THE INFLUENCE OF CULTURAL FACTORS ON TRUST IN AUTOMATION

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Human interaction with automation is a complex process that requires both skilled operators and complex system designs to effectively enhance overall performance. Although automation has successfully managed complex systems throughout the world for over half a century, inappropriate reliance on automation can still occur, such as the recent malfunction in Tesla autopilot mechanisms that resulted in a fatality. Research has shown that trust, as an intervening variable, is critical to the development of appropriate reliance on automated systems. Because automation inevitably involves uncertainty, trust in automation is related to a calibration between a user's expectations and the capabilities of automation. Prior studies suggest that trust is dynamic and influenced by both endogenous (e.g., cultural diversity) and exogenous (e.g., system reliability) variables. To determine how cultural factors affect various aspects of trust in and reliance on automation, the present research has developed a cross-cultural trust questionnaire and an air traffic control simulator that incorporates a variety of scenarios identified from a review of relevant literature. The measures and tasks have been validated by a crowdsourcing system (Amazon Mechanical Turk), as well as through experimental studies conducted in the U.S., Turkey, and Taiwan, with approximately 1000 participants. The results indicate that the developed trust instrument can effectively measure human trust in automation across cultures. The findings reveal substantial cultural differences in human trust in automation, which have a significant impact on the design, implementation, and evaluation of automated

systems to make them more trustworthy in determining the appropriate trust calibration for optimized reliance across cultures.

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1.0 INTRODUCTION

The use of automation has been greatly increasing in recent decades. Due to the rapid growth in overall task complexity, which involves a variety of information types and source leads, conventional stable procedure-oriented operations are no longer efficient. As a result, more flexible and agile automated systems have been developed to increase competitiveness. Although automation can enhance a system's efficiency, it also generates more uncertain and complicated states during computational processes. Because sophisticated automated applications consist of various complex features, operators may have insufficient knowledge of existing automated procedures, and may therefore perceive extensive difficulties in retaining needed situation awareness (SA), which may inadvertently violate critical assumptions and worsen the consequences of failures, such as in the Three Mile Island nuclear accident. Additionally, because of a lack of SA, when expected results are violated, operators are less likely to retain their previous levels of reliance on automation. The beneficial effects of using automation (e.g., delivering more accurate information, lowering operator workload, or allowing the operator to make faster decisions) may not be fully realized, due to maladaptive use of the automation. Parasuraman and Riley (1997) show that operators' reliance behaviors could significantly affect the human-automation relationship. For instance, it has been observed that human operators may fail to use automation in situations when it would be advantageous. This has been called disuse (underutilization or under-reliance) of the automation (Parasuraman & Riley, 1997). On the other hand, people have been observed to fail to monitor a system properly (e.g., turning off alarms) when the automation is in use, or to accept automated recommendations in situations when they are inappropriate (Lyons, Stokes, Eschleman, Alarcon, & Barelka, 2011). This has been called misuse, complacency, over-reliance, or automation bias. Both misuse and disuse are associated with an improper calibration of trust and have contributed to accidents. Misuse has led to mishaps in aviation and marine navigation (Funk et al., 1999), while disuse has been shown to damage performance through various behaviors, such as ignoring safety alarms in air traffic control scenarios (Parasuraman & Riley, 1997). A growing body of literature suggests that trust significantly contributes to human decisions about the use of automation (Hoff & Bashir, 2015; Kuo, 2011; Lyons et al., 2016; Martelaro, Nneji, Ju, & Hinds, 2016; Wang, Pynadath, & Hill, 2016). For example, trust has been frequently cited (Lee & Moray, 1992; Muir, 1994) as a contributor to human decisions about monitoring and using automation. In other words, people tend to rely on automation that they trust and not to use automation that they do not trust. For optimal performance of a human-automation system, human trust in automation should be well-calibrated so that appropriate reliance can be achieved.

Lee and See (2004) note that "*trust (in automation) can be defined as the attitude that an agent will help achieve an individual's goals in a situation [that is] characterized by uncertainty and vulnerability*." Human intentions and willingness to act alongside automation are highly related to the trust that has been derived from the expectancy of favorable responses, which translates beliefs into behaviors in various uncertain situations. For example, Lyons and Stokes (2012) observe that participants reduce their reliance on human aids when faced with high-risk missions, which indicates an increased reliance on automated recommendations in dangerous situations. Due to the complexities of contexts that may not work perfectly under all situations (despite the best design efforts), placing the same degree of trust in automation across all automated systems is improper and may be questionable. Inappropriate trust calibration (i.e., over-reliance or under-reliance) occurs due to less attentive cross-checking behaviors, rather than from a complete lack of automation verification (Manzey, Reichenbach, & Onnasch, 2008), which indicates that trust guides reliance either when the automation is too complex to understand or when the procedures fail to guide the operator to appropriate behaviors.

Trust in automation has been indirectly studied through its purported influences on reliance behaviors. Prior studies have showed that cultural differences greatly affect the development of trust attitudes and reliance behaviors on automated systems (Chien, Lewis, Hergeth, Semnani-Azad, & Sycara, 2015; Li, Rau, & Li, 2010; Rau, Li, & Li, 2009; Wang, Rau, Evers, Robinson, & Hinds, 2010). For instance, Merritt (2000) measures pilots' attitude and behaviors with respect to the use of automated systems across countries. The results suggest that, even in a highly specialized and regulated profession, national culture still exerts a meaningful influence on attitude and behavior, over and above any occupational context. A recent study (Kachouie, Sedighadeli, Khosla, & Chu, 2014) also indicates that participants' cultural backgrounds can significantly affect their attitudes toward intelligent agents.

Since the perception of automation attributes (e.g., perceived ease of use) and interpretation of aids (e.g., information transparency) may differ considerably across populations, cultural values and norms are the important factors that influence an individual's trust attitudes and reliance behaviors. However, while much of current research has focused on the effects of system-related variables (e.g., source reliability), little attention has been paid to studying the joint effects between cultural influences and trust in automation. In addition, most of the limited work in this field has been both abstract and suggestive, and has been derived from performing statistical modeling approaches (such as meta-analysis or path analysis) without empirical validation. Given the influence of culture-sensitive interactions on the willingness of adopting an information technology that involves various factors, the overall objective of this research is to develop a fundamental understanding of general principles and factors pertaining to trust in automation and determine the ways in which trust mediates reliance on automation across cultures.

1.1 RESEARCH CHALLENGES

Various factors, such as perceived ease of use, automation reliability, severity of faults, level of automation, operator workload, and operator's propensity to trust have been studied in the literature as factors that affect trust in automation. However, the majority of research has focused on the relation between system reliability and operator usage, and scant attention has been paid to the ways in which culture may influence human trust in automation. Moreover, most of the existing studies on trust in automation were performed within Western cultures. As the use of technology becomes increasingly globalized, there is an urgent need to study factors that would aid in determining how users in different cultures will adopt and use technologies, as well as how trust in automation functions in different cultures. The current literature has two significant limitations. First, most of the work on cultural influences on trust has been done in the context of interpersonal trust (Fulmer & Gelfand, 2010; Gunia, Brett, Nandkeolyar, & Kamdar, 2011). Second, most of the work studying culture and trust in automation has either been suggestive (without empirical evidence to support) or has focused mainly on the Western cultures. To examine the interrelations and commonalities of concepts that involve trust in automation, empirical research is needed to integrate divergent manifestations of trust within a single task and test population. However, cognitive measures, such as NASA-TLX (Hart & Staveland, 1988) for workload that examine the influences of cultural factors on trust in automation have yet to be developed, which exacerbates the difficulties in measuring trust attitudes and reliance behaviors in automation across cultures. Wasti, Tan, Brower, and Onder (2007), for example, found the widely used Mayer and Davis' (1999) Ability-Benevolence-Integrity trust scale to have "*poor psychometric properties across the board*" when attempting to assess measurement invariance across samples from the U.S., Turkey, and Singapore. Principled cross-cultural studies of trust in automation will require developing reliable and valid measures of trust that can allow for accurate comparisons across cultures.

1.2 RESEARCH GOALS

Measuring the effects of cultural dynamics on trust in automation is a difficult challenge, which involves many different facets of automation and factors that affect the use of automation (especially in critical circumstances, such as aviation, military, and crisis response). Despite the plethora of existing research in examining trust and culture relations, to investigate the factors that influence trust in automation across cultures, this research has the following goals:

Objective 1: Develop a reliable psychometric instrument that captures the nature and antecedents of trust in automation across cultures. While a large body of work on trust in automation has developed over the past two decades, standard measures have remained elusive, with research relying on short, idiosyncratically-worded questionnaires. These challenges are exacerbated when examined in the context of measuring the effects of culture in trust in automation.

Objective 2: Develop a trust-sensitive task (TST) and its associated computational and simulation infrastructure. Current literature on trust in automation has used a variety of both tasks and types of automation. To validate cultural influences on trust in automation, the proposed TST and the testbed system combine the characteristics of important task categories and variable manipulations to enable replication studies of known effects to allow for valid cross-cultural comparisons.

Objective 3: Conduct theoretically guided experimental studies to determine how cultural factors affect the various aspects of trust and reliance on automation. The studies will encompass the propensity to trust, information transparency, source reliability, workload, and trust dynamics; namely, the processes of trust formation, dissolution after trust violations and restoration. Most crucially, the proposed study focuses on examining whether cultural factors have large effects on trust attenuation or amplification, which may contribute to automation bias, misuse, or disuse.

1.3 RESEARCH STRUCTURE

The remainder of this thesis is structured as follows: related work is described in Chapter 2. Chapter 3 introduces the research questions and hypotheses. Chapter 4 describes the initial scale development. Chapter 5 delineates the classification of instrument items purposes. Chapters 6 and 7 describe the scale development via the online crowdsourcing system (Amazon Mechanical

Turk). Chapter 8 presents the first round of cross-cultural instrument validation. Chapter 9 shows the cross-cultural task based empirical studies. Chapter 10 presents the details of the cross-cultural scale refinement. Chapter 11 shows the overall results, including survey and behavioral data. Discussion and conclusions are included in Chapters 12 and 13, respectively.

2.0 RELATED WORK

Trust has been studied in a variety of disciplines (including social psychology, human factors, robotics, and industrial engineering), and these wide contexts have led to various definitions and theories of trust. A brief overview of the extant literature on the conceptualization of trust and factors that influence trust in automation are included in this section, which involve system-related factors, human-related properties, and environmental variables. Although automation has a wide variety of definitions, the following definition will be used throughout this study: "*Automation is any sensing, detection, information processing, decision making, or control action that could be performed by humans but is actually performed by machine*" (Moray, Inagaki, & Itoh, 2000).

2.1 CONCEPTUALIZATION OF TRUST

Trust (in automation) refers to a cognitive state or attitude, yet it has most often been studied indirectly through its purported effects on behaviors, without any direct cognitive measurement. The nature and complexity of these tasks have varied greatly and have ranged from simple automatic target recognition classification (Dzindolet, Pierce, Beck, & Dawe, 2002) to erratic responses of a controller embedded within a complex automated system (Lee & Moray, 1992).

The variety of reported effects (automation bias, complacency, reliance, compliance, and so forth) mirrors these differences in tasks and scenarios.

Trust has been defined as an attitude, an intention, or a behavior (Madsen & Gregor, 2000; Mayer, Davis, & Schoorman, 1995; Moray & Inagaki, 1999). Both within existing inter-personal literature and human-automation trust literature, a widely accepted definition of trust is lacking (Adams & Webb, 2002). However, it is generally agreed that trust is best conceptualized as a multidimensional psychological attitude that involves beliefs and expectations about the trustee's trustworthiness that are derived from experience and interactions with the trustee (Jones & George, 1998). In both interpersonal trust literature and automation trust literature, trust has been said to have both cognitive and affective features. In interpersonal literature, trust is seen to involve affective processes, since trust development requires seeing others as personally motivated by care and concern to protect the trustor's interests (Lewis & Weigert, 1985). In automation literature, cognitive processes, rather than affective processes, may play a dominant role in the determination of trustworthiness; i.e., the extent to which automation is expected to do the task that it was designed to do (Muir, 1994). In trust in automation literature, it has been argued that trust is best conceptualized as an attitude (Lee & See, 2004) and a relatively well-accepted definition of trust is: "*an attitude which includes the belief that the collaborator will perform as expected, and can, within the limits of the designer's intentions, be relied on to achieve the design goals*" (Moray & Inagaki, 1999). The conceptualization of trust as an attitude that has both cognitive and relational aspects is especially relevant to the proposed research on how culture may modulate a trust construal and dimensions of trustworthiness.

