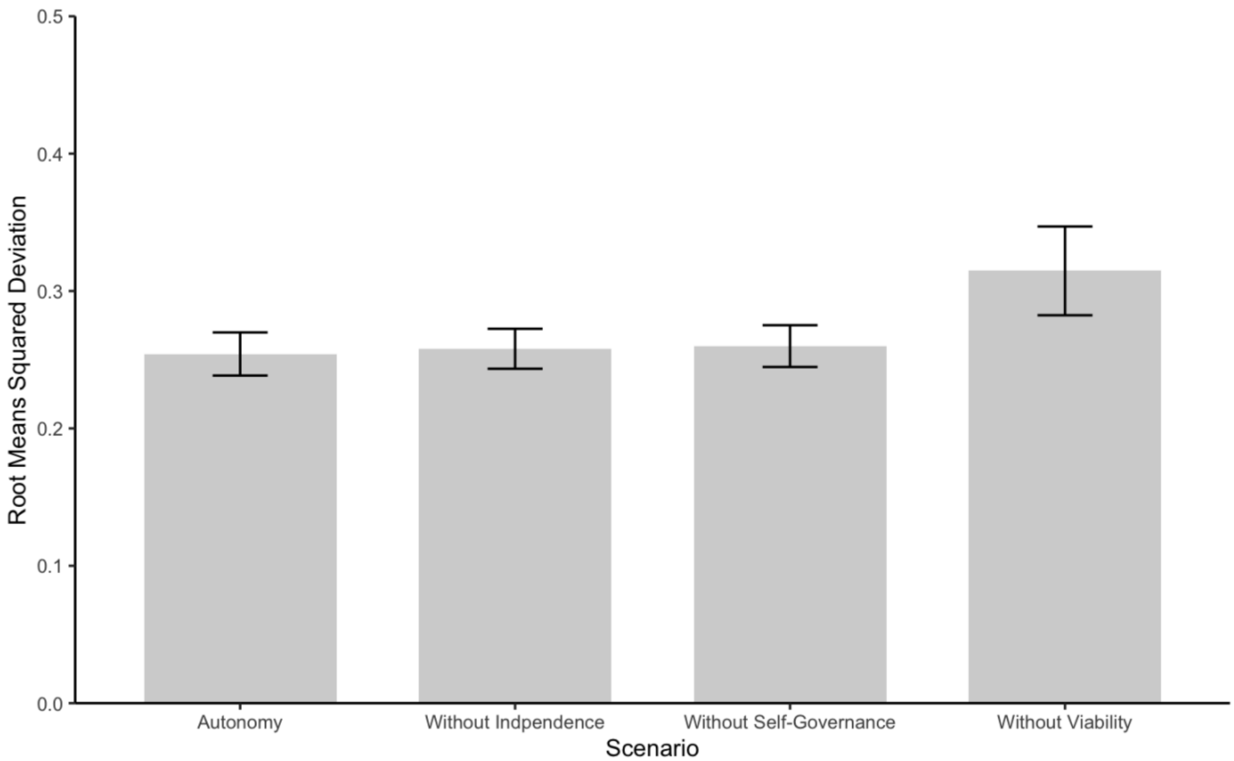
Mean RMSD between task load conditions.



Note. Error bars represent 95% confidence intervals.

Figure 6

Mean RMSD across different agent characteristics.



Note. Error bars represent 95% confidence intervals.

SYSTEM MONITORING PERFORMANCE

RT During Hit Events

There was substantial evidence against the main effect of time epoch [$F < 1$, $B_{10} = 1/9.23$, $\eta^2_G < 0.01$]. Data indicated no evidence for and against the main effect of task load [$F(1, 64) = 1.40$, $B_{10} = 1/1.02$, $\eta^2_G = 0.02$] and agent characteristics [$F(3, 64) = 1.41$, $B_{10} = 1/1.33$, $\eta^2_G = 0.05$]. Also, data gave substantial evidence that time epoch did not interact with task load [$F < 1$, $B_{10} = 1/7.15$, $\eta^2_G < 0.01$] and agent characteristics [$F(6, 128) = 1.32$, $B_{10} = 1/3.58$, $\eta^2_G = 0.01$]. However, data gave no evidence for and against the presence of the interaction between task load and agent characteristics [$F < 1$, $B_{10} = 1/1.30$, $\eta^2_G = 0.03$]. Additionally, data indicated substantial evidence for the absence of a three-way interaction effect [$F < 1$, $B_{10} = 1/6.12$, $\eta^2_G < 0.01$].

Error Rate During Hit Events

Data indicated substantial to strong evidence against the main effect of task load [$F(1, 64) = 0.23$, $B_{10} = 1/4.10$, $\eta^2_G < 0.01$], agent characteristics [$F(3, 64) = 0.18$, $B_{10} = 1/13.03$, $\eta^2_G < 0.01$], and time epoch [$F(2, 128) = 3.97$, $B_{10} = 1/16.25$, $\eta^2_G < 0.01$]. There was very strong evidence against the interaction effect between time epoch and agent characteristics [$F < 1$, $B_{10} = 1/42.43$, $\eta^2_G < 0.01$]. Also, there was substantial evidence against the interaction effect between task load and time epoch [$F < 1$, $B_{10} = 1/6.52$, $\eta^2_G < 0.01$]. However, data indicated no evidence for and against the presence for the remaining interaction effect [$F(3, 64) = 1.14$, $B_{10} =1/2.95$, $\eta^2_G = 0.03$]. Finally, data gave substantial evidence against a three-way interaction effect [$F(6,128) = 1.18$, $B_{10} = 1/3.52$, $\eta^2_G = 0.02$].

Error Rate During FA Events

Data gave strong evidence against the main effect of time epoch [$F < 1$, $B_{10} = 1/18.30$, $\eta^2_G < 0.01$] and agent characteristics [$F < 1$, $B_{10} = 1/13.43$, $\eta^2_G = 0.01$]. There was no evidence for and against the main effect of task load [$F(1, 64) = 2.50$, $B_{10} = 1/1.93$, $\eta^2_G = 0.01$]. Data indicated substantial evidence that agent characteristics did not interact with task load [$F(3, 64) = 1.50$, $B_{10} = 1/3.24$, $\eta^2_G = 0.03$] and time epoch [$F(6, 128) = 1.15$, $B_{10} = 1/5.50$, $\eta^2_G = 0.03$]. Also, data indicated strong evidence against the remaining two-way interaction effects [$F < 1$, $B_{10} = 1/10.35$, $\eta^2_G < 0.01$]. Lastly, there was no substantial evidence for a three-way interaction effect [$F(6, 128) = 1.15$, $B_{10} = 1/3.06$, $\eta^2_G = 0.03$].