2.1.1 General and specific trust in automation

Early research, such as that of Driscoll (1978) and Scott (1980), suggests that human trust attitudes are composed of both global and specific components. Global components are largely related to early experiences with human machine systems, which convert prior understandings to stable traits and translate to an individual's initial attitude to trust or distrust in other similar applications (Merritt & Ilgen, 2008). Specific components are based on the ongoing interactions with and feedback from a machine, and the analytic processes regarding the perception of system capabilities contribute to an individual's trust beliefs about specific machines. In addition, Mcknight and Carter (2011) investigate various types of trust constructs, which differentiate trust propensities into both general and specific attributes. The proposed general and specific trust traits in McKnight's study are consistent with the aforementioned global and specific components, respectively.

Mayer et al., (1995) define general trust in automation as "*the general tendency to be willing to depend on technology across a broad spectrum of situations and technologies*." Lee and See (2004) identify three systematical dimensions (performance, process, and purpose) as the general base for trust, which significantly involve the development of general trust attitudes in automation. For instance, an individual with a high general trust level might assume that automated systems are usually reliable, dependable, and offer the needed assistance. As a result, the individual tends to rely on automated aids to achieve better outcomes across task situations and information technologies.

Specific trust in automation reflects an individual's beliefs that a specific system has suitable features for performing the task and resolving the potential issues in a specific condition (Mayer et al., 1995). Hancock et al., (2011) proposes a three-factor model to measure human-robot trust, which categorizes the trust attitudes into human-related, robot-related, and environment-related factors. Several researchers advocate for the relevance of situational trust in specific automated aids, and suggest that increased specific beliefs and motivations (e.g., purposes of systems) could enhance the process of adoption of new technologies (Dabholkar, 1996; Davis, Bagozzi, & Warshaw, 1989). In other words, through direct interactions with an automated system, operators continuously evaluate the machine's characteristics and (re)calibrate their trust in automation.

As trust has been suggested to have both cognitive and affective features in the areas of interpersonal trust literature and automation trust literature (Lewis & Weigert, 1985; Moray & Inagaki, 1999; Muir, 1994), Lee and See (2004) conclude that general trust is greatly related to both attitudinal and affective processes, while specific trust is heavily influenced by situational and cognitive processes. In addition, both automation and interpersonal trust studies suggest that trust should be measured multiple times to study its changes (establishment, dissolution, and restoration) throughout different phases. Since general trust indicates an individual's trust beliefs in relying on automated assistance, it should be examined before exposure to a specific system (i.e., pre-experiment). Specific trust identifies participants' beliefs in a specific automated system and should be measured after experiencing a specific system (i.e., post-experiment). Therefore, to reliably measure the changes in trust attitudes and accurately study the development of trust beliefs, it is essential to evaluate trust perceptions through both its general and specific characteristics in different situations.

2.2 FACTORS AFFECTING TRUST

Lee and See (2004) have provided a thorough review on trust in automation, which indicates that the factors that are likely to affect trust in and reliance on automation have generally occurred at the intersection of human operators, information technologies, and task contexts. Research suggests that human-related variables, such as personality traits or cultural characteristics; system-related variables, such as system reliability or information transparency, and task-related variables, such as task complexity or task load, have all significantly influenced the use and trust calibration of automation (Hancock et al., 2011). Here is a summary of the relevant work on these important variables.

2.2.1 System properties

As manual control may lead to excessive operator workload and manual intervention has a limited probability to manage rapid failures in time, while automation is being performed, an operator may need to spend extra time monitoring the various types of automation, and as a result, little attention will be allocated to highly trusted systems (Muir & Moray, 1996). The most important correlations to the use of automation have been the levels of system reliability and the effects of system faults. Reliability typically refers to automation that has some error rates (such as misclassifying targets). This rate is generally constant, and data is analyzed using session means. System faults are typically single events that are studied as a time series, such as if an automated controller fails to function properly and makes the whole system behave erratically as a result. In addition, when the level of automation is increased, providing appropriate system transparency is critical, which can enhance the use of automated applications. The relevant work on important system-related factors is summarized as follows (for a more detailed overview of these factors, please see Appendix A).

2.2.1.1 System reliability

Prior literature has provided empirical evidence that changing the reliability of automation has influenced people's use of autonomy and their trust in the system (Desai et al., 2012; Hancock et al., 2011; Kaniarasu & Steinfeld, 2012; Moray & Inagaki, 1999; Parasuraman & Manzey, 2010; Parasuraman & Riley, 1997; Rovira & Parasuraman, 2010; Ericka Rovira, McGarry, & Parasuraman, 2007; Visser & Parasuraman, 2011). For example, Moray et al., (2000) concluded that there was little difference in trust and self-confidence while system reliability was above 90%; however, a significant effect was observed with system reliability between 70% and 90% in both aspects. A follow-up study (Rovira & Parasuraman, 2010) suggested that automation reliability that was lower than a threshold of approximately 70% led to worse overall performance than having no automation. However, Visser and Parasuraman (2011) found that even when the system reliability was as low as 30%, overall performance was still improved.

Bagheri and Jamieson (2004) investigated user reliance behaviors under constant and variable reliability conditions in automated monitoring systems. While little effect was found on the low-reliability conditions, the results showed that performance was significantly worse in a constant high-reliability condition. In other words, the detection of automation failures was significantly worse for constant-reliability automation than for variable-reliability automation. Research also revealed that the timing of dropped reliability appeared to have an impact on trust and influences different trusting behaviors. When the reliability drops occurred in the middle of or late in the processes, they led to immense increases of operators switching away from autonomy, while early drops in reliability only slightly affected the operators' switching behaviors (Desai et al., 2012; Kaniarasu & Steinfeld, 2012). However, although users' trust decreased during system reliability drops (for example, users switching away from autonomy), the subjective measure found that users' self-confidence increased as reliability decreased (Visser & Parasuraman, 2011).

2.2.1.2 System faults

System faults affect system reliability, but are treated separately because they concern discrete system events and involve different experimental designs. Because of their dynamic nature, various aspects of faults have a different influence on trust in automation, in which trust attitudes and resulting reliance behaviors depend not only on the progress of the current system, but also on recent values of system performance and the presence of fault size (Lee & Moray, 1992; Lee & See, 2004). Lee and Moray (1992) showed that in the presence of continual system faults, trust in the automated application significantly decreased after the failure happened, but gradually recovered, even as faults continued. The results also indicated that faults of varying magnitude diminished trust more than constant faults. The magnitude of system faults had differential effects on trust, in which smaller faults had a minimal effect on trust, while large faults negatively affected trust and resulted in slower trust recovery. Muir and Moray (1996) found that chronic faults led to slower recovery of trust in automated aids, whereas little lasting effect was observed in the transient errors. Additionally, the study also found that when faults occurred in a subsystem, the corresponding distrust spread to other functions controlled by the same subsystem; however, the distrust did not spread to independent or similar subsystems.

An early study showed that when autonomy provided inaccurate recommendations, participants in the non-automation condition performed better on the same events than those in the automation condition (Skitka, Mosier, Burdick, State, & Ames, 1999). Different types of faulty automation, such as false-alarm prone (FAP) vs. miss-prone (MP) automation, led to significant differences in task performance, attention allocation, trust attitude, and reliance behaviors (Chen, Barnes, & Kenny, 2011; Dixon, Wickens, & McCarley, 2007; Rovira et al., 2007; Wickens, Dixon, Goh, Hammer, & Savoy, 2005). Research showed that MP failures degraded concurrent task performance, in which a lack of faith in the automated system led the operator to devote more attention to managing the automated tasks. On the contrary, in the FAP condition, as operators reduced their compliance on the automated suggestions, ignoring or terminating the alerted messages resulted in a degradation of the response to system failures (Dixon et al., 2007; Meyer, 2004; Wickens et al., 2005). Chen et al., (2011) found that participants' SA was significantly better in the MP than in the FAP condition. Although participants reported that the FAP condition was more deceptive than the MP condition, higher trust was rated in the FAP than the MP condition. Dixon et al., (2007) concluded that FAP appeared to be more damaging to overall performance than MP (in which FAP affected both operator compliance and reliance), whereas MP appeared to affect only operator reliance.

2.2.1.3 System transparency

It has been suggested that system understandability is an important factor for trust development (Muir, 1994). Research has shown that revealing system vulnerabilities (such as weaknesses) increased user trust, and that when people have appropriate knowledge of faults, these flaws do not necessarily diminish trust in the system (Lewandowsky, Mundy, & Tan, 2000; Martelaro, Nneji, Ju, & Hinds, 2016; Parasuraman & Riley, 1997). A plausible explanation for these findings is that knowing the limitation in automation reduces the uncertainty and the consequent risk associated with the use of automated aids. In other words, operators may calibrate trust and develop efficient strategies to work with faulty automation. To facilitate the processes and provide the operator with sufficient SA, systems that can explain their reasoning processes and ongoing progresses will be more likely to be trusted, since users would more easily be able to understand any problems that they encounter (Lewis, 1998; Simpson & Brander, 1995; Sycara & Lewis, 1998). Such explanatory facilities may also allow the operator to query the system during periods of low system operation in order to incrementally acquire and increase trust (Clare, Maere, & Cummings, 2012). To synchronize the mutual understanding between human operators and automated aids, system transparency is a critical factor that affects perceived difficulty in reasoning with provided automated suggestions. Research has shown that self-reported trust in the system's ability is highly correlated with the understanding of the system's decision-making processes (Wang et al., 2016). Increasing information transparency contributes to higher trust in and better use of complex automated systems (Lyons et al., 2016).

2.2.1.4 Level of automation

Another factor that may influence trust in automated systems is the level of automation (LOA). Sheridan and Verpank (1978) developed the first LOA taxonomy, which classified autonomy into ten levels that are based on the range of control that an operator could manipulate. Operators must (partially) manually control the machines and make decisions in low LOA conditions, while fully autonomous systems are used under high LOA conditions, with operators and automation sharing controls and collaborating closely to make decisions in middle LOA conditions. However, during shared control processes, operators and automation may perform similar operations with different purposes. These contradictory intentions may mislead the operator to automate the tasks and may provide unexpected results (Inagaki, 2003). LOA has been found to affect trust and use of automation (Moray et al., 2000; Ruff, Narayanan, & Draper, 2002; Walliser, 2011), in which most comparisons have involved either the monitoring of automation (e.g., management by exception) or interaction with decision aids (e.g., management by consent). Thus, the degree of functional allocation between the human operator and the automated system has greatly affected the use of automation and its resulting behaviors. Sheridan and Hennessy (1984) indicated that an operator would interact with automation as an extension of trust; otherwise, the operator would choose manual control, because of the low level of trust in the automated device. However, due to the complexity of real-world problems and other factors, LOA depends strongly on the characteristics of the system being controlled, as well as upon the characteristics of task contexts. Research shows that shifting from a system with a higher LOA to one with a lower LOA led to decreased performance, but when shifting from higher LOA systems back to manual control, the lack of SA resulted in poor performance (Nocera, Lorenz, & Parasuraman, 2005). Systems with a high LOA are generally more complex, in which sophisticated features are more opaque to the operator and may engender less trust. Placing the same amount of trust in systems with different LOA is improper and questionable, because of the complexity of involved context. Moray et al. (2000) investigated trust in different degrees of automation and found diverse results between systems with high and low LOA, which suggested that systems with a different LOA may have different implications for trust and its resulting behaviors. Recent studies showed that an operator took longer to switch between different tasks when supervising a system at a high LOA, as compared to one at a low LOA (Squire & Parasuraman, 2010), and waited longer to switch back to autonomous mode than to switch away (Kaniarasu & Steinfeld, 2012).