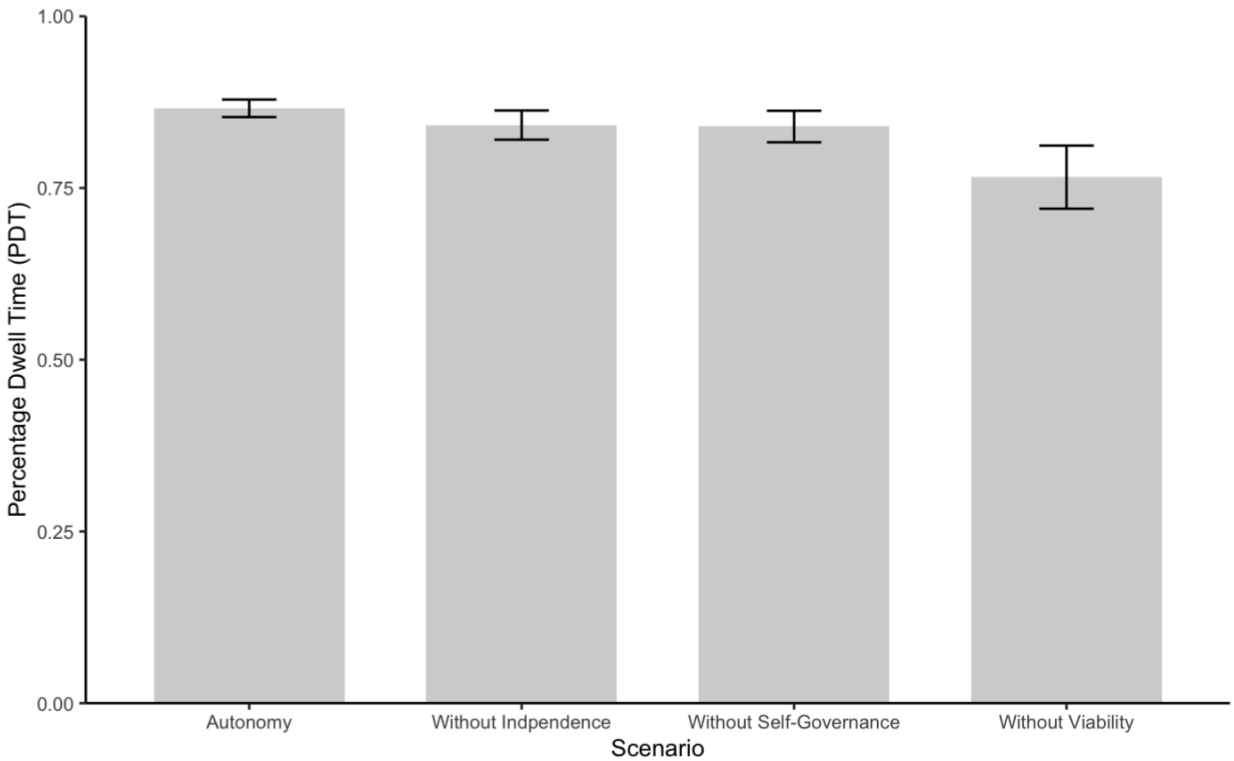
ATTENTION ALLOCATION

PDT Within Tracking Display

Data indicated substantial evidence that visual sampling of the tracking task varied across agent characteristics [$F(3, 64) = 3.93$, $B_{10} = 5.01$, $\eta^2_G = 0.12$]. Follow-up t-test indicated decisive to substantial evidence that participants visually sampled the tracking task more frequently when the signaling system was assumed to be an automated agent without viability compared to when the signaling system was an autonomous agent [M = 0.77 vs 0.87, respectively; $t(106) = 4.21$, $B_{10} = 389.47$, $d = 0.81$], an automated agent without independence [M = 0.77 vs 0.84, respectively; $t(106) = 3.00$, $B_{10} = 10.46$, $d = 0.58$], and an automated agent without self-governance [M = 0.77 vs 0.84, respectively; $t(106) = 2.88$, $B_{10} = 7.66$, $d = 0.55$]. However, data indicated no substantial evidence that participants visually sampled the tracking task more frequently when they assumed that the signaling system was an automated agent without independence compared to when the signaling system was an automated agent without self-governance [$t(106) = 0.13$, B_{10}=1/4.87, $d = 0.89$]. Also, data gave no evidence that participant's visual sampling of the tracking task differed when comparing a scenario involving an autonomous agent with a scenario involving an automated agent without independence [$t(106) = 1.97$, $B_{10} = 1.14$, $d = 0.38$] and a scenario involving an automated agent without self-governance [$t(106) = 2.02$, $B_{10} = 1.25$, $d = 0.39$]. Figure 7 presents the mean PDT within the tracking display across different agent characteristics. Data gave no substantial evidence for the main effect of time epoch [$F(2, 128) = 1.71$, B_{10}=1/4.51, $\eta^2_G = 0.01$]. Also, there was no evidence for the presence and absence of the main effect of task load [$F < 1$, B_{10}=1/2.31, $\eta^2_G = 0.01$]. Data indicated no substantial evidence that agent characteristics interacted with time epoch [$F < 1$, $B_{10} = 1/9.97$, $\eta^2_G = 0.01$] and task load [$F < 1$, $B_{10} = 1/3.41$, $\eta^2_G = 0.01$]. However, there was no evidence for and against the interaction effect between task load and time epoch [$F(2, 128) = 2.12$, B_{10}=1/2.13, $\eta^2_G = 0.01$]. Interestingly, there was substantial evidence that visual sampling of the tracking task was qualified by a three-way interaction effect [$F(6, 128) = 2.79$, B_{10} = 4.37, $\eta^2_G = 0.03$]. To further explore this three-way interaction effect, a two-way Bayesian AVOVA was conducted between high and low task load conditions. Surprisingly, the analysis did not yield substantial evidence for an two-way interaction effect in both high task load condition [$F(6, 64) = 1.69$, B_{10} = 1/1.70, $\eta^2_G = 0.03$] and low task load condition [$F(6, 64) = 1.99$, B_{10} = 1/1.03, $\eta^2_G = 0.04$]. Figure 8 and Figure 9 presents a two-way interaction effect on mean PDT within the tracking display between task load conditions.

Figure 7

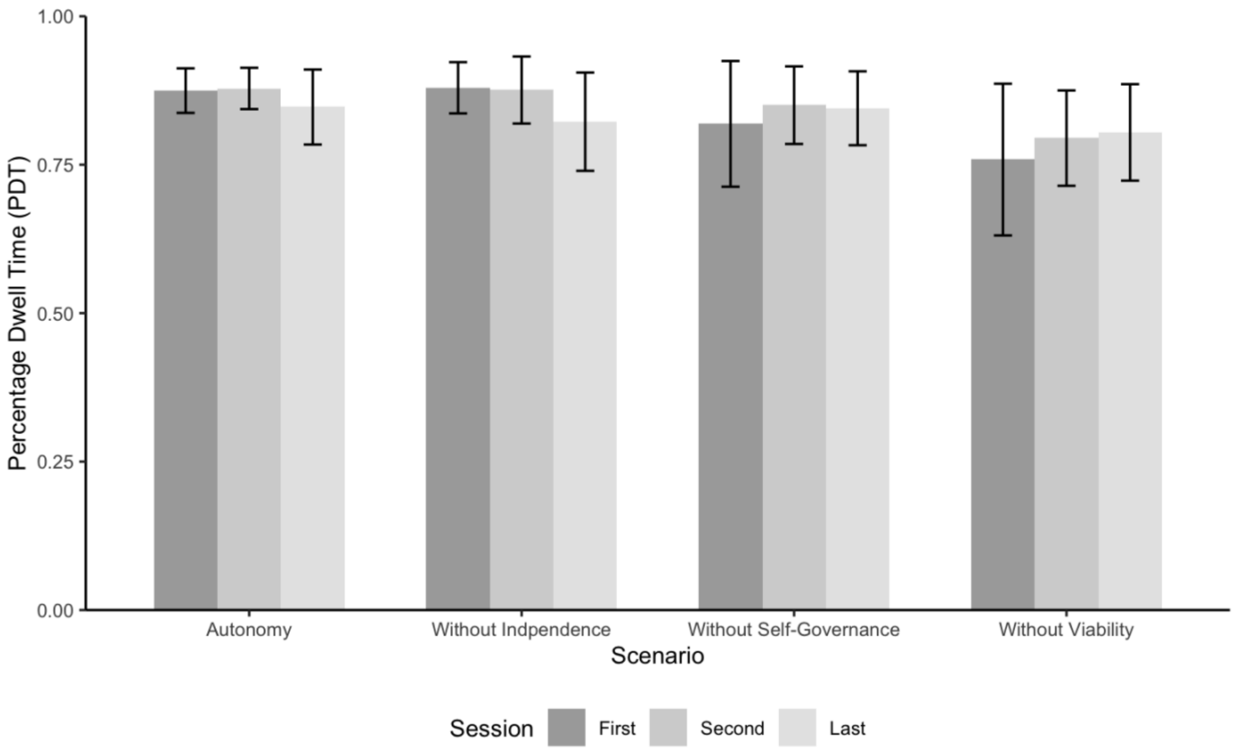
Mean PDT within the tracking display across agent characteristics.



Note. Error bars represent 95% confidence intervals.

Figure 8

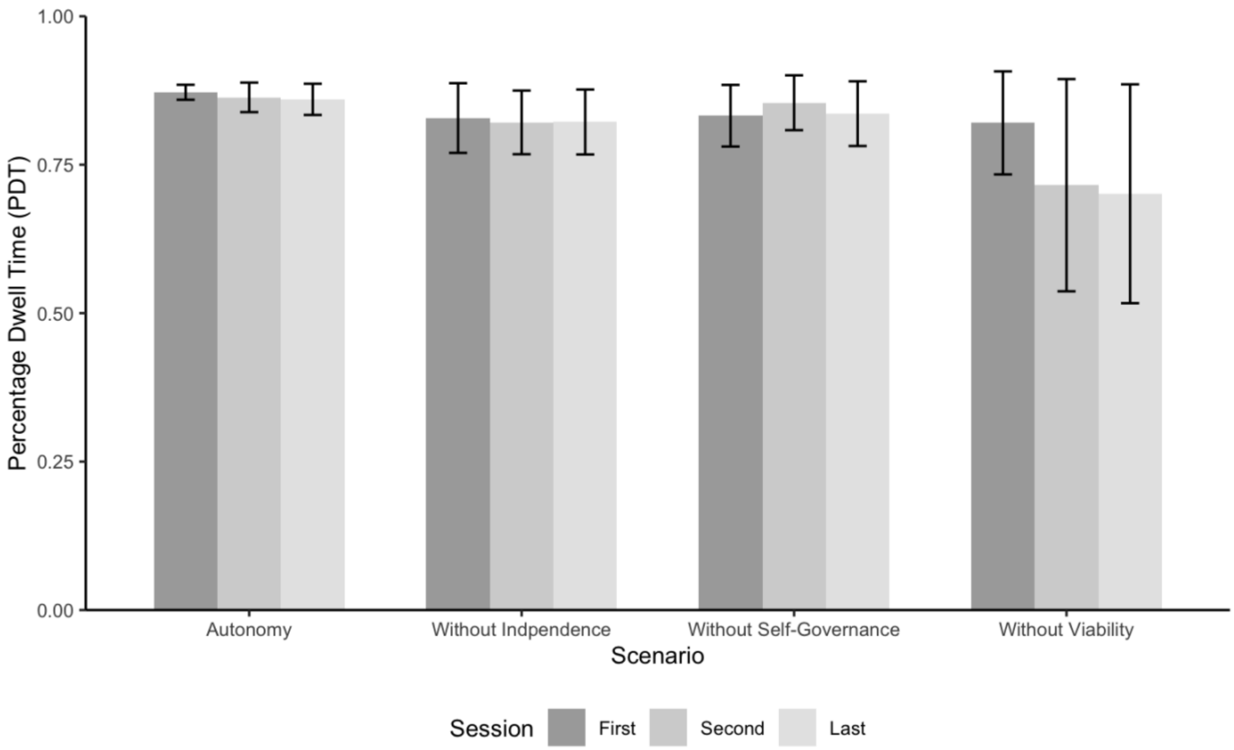
Mean PDT within the tracking display in the high task load condition.



Note. Error bars represent 95% confidence intervals.

Figure 9

Mean PDT within the tracking display in the low task load condition.



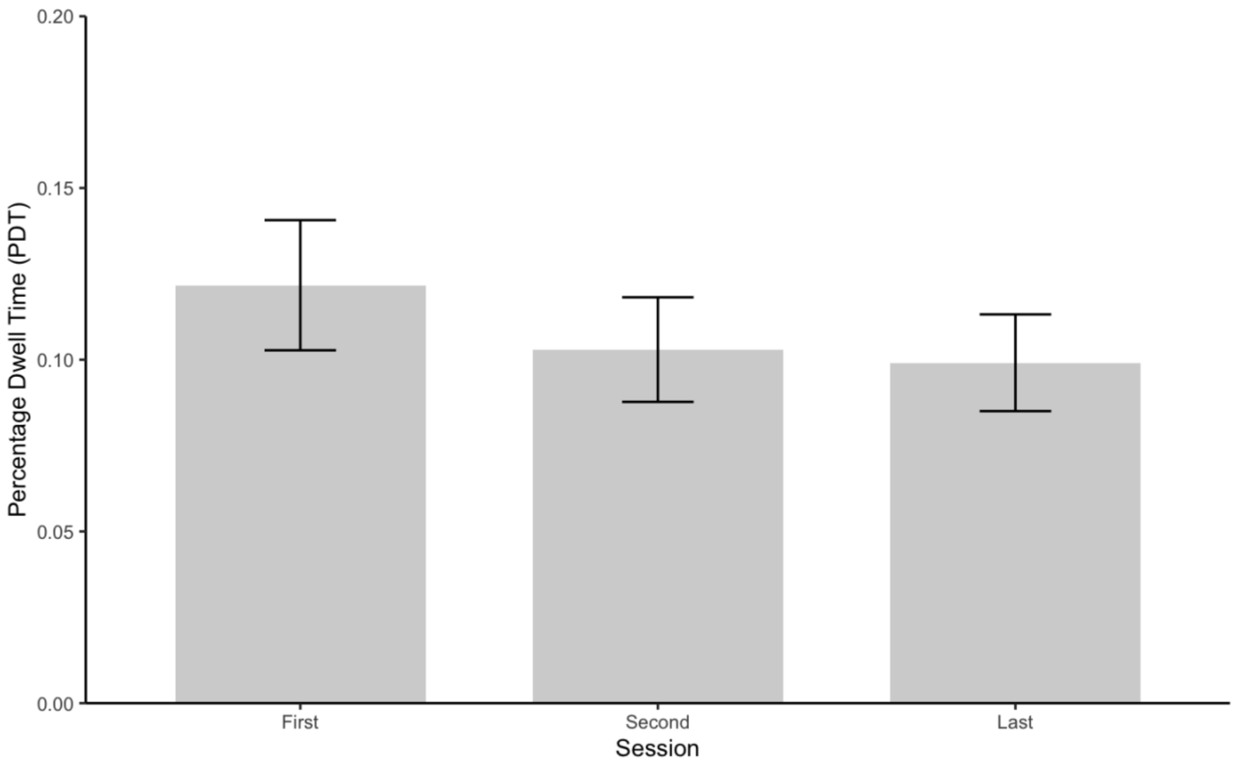
Note. Error bars represent 95% confidence intervals.

PDT Within System Monitoring Display

Data gave decisive evidence that visual sampling of the system monitoring task varied across time epochs [$F(2, 128) = 13.57$, $B_{10} = 8753.50$, $\eta^2_G = 0.02$]. Post-hoc t-test indicated decisive evidence that participants visually sampled the system monitoring display more frequently during the first experimental session compared to during the second experimental session [M = 0.08 vs 0.06, respectively; $t(71) = 4.22$, $B_{10} = 281.16$, $d = 0.26$]. Also, there was very strong evidence that participants visually sampled the system monitoring display more frequently during the first experimental session compared to during the third experimental session [M = 0.08 vs 0.06, respectively; $t(71) = 3.81$, $B_{10} = 76.02$, $d = 0.32$]. However, data gave no substantial evidence that PDT differed between the second experimental session and the third experimental session [$t(71) = 1.25$, $B_{10} = 1/3.65$, $d = 0.06$]. Figure 10 presents the mean PDT within the system monitoring task across time epochs. Data gave no evidence for and against the main effect of task load [$F < 1$, $B_{10} = 1/2.10$, $\eta^2_G < 0.01$] and agent characteristics [$F(3, 64) = 1.10$, $B_{10} = 1/1.61$, $\eta^2_G = 0.04$]. Furthermore, data indicated no substantial evidence that time epoch interacted with the agent characteristics [$F(3, 64) = 1.10$, $B_{10} = 1/7.79$, $\eta^2_G = 0.04$] and task load [$F(3, 64) = 1.10$, $B_{10} = 1/5.87$, $\eta^2_G = 0.04$]. However, there was no evidence for the presence and the absence of an interaction effect between task load and agent characteristics [$F(3, 64) = 1.10$, $B_{10} = 1/1.83$, $\eta^2_G = 0.04$]. Finally, data gave substantial evidence against a three-way interaction effect [$F(3, 64) = 1.10$, $B_{10} = 1/6.60$, $\eta^2_G = 0.04$].

Figure 10

Mean PDT within the system monitoring display across time epochs.



Note. Error bars represent 95% confidence intervals.

TRUST DEVELOPMENT

Prior to conducting Bayesian linear regression analysis and stepwise regression analysis, the present study applied the Variance Inflation Factor (VIF) to check multicollinearity for the model of interest (i.e., Predictability + Dependability + Faith and Performance + Process + Purpose) across experimental sessions. Results indicated that all experimental sessions had a VIF value less than 5 indicating that multicollinearity is not a problem. Bayesian linear regression analysis indicated that dependability was the best predictor of overall trust during the first experimental session [predictability, $B_{10} = 15.93$; dependability, $B_{10} = 1489.94$; faith, $B_{10} = 1.83$].

Faith was the best predictor of overall trust during the second experimental session [predictability, B_{10} = 1/5.11; dependability, B_{10} = 3.85; faith, B_{10} = 980.18] and the third experimental session [predictability, B_{10} =1/2.61; dependability, B_{10} = 38.43; faith, B_{10} = 1166.81]. Table 3 presents the R-squared value from stepwise regression analysis for each regression model of predictability, dependability, and faith. Interestingly, an exploratory Bayesian linear regression analysis indicated that performance was the best predictor of overall trust during the first experimental session [performance, B_{10} = 1327.84; process, B_{10} =1/2.73; purpose, B_{10} = 1/1.59], second experimental session [performance, B_{10} = 2610.01; process, B_{10} = 1/3.96; purpose, B_{10} =1/4.33], and the third experimental session [performance, B_{10} = 504.26; process, B_{10} =1/4.71; purpose, B_{10} =1/4.57]. Table 4 presents the R-squared value form stepwise regression analysis for each regression model of performance, process, and purpose.

Table 3

R-squared value for each regression model (predictability, dependability, and faith) across time epochs.

Experimental Session	R^2 Predictability	R^2 Dependability	R^2 Faith
First	0.22	0.38	0.30
Second	0.22	0.32	0.47
Third	0.13	0.39	0.45

Table 4

R-squared value for each regression model (performance, process, and purpose) across time epochs.

Experimental Session	R^2 Performance	R^2 Process	R^2 Purpose
First	0.41	0.15	0.25
Second	0.38	0.12	0.17
Third	0.44	0.26	0.23

Additionally, the present study examined whether agent characteristics impacted Muir and Moray's (1996) trust development. Therefore, the present study ran an exploratory Bayesian linear regression analysis for each agent characteristics, separately. The present study employed VIF to check for multicollinearity for the model of interest (i.e., Predictability + Dependability + Faith) across agent characteristics. Results indicated that most agent characteristics had a VIF value below 5 except for an automated agent without self-governance. VIF value for predictability [VIF = 6.30] and faith [VIF = 5.11] was above 5 in the second experimental session, indicating a moderate level of multicollinearity. Interpretations of the development of trust in an automated agent without self-governance should be made with caution. Table 5-8 presents the R-squared value from stepwise regression analysis for each regression model across agent characteristics.

Autonomous Agent

Data gave strong evidence that dependability best predicted overall trust during the third experimental session [predictability, B_{10}=1/2.25; dependability, B_{10}= 11.78; faith, B_{10}=1/2.77].

However, data indicated no evidence for the presence and absence of predictors of overall trust during the first experimental session [predictability, B_{10}=1/2.96; dependability, B_{10}= 1.44; faith, B_{10}= 2.98] and the second experimental session [predictability, B_{10}=1/2.48; dependability, B_{10}= 1.87; faith, B_{10}= 1/1.28].

Table 5

R-squared value for each regression model (predictability, dependability, and faith) across time epochs when a scenario involves an autonomous agent.

Experimental Session	R^2 Predictability	R^2 Dependability	R^2 Faith
First	0.02	0.47	0.54
Second	0.03	0.51	0.44
Third	0.25	0.79	0.67

Automated Agent Without Viability

Data indicated substantial evidence that faith best predicted overall trust during the first experimental session [predictability, B_{10}=1/2.80; dependability, B_{10}= 2.63; faith, B_{10}= 6.47] and the third experimental session [predictability, B_{10}= 1.41; dependability, B_{10}=1/2.95; faith, B_{10}= 13.98]. Interestingly, data gave strong evidence that dependability best predicted overall trust during the second experimental session [predictability, B_{10}= 1/3.12; dependability, B_{10}= 19.69; faith, B_{10}= 1/1.65].

Table 6

R-squared value for each regression model (predictability, dependability, and faith) across time epochs when a scenario involves an automated agent without viability.

Experimental Session	R^2 Predictability	R^2 Dependability	R^2 Faith
First	0.19	0.40	0.49
Second	0.10	0.64	0.35
Third	0.04	0.33	0.56

Automated Agent Without Independence

Data gave substantial evidence that predictability best predicted overall trust during the first experimental session [predictability, B_{10} = 4.35; dependability, B_{10} = 2.56; faith, B_{10} =1/2.36]. Surprisingly, there was substantial to strong evidence that faith best predicted overall trust during the second experimental session [predictability, B_{10} =1/2.56; dependability, B_{10} =1/2.46; faith, B_{10} = 11.89] and the third experimental session [predictability, B_{10} =1/2.39; dependability, B_{10} = 1.05; faith, B_{10} = 3.05].

Table 7

R-squared value for each regression model (predictability, dependability, and faith) across time epochs when a scenario involves an automated agent without independence.

Experimental Session	R^2 Predictability	R^2 Dependability	R^2 Faith
First	0.26	0.19	0.11
Second	0.11	0.09	0.54
Third	0.22	0.26	0.44

Automated Agent Without Self-governance

Data gave very strong evidence that predictability best predicted overall trust during the first experimental session [predictability, B_{10} = 78.38; dependability, B_{10} = 70.36; faith, B_{10} =1/2.03]. Also, there was substantial evidence that dependability best predicted overall trust during the third experimental session [predictability, B_{10} = 1/1.25; dependability, B_{10} = 8.65; faith, B_{10} =1/2.29]. Data gave no substantial evidence that faith best predicted overall trust during the second experimental session [B_{10} = 1/3.72]. However, data indicated no evidence onto whether predictability [B_{10} =1/2.18] and dependability [B_{10} = 1.34] best predicted overall trust during the second experimental session.

Table 8

R-squared value for each regression model (predictability, dependability, and faith) across time epochs when a scenario involves an automated agent without self-governance.

Experimental Session	R^2 Predictability	R^2 Dependability	R^2 Faith
First	0.47	0.49	0.18
Second	0.66	0.69	0.56
Third	0.02	0.39	0.08

CHAPTER IV

DISCUSSION

This dissertation investigated how trust evolves differently with automated and autonomous agents in attention demanding environment. Previous studies showed that operators under high task load reported lower levels of trust in automation (Karpinsky et al., 2018; Sato et al., 2020; Sato et al., 2023c; Sato et al., 2024). To date, however, it is unclear how the development of trust in automation differs from the development of trust in autonomy. In a simulated multitasking environment, participants completed three experimental sessions in which participants concurrently performed the tracking task and the system monitoring task. A 70% reliable signaling system was available to support their performance in the system monitoring task. In the tracking task, the frequency force function of the moving circular target was manipulated to be greater in the high task load condition than the low task load condition. Additionally, agent characteristics of the signaling system was manipulated following Kaber's (2018) conceptual framework on automation and autonomy which defines technological maturity in three independent dimensions of viability, independence, and self-governance. Participants read one of the four vignettes, each describing a signaling system that is either an autonomous agent (i.e., an agent that possesses all three dimensions of autonomy) or an automated agent (i.e., an agent that does not possess one of the three dimensions of autonomy). Upon completion of each trial, participants completed a series of questionnaires that assessed trust (Chancey et al., 2017; Jian et al., 2000; Muir & Moray, 1996) and workload (Hart & Staveland, 1988). The following section discusses the result of each hypothesis, and a summary of each hypothesis is presented in Table 9-15.