2.2.2 Environmental factors

Manual control of complex tasks may result in an excessive workload and decreased performance. These decreases in performance can exacerbate users' perceived workload and self-confidence, which in turn can lead to higher acceptance of aided information (Donmez, Boyle, Lee, & McGehee, 2006). Research shows that an unbalanced task workload could increase reliance on automation to decrease stresses on cognitive capacity (Bailey, 2004). However, inappropriate trust in automated systems (such as under-reliance) could increase a user's perceived difficulties in concentrating on tasks and may lead users to become overly reliant on automated aids. For example, environmental variables such as high system complexity and heavy task workload can cause operators to over-trust automated aids and may cause them to be inclined to automation complacency (Dixon & Wickens, 2006; McFadden, Vimalachandran, & Blackmore, 2004). The negative relationship between trust and workload was found in a variety of contexts (Rajaonah, Tricot, Anceaux, & Millot, 2008; Scott, Mercier, Cummings, & Wang, 2006; Spain & Bliss, 2008), which suggested that the increases of task workload lead to degradations of trust in automated applications. In other words, a lower workload contributed to a higher level of trust in the automation (Wang, Jamieson, & Hollands, 2011) as well as satisfaction with automated aids (Goddard, Roudsari, & Wyatt, 2012). Although higher task workloads tended to have negative influences on trust in automation, Xu, Wickens and Rantanen (2007) found a contrasting result, in which higher workloads (increased task difficulty) led to a thorough inspection of the raw data, which decreased the effects of automation complacency. Reagan and Bliss (2013) concluded that the amount of processing information and users' attention allocation strategies may vary, either increasing (Rovira & Parasuraman, 2010) or decreasing (Xu et al., 2007) the effects of perceived task workloads, in which different workload components may participate in diverse effects on trust in automation. In other words, the trade-off between trust and workload might only exist in a certain type of (sub) task contexts.

2.2.3 Propensity to trust

Individual differences in personality traits can significantly affect operators' trust attitudes and reliance behaviors on automated systems. Self-confidence is a factor of individual differences and is one of the few operator characteristics that have been studied in existing trust in automation literature. Lee and Moray's (1992) work suggested that when trust was higher than self-confidence, automation (rather than manual control) would be used, and vice versa (when trust was lower than self-confidence). However, later work (Moray et al., 2000), which was conducted with a higher LOA than that of previous studies (Lee & Moray, 1992) did not obtain similar results. Instead, it was found that trust was influenced by system properties (such as real or apparent false diagnoses), while self-confidence was influenced by operators' own personality traits and experiences. An interesting finding from Moray et al. (2000) indicates that if an operator takes the manual mode first, the operator would have higher self-confidence. It was also found that self-confidence was not affected by system reliability, in which Lewandowsky et al. (2000) suggested that self-confidence was not influenced by shifts in automation reliability.

2.2.4 Cultural factors

Cultural differences have been observed in various contexts. For example, Chua, Boland and Nisbett (2005) reported that Western participants focused on focal objects, such as brightly colored or rapidly moving stimuli, whereas Eastern participants' judgments were more dependent on contextual factors, such as background colors and details. In recent decades, there has been an increase in interest in measuring the effects of cultural factors on trust in automated systems. Although cultural factors can greatly influence an individual's levels of trust and reliance, little is known about the ways in which cultural differences affect trust in automation. To identify how cultural diversity may affect trust in and reliance on automation, Hofstede's cultural dimensions (Hofstede, 1991) and cultural syndromes (Triandis, 1996) were adopted to guide our research hypotheses and examine overall cultural effects.

2.2.4.1 Hofstede cultural dimensions

To measure the cultural differences on trust in automation, three of *Hofstede's cultural dimensions* (power distance, individualism/collectivism, and uncertainty avoidance) were used in our studies, which have been well studied in prior research.

- *Power distance (PD)* is defined as "*the extent to which the less powerful accept and expect that power is distributed unequally*" (Hofstede, 1991). In societies with high PD, a less powerful person must accept instructions given by more senior or powerful members of the organization. People in societies with a large PD expect authority figures to be benign, competent, and of high integrity, and therefore engage in less vigilance and monitoring for possible violations by authority figures (House, Hanges, &Javidan, 2004). This factor may affect the extent to which an individual from PD cultures perceives the automation as authoritative, and as a result, the operator will be quick to establish trust in the automated suggestions.
- *Individualism/Collectivism (IDV)* is "*the degree of interdependence a society maintains among its members*" (Hofstede, 1991). It represents an individual's self-image between "I" or "We" in a society. People from an individualistic culture tend to take care of only

themselves and direct family members, while an individual from a collectivist society will take care of others in exchange for unquestioning loyalty. In addition, an individual from a high IDV society focuses more on their own achievements, rather than on group goals. Nishishiba and Ritchie (2000) found that in a conceptualization of trustworthiness, Japanese businessmen emphasize organizational commitment, while Americans emphasize personal integrity. Prior studies suggested that collectivists will have high levels of trust of in-group members (Semnani-Azad, Sycara, Lewis, & Adair, 2012; Triandis, 1995); however, Fulmer and Gelfand (2010) found a "black sheep" effect in collectivist societies, in which operators from this culture became less trusting after experiencing violations from in-group rather than out-group members.

- *Uncertainty avoidance (UA)* is defined as "*the extent to which the members of a culture feel threatened by uncertain or unknown situations*" (Hofstede, 1991). People in greater UA cultures look for structured formats and clear instructions to shun ambiguous conditions and make events more interpretable and predictable. Prior studies (Li, Rau, & Li, 2010; Li et al., 2014; Rau, Li, & Li, 2009) found cultural differences in people's reactions and preferences regarding both implicit and explicit communication styles, in which an individual from an Eastern country preferred an implicit communication style, while people from a Western country favored an explicit communication style. Thus, participants' evaluations of the automated systems and their acceptance of the aided recommendations may greatly depend on how the information is presented to them.

2.2.4.2 Cultural syndromes

Although Hofstede's cultural dimensions have been well studied in the literature and continue to be relevant when examining the general effects of cross-cultural differences, recent research

(Leung & Cohen, 2011) has indicated that Hofstede's metrics have failed to measure an individual's behaviors in terms of adherence to cultural norms in their interactions with various situations, and consequently, the influence on their values by a particular member. To address the gaps, *cultural syndromes* (Triandis, 1996) were also included in our study, which provide complementary approaches to measuring individual diversities among cultural differences. Cultural syndromes encompass cultures of dignity, cultures of honor, and cultures of face, which contrast with the meaning and importance that are given to norms of exchange, reciprocity, punishment, honesty, and trustworthiness. Recently, interest in the cultural syndromes of dignity, honor, and face has resurfaced (Aslani, Ramirez-Marin, Semnani-Azad, Brett, & Tinsley, 2013; Aslani et al., 2016; Leung & Cohen, 2011) with particular significance for antecedents of trust. For example, Bohnet and Zeckhauser (2004) suggested that it is betrayal aversion (people's aversion toward risk caused by other people) and not simply risk aversion that affects people's trust decisions. A betrayal-averse individual would be more likely not to trust another individual at the beginning of a trust relation, would be more likely to monitor for trust violations, and would be more likely to make negative attributions if trust violations do occur. Betrayal aversion is relevant in the honor cultures that are prevalent in Middle Eastern and Arab countries. Indeed, Bohnet, Herrmann, and Zeckhauser (2009) found that people in the Persian Gulf required a higher level of trustworthiness before they were willing to trust other individuals than either Americans or Swiss. The socio-cultural factors of distrust include surveillance and monitoring (Sitkin & Roth, 1993), cultures of honor (Nisbett & Cohen, 1997), and collectivism (Triandis, 1995). In particular, surveillance and monitoring have been shown to be relevant to misuse and disuse of automation, and the cultural characteristics that may be linked to them will be the subject of careful study in our research.

- *Dignity cultures* are prevalent in Western Europe and North America. In dignity cultures, self-worth is generally associated with independence and focusing on personal and individual goals (Schwartz, 1992), which are evaluated by the individual's own criteria, rather than by other people's values (Leung & Cohen, 2011). Research shows that people from dignity societies tend to make a "swift trust" assumption, in which others deserve to be trusted until they prove otherwise (Dirks, Lewicki, & Zaheer, 2009).
- *Face cultures* are usually observed in East Asia. In cultures like these, self-worth is extrinsically derived, based on social interactions with other members in the society (Leung & Cohen, 2011). In other words, individuals from face cultures cherish the view that others have of them. For example, people may lose face if another person or group of people believes they have acted out, and other people may lose face because of your own views of their behavior. Thus, power and status in face cultures is relatively hierarchical and generally stable. Social interaction in face cultures is governed by norms that are provided by social institutions, like religion, family, community, or the state, and people's conformity to those norms is monitored and, if necessary, managed by institutional sanctioning (Gunia et al., 2011; Takahashi et al., 2008; Yamagishi, Cook, & Watabe, 1998). Research suggests that the presence of institutional monitoring and sanctioning reduces a society's need for interpersonal trust by affording a reliable external guarantor of behavior (Takahashi et al., 2008; Yamagishi & Yamagishi, 1994).
- *Honor cultures* are widespread in the Middle East, Latin America, and Mediterranean countries, along with the southern United States. Due to unstable social hierarchies, people from honor cultures tend to have a reputation for toughness in protecting themselves, and direct family members not to let others take advantage of them (Nisbett

& Cohen, 1997). In other words, honor must be claimed as well as paid to others (Leung & Cohen, 2011). Consequently, members of honor cultures tend to have relatively low levels of both institutional and interpersonal trust.

- The defining characteristics of cultural syndromes (dignity, honor, and face cultures) have elements that are also examined by Hofstede's dimensions, especially in PD, IDV, and UA. Thus, cultural syndromes can bring relevant elements in addition to Hofstede's dimensions, which can contribute to a basis for greater discriminatory power. An interesting observation we made is in the dimension of IDV: dignity cultures are high on IDV, honor cultures are medium, and face cultures are low. For example, since people in face cultures are high on collectivism, they would have high in-group trust, which can relate to the use of automation (autonomous-self vs. relational-self). Therefore, cultural syndromes could bring relevant elements, in addition to Hofstede's dimensions, that may provide a basis for greater discriminatory power.

As the hypotheses based on Hofstede's dimensions (1991) and a more recent theory of cultural syndromes (Leung & Cohen, 2011; Triandis, 1994) suggest, it is reasonable to expect an individual's culture to affect trust and use of automation in a variety of ways. These cultural characteristics that have been identified as influencing levels of inter-personal trust will guide the proposed research on how cultural factors may influence trust and use of automation, and will help formulate research hypotheses.

3.0 RESEARCH QUESTIONS AND HYPOTHESES

As these hypotheses are fused with Hofstede's cultural dimensions and with a more recent theory of cultural syndromes, we expect cultural dynamics to affect trust and use of automation in a variety of ways. To examine the influences of cultural factors on trust in automation, we select the U.S. as a prototypical dignity culture, Taiwan as a prototypical face culture, and Turkey as a prototypical honor culture. In addition, the contrasts that these countries provide on Hofstede's dimensions (Fig. 1) reveal some substantial cultural differences. For instance, Turkey is high on power distance (PD) and uncertainty avoidance (UA), but low on individualism (IDV); the US is high on IDV but low on PD and UA, and Taiwan is in the middle among these three constructs.

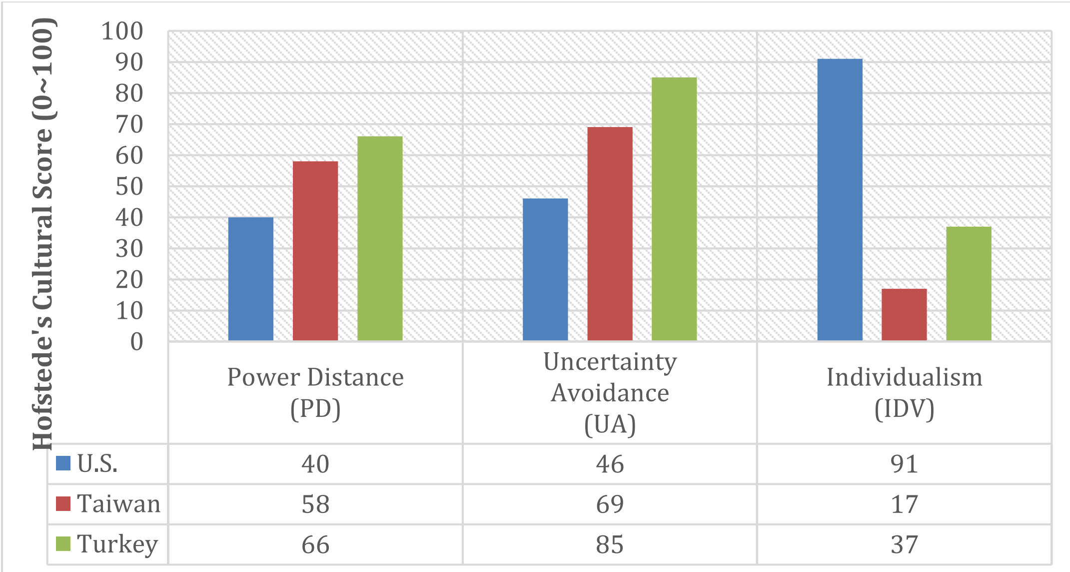


Figure 1. Country comparisons shown in Hofstede's cultural dimensions. The cultural values of each construct are taken from Hofstede's cultural study.