INFLUENCE OF TASK LOAD

I hypothesized that increasing the attentional demand of the tracking task would result in higher subjective workload (Hypothesis 1), poor tracking task performance (Hypothesis 2), fewer visual sampling of the automation (Hypothesis 3), lower Jian et al.'s (2000) trust (Hypothesis 4), lower performance-based trust (Hypothesis 5), and lower process-based trust (Hypothesis 5; Karpinsky et al., 2018; Sato et al., 2023c; Sato et al., 2024). The results indicated that the manipulation of task load did not influence their subjective workload. Furthermore, I conducted a follow-up analysis to examine whether task load influenced each subscale in NASA-TLX. Results indicated no evidence for and against the effect task load on all subscales in NASA-TLX [$2.51 < B_{10} < 1.46$]. However, the participant's tracking task performance degraded in the high task load condition compared to the low task load condition, supporting Hypothesis 2. Specifically, participants exhibited poor tracking task performance when the tracking task demanded more attentional resources. The results thus indicate dissociations between task performance and subjective workload, some found in the literature (e.g., Yeh & Wickens, 1988). Data indicated no evidence on the effect of task load on attention allocation, failing to support Hypothesis 3. Interestingly, data indicated no evidence on whether the manipulation of task load influenced Jian et al.'s (2000) trust and Chancey et al.'s (2018) trust, also failing to support Hypotheses 4 and 5. Comparison of mean scores indicated that ratings of performance-based trust [M = 36.92 vs. 38.18], process-based trust [M = 45.88 vs. 46.23], and purpose-based trust [M = 23.51 vs. 24.01] decreased in the high than the low task load condition, showing the consistent direction of the effect of task load on trust as found in previous studies (Karpinsky et al., 2018; Sato et al., 2023c; Sato et al., 2024). On the contrary, comparison of mean scores indicated that Jian et al.'s (2000) trust ratings degraded under low task load condition [$M = 54.04$ vs. 53.38]. This discrepancy between Chancey et al.'s (2017) and Jian et al.'s trust scale could be attributed to the fact that both scales capture different aspects of trust (Yamani et al., 2024). That is, constructs measured in Chancey et al.'s (2017) trust scale may be only weakly related to those measured in Jian et al.'s (2000) trust scale, thus manifesting different effects of task load. However, these speculations should be taken with caution since my dissertation did not provide conclusive evidence.

Table 9

Summary of each hypothesis on the effect of task load.

Hypothesis	Description of Hypothesis	Result
H1	Higher subjective workload under high task load condition than low task load condition.	Not Supported
H2	Better tracking performance under low task load condition than high task load condition.	Fully Supported
H3	Lower PDT on the system monitoring display and higher PDT on the tracking display under high task load condition than low task load condition.	Not Supported
H4	Lower Jian et al.'s (2000) trust rating under high task load condition than low task load condition.	Not Supported
H5	Lower performance- and process-based trust rating under high task load condition than low task load condition, but purpose-based trust ratings will be comparable between task load conditions.	Not Supported

HUMAN-AUTOMATION INTERACTION AND HUMAN-AUTONOMY TEAMING

In recent years, there has been growing interest in human-autonomy teaming due to technical advancement of automation (Demir et al., 2021; Graham et al., 2022; M. C. Cohen et al., 2021). Yet, limited work has been conducted to compare trust in automation and autonomy (Sato et al., 2023a). Present results indicated that Jian et al.'s (2000) trust increased when participants assumed that an agent was an autonomous agent (Hypothesis 6) or an automated agent without independence (Hypothesis 7). Additionally, similar data patterns were observed in performance-based trust rating, but not process- and purpose-based trust rating (Hypotheses 8 and 9). Data indicated, however, no evidence that Jian et al.'s (2000) trust varied across agent characteristics, failing to support Hypotheses 6 and 7. Interestingly, data indicated small effect size for the difference in Jian et al.'s (2000) trust rating across agent characteristics. Specifically, participants rated greater trust towards an automated agent without self-governance [$M = 58.00$] than an autonomous agent [$M = 55.83$], an automated agent without independence [$M = 51.74$], and an automated agent without viability [$M = 49.26$]. This data pattern is consistent with other works that demonstrated higher trust towards an automated agent with lower degree of human control for decision making (Amato et al., 2011; Calhoun et al., 2009; Nam et al., 2018). On the contrary, there was strong evidence that performance-based trust did not differ across agent characteristics, failing to support Hypotheses 8 and 9. Note that the performance characteristics of the automated aid was identical among the four agent characteristics. The current results thus indicate that, even though the context of the automation is varied, performance-based trust may depend primarily on observable behaviors of automation, providing some evidence for construct validity.

Table 10

Summary of each hypothesis on the effect of agent characteristics on trust.

Hypothesis	Description of Hypothesis	Result
H6	Jian et al.'s (2000) trust rating will be greater with an autonomous agent than with an automated agent without viability and with an automated agent without self-governance.	Not Supported
H7	Jian et al.'s (2000) trust rating will be greater with an automated agent without independence than with an automated agent without viability and with an automated agent without self-governance.	Not Supported
H8	Higher performance-based trust rating towards an autonomous agent than an automated agent without viability and an automated agent without self-governance, but not on the process- and purpose-level of attributional abstraction.	Not Supported
H9	Higher performance-based trust towards an automated agent without independence than an automated agent without viability and an automated agent without self-governance, but not on the process- and purpose-level of attributional abstraction.	Not Supported

In Sato et al.'s (2023a) study, participants exhibited greater levels of trust towards an autonomous agent and an automated agent without independence. If trust negatively correlates with attentional allocation (2023b), participants should allocate less attentional resources to the system monitoring task when engaging with an autonomous agent and an automated agent without independence (Hypotheses 10 and 11, respectively). Furthermore, participants should allocate more attentional resources to the tracking task when engaging with an autonomous agent and an automated agent without independence (Hypotheses 12 and 13, respectively). The present study indicated no evidence on the participant's fixation within the system monitoring display, failing to support Hypotheses 10 and 11. Also, there was substantial evidence that participants fixated the tracking display less frequently when they assumed that the signaling system was an automated agent without viability, failing to support Hypotheses 12 and 13. This could indicate that attentional resources supplied to perform the tracking task were reallocated to monitor a signaling system that does not have viability. Indeed, participants exhibited numerically greater fixation on the system monitoring display when they assumed that the signaling system was an automated agent without viability [$M = 0.13$] compared to an autonomous agent [$M = 0.09$], and an automated agent without independence [$M = 0.11$], and an automated agent without self-governance [$M = 0.11$].

Table 11

Summary of each hypothesis on the effect of agent characteristics on attention allocation.

Hypothesis	Description of Hypothesis	Conclusion
H10	Lower PDT on the system monitoring display when participants assume that aid is an autonomous agent compared to when participants assume that the aid is an automated agent without viability or an automated agent without self-governance.	Not Supported
H11	Lower PDT on the system monitoring display when participants assume that the aid is an automated agent without independence compared to when participants assume that the aid is an automated agent without viability or an automated agent without self-governance.	Not Supported
H12	Greater PDT on the tracking display when participants assume that the aid is an autonomous agent compared to when participants assume that the aid is an automated agent without viability or an automated agent without self-governance.	Not Supported
H13	Greater PDT on the tracking display when participants assume that the aid is an automated agent without independence compared to when participants assume that the aid is an automated agent without viability or an automated agent without self-governance.	Not Supported

According to the general HIP model, human performance is a function of the number of attentional resources supplied to support the human to complete a task. Based on the general HIP model, system monitoring performance should improve whereas tracking performance should degrade in a scenario involving an autonomous agent (Hypothesis 14) or an automated agent without independence (Hypothesis 15) since attentional resources should be reallocated from the tracking task to the system monitoring task. Interestingly, tracking performance degraded when participants assumed that the signaling system was an automated agent without viability, failing to support Hypotheses 14 and 15. Participants could have exhibited poor tracking performance with an agent that lacks viability because the attentional demand imposed by the tracking task exceeded the attentional resources supplied to perform the tracking task.

Table 12

Summary of each hypothesis on the effect of agent characteristics on tracking and system monitoring performance.

Hypothesis	Description of Hypothesis	Result
H14	Tracking performance will degrade while system monitoring performance will improve when participants assume that the aid is an autonomous agent compared to when participants assume that the aid is an automated agent without viability or an automated agent without self-governance.	Not Supported
H15	Tracking performance will degrade while system monitoring performance will improve when participants assume that the aid is an automated agent without independence compared to when participants assume that the aid is an automated agent without viability or an automated agent without self-governance.	Not Supported

TEMPORAL EFFECT ON TASK PERFORMANCE, WORKLOAD, ATTENTION, AND TRUST

Based on previous works (Dikemen & Burns, 2017; Ebinger et al., 2023; Gold et al., 2015; Wilson et al., 2020), I hypothesized that Jian et al.'s (2000) trust and Chancey et al.'s (2017) trust dimensions will evolve over time (Hypotheses 16). Data indicated that Jian et al.'s (2000) trust and Chancey et al.'s (2017) performance-based trust increased over time but not process-based trust nor purpose-based trust, partially supporting Hypothesis 16. One account for the increase of trust rating over time is the system transparency of the agent. Studies have shown that increasing the system transparency of an agent could mitigate trust reduction due to system malfunction (Kraus et al., 2020) and the cry wolf effect (Yang et al., 2017). Thus, it is possible that participants became more familiar with the signaling system's behavior over time, mitigating trust reduction due to false alarm events. Consequently, participant's trust ratings elevated after completing each experimental session.

Sato et al.'s (2023b) meta-analysis indicated a negative correlation between trust and attention allocation towards the system monitoring task. Thus, I hypothesized that participants would fixate the system monitoring display less frequently and the tracking display more frequently over time (Hypothesis 17). The present work indicated that participants spent less time visually sampling the system monitoring display over time, suggesting that participants allocated less attentional resources to the automated task over time. However, participant's visual sampling of the tracking task display did not increase over time, partially supporting Hypothesis 17.

Based on Haga et al.'s (2002) findings, I hypothesized that tracking performance and system monitoring performance will degrade over time (Hypothesis 18), but not subjective workload (Hypothesis 19). Contrary to Haga et al.'s (2002) findings, data indicated no temporal effect on tracking performance and system monitoring performance, failing to support Hypothesis 18. Data did not provide substantial evidence for the temporal effect on subjective workload, supporting Hypothesis 19.

Table 13

Summary of each hypothesis on the temporal effect.

Hypothesis	Description of Hypothesis	Result
H16	Jian et al.'s (2000) and Chancey et al.'s (2017) trust rating will increase over time.	Partially Supported
H17	PDT on the system monitoring display will degrade over time while PDT on the tracking display will increase over time.	Partially Supported
H18	Tracking performance and system monitoring performance will degrade over time.	Not Supported
H19	Subjective workload will not change over time.	Supported

Previous works demonstrated evidence for the presence of a temporal effect on trust in automation (Sato et al., 2023b) and trust in autonomy (Dikmen & Burns, 2017). Thus, I hypothesized that there will be no interaction effect between time and agent characteristics on trust (Hypothesis 20) as well as attention allocation (Hypothesis 21). Data indicated no interaction effect between time and agent characteristics on Jian et al.'s (2000) trust and Chancey et al.'s (2017) purpose-based trust. However, data were indifferent to the presence or absence of an interaction effect between time and agent characteristics on Chancey et al.'s (2017) performance-based trust and process-based trust. Thus, these findings partially support Hypothesis 20. Additionally, data indicated no interaction effect on attention allocation within the system monitoring display and the tracking display, supporting Hypothesis 21. These findings are inconsistent with Hoff and Bashir's (2015) theoretical model where variability of trust is influenced by perceived system performance during interaction with the automation.

Following Hoff and Bashir's (2015) theoretical model, trust ratings could have varied across agent characteristics before participants interacted with the signaling system since trust was presumably initially developed based on the vignette which provides different description of the agent. However, during the experimental session, trust could have developed based on the signaling system's performance which was comparable across agent characteristics, offsetting the effects of perceived agent characteristics.

Table 14

Summary of each hypothesis on the interaction between time and agent characteristics on trust and attention allocation.

Hypothesis	Description of Hypothesis	Result
H20	Jian et al.'s (2000) and Chancey et al.'s (2017) trust rating will elevate over time regardless of agent characteristics.	Partially Supported
H21	PDT on the system monitoring display will degrade over time while PDT on the tracking display will increase over time regardless of agent characteristics.	Supported

A few studies examined the development of trust development when performing a plant monitoring task (Lee et al., 2021; Long et al., 2022; Muir & Moray, 1996). However, these studies indicated varying progression of trust development. Based on recent finding (Long et al., 2022), I hypothesized that overall trust would develop from dependability, to predictability, and to faith (Hypothesis 22). Consistent with Long et al.'s (2022) finding, the present work indicated that overall trust was initially predicted by dependability. As suggested by Lee et al. (2021), overall trust could be best predicted by dependability due to low self-confidence. Indeed, combining trust with self-confidence can influence automation use (Lee & Moray, 1994; Lee & See, 2004). For example, human operators are more likely to use automation when they exhibit high trust in automation and low self-confidence (Patton, 2023). Although overall trust was predicted by dependability during the first experimental session, overall trust was best predicted by faith in subsequent experimental sessions, partially supporting Hypothesis 22. One possible account is that the participant's cognitive processing shifted from analytical process to analogical process (Lee & See, 2004) after the first experimental session. That is, participants relied on analytical process to analyze information on the agent's characteristics during the first experimental session. Consequently, participants gained enough information to anticipate the future state of the agent. In subsequent experimental sessions, participants developed trust based prior knowledge of the agent's characteristics (i.e., analogical process). Theoretically, analogical process requires less attentional resources than analytical process because it does not require human operators to directly observe and process the agent's characteristics (Lee & See, 2004; Miller, 2005). This study showed that attentional resources for monitoring the signaling system degraded over time, partially supporting the notion that participant's cognitive processing shifted from analytical process to analogical process.

Interestingly, exploratory analysis indicated that the dynamics of trust varied across agent characteristics in the last experimental session. Specifically, trust in an autonomous agent and trust in an automated agent without self-governance was governed by dependability, while trust in an automated agent without viability and trust in an automated agent without independence was governed by faith. This finding could indicate temporal differences in trust formation across agent characteristics. For example, participants may require more time to interact with an autonomous agent to evolve trust from faith than with an automated agent without viability or an automated agent without independence. One possible account is that the duration of use varied across agent characteristics. Previous work showed that trust elevated over time with higher level of trust towards adaptive cruise control (ACC) than lane-keeping assistance (LA; Ebinger et al., 2023). Furthermore, results indicated that participants exhibited high levels of trust in ACC because the duration of using ACC was longer than LA. These findings suggest that the development of trust could vary across agent characteristics depending on the duration of use. That is, participants could have spent longer time to use an automated agent without viability or an agent without independence, resulting trust to evolve from faith.

Interestingly, exploratory analysis indicated that overall trust was governed by performance. This suggests that participants developed trust over time by accumulating information on the agent's behavior, but not the agent's functionality and the system designer's intention for developing the agent. Indeed, a few works demonstrated that trust development was based only on the automation's behavior (Sato et al., 2020; Sato et al., 2023c). For example, Sato et al.'s (2020) study demonstrated that participant's performance-based trust rating elevated in high task load condition when they perceived high risk. Furthermore, these findings suggest that Lee and See's (2004) trust dimensions do not correspond with Muir and Moray's (1996) trust attribution. However, a follow-up Bayesian correlation analysis indicated decisive evidence for a positive relationship between Lee and See's (2004) trust dimension and Muir and Moray's (1996) trust attribution [Predictability and Performance, $r = .46$, $B_{10} < 1.3 \times 10^{10}$; Dependability and Process, $r = .42$, $B_{10} < 1.1 \times 10^{8}$; Faith and Purpose, $r = .41$, $B_{10} < 3.4 \times 10^{7}$]. One possible account for this phenomenon is the low system transparency of the signaling system's functionality and the system designer's intention for developing the signaling system. Indeed, participants can only obtain real-time information on the signaling system's behavior such as the accuracy of the signaling system. Thus, participant's trust could be governed by other trust dimensions if the signaling system provides real time information on the signaling system's functionality and the system designer's intention for developing the signaling system.

Table 15

Summary of each hypothesis on trust development.

Hypothesis	Description of Hypothesis	Result
H22	Trust will develop from dependability, to predictability, and to faith.	Partially Supported

THEORETICAL IMPLICATIONS

Several major findings of the present study offer theoretical implications for understanding the dynamic nature of trust in automation and trust in autonomy. First, the present study indicated a temporal effect on Chancey et al.'s (2017) performance-based trust and Jian et al.'s (2000) trust whereby participant's trust ratings elevated over time, consistent with previous findings on trust development (Dikemen & Burns, 2017; Ebinger et al., 2023; Gold et al., 2015; Wilson et al., 2020). Not only this finding accord with previous findings on trust development, but it also identified the basis of trust development. Specifically, results show the development of trust is governed by the human operator's understanding of the agent's behavior, but not the agent's mechanism nor the system designer's intention for developing the agent. Second, the present study indicated that overall trust was initially predicted by dependability which was consistent with Lee et al.'s (2021) and Long et al.'s (2022) finding. However, after the first experimental session, the trajectories of trust development departed from the prediction of these studies. The present findings could indicate that the underlying mechanisms of trust development is dependent on differences and the human operator's perceived system performance. Third, recent studies have examined human-autonomy teaming (Demir et al., 2021; Graham et al., 2022; M. C. Cohen et al., 2021), but none of these works directly compared human-automation interaction and human-autonomy teaming. The present study indicated that trust in automation was comparable to trust in autonomy which was inconsistent with previous finding (Sato et al., 2023a). Also, this finding was inconsistent with Hoff and Bahir's (2015) theoretical model which postulates that the variability of trust is accounted by the automation's capability. Interestingly, an exploratory analysis indicated varying progression of trust development across agent characteristics. Yet, a few caveats should be taken into consideration when interpreting this finding. First, this study was not a comprehensive study on the difference between the dynamics of trust in automation and trust in autonomy. Results show no conclusive evidence on the development of trust in autonomy in the first and second experimental session, making it difficult to compare trust development between human-automation interaction and human-autonomy teaming. Second, this finding may not generalize to all kinds of automation because results could vary depending on the type of aid. For example, participants in Fahnenstich et al.'s (2024) study exhibited reduced behavioral trust when interacting with an aid that estimated the number of bacteria in an image (i.e., decision selection) under high-risk condition, while participants in Satterfield et al.'s (2017) study exhibited increased behavioral trust when interacting with an aid that controls a UAV (i.e., action implementation) under high-risk condition. These studies suggest that trust could vary depending on the different stages of HIP that receives support from the aid. As industries shift from automation to autonomy, the development of trust will likely differ from previous findings (Lee et al., 2021; Long et al., 2022; Muir & Moray, 1996). To sum, the present study provided theoretical foundation for understanding the development of trust between human-automation interaction and human-autonomy teaming.

PRACTICAL IMPLICATIONS

Practically, two major findings offer insights for improving human-automation interaction and human-autonomy teaming in various domains. First, this study characterized a temporal effect of perceived automation characteristics on trust development when participants performed the identical tasks. Results indicated that continuous interaction with an agent increased trust regardless of the agent characteristics. Moreover, trust elevated by accumulating information on the agent's behavior, but not the agent's functionality nor the system designer's intention for developing the agent. System designers can leverage this finding to implement systems that provide real-time feedback on the agent's behavior, controlling trust in an agent and the use of agent. Second, this study indicated that attention allocation strategy varied across agent characteristics. Specifically, participants allocated more attentional resources for performing an automated task when they assumed that the agent did not have viability. Moreover, tracking task performance degraded when they assumed that the agent lacks viability perhaps due to degraded attentional resources for performing the tracking task (Wickens et al., 2015). System designers can leverage this finding to develop a gaze-based system that alert operators to perform manual tasks that are not visually scanned frequently, potentially maintaining task performance in a manual task.

LIMITATIONS AND FUTURE STUDY

Several caveats exist for interpreting the current results. First, the present study did not replicate the effect of agent characteristics throughout the experiment. That is, the manipulation of agent characteristics could have been eliminated as participants completed the experimental sessions. It is possible that participants could not retain information from the vignette in their working memory because information stored in the working memory either degraded or is displaced with real-time information on the signaling system's behavior (Nyberg & Eriksson, 2016). These two forms of information, direct observation of the system's behavior and verbal information about the automation characteristics, may compete for calculating trust levels throughout their interaction. Future research should examine how retention of information in working memory influences trust in automation and trust in autonomy.