There are three general research questions we examine in our studies:

(a) Do the effects of trust that have been observed in prior research on Western cultures apply universally in all three cultural syndromes? Such effects include an increase in trust in automation with an increase in reliability, as well as an increase in reliance with an increase in task load.

(b) Even if trust effects are universal across all cultural syndromes, do they differ in terms of magnitude in different cultures?

(c) Do some of the effects work in one way in one culture and in a different way in another? In other words, are there interactions between the various cultural effects?

Based on the cultural characteristics of the three syndromes, along with Hofstede's dimensions, we form the following research hypotheses to answer the research questions above. With respect to the effects of cultural factors on *initial trust*, we hypothesize:

H1: Individuals from dignity cultures are more likely to have a higher level of initial trust in automation than those from honor and face cultures.

- This is because dignity cultures make a swift trust assumption.

In terms of the cultural influences on *trust establishment*, we hypothesize:

H2: If use of automation was encouraged by the user's organization, face culture operators will have higher ratings of trust and reliance than operators from honor and dignity cultures.

- This is because of the high PD values in face cultures.

H3: Honor culture operators will require a longer interaction time than operators from dignity and face cultures to develop an equal degree of trust.

- Operators from honor cultures are more distrustful than those from either face or dignity cultures, due to their lower level of initial trust.

H4: Operators from dignity and honor cultures will be more self-confident, and would therefore be less likely to rely on automation than operators from face cultures.

- Dignity cultures are characterized by high IDV and self-reliance, hence their members will be more self-confident. In honor cultures, self-worth is derived both internally and externally. Therefore, members of honor cultures will be more self-confident than those from face cultures, where self-worth is derived externally.

Since providing perfectly reliable automated systems is infeasible in reality, for *trust restoration*, we hypothesize:

H5: Honor operators will either stop using automation or will take longer to regain trust after a failure occurs and may not recover trust at their original level *(miscalibrate), as compared to operators from face and dignity cultures. The dynamic relation between use and trust may magnify these effects.*

- Honor cultures have high level of UA, which subjects their members to the betrayal effect, and as a result, causes them to be more mistrustful than operators from face and dignity cultures.

H6: Face culture operators will recover their trust in automation after failure more quickly than honor and dignity culture operators. Honor culture operators would be slowest in recovering trust.

- Because the social context of honor cultures results from unstable social hierarchies, members of those cultures would be the slowest to exhibit trust and equally slow to regain it once lost.

Studies have shown that a decrease in system reliability will decrease operators' trust in and reliance on automation (Chien, Mehrotra, Lewis, & Sycara, 2013; Rovira et al., 2007; Visser & Parasuraman, 2011). Therefore, in terms of *system reliability*, we hypothesize:

H7: Face culture operators will be more influenced by the purpose of automation than either honor or dignity culture operators.

- Since the social context of face cultures is based on stable hierarchies, the purpose of the automation will engender relatively higher levels of trust.

H8: Unreliable automation will lower trust ratings of operators from all cultures, but face culture operators will continue to rely on unreliable automation.

- Prior research suggests that low trust is positively correlated with unreliable automation. Face cultures have a higher PD and therefore will be more likely to continue relying on automation, regardless of its reliability.

Research in trust in automation suggests that system transparency significantly influences the use of automation (Chen et al., 2014; Cramer et al., 2008; Mercado et al., 2016). For instance, knowing the failure behaviors of the automation in advance may modify the perception of risk, and therefore, the overall level of trust in the automated system will not be affected by the system failures (Parasuraman & Riley, 1997). In other words, it is not only the system performance (history of interaction) that has an evident influence, but also that the automation process transparency and its perceived purpose are involved in the development of trust. For example, a system with high LOA prescribes actions to reduce operator authority and may contribute to better performance; however, such a scenario may decrease system transparency and provide little knowledge of SA to the operators. Therefore, with respect to *automation transparency*, we hypothesize:

H9: Face culture operators will trust and exhibit automation bias and accept recommendations even if their basis is not well understood, while dignity and honor culture operators will be less likely to trust or accept recommendations on this basis.

- This is because dignity cultures have high levels of IDV, and honor cultures require automated aids to have a structured formation.

H10: Dignity and honor culture operators will be less likely to comply with high LOA than face culture operators, who, as a result, will be more likely to exhibit complacency and automation bias. There will be no difference in the use of low LOA.

- This hypothesis relies on the rationale for H9 above. A high LOA contains little system transparency, while in low LOA, operators have more chances to interact with the automated systems and gain better knowledge to calibrate their trust in automation.

H11: Honor operators will require a greater support of trust from knowledge of process and/or purpose than dignity and face cultures, and will be prone to disuse.

- This is due to the high level of UA in honor cultures.

Some effects associated with trust (such as over-reliance) have been found to occur only under multitasking or heavy workload conditions (Visser & Parasuraman, 2011). Because fewer resources were available for secondary tasks in high workload situations, participants may have a higher tendency to rely on automated assistance when they are experiencing heavy task loads.

H12: Operators will have higher levels of trust and accept more automated recommendations or exhibit fewer checking behaviors on automation while perceiving high workload conditions.

- We hypothesize that this will be a general finding that is valid across all cultures.

While monitoring automated systems, operators may check the provided automated aids to verify the system's accuracy, as well as maintaining efficient SA. With respect to the vigilance behaviors, we hypothesized:

H13: Honor and face culture operators will exhibit more vigilance and more monitoring behavior than operators from dignity cultures.

- Honor culture operators tend to be more distrustful, and the social interactions of face culture operators are managed by institutional sanctioning.

The above hypotheses will be evaluated through cross-cultural experimental studies. In the experiments, participants' levels of trust will be measured using the trust instruments that we developed in prior research.

4.0 INITIAL SCALE DEVELOPMENT

Attempts to measure trust in automation have emphasized specific contexts, such as e-commerce systems (Kim, Ferrin, & Rao, 2008; Mcknight & Carter, 2011; McKnight, Choudhury, & Kacmar, 2002) or intelligent agents (Li et al., 2010; Wang et al., 2010); and as a result, its applications have not contributed to a well-defined framework for studying the relationship between cultural dynamics and attitudes toward trust in automated aids. To develop a psychometrically grounded measure that can be used to measure trust attitudes across cultures, the proposed culture trust instrument collected relevant items from existing research studies and examined the items through various rounds of reliability and validity tests in different countries to retrieve the potential factors that influence trust attitudes.

The initial phase seeks to construct a reliable psychometric instrument that captures the nature and antecedents of trust in automation across cultures, which begins with a pool of items from the empirically derived, human-computer trust, and SHAPE Automation Trust Index instruments, as well as augmented items from five existing studies, to increase the reliability of the discovered dimensions. A brief summary of the adopted eight instruments is as follows.

4.1 EMPIRICALLY DERIVED

Jian, Bisantz, and Drury (2000) developed an empirically derived (ED) scale in three phases, beginning with a word elicitation task. Participants were asked to describe their concepts of trust and distrust towards people, automation, and trust in general. The participants then rated 138 words involving trust for their association with these concepts. They rated the words again for their association with trust and distrust to determine whether the poles could safely be treated as a continuum. Participants were finally required to compare and rate 30 positively and negatively trust-related words for use in future analyses. The extracted 12-factor structure was then used to develop a 12-item scale based on the examination of clusters of words, in which the 12-factor extracted items roughly correspond to the classic three dimensions: ability-performance, integrity-process, and benevolence-purpose. The result was a collection of items (such as “The system is deceptive,” “I am wary of the system,” or “I can trust the system”) that examined automated systems in a general fashion, rather than in specific instances.

4.2 HUMAN-COMPUTER TRUST

Madsen and Gregor's (2000) human-computer trust (HCT) instrument demonstrated construct validity and high reliability within their validation sample, and has subsequently been used to assess automation in a variety of simulations (Luz, 2009). In the development of the HCT scale, subjects initially identified constructs that they believed would affect their level of trust in a decision aid. Following refinement and modification of the constructs and potential items, the instrument was reduced to five constructs (reliability, technical competence, understandability, faith, and personal attachment). A subsequent principal components analysis limited to five factors found that most scale items were related to their proposed factor. The resulting instrument was comprised of 25 items that were focused on decision aiding, such as: "The system analyzes problems consistently."

4.3 SHAPE AUTOMATION TRUST INDEX

The SHAPE automation trust index (SATI), which was developed by the European Organization for the Safety of Air Navigation (Goillau & Kelly, 2003), is the most pragmatically oriented of the three measures (ED, HCT, and SATI). Preliminary measures of trust in air traffic control (ATC) systems were constructed, based on literature review and a model of the task. This resulted in a seven-dimensional scale (reliability, accuracy, understanding, faith, liking, familiarity, and robustness). The measure was then refined through work with focus groups, with air traffic controllers from different cultures rating two ATC simulations. Scale usability evaluations and construct validity judgments were also collected. Because the items were refined to reduce ambiguities and the constructs were selected for appropriateness by multicultural groups of air traffic controllers, these scales had the highest face validity of the measures considered. For example, a representative item from the SATI: "Do you understand the behavior and displayed intent of the automation?"

4.4 CULTURE-TECHNOLOGY FIT

Culture-technology fit (CTF) investigates the trustworthy relationship between cultural contexts and post-adoption beliefs in the use of mobile devices (Lee, Choi, Kim, & Hong, 2007). CTF includes 30 items within 10 factors (3 items for each), in which two of the cultural profiles, individualism and uncertainty avoidance, were selected for our initial scale-development phase (i.e., our study adopted 6 items within 2 constructors).

4.5 INTERNATIONAL COMPARISON OF TECHNOLOGY ADOPTION

The international comparison of technology adoption (ICTA) examined the cultural effects of user intentions on information technologies (Im, Hong, & Kang, 2011) via the UTAUT instrument (Venkatesh, Morris, Davis, & Davis, 2003). The UTAUT questionnaire comprised 14 items within 5 factors, in which 11 items within 4 factors were chosen for our study.

4.6 ONLINE TRUST BELIEFS

Online trust beliefs (OTB) examines the moderating role of uncertainty avoidance in online trust beliefs between subjective norms, integrity, and ability dimensions (Hwang & Lee, 2012). OTB includes 16 items within 6 factors, in which 12 items within 5 constructs were selected for inclusion in our study.

4.7 TECHNOLOGICAL ADOPTIVENESS SCALE

The technological adoptiveness scale (TAS) was a 12-item measure that examined a person's relative openness to adopting and using new technology (Halpert, Horvath, Preston, Somerville, & Semnani-azad, 2008), in which 9 items were chosen for our initial scale-development phase.

4.8 TRUST IN SPECIFIC TECHNOLOGY

The measure of trust in specific technology (TIST) examined different types of trust attitudes across task contexts and information technologies, from specific (e.g., Excel or spreadsheet products) to general uses in various automated tools (Mcknight & Carter, 2011). The scale comprised 26 items within 7 factors, in which 19 items within 6 constructs were selected for our study.

4.9 COLLECTED ITEMS OF THE INITIAL SCALE DEVELOPMENT

The collected items of the initial instrument development were based on questions about human participants' trust attitudes in a variety of contexts:

(a) General trust attitudes toward automation without reference to any specific uses of automated applications—these items involved predisposition to trust and were adapted from ED, TAS, and TIST (e.g., I am confident in an automation/ I believe that most automations are effective at what they are designed to do).

(b) Specific trust attitudes were invoked after human participants had been cued to think about particular instances of automation (such as an automated navigation/GPS aid)—items were adapted from HCT, SATI, ICTA, OTB, and TIST (e.g., the advice that a GPS provides is as good as that which a highly competent person could produce).

(c) Attitudes across cultural-technological contexts (such as uncertainty avoidance and subjective norms)—items were adapted from CTF, ICTA, and OTB (e.g., I feel okay using automation because it is backed by vendor protections).

The initial instrument comprised 110 items that fell into a variety of constructs. Appendix B shows a more detailed overview of these factors

5.0 STUDY 1 - CLASSIFICATION OF ITEMS PURPOSE

Due to the variety of automated systems and the fact that relationships between attitudes involve both general and specific uses of automation (e.g., smartphone apps vs. cockpit automated aids), trusting beliefs were significantly affected with respect to the purpose of automated aids. Rather than being a unitary concept, the antecedents of trust in automation and subsequent automation uses include a number of facets with at least two common elements: namely, the general and domain-specific uses of applications. To develop an instrument that is capable of reliably assessing trust in automation, the initial step was to categorize the characteristics of the items into either a general or a specific purpose. 45 student participants were recruited from the University of Pittsburgh community to identify the referents of the selected items, and most of the participants were frequent computer users. To classify each item's purpose, the participants were given the following instructions:

> "Please respond to the following statements about your trust in automation. By automation, we mean any technology or service that you have used before, including apps, devices, functions, or systems. Based on your experience, use the following scale to rate the extent to which you disagree (1) or agree (5) with the statements below. Note: there are no wrong responses to any of the statements: the most critical need is to record your own true opinion on each item. If you think the provided instruction is not sufficient to answer a question, please rate it as having insufficient information."

	Strongly Disagree 1	2	3	4	Strongly Agree 5	Insufficient information
Automation has the functionality I need	○	○	○	○	○	○
I always feel confident that the right things will happen when I use automation	○	○	○	○	○	○
I believe automation in unknown situations	○	○	○	○	○	○
Automation is reliable	○	○	○	○	○	○

Figure 2. Classification of item's purpose

A 5-point Likert scale, which ranged from strongly disagree (1) to strongly agree (5), was adopted in the initial test; however, participants were allowed to rate an item as insufficient if they felt the item was too closely associated with a specific automated system for general use (Fig. 2). If an item was rated as insufficient more than once or more than one-third of the ratings fell into the neutral characteristic, the item was categorized to measure the specific use of automation. Among 110 selected items, 70 items were identified as addressing automation in general, whereas 40 items involved judgments about particular instances of automation. The results were consistent with prior research and suggested that trust attitudes had different attributes (i.e., either a general or a specific trust in automation) that were critical and necessary to include for classifying human trust development and the uses of automated applications. These classified items were used in the next round of data collection.

6.0 STUDY 2: FIRST ROUND OF SCALE DEVELOPMENT

To examine the relationship between the measured items, the second study focused on grouping the collected items and identifying latent constructs. An empirical study was conducted through Amazon Mechanical Turk (MTurk). MTurk is an online crowdsourcing system that enables researchers to post a variety of tasks and collect data in efficient and inexpensive ways. The collected responses were used to examine the underlying relationships between measured variables, as well as to refine our scale by rewording or identifying problematic items.

6.1 EXPERIMENTAL METHOD

A total of 110 items, along with 2 perceptions (general vs. specific use of automation), were used in the second study and were tested by 65 MTurk participants. The instrument was measured on a 5-point Likert scale, in which respondents were asked to rate their trust beliefs in automated systems based on the description shown in Table 1. In general automation, instead of pointing out a targeted system, the participants were able to name any automated applications that they have experienced, while GPS navigation devices were introduced as a specific use of automation.

Table 1. Descriptions of general and specific uses of automation

Type	Description
General Automation	By “Automation,” we mean any technologies or service that takes actions automatically and that you have used, including apps, devices, functions, or systems.
Specific Automation	By “Automation,” we focus mainly on GPS navigation systems, including all types of navigation devices that you have used, such as an automotive navigation system (e.g., Garmin) or smartphone navigation apps (e.g., Google maps).

6.2 RESULTS: EXPLORATORY FACTOR ANALYSIS

To refine the instrument, exploratory factor analysis (EFA) was used to determine the dimensionality of the data and item loadings among constructs. A principal components analysis with varimax rotation was performed to examine the number of factors that were produced. A five-factor model was returned that explained 52.4% of the variance in general automation, while 70.2% of the variance of the specific automation was represented by another five-factor model. The overall item reliability was examined, and if the resulting Cronbach's alpha was lower than 0.7, the factor was eliminated (as with Factor 4 under specific automation in Table 2).

Table 2. Reliability statistics in general and specific automation

General Automation	Cronbach's Alpha	Number of Items
Factor 1	.922	13
Factor 2	.871	6
Factor 3	.890	9
Factor 4	.870	7
Factor 5	.732	5
Specific Automation	Cronbach's Alpha	Number of Items
Factor 1	.944	10
Factor 2	.835	3
Factor 3	.821	3
Factor 4	.628	2
Factor 5	.797	3

After the EFA and reliability tests, 40 *general* items within 5 factors and 19 *specific* items within 4 factors that met the criteria were retrieved from the initial instrument. In the general cluster, the first three factors were greatly involved in the systematical dimensions (performance expectancy, process transparency, and purpose influence) and the fourth factor corresponded to the task characteristics. Additionally, in the specific cluster, the top three factors involved items that were also related to the three systematical variables. The fifth factors in both the general and specific groups failed to form a meaningful construct and were dropped as was Factor 4 in the specific group that failed to reach the statistical criterion. After eliminating the redundant items, 26 general items within 4 constructs and 16 specific items within 3 constructs remained for use in constructing the proposed trust model and validation in a second round of data collection.

6.3 MODEL DEVELOPMENT

To capture the direct and indirect effects of trust on various situations, the proposed model (Fig. 3) includes three systematic constructs (performance expectancy, process transparency, and purpose influence) that closely resemble those of Lee and See's model (Lee & See, 2004), in which they compared fourteen relevant measures and found that most involved only two to three dimensions. This three-dimensional structure fits nicely with the ability definition from Mayer et al., (1995) of ability (performance), integrity (process), and benevolence (purpose), which has been widely adopted in social psychological studies of trust and suggests that candidate items for an instrument measuring trust in automation should contain at least these dimensions.

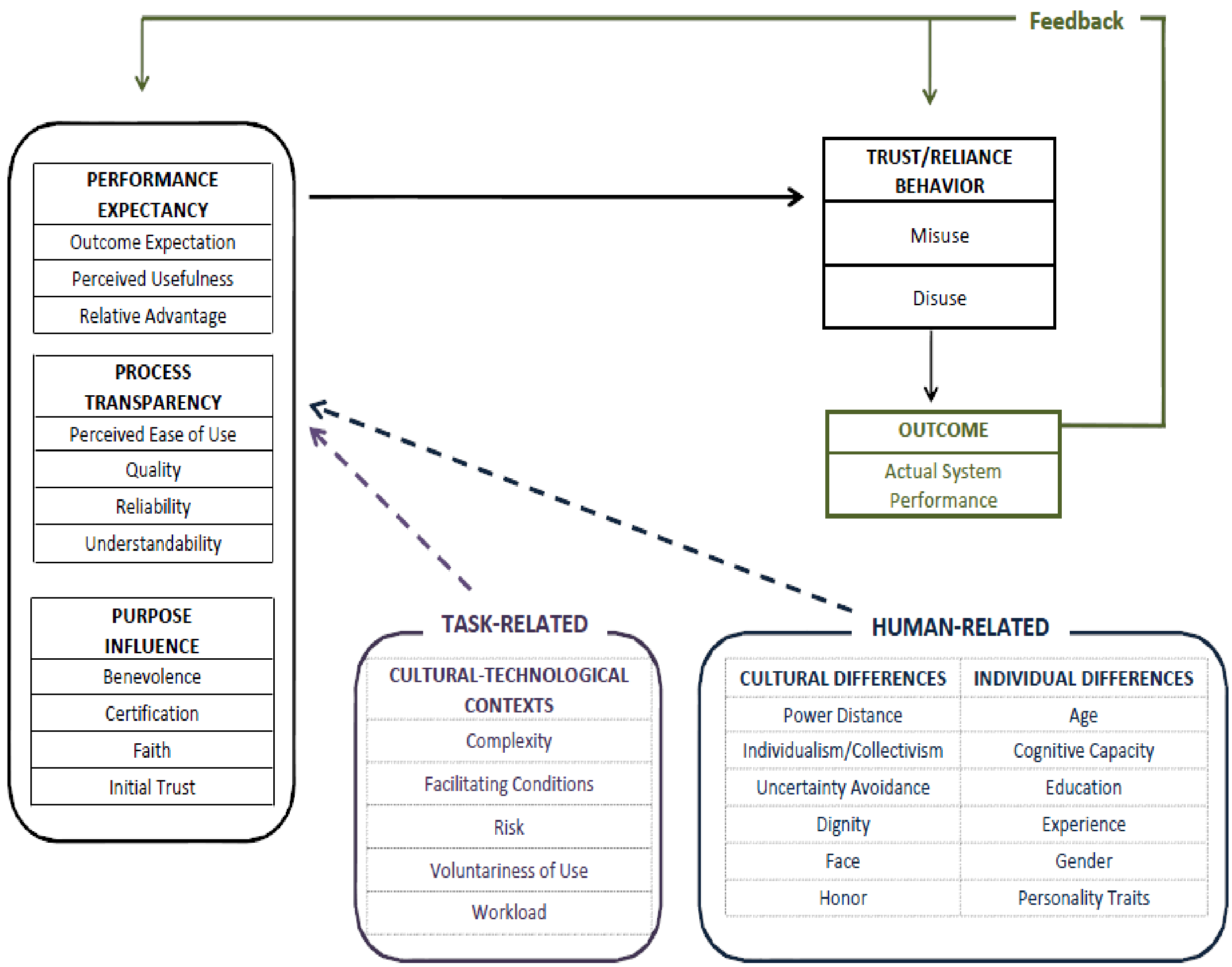


Figure 3. Model of factors of trust development in automation. Performance expectancy, process transparency, and purpose influence are the constructs (solid lines); individual differences, task contexts, and cultural differences are the moderators (dotted arrows).

These three main constructs, along with three types of moderators, are expected to interact in complex ways to produce trust mediated behaviors. The following sections describe the model's constructs and moderators in greater detail.

6.3.1 Performance expectancy

Performance expectancy is defined as an individual's belief that applying automation will help enhance overall job performance. The degree of trust will be affected by the past results and consequences of system performance. Eight general and four specific items are involved this cluster, along with three dimensions: outcome expectancy, perceived usefulness, and relative advantage.

6.3.1.1 Outcome expectation

Outcome expectancy relates to the belief that by receiving assistance from a system, an individual believes the job performance would be enhanced.

6.3.1.2 Perceived usefulness

Perceived usefulness refers to the degree to which a person believes that using an automated system would enhance the job performance. For example, an individual may feel that automation is useful on her tasks or that using automation makes her tasks easier.

6.3.1.3 Relative advantage

Relative advantage compares the differences in a user's preferences between interacting with another individual and relying on a particular instance of automation. For instance, a person may accept system predictions, rather than the recommendations from a group of consultants.

6.3.2 Process transparency

The transparency of automation may affect an individual's degree of perceived difficulty in using it (i.e., how it functions). Twelve items (five general and seven specific) were adopted, distributed among four constructs: perceived ease of use, quality, reliability, and understandability.

6.3.2.1 Perceived ease of use

Perceived ease of use reports an individual's perceived cost or effort in learning and using an instance of automation to perform a job.

6.3.2.2 Quality

The quality of provided information might affect a person's trust in automation. For example, if the automation fails to provide sufficient information, an individual may ignore recommendations and switch off the automation.

6.3.2.3 Reliability

The reliability of assistance may directly influence the decision to use automation. The failure rate, for example, may influence an individual's willingness to rely on a particular type of automation.

6.3.2.4 Understandability

Understandability refers to difficulties in comprehending how automation performs tasks and in predicting the outcomes and consequences.

6.3.3 Purpose influence

Purpose influence relates to a person's knowledge of what the automation is supposed to do. Seven general and five specific items from the conducted study were involved in this cluster and cover four dimensions: benevolence, certification, faith, and initial trust.

6.3.3.1 Benevolence

Benevolence refers to an individual's beliefs that automation is designed with good intentions and will not diminish their performance.

6.3.3.2 Certification

The presence of a certification or product guarantee may lead to less worry about its potential flaws. For example, a third-party seal would be critical for online banking systems.