Second, the actual capability of the signaling system was comparable across agent characteristics. Consequently, participants exhibited similar trust ratings across agent characteristics since trust was developed by accumulating information on the signaling system's behavior. Future research should control the actual capability of the agent to be congruent with the description of its capability introduced in the vignette and compare the development of trust in automation and autonomy.

Third, the present study did not control risk which is a critical construct for developing trust in automation (Chancey et al., 2017; He et al., 2022; Hoesterey & Onnasch, 2023; Hoff & Bashir, 2015; Lee & See, 2004; Mayer et al., 1995; Sato et al., 2020; Stuck et al., 2022). That is, trust is proposed to only develop in situations that involve increased levels of uncertainty and risk. Indeed, several studies have demonstrated the importance of risk for developing trust in automation (He et al., 2022; Hoesterey & Onnasch, 2023; Sato et al., 2020) and trust in autonomy (Chancey et al., 2022; Demir et al., 2021). Yet, it is uncertain how risk influence trust in autonomy when direct interaction with autonomy exists. Therefore, future research should compare the direct or indirect effect of risk on trust in automation and trust in autonomy.

Fourth, my dissertation primarily used PDT as an aggregate measure of attentional resources supplied to each task. One caveat of using PDT is that it does not reveal the transition of attentional resources between different tasks across time. Two potential candidates could capture the dynamic nature of attention including scan path-based analysis (Holmqvist et al., 2011) and gaze entropy analysis (Krejtz et al., 2015; Cui et al., under review). Scan path-based analysis may be used to reveal the sequence of eye movement events across specific time periods in space. Measures of scan path include scan path direction, scan path duration, and scan path length. Scan path direction measures the trajectory of sequence of gaze and saccade (i.e., in degrees). Scan path duration measures the total time of saccade within a scan path. Scan path length measures the total saccade distance (i.e., in degrees or pixels).

Alternatively, gaze entropy analysis can reveal the spatio-temporal gaze behavior with stationary gaze entropy (SGE) and gaze transition entropy (GTE). GTE estimates the predictability of gaze transition patterns, while SGE estimates the uniformity of gaze transitions across AOIs. These eye movement measures have been applied to examine the dynamics of attention in various domains including aviation (Ayala et al., 2023; Diaz-Piedra et al., 2019) and surface transportation (Navarro et al., 2021; Shiferaw et al., 2019). Interestingly, several works suggested that scan path-based measures (Lu & Sarter, 2019) and gaze entropy measures (Cui et al., under review; Zhang et al., 2024) could be used to measure trust in automation. Future research should apply scan path-based measures and gaze entropy measures to examine the spatio-temporal features of attention allocation and the dynamic nature of trust.

Fifth, findings from my dissertation do not necessarily corroborate with Sato et al.'s (2023a) findings perhaps due to the discrepancy between the user's mental model of the agent (i.e., Users Model) and the information available to the user for analyzing the agent (i.e., System Image; Chancey et al., 2021). Specifically, participants could have constructed their mental model of the signaling system after reading the vignette. However, participant's mental model of the signaling system's behavior (i.e., Performance-based User Model) did not align with the agent's behavior (i.e., Task Model). Consequently, participants could have supplied attentional resources to visually sample the signaling system's actual behavior, resulting trust levels to be statistically comparable across agent characteristics. Future research should examine whether the discrepancy between the Users Model and the Design Model could have eliminated the effect of agent characteristics on trust. For example, researchers could apply Pathfinder Network Analysis which is a psychometric technique that can quantify and compare mental models (Schvaneveldt et al., 1989).

Finally, the present study may benefit from participation of pilots with more experiences with flight operations with automation for greater generalizability of the current findings. In most professional environment, operators are interacting with an automation or an autonomy to accomplish a certain task. However, the present study recruited novices who have less experience interacting with an automation or an autonomy. Also, the present study employed a low-fidelity flight simulator that may not necessarily generalize to applied working environment. Future research should recruit participants with expertise and employ a high-fidelity simulator that generalizes to applied environment such as the X-Plane 10 simulator.

CHAPTER V

CONCLUSION

This dissertation investigated the dynamic nature of trust and attention allocation with automation and autonomy. Three major findings emerged from the experiment. First, participants allocated more attentional resources to perform the system monitoring task when they assumed that an agent lacks viability compared to an autonomous agent, an agent that lacks independence, and an agent that lack self-governance. Second, participant's trust increased as they spend more time interacting with an agent. Third, participants monitored the aid less frequently over time. These major findings indicate that the trajectory of trust development does not differ between human-automation interaction and human-autonomy teaming. Furthermore, human operators will likely allocate less attentional resources for monitoring an agent as technologies shift from automation to autonomy. Practitioners and system designers can leverage these findings to control trust in automation or trust in autonomy, ultimately preventing human operators from misusing and overtrusting unreliable systems.

REFERENCES

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Upper Saddle River, NJ: Prentice Hall.

Amato, F., Felici, M., Lanzi, P., Lotti, G., Save, L., & Tedeschi, A. (2011). Trust observations in validation exercises. *2011 Fifth International Conference on Secure Software Integration and Reliability Improvement*, 216-223.

Bailey, N. R., & Scerbo, M. W. (2007). Automation-induced complacency for monitoring highly reliable systems: the role of task complexity, system experience, and operator trust. *Theoretical Issues in Ergonomics Science*, *8,* 321-348.

Bainbridge, L. (1983). Ironies of automation. *Automatica*, *19*, 775-779.

Barber, B. (1983). *The logic and limits of trust* (Vol. 96). New Brunswick, NJ: Rutgers University Press.

Billings, C. E. (1991). *Human-centered aircraft automation: A concept and guidelines*. National Aeronautics and Space Administration, Ames Research Center.

Bliss, J. P., & Dunn, M. C. (2000). Behavioural implications of alarm mistrust as a function of task workload. *Ergonomics*, *43*, 1283-1300.

Bolton, M. L. (2022). Trust is not a virtue: Why we should not trust trust. *Ergonomics in Design*, 10648046221130171.

Calhoun, G. L., Draper, M. H., & Ruff, H. A. (2009). Effect of level of automation on unmanned aerial vehicle routing task. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *53*, 197-201.

Cegarra, J., Valéry, B., Avril, E., Calmettes, C., & Navarro, J. (2020). OpenMATB: A Multi-

Attribute Task Battery promoting task customization, software extensibility and experiment replicability. *Behavior Research Methods*, *52*, 1980-1990.

Chancey, E. T., Bliss, J. P., Yamani, Y., & Handley, H. A. (2017). Trust and the compliance–reliance paradigm: The effects of risk, error bias, and reliability on trust and dependence. *Human Factors*, *59*, 333-345.

Chancey, E. T., Politowicz, M. S., & Le Vie, L. (2021). Enabling Advanced Air Mobility Operations through Appropriate Trust in Human-Autonomy Teaming: Foundational Research Approaches and Applications. *AIAA Scitech 2021 Forum*.

Cohen, A. P., Shaheen, S. A., & Farrar, E. M. (2021). Urban Air Mobility: History, Ecosystem, Market Potential, and Challenges. *IEEE Transactions on Intelligent Transportation Systems*, *22*, 6074-6087.

Cohen, M. C., Demir, M., Chiou, E. K., & Cooke, N. J. (2021). The dynamics of trust and verbal anthropomorphism in human-autonomy teaming. *2021 IEEE 2nd International Conference on Human-Machine Systems*, 1-6.

Cui, Z., Sato, T., Jackson, A., Jayarathna, S., Politowicz, M. S., Chancey, E. T., Itoh, M., & Yamani, Y. (2024). Gaze transition entropy as a measure of attention allocation and a predictor of automation trust. [Manuscript submitted for publication].

Demir, M., McNeese, N. J., Gorman, J. C., Cooke, N. J., Myers, C. W., & Grimm, D. A. (2021). Exploration of teammate trust and interaction dynamics in human-autonomy teaming. *IEEE Transactions on Human-Machine Systems*, *51*, 696-705.

Dikmen, M., & Burns, C. (2017, October). Trust in autonomous vehicles: The case of Tesla Autopilot and Summon. Proceedings of *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 1093-1098.

Ebinger, N., Neuhuber, N., Moser, J., Trösterer, S., & Stocker, A. (2023). What do drivers prefer? A field study on longitudinal and lateral driving automation. *Transportation Research Procedia*, *72*, 351-358.

Endsley, M. R., & Kiris, E. O. (1995). The out-of-the-loop performance problem and level of control in automation. *Human Factors*, *37,* 381-394.

Fahnenstich, H., Rieger, T., & Roesler, E. (2024). Trusting under risk–comparing human to AI decision support agents. *Computers in Human Behavior*, *153*.

Gold, C., Körber, M., Hohenberger, C., Lechner, D., & Bengler, K. (2015). Trust in automation– before and after the experience of take-over scenarios in a highly automated vehicle. *Procedia Manufacturing*, *3,* 3025-3032.

Gutzwiller, R. S., & Sitzman, D. M. (2017). Examining task priority effects in multi-task management. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *61*, 762-766.

Gutzwiller, R. S., Wickens, C. D., & Clegg, B. A. (2014). Workload overload modeling: An experiment with MATB II to inform a computational model of task management. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *58*, 849-853.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. *Advances in Psychology*, *52,* 139-183.

He, X., Stapel, J., Wang, M., & Happee, R. (2022). Modelling perceived risk and trust in driving automation reacting to merging and braking vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *86*, 178-195.

Hoesterey, S., & Onnasch, L. (2022). The effect of risk on trust attitude and trust behavior in interaction with information and decision automation. *Cognition, Technology & Work*, 1-15.

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors, 57,* 407-434.

Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & Van de Weijer, J. (2011). *Eye tracking: A comprehensive guide to methods and measures*.OUP Oxford.

Ishihara, S. (2014). *Ishihara's tests for colour deficiency*. Tokyo: Kanehara Trading Inc.

Jeffreys, H. (1961). *Theory of probability (3rd ed.)*. New York, NY: Oxford University Press.

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,* 53-71.

Kahneman, D. (1973). *Attention and effort.* Englewood Cliffs, NJ: Prentice-Hall.

Karpinsky, N. D., Chancey, E. T., Palmer, D. B., & Yamani, Y. (2018). Automation trust and attention allocation in multitasking workspace. *Applied Ergonomics, 70,* 194-201.

Kohn, S. C., De Visser, E. J., Wiese, E., Lee, Y. C., & Shaw, T. H. (2021). Measurement of trust in automation: A narrative review and reference guide. *Frontiers in Psychology, 12*.