6.3.3.3 Faith

Faith refers to an individual's belief in future behavior of an instance of automation. For instance, people may rely on the recommendation from automation rather than themselves when they are unsure about a decision.

6.3.3.4 Initial trust

Initial trust refers to a person's instinctive tendency of trust when using an innovation. An individual may give a particular type of automation the benefit of doubt when they first use it.

6.3.4 Moderators

It is generally believed that trust is dynamic and that it interacts with a variety of other influences to determine behaviors. For example, a self-confident operator may operate a system manually because the operator believes she can do a better job, while an operator from a culture with high levels of uncertainty avoidance may choose manual operation to avoid the slight possibility of automation error. Although the observed disuse of automation is the same in both of these cases, its cause and any potentially effective interventions are significantly different. To ensure that the measurement instruments are reliable across various contexts, so as to avoid confounding, investigating the role of trust in the use of automation requires pairing subjective measurements of the intervening variable, trust, with observations of behavior.

To enhance the explanatory power, three types of moderators are included in the proposed model to study how task contexts affect trust intention and consequence behaviors and to capture both individual and cultural differences for better predicting trust behaviors. It's hypothesized that these moderators will affect the main constructs and will therefore indirectly influence changes in trust behaviors. An individual's trust could influence the resulting reliance on automation, as well as the task performance. Despite the system outcome, an individual might reevaluate her strategies for interacting with the automation.

6.3.4.1 Cultural-technological contexts

Cultural-technological contexts represent the distinct situations of the involved task complexity, and facilitate conditions, risk, voluntariness of use, and workload.

6.3.4.2 Cultural differences

Cultural differences contain Hofstede’s cultural dimensions (power distance, individualism/collectivism, and uncertainty avoidance) and cultural syndromes (cultures of dignity, cultures of face, and cultures of honor).

6.3.4.3 Individual differences

Individual differences refer to an individual’s background, including age, instinctive cognitive capacity, education, prior experience, gender, and personality traits.

7.0 STUDY 3: SCALE CONSTRUCTS REFINEMENT

To strengthen item quality and further examine the external validity of the instrument, before conducting another round of data collection, items that fulfilled the concept of the general and specific constructs were pooled from twelve reputable measurements to create the instrument. Details of the root constructs and definitions are also shown in Appendix B. A total of 76 items, 26 (1st MTurk) + 50 (new), and 33 items, 16 (1st MTurk) + 17 (new), were included in the lists of general and specific automation, respectively. The collected 109 items, along with two perceptions (76 items in the general group and 33 items in the specific group), were used in the second round of scale refinement. Smartphones were chosen as a general use of automation and GPS navigation systems were chosen as an instance of specific automation. After eliminating the invalid samples (i.e., those where the participants failed to answer the verifiable questions correctly), 107 responses were collected from MTurk.

7.1 INSTRUMENT RELIABILITY AND VALIDITY TESTS

The results of reliability tests (in Table 3) showed that the instrument was robust, as observed in the measures of Cronbach's alpha values, in which the range from 0.785 to 0.915 exceeded the suggested criteria of 0.70 (Venkatesh et al., 2003). To capture the dominant items under each latent construct, as recommended by Bentler and Chou (1987) each latent variable should be measured by at least three observable indicators. The top eight loading items (loading range 0.69~0.86) in the general cluster and the top six loading items (loading range 0.77~0.89) in the specific group were remained for constructing the *cultural trust instrument* (CTI). In other words, a total of 50 dominant items (32 general and 18 specific) were retrieved.

Table 3. Reliability statistics for general and specific uses of automation

<table>
<tr><td colspan="12">General Automation (suggested Cronbach's alpha > 0.7)</td></tr>
<tr><td colspan="3">Performance expectancy</td><td colspan="3">Process transparency</td><td colspan="3">Purpose influence</td><td colspan="3">Task contexts</td></tr>
<tr><td colspan="3">.908</td><td colspan="3">.897</td><td colspan="3">.915</td><td colspan="3">.871</td></tr>
<tr><td colspan="12">Specific Automation (Cronbach's alpha)</td></tr>
<tr><td colspan="4">Performance expectancy</td><td colspan="4">Process transparency</td><td colspan="4">Purpose influence</td></tr>
<tr><td colspan="4">.879</td><td colspan="4">.873</td><td colspan="4">.785</td></tr>
</table>

The reliability and validity tests were performed again on these dominant items. In addition, to ensure that the retrieved items can well represent their designated factors, the cover variances were also examined. The results revealed that the items succeeded in both reliability (Cronbach's alpha value: 0.890~0.929, threshold value of 0.7) and validity tests (average variance extracted (AVE): 0.567~0.738, threshold value of 0.5) along with a high cover variance (0.946~0.987), as shown in Table 4.

Table 4. Reliability tests, validity tests, and the results of cover variance of the dominant items

General *Automation*	**Cronbach's Alpha**	**AVE**	**Cover Variance**
Performance expectancy	.928	.667	.966
Process transparency	.929	.668	.962
Purpose influence	.899	.585	.946
Task contexts	.890	.567	.948
Specific *Automation*	**Cronbach's Alpha**	**AVE**	**Cover Variance**
Performance expectancy	.929	.738	.987
Process transparency	.921	.718	.962
Purpose influence	.899	.664	.979

Through the empirical validation, a total of 50 items (32 general and 18 specific) were retrieved. To further examine the external validity of the instrument, another round of data collection was conducted across three different countries to cross-validate the instrument.

8.0 STUDY 4: CROSS CULTURAL VALIDATION: INSTRUMENT PRETEST

To investigate how cultural diversity may affect trust in automation, another round of data collection was conducted in the U.S., Taiwan, and Turkey to validate the instrument across cultures. Student populations were used in Taiwan and Turkey, due to less widespread participants in MTurk in these countries. Taiwanese participants were recruited from Chengchi University and Turkish participants were recruited from Özyeğin University. In order to increase the diversity of the sample, U.S. army war college students were also recruited. For the Taiwanese and Turkish participants, smartphones were introduced as a context for considering the general use of automation, while GPS was used as the specific use of automation. However, due to a particular style that is peculiar to the U.S. group, participants were allowed to name all the types of automation that they may have previously encountered in military service as the general purpose of automation; while an iPad, as a course device issued by the college, was chosen as the specific use of automation.

8.1 DATA ANALYSIS

After eliminating the unengaged responses (i.e., participants failed to answer the verifiable questions correctly), a total of 311 student responses were collected and used to refine the CTI. Reliability and validity tests were conducted to ensure the item's consistency.

Table 5. Cross-country scale rating comparisons

(Suggested threshold values: Cronbach's α>0.7 and AVE>0.5)

General Automation (number of responses)	United States (100)		Taiwan (120)		Turkey (91)	
	α	AVE	α	AVE	α	AVE
Performance expectancy	0.888	0.619	0.862	0.527	0.878	0.552
Process transparency	0.869	0.546	0.856	0.503	0.855	0.513
Purpose influence	0.844	0.500	0.777	0.409	0.85	0.491
Task contexts	0.704	0.432	0.743	0.415	0.8	0.440
Specific Automation	United States		Taiwan		Turkey	
	α	AVE	α	AVE	α	AVE
Performance expectancy	0.847	0.587	0.859	0.594	0.903	0.675
Process transparency	0.813	0.531	0.824	0.539	0.886	0.639
Purpose influence	0.809	0.516	0.84	0.56	0.887	0.642

The results (Table 5) satisfied the reliability tests (i.e., the Cronbach's alpha values were higher than the threshold value of 0.7 in all dimensions). However, some of the constructs failed to pass the validity tests (i.e., AVE<0.5), such as purpose influence and task contexts, and will be further validated in the next round of study.

8.2 SUMMARY

The preliminary results largely confirmed the adopted tripartite constructs (performance, process, and purpose). Items were empirically categorized into two types (either a general or specific use of automation) and were then tested through an online crowdsourcing platform (Amazon MTurk) and cross-cultural empirical validation. After eliminating inappropriate items, 50 items were extracted to refine the instrument, with 32 items falling into the general cluster and 18 items involving specific uses of automation. To further examine whether the developed 50-item instrument was able to capture users' initial levels of trust, as well as instantaneous trust after experiencing a certain type of automated system, another round of cross-cultural validation was conducted in the U.S., Taiwan, and Turkey.

9.0 STUDY 5: TASK BASED EMPIRICAL STUDY

Existing literature on trust in automation has invariably acknowledged the richness and multiplicity of influences. To study both the theoretical and empirical effects of cultural and individual contexts on trust in automation, task-based empirical studies were conducted in the U.S., Taiwan, and Turkey. We used an air traffic control system to incorporate various types of tasks identified from the area of trust in automation literature. Through experimental studies, we further validated the instrument, and investigated trust in automation and its effect on automation reliance in different cultural populations.

9.1 APPARATUS

These experimental studies were developed by modifying an existing air traffic control (ATC) system, RESCHU (Boussemart & Cummings, 2008), to simulate a traffic control scenario with multiple unmanned air vehicles (UAVs). RESCHU provided multiagent search and attack environments by performing both UAV navigation tasks and target identification tasks, in which the simulated multitasking environment was essential for observing the effects of over-trust and overreliance on automated aids. RESCHU provided a payload window (shown in the top left in Fig. 4) for target detection tasks, map display for UAVs routes for navigation tasks, a message box for assigned enemy targets in payload tasks, status panels for each of the UAV's current states, and a mission timeline for both ongoing and upcoming tasks. Task results were included in the message box and a real-time feedback panel (yellow text at the top right in Fig. 4) provided instant feedback to support task awareness, as well as assisting the operator in optimizing their multitasking strategy.

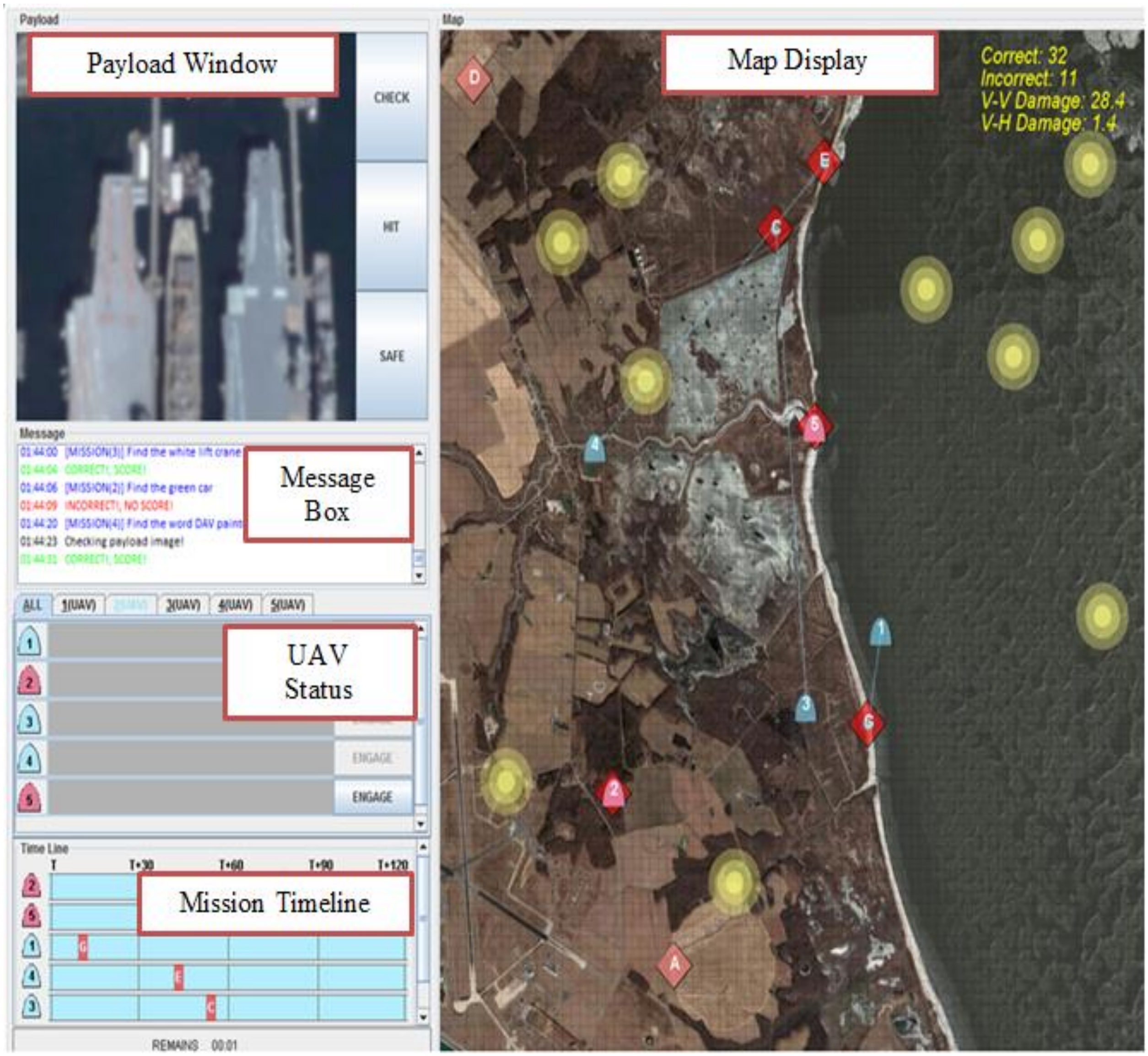


Figure 4. The RESCHU user interface. The map window shows the numbered UAVs (blue ovals) with paths to targets (red diamonds); threat areas are marked by the yellow circles. When a UAV reaches a target, the engage button will be switched on in the UAV status window and the UAV icon will begin flashing in the mission timeline.

9.2 EXPERIMENTAL TASKS

Five UAVs were assigned in the experiments, along with two experimental tasks, in which *payload* tasks involved identifying enemy targets and *navigation* tasks required participants to reroute the UAVs' paths to avoid possible path conflicts and threat areas (which are shown as yellow dots in Fig. 4).

9.2.1 Experimental Task I – Payload Tasks

As soon as a UAV reached a target area (shown as red squares in Fig. 4), a series of actions needed to be performed to accomplish the payload tasks. Upon reaching a target, the operator was presented with a panorama in the payload window and was asked to search for a specific target (the assigned enemy object was revealed in the message box). The operator first observed a low-resolution image in the payload window (Fig. 5a), along with three options: Check, Hit, and Safe. By clicking the "Check" button, after a three-second delay, the system provided the operator with a picture at higher resolution to further identify the existence of the assigned target (Fig. 5b).

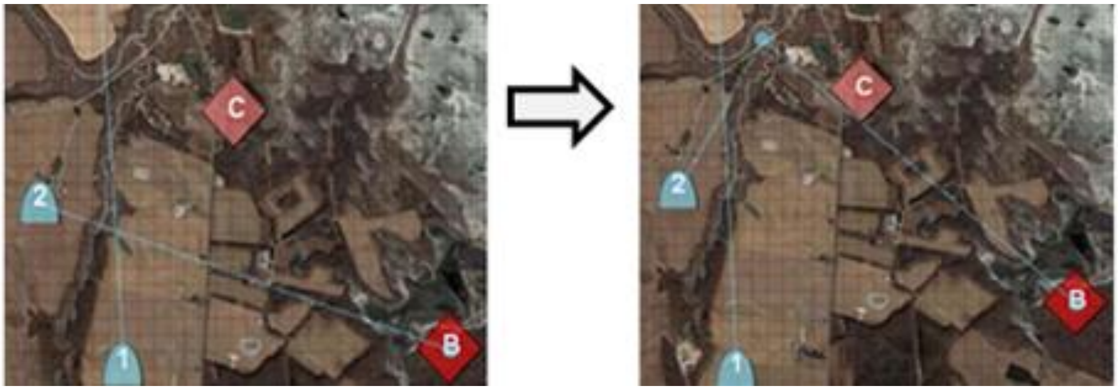
If an operator believed that the assigned hostile target was not in the panorama, the operator could select "Safe" mode to terminate the attack; otherwise, the "Hit" mode would be chosen to launch a strike on the enemy target. Following a payload submission (of either Hit or Safe mode), the UAV was assigned to another available target and the process was repeated. In addition, the message box and real-time feedback panel informed the operator as to whether the submitted decision was correct or not.

(5a) Before checking (5b) After checking

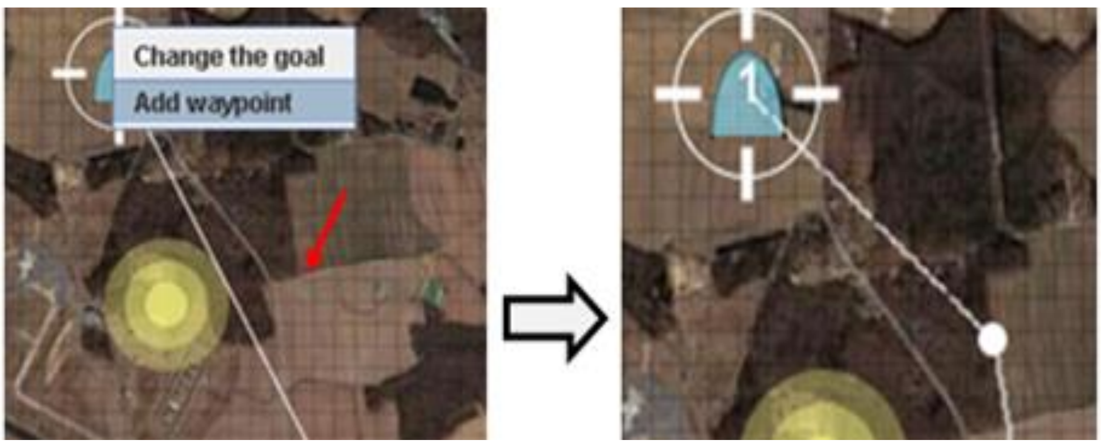
Figure 5. The checking function in target detection tasks

9.2.2 Experimental Task II – Navigation Tasks

An autonomous path planner was used to generate the UAV paths by following a shortest-distance criterion. As each of the UAVs was randomly assigned to a new target, the operator needed to coordinate UAVs to keep them from interfering each other (i.e., to avoid conflicting paths between UAVs). Meanwhile, the navigation tasks required the operator to monitor the UAVs' paths (Fig. 6a) and avoid passing through the hazard areas (shown as yellow dots in Fig. 6b). The need for assistance arose when the UAVs found themselves in the above risky conditions, such as path conflicts or threat areas; and as a result, the operators needed to add waypoints either to avoid collisions or to navigate around the threats.



(6a) Adding waypoints to avoid path conflicts



(6b) Adding waypoints to avoid threat areas

Figure 6. Adding waypoints to avoid collisions

9.3 AUTOMATED ASSISTANCE

To assist operators, two types of autonomy were included in the experimental tasks. A target finder was used in the payload tasks, whereas a conflict detector was used in the navigation tasks.

9.3.1 Automated Assistance I – Target Finder

A target finder is used in the payload tasks to assist operators in locating enemy targets. A likelihood alarm system (LAS) is introduced to the target finder to measure participants' attitude on uncertain information (Fig. 7), in which the LAS generates three types of automated suggestions to provide information about the likelihood of suspicious events occurring (Wickens & Colcombe, 2007; Wiczorek & Manzey, 2014). Based on the automated diagnosis, the target finder provides a bounding box on top of the suspicious hostile target and highlights the payload window in different colors (a red box/border in Fig. 8a, a yellow box/border in Fig. 8b). The alarm condition is represented by the red box/border (Fig. 8a), which suggests that there is a *good possibility* that the bounding box indicates the assigned target, while the yellow box/border specifies a warning condition (Fig. 8b) that is associated with a higher level of information uncertainty, which suggests that the assigned hostile target *might be* located by the bounding box. A green border suggests a non-alert event (Fig. 8c), which presents a *low possibility* that the assigned enemy target is included in the picture.

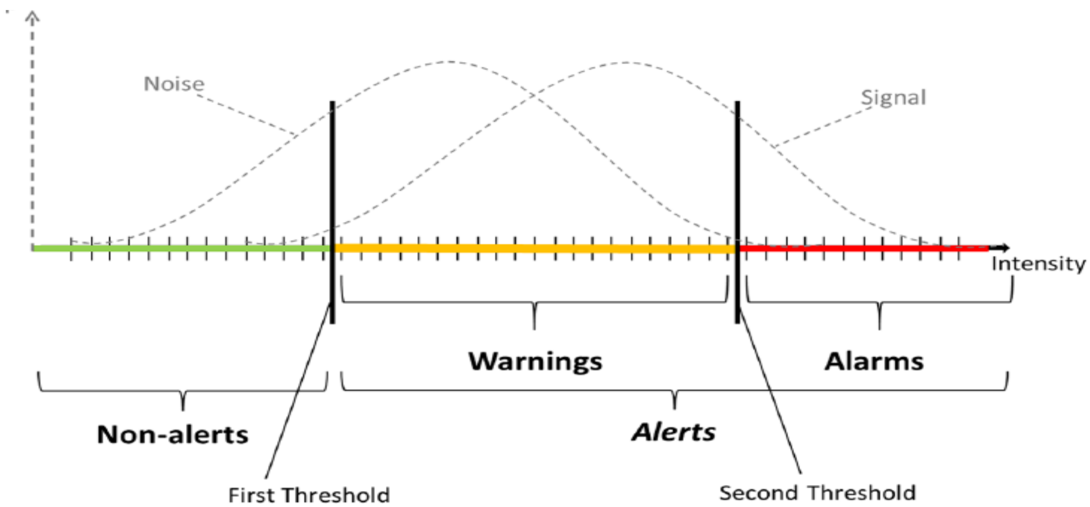
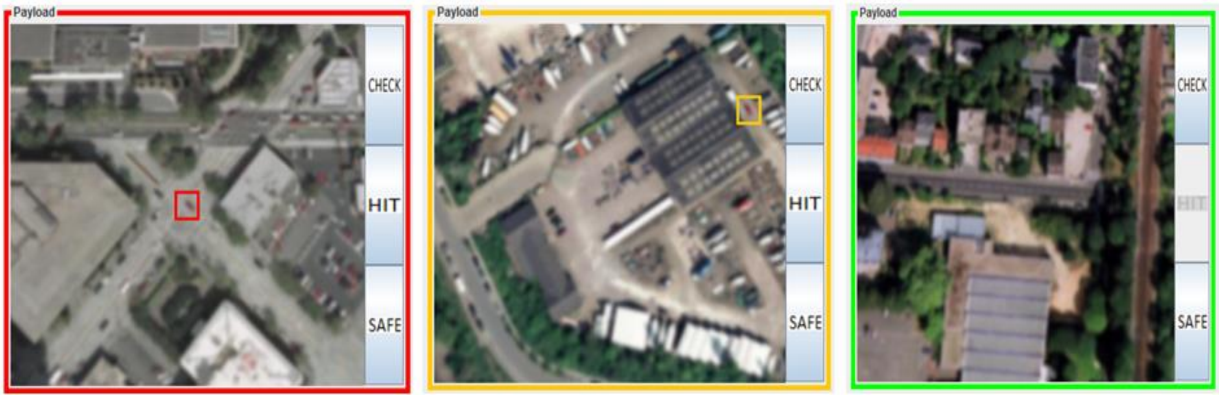


Figure 7. The likelihood alarm system (LAS) is applied to examine the effects of operators' uncertainty avoidance (Wiczorek & Manzey, 2014)

In the alarm and warning conditions, instead of searching for the assigned target, the operator is asked to determine whether the bounding box precisely indicates the assigned target or not. Hit mode will be chosen when the operator believes that the box has located the target correctly; otherwise Safe mode will be selected. With the green cue (the non-alert condition), if an operator detects a target, the operator must manually add a bounding box on the suspected target to proceed to Hit mode.



(8a) Alarm condition (8b) Warning condition (8c) Non-alert condition

Figure 8. Conditions shown in the target finder

9.3.2 Automated Assistance II – Conflict Detector: *Path Re-planning*

One of the common problems in performing multi-UAV tasks is conflicting paths between vehicles. A conflict detector is used in the navigation tasks, which provides alternative paths to resolve collisions. Based on the planned route information, the path re-planning algorithm suggests new paths to keep an UAV at the appropriate distance from another UAV to reduce the risk of the aircraft colliding. By selecting the Auto button (Fig. 9), the suggested new paths are applied to the involved UAVs in order to prevent the minimum separation from being violated. In other words, instead of following the shortest-distance discipline, after activating the path re-plan function, the UAVs reach the desired destinations with additional costs (in both traveling distance and time) to meet the constraints of collision avoidance.