Kramer, R. M. (1999). Trust and distrust in organizations: Emerging perspectives, enduring questions. *Annual Review of Psychology, 50,* 569-598.

Kraus, J., Scholz, D., Stiegemeier, D., & Baumann, M. (2020). The more you know: trust dynamics and calibration in highly automated driving and the effects of take-overs, system malfunction, and system transparency. *Human Factors*, *62*, 718-736.

Krejtz, K., Duchowski, A., Szmidt, T., Krejtz, I., González Perilli, F., Pires, A., Vilaro, A., &

Villalobos, N. (2015). Gaze transition entropy. *ACM Transactions on Applied Perception (TAP)*, *13*, 1-20.

Lee, J. D., & Moray, N. (1994). Trust, self-confidence, and operators' adaptation to automation. *International Journal of Human-Computer Studies*, *40*, 153-184.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors*, *46*, 50-80.

Lee, J., Yamani, Y., Long, S. K., Unverricht, J., & Itoh, M. (2021). Revisiting human-machine trust: a replication study of Muir and Moray (1996) using a simulated pasteurizer plant task. *Ergonomics*, *64*, 1132-1145.

Long, S. K., Lee, J., Yamani, Y., Unverricht, J., & Itoh, M. (2022). Does automation trust evolve from a leap of faith? An analysis using a reprogrammed pasteurizer simulation task. *Applied Ergonomics*, *100*, 103674.

Lu, Y., & Sarter, N. (2019). Eye tracking: a process-oriented method for inferring trust in automation as a function of priming and system reliability. *IEEE Transactions on Human-Machine Systems*, *49*, 560-568

Madsen, M., & Gregor, S. (2000). Measuring human-computer trust. *11th Australasian Conference on Information Systems*, 53, 6-8.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*, 709-734.

Meyer, J. (2001). Effects of warning validity and proximity on responses to warnings. *Human Factors*, *43*, 563-572.

Miller, C. A. (2005). Trust in adaptive automation: the role of etiquette in tuning trust via analogic and affective methods. *Proceedings of the 1st International Conference on Augmented Cognition*, 22-27.

Muir, B. M. (1994). Trust in automation: Part I. Theoretical issues in the study of trust and human intervention in automated systems. *Ergonomics*, *37*, 1905-1922.

Muir, B. M., & Moray, N. (1996). Trust in automation. Part II. Experimental studies of trust and human intervention in a process control simulation. *Ergonomics*, *39*, 429-460.

Nam, C., Li, H., Li, S., Lewis, M., & Sycara, K. (2018). Trust of humans in supervisory control of swarm robots with varied levels of autonomy. In 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 825-830.

National Academies of Sciences, Engineering, and Medicine. (2020). *Advancing aerial mobility: A national blueprint*. National Academies Press.

National Aeronautics and Space Administration (2021, September). *NASA and Joby Complete Flights Tests*. https://www.nasa.gov/centers/armstrong/features/nasa-and-joby-complete-flight-tests.html.

National Transportation Safety Board (2017). Collisions with Terrain Hageland Aviation Services, Inc. dba Ravn Connect Flight 3153 Cessna 208B, N208SD, Togiak, Alaska October 2, 2016 (Rep. NTSB-AAR1802). Washington, DC: Author.

Navarro, J., Lappi, O., Osiurak, F., Hernout, E., Gabaude, C., & Reynaud, E. (2021). Dynamic scan paths investigations under manual and highly automated driving. *Scientific Reports*, *11*, 3776.

Nyberg, L., & Eriksson, J. (2016). Working memory: maintenance, updating, and the realization of intentions. *Cold Spring Harbor Perspectives in Biology*, *8*, a021816.

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors*, *39*, 230-253.

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*, 286-297.

Patton, C. E. (2023). Automation Use: The Roles of Self-Confidence, Trust, and Workload. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 67, 965-970.

Rempel, J. K., Holmes, J. G., & Zanna, M. P. (1985). Trust in close relationships. *Journal of Personality and Social Psychology*, *49*, 95.

Rice, S. (2009). Examining single-and multiple-process theories of trust in automation. *The Journal of General Psychology*, *136*, 303-322.

Rotter, J. B. (1967). A new scale for the measurement of interpersonal trust 1. *Journal of Personality*, *35*, 651-665.

Rouder, J. N., & Morey, R. D. (2012). Default Bayes factors for model selection in regression. *Multivariate Behavioral Research*, *47*, 877-903.

Rouder, J. N., Morey, R. D., Speckman, P. L., & Province, J. M. (2012). Default Bayes factors for ANOVA designs. *Journal of Mathematical Psychology*, *56*, 356-374.

Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review*, *16*, 225-237.

Rubio, S., Díaz, E., Martín, J., & Puente, J. M. (2004). Evaluation of subjective mental workload: A comparison of SWAT, NASA-TLX, and workload profile methods. *Applied Psychology*, *53*, 61-86.

Safar, J. A., & Turner, C. W. (2005). Validation of a two factor structure for system trust. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *49*, 497-501.

Santiago-Espada, Y., Myer, R. R., Latorella, K. A., & Comstock, J. R. (2011). The Multi-Attribute Task Battery II (MATB-II) Software for Human Performance and Workload Research: A User's Guide (NASA/TM-2011–217164). *Hampton, VA: National Aeronautics and Space Administration, Langley Research Center*.

Sato, T., Inman, J., Politowicz, M., Chancey, E. T., & Yamani, Y. (2023a). The influence of viability, independence, and self-governance on trust and public acceptance of uncrewed air vehicle operations. *Proceedings of the Human Factors and Ergonomics Society 2023 Annual Meeting.*

Sato, T., Inman, J., Politowicz, M. S., & Yamani, Y. (2023b). A meta-analytic approach to investigating the relationship between trust and attention allocation. *Proceedings of the Human Factors and Ergonomics Society 2023 Annual Meeting.*

Sato, T., Islam, S., Still, J. D., Scerbo, M. W., & Yamani, Y. (2023c). Task priority reduces an adverse effect of task load on automation trust in a dynamic multitasking environment. *Cognition, Technology & Work*, 1-13.

Sato, T., Jackson, A., & Yamani, Y. (2024). Number of Interrupting Events Influences Response Time in Multitasking, but not Trust in Automation. *The International Journal of Aerospace Psychology*, 1-17.

Sato, T., Politowicz, M. S., Islam, S., Chancey, E. T., & Yamani, Y. (2022). Attentional considerations in advanced air mobility operations: Control, manage, or assist? *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *66*, 28-32.

Sato, T., Yamani, Y., Liechty, M., & Chancey, E. T. (2020). Automation trust increases under high-workload multitasking scenarios involving risk. *Cognition, Technology & Work*, *22*, 399-407.

Satterfield, K., Baldwin, C., de Visser, E., & Shaw, T. (2017). The influence of risky conditions in trust in autonomous systems. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *61*, 324-328.

Schvaneveldt, R. W., Durso, F. T., & Dearholt, D. W. (1989). Network structures in proximity data. *Psychology of learning and motivation*, *24*, 249-284.

Sheridan, T. B., & Verplank, W. L. (1978). *Human and computer control of undersea teleoperators*. Massachusetts Inst of Tech Cambridge Man-Machine Systems Lab.

Sitkin, S. B., & Pablo, A. L. (1992). Reconceptualizing the determinants of risk behavior. *Academy of Management Review*, *17*, 9-38.

Stuck, R. E., Tomlinson, B. J., & Walker, B. N. (2022). The importance of incorporating risk into human-automation trust. *Theoretical Issues in Ergonomics Science*, *23*, 500-516.

Wickens, C. D., Gutzwiller, R. S., Vieane, A., Clegg, B. A., Sebok, A., & Janes, J. (2016). Time sharing between robotics and process control: Validating a model of attention switching. *Human Factors*, *58*, 322-343.

Wickens, C.D., Hollands, J.G., Banbury, S., & Parasuraman, R. (2015). *Engineering Psychology and Human Performance,* Psychology Press.

Wiener, E. L., & Curry, R. E. (1980). Flight-deck automation: Promises and problems. *Ergonomics, 23,* 995-1011.

Wilson, K. M., Yang, S., Roady, T., Kuo, J., & Lenné, M. G. (2020). Driver trust & mode confusion in an on-road study of level-2 automated vehicle technology. *Safety Science*, *130*, 104845.

Yamani, Y., & Horrey, W. J. (2018). A theoretical model of human-automation interaction grounded in resource allocation policy during automated driving. *International Journal of Human Factors and Ergonomics*, *5*, 225-239.

Yamani, Y., Long, S. K., & Itoh, M. (2020). Human–automation trust to technologies for naïve users amidst and following the COVID-19 pandemic. *Human Factors*, *62*, 1087-1094.

Yamani, Y., Long, S. K., Sato, T., Braitman, A., Politowicz, M., & Chancey, E. T. (2024). Multi-level confirmatory factor analysis of human-automation trust questionnaires. *Human Factors*.

Yang, X. J., Unhelkar, V. V., Li, K., & Shah, J. A. (2017). Evaluating effects of user experience and system transparency on trust in automation. *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, 408-416.

Yeh, Y. Y., & Wickens, C. D. (1988). Dissociation of performance and subjective measures of workload. *Human Factors*, *30*, 111-120.

Zhang, Y., Yadav, A., Hopko, S. K., & Mehta, R. K. (2024). In gaze we trust: Comparing eye tracking, self-report, and physiological indicators of dynamic trust during HRI. *Companion of the 2024 ACM/IEEE International Conference on Human-Robot Interaction*, 1188-1193.

APPENDIX A

INFORMED CONSENT FORM

PROJECT TITLE: Examining relationships between visual attention and automation trust using eye tracking technique

INTRODUCTION

The purposes of this form are to give you information that may affect your decision whether to say YES or NO to participation in this research, and to record the consent of those who say YES. This research project, *Examining relationships between visual attention and automation trust using eye tracking technique*, will be conducted in Applied Cognitive Performance Laboratory (MGB 325B) at Old Dominion University.

RESEARCHERS

Yusuke Yamani, Ph.D., Assistant Professor, College of Sciences, Department of Psychology, Principal Investigator

Tetsuya Sato, Ph.D. Candidate, College of Sciences, Department of Psychology

Micheal Politowicz, Master's Student, College of Sciences, Department of Psychology

Jessica Inman, Staff, Applied Cognitive Performance Laboratory, Old Dominion University

DESCRIPTION OF RESEARCH STUDY

This research is designed to investigate the ability to perform three concurrent tasks that simulate the control of an aircraft while one of the tasks will be controlled by an automated system with various reliability. We will record both your eye movements and responses during the session. The task will take approximately 2 hours to complete.

EXCLUSIONARY CRITERIA

All participants in this research study must be at least 18 years of age with normal or corrected-to-normal visual acuity and normal color perception.

RISKS AND BENEFITS

RISKS: There may be minimal risk such as eyestrain. The researchers will take all precautions to minimize any of these potential risks. Eye movements will be monitored by a device that reflects infrared light off the lens and the cornea of the eye. The lens, cornea, and other parts of the eye absorb a small amount of energy from the infrared light, but the energy is less than 1% of the Maximum Permissible Exposure level as certified by the American Standards Institute (ANSI Z 136.1-1973). This is about as much energy you get on a bright sunny day.

BENEFITS: You may not benefit directly from the present study. However, your participation in the study will serve to enhance our understanding of the mechanisms that underlie visual attention.

COSTS AND PAYMENTS

The researchers want your decision about participating in this study to be absolutely voluntary. The main benefit to you for participating in this study is the extra credit or course credit points that you will earn for your class. Although they are unable to give you payment for participating in this study, if you decide to participate in this study, you will receive 2.5 Psychology Department research credit, which may be applied to course requirements or extra credit in certain Psychology courses. Equivalent credits may be obtained in other ways. You do not have to participate in this study, or any Psychology Department study, to obtain this credit.

CONFIDENTIALITY

The researchers will take reasonable steps to keep private information confidential. The researchers will keep any record of your participation in locked storage in the psychology department. Furthermore, individual participants results will not be distributed in any form. The results of the study aggregated across participants will be published in professional journals and/or book chapters.

WITHDRAWAL PRIVILEGE

It is OK for you to say NO. Even if you say YES now, you are free to say NO later, and walk away or withdraw from the study at any time. Your decision will not affect your relationship with Old Dominion University, or otherwise cause a loss of benefits to which you might otherwise be entitled.

COMPENSATION FOR ILLNESS AND INJURY

If you say YES, then your consent in this document does not waive any of your legal rights. However, in the event of illness arising from this study, neither Old Dominion University nor the researchers are able to give you any money, insurance coverage, free medical care, or any other compensation for such injury. In the event that you suffer injury as a result of participation in any research project, you may contact Dr. Yusuke Yamani at 757-683-

4457 or Dr. Tancy Vandecar-Burdin the current IRB chair at 757-683 3802 (or at tvandeca@odu.edu) at Old Dominion University, or the Old Dominion University Office of Research at 757-683-3460 who will be glad to review the matter with you.

VOLUNTARY CONSENT

By verbally agreeing to this form, you are saying several things. You are saying that you have read this form or have had it read to you, that you are satisfied that you understand this form, the research study, and its risks and benefits. The researchers should have answered any questions you may have had about the research. If you have any questions later on, then the researchers should be able to answer them:

If at any time you feel pressured to participate, or if you have any questions about your rights or this form, then you should call Dr. Vandecar-Burdin, the current IRB chair, at 757 683 3802, or the Old Dominion University Office of Research, at 757 683 3460.

And importantly, by verbally agreeing, you are telling the researcher that you DO agree to participate in this study.

APPENDIX B

DEMONGRAPHICS FORM

ACP v. 1.0 Appendix A.

Demographic Information Sheet
Applied Cognitive Performance Laboratory

Office Use: ACP ID:_________
Near Vision: ______ Far: _______ Color: ______

Name:
____

Date of Birth: _____________ Age: ____

Health: 1 2 3 4 5
Poor -> Excellent (circle one)

Gender: □Male □Female

Race: ______________________________

Native Language: _____________________ Second Language: ________________

Please circle True/False for the following.

Do you wear Glasses/Contacts on a regular basis? True False
Have you been diagnosed with any neuropsychological dysfunction? True False
If so, are you currently taking any medication for this? True False

How many years of education have you completed (Please record a number)? ____
Please note: grade school through high school is usually 12 years in the US, if needed, add on how many years of college you have completed.

Contact Information
*Home Phone Number : (____)_____________ *Cellular : (____)_____________

*Email : ____

*Address: ____

*If you are interested in receiving information about future experiments, please include your address and please answer below. Your address, phone number and email will not be used for any other purpose.

Can we contact you to participate in additional paid experiments? Yes No

Where did you hear about us? ____

Signature of Participant: _______________________________________

Name (please print): ____

APPENDIX C

NASA-TASK LOAD INDEX (TLX) WORKLOAD QUESTIONNAIRE

(Hart & Staveland, 1998)

Figure 8.6

NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Name	Task	Date

Mental Demand — How mentally demanding was the task?

Very Low — Very High

Physical Demand — How physically demanding was the task?

Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?

Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?

Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?

Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?

Very Low — Very High

APPENDIX D

TRUST QUESTIONNAIRE (Chancey et al., 2017)

TRUST QUESTIONNAIRE

Part. #: _______________ Group: ________________ Session: ________________

Below is a list of statements for evaluating trust between people and automated systems. Please circle the number that best describes your feeling or your impression of the automated aid you used during the task.

1. Even when the automated aid gives me unusual advice, I am certain that the aid's advice will help me to perform well.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

2. For me to perform well, I can rely on the automated aid to function properly.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

3. It is easy to follow what the automated aid does to help me perform well.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

4. The automated aid's advice reliably helps me perform well.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

5. The automated aid's advice consistently helps me perform well.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

6. I understand how the automated aid will help me perform well.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

7. Even if I have no reason to expect that the automated aid will function properly, I still feel certain that it will help me to perform well.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

8. Although I may not know exactly how the automated aid works, I know how to use it to perform well.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

9. To help me perform well, I believe advice from the automated aid even when I don't know for certain that it is correct.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

10. To help me perform well, I recognize what I should do to get the advice I need from the automated aid the next time I use it.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

11. I will be able to perform well the next time I use the automated aid because I understand how it behaves.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

12. The automated aid always provides the advice I require to help me perform well.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

13. The automated aid adequately analyzes the system consistently, to help me perform well.

Not descriptive: 1 2 3 4 5 6 7 8 9 10 11 12 : Very Descriptive

APPENDIX E

CATEGORIZED SCALE ITEMS (Chancey et al., 2017)

Performance

- For me to perform well, I can rely on the automated aid to function.
- The automated aid's advice reliably helps me perform well.
- The automated aid's advice consistently helps me perform well.
- The automated aid always provides the advice I require to help me perform well.
- The automated aid adequately analyzes the system consistently, to help me perform well.

Process

- It is easy to follow what the automated aid does to help me perform well
- I understand how the automated aid will help me perform well.
- Although I may not know exactly how the automated aid works, I know how to use it to perform well.
- To help me perform well, I recognize what I should do to get the advice I need from the automated aid the next time I use it.
- I will be able to perform well the next time I use the automated aid because I understand how it behaves.

Purpose

- Even when the automated aid gives me unusual advice, I am certain that the aid's advice will help me to perform well.

- Even if I have no reason to expect that the automated aid will function properly, I still feel certain that it will help me to perform well.
- To help me perform well, I believe advice from the automated aid even when I don't know for certain that it is correct.

APPENDIX F

TRUST QUESTIONNAIRE (Jian et al., 2000)

Checklist for Trust between People and Automation

Below is a list of statement for evaluating trust between people and automation. There are several scales for you to rate intensity of your feeling of trust, or your impression of the system while operating a machine. Please mark an "x" on each line at the point which best describes your feeling or your impression.

(Note: not at all=1; extremely=7)

1 The system is deceptive

1 2 3 4 5 6 7

2 The system behaves in an underhanded manner

1 2 3 4 5 6 7

3 I am suspicious of the system's intent, action, or outputs

1 2 3 4 5 6 7

4 I am wary of the system

1 2 3 4 5 6 7

5 The system's actions will have a harmful or injurious outcome

1 2 3 4 5 6 7

6 I am confident in the system

1 2 3 4 5 6 7

7 The system provides security

1 2 3 4 5 6 7

8 The system has integrity

1 2 3 4 5 6 7

9 The system is dependable

1 2 3 4 5 6 7

10 The system is reliable

1 2 3 4 5 6 7

11 I can trust the system

1 2 3 4 5 6 7

12 I am familiar with the system

1 2 3 4 5 6 7

APPENDIX G

TRUST QUESTIONNAIRE (adapted from Muir & Moray, 1996)

- Competence: To what extent does the signaling system perform its function properly?
- Predictability: To what extent can the signaling system's behavior be predicted from moment to moment?
- Dependability: To what extent can you count on the signaling system to do its job?
- Responsibility: To what extent does the signaling system perform the task it was designed to do in the system?
- Reliability over time: To what extent does the signaling system respond similarly to similar circumstances at different points in time?
- Faith: To what extent will the signaling system be able to cope with other system states in the future?
- Trust in the signaling system: To what extent do you trust the signaling system to respond accurately?
- Trust in the signaling system's display: To what extent do you trust the accuracy of the signaling system's display?
- Overall trust: To what extent do you trust the signaling system?

VITA

Tetsuya Sato, M.S.
Department of Psychology
250 Mills Godwin Life Sciences Building
Norfolk, VA 23529

Education

2024	Doctor of Philosophy, Human Factors Psychology Old Dominion University, Norfolk, VA
2020	Master of Science, Psychology – Human Factors concentration Old Dominion University, Norfolk, VA
2018	Bachelor of Science, Psychology Old Dominion University, Norfolk, VA

Research & Teaching Experience

2018 – 2024	Graduate Research Assistant Old Dominion University, Norfolk, VA
2018 – 2024	Graduate Teaching Assistant Old Dominion University, Norfolk, VA
2019	Research Assistant University of Tsukuba, Tsukuba, Tsukuba, Japan

Selected Publications

Sato, T., Jackson, A., & Yamani, Y. (2024). Number of Interrupting Events Influences Response Time in Multitasking, but not Trust in Automation. *The International Journal of Aerospace Psychology*, 1-17.

Sato, T., Islam, S., Still, J. D., Scerbo, M. W., & Yamani, Y. (2023). Task priority reduces an adverse effect of task load on automation trust in a dynamic multitasking environment. *Cognition, Technology & Work*, *25*, 1-13.

Sato, T., Inman, J., Politowicz, M. S., & Yamani, Y. (2023). A meta-analytic approach to investigating the relationship between trust and attention allocation. *Proceedings of the Human Factors and Ergonomics Society 2023 Annual Meeting.*

Sato, T., Yamani, Y., Liechty, M., & Chancey, E. T. (2020). Automation trust increases under high-workload multitasking scenarios involving risk. *Cognition, Technology & Work*, *22*, 399-407.