Figure 9. By clicking the auto button, new paths are applied to divert UAVs from a collision course

9.3.3 Automated Assistance II – Conflict Detector: *Highlight*

Automation transparency substantially affects an operator's perceived difficulties in either following or rejecting the automated recommendations. To enhance an operator's understanding of the autonomy, based on the path information used in the path re-plan mechanism, the highlighting application indicates path conflicts by placing a red square on the map (Fig. 10a) or adding red dots (Fig. 10b) if the UAV has travelled through hazardous areas.

(10a) Path conflicts

(10b) Hazardous areas

Figure 10. Highlighting UAVs' path conflicts or adding dots if paths pass through hazards

9.4 EXPERIMENTAL DESIGN

Research shows that perceived system reliability, system transparency, and task load all significantly influence trust attitude and reliance behaviors. These variables were manipulated in the task-based empirical experiments.

9.4.1 Source Reliability

The reliability of automation for the target detection task was manipulated through injecting false alarms into the target finder system, in which 80% of source reliability was used in the high-reliable condition and 20% of source reliability was used in the low-reliable condition. The source reliability of the target finder for the alarm and non-alert events (the red and green cues, respectively) remained at 80% across all experimental conditions, whereas the warning condition (the yellow border) is set at 80% in the high-reliability condition and at 20% in the low-reliability condition.

9.4.2 Automation Transparency

The operators were provided with three types of system transparency in the conflict detector. In the highlight condition, the system highlighted the potential collisions (as in the red square/dots shown in Fig. 10) and then the operator manually revised the involved UAVs' routes to avoid conflicts. In the path re-plan condition, once a collision was detected, the system generated alternate routes for the UAVs and the operator needed to click the Auto button (Fig. 9) to apply the new routes; however, no explanations (i.e., highlights) were included in this condition. The third condition included both highlighted and path re-planning applications, which showed the operators alternate paths with appropriate highlighting on the potential UAVs' collisions. To better examine the effect of system transparency on subtasks, a control condition was also included, which served as a baseline comparison and provided no assistance for the navigation tasks (i.e., an operator was required to detect the collisions and develop new routes on their own).

9.4.3 Task Load

Prior research showed that adding the number of controlled agents may merely increase the perception of workload (Visser & Parasuraman, 2011). To examine the relationship among workload, trust, and reliance, the task load is manipulated through the changes of the UAVs' moving speed, in which the vehicles move at 5.0 pixels/second in the high task load condition and 2.5 pixels/second in the low task load condition. Increasing the UAVs' travelling speed resulted in more frequent payload requests for the target detection tasks, as well as a higher chance for potential collisions between UAVs in the navigation tasks.

9.5 EXPERIMENTAL DESIGN AND CONDITIONS

The empirical study follows a mixed repeated-measures design, with countries (U.S., Taiwan, and Turkey), automation reliability (high: 80% or low: 20%), information transparency (control condition, path re-plan, highlight, and path re-plan x highlight) as the between-subject factors; and task load (UAVs' speed doubled between conditions) as the within-subject variable.

Table 6. Experimental designs and conditions

Conflict Detector **Between Variables** *Target Finder*	**Control Condition (C)**	**Path Re-plan (PR)**	**Highlight (HL)**	**Path Re-plan x Highlight (PRHL)**
High Reliability	HRC	HRPR	HRHL	HRPRHL
Low Reliability	LRC	LRPR	LRHL	LRPRHL

Within Variables (High and Low Task Loads)

The experiments were composed of eight conditions (Table 6), and each cell included 15 participants. 120 student participants were recruited in each of the three countries, and a total of

360 responses (120*3=360) were collected for the study. The U.S. participants were recruited from the University of Pittsburgh; Taiwanese participants were recruited from National Chengchi University; and Turkish participants were recruited from Özyeğin University. None of the participants had prior experience with ATC systems. Additionally, to better capture cultural characteristics, a qualified participant must have attended K–12 schooling in the represented country.

Fig. 11 shows the experimental procedures. After providing demographic data, participants were asked to rate their initial level of trust in automation through the cultural trust instrument (CTI) that we had developed. Because of the variety of automated systems (e.g., smartphone apps vs. self-driving cars), trusting attitudes varied significantly with respect to the use of the automation. To measure a general level of trust in automated systems, participants were asked to rate their general trust attitudes, based on their beliefs about smartphones. After finishing the pre-experiment phase, in the following 20-minute training sessions, based on a randomly assigned condition, participants took an interactive training tutorial to learn control operations with the automated applications (target finder and/or conflict detector). Participants were informed that the goal was to avoid UAV path conflicts and threat areas, as well as to identify and attack as many enemy targets as possible.

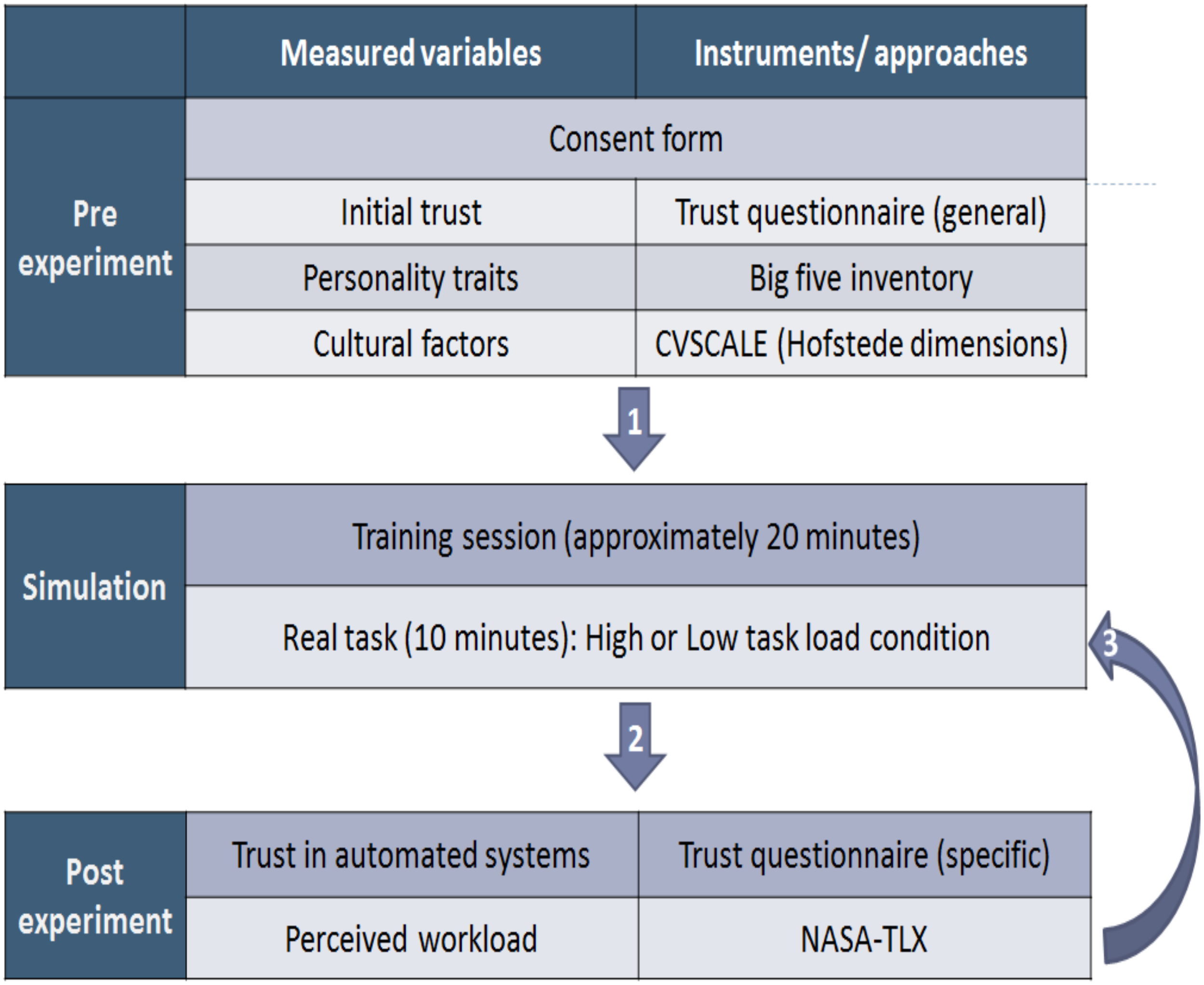


Figure 11. Experimental procedures

After the training tasks, participants began their first 10-minute experimental session, in which they performed the target classification tasks by controlling five UAVs. At the conclusion of the session, participants were asked to complete the trust instrument to evaluate their levels of trust in the specific uses of the automated applications. After a brief break, the other task load condition was run, accompanied by a repeated trust questionnaire. Conditions were fully counterbalanced for source reliability in the target finder and automation transparency in the conflict detector with different task load levels.

To avoid any language issues, before conducting the study, the CTI as well as system aids in the testbed (RESCHU) system were translated into Chinese by two instructors in the Department of East Asian Languages and Literatures at the University of Pittsburgh, and into Turkish by our collaborators at Özyeğin University. In addition, the Chinese and Turkish versions of BFI scales were adopted from (Leung, Wong, Chan, & Lam, 2012) and (Vazsonyi, Ksinan, Mikuška, & Jiskrova, 2015) respectively; the Chinese version of CVSCALE was retrieved from (Yoo, Donthu, & Lenartowicz, 2011) and the Turkish version was also translated by our collaborators at Özyeğin University.

10.0 FINAL CULTURAL TRUST INSTRUMENT REFINEMENT

To further refine the instrument, exploratory factor analysis (EFA) was performed again to determine the factor structures and the loading of items. Principal component analysis (PCA) with orthogonal rotation (varimax) is the most frequently reported extraction approach in EFA (Hinkin, 1995) and was adopted for our analysis as a result. However, the resulting pattern matrix revealed unexpected cross-loading problems among the items, which represented some items that shared excessive variances between the constructs. To solve the cross-loading issue (i.e., the violation of convergent validity), any items that failed to relate more strongly to the designated construct (Boudreau, Gefen, & Straub, 2001), or where the loading differences between intended and unintended factors were less than 0.200 (Asparouhov, Muthén, & Morin, 2015) were dropped. After another round of scale refinement, a total of 21 items (12 general items, along with 4 constructs and 9 specific items that fell into 3 constructs) were retrieved from the original pool of 50 items.

10.1 RELIABILITY

To measure the scale's reliability, each item's internal consistency was tested. As in the reliability results in Table 7, the alpha value of the purpose construct in general automation failed to satisfy the suggested threshold (α-value>0.7), and was therefore eliminated. Therefore, after eliminating the purpose construct, only 3 general constructs (9 items) and 3 specific constructs (9 items), a total of 18 items, were included in our final CTI.

Table 7. Cross-cultural scale reliability tests

Reliability tests (suggestive threshold values: Cronbach's α > 0.7)				
General **Automation**	**ALL**	**US**	**TW**	**TK**
Performance expectancy	0.805	0.857	0.781	0.775
Process transparency	0.816	0.799	0.766	0.775
~~Purpose influence~~	0.668	0.572	0.695	0.657
Task context	0.748	0.695	0.788	0.723
Specific **Automation**	**ALL**	**US**	**TW**	**TK**
Performance expectancy	0.863	0.853	0.858	0.869
Process transparency	0.778	0.700	0.800	0.790
Purpose influence	0.844	0.840	0.838	0.860

10.2 CFA RESULTS: CONVERGENT AND DISCRIMINANT VALIDITY

Due to construct elimination, to ensure the consistency of the items, factor structures and item loadings were examined again. The resulting pattern matrix in both the general and specific clusters satisfied the convergent validity and accounted for the high percentage of total variance with sufficient Kaiser-Meyer-Olkin (KMO) values (see Appendix C for more information).

Discriminant validity was examined, based on the shared variance between the construct and its measures, in which the square roots of the shared variance must be larger than the correlations across constructs in the matrix (see Appendix D). The results revealed that most of the constructs in both general and specific automation supported the discriminant validity.

Table 8. Model fit assessment

General Automation					
	$\chi2$	**df**	**CFI >0.90**	**RMSEA <0.08**	**TLI >0.90**
US (n=120)	22.793	24	1.00	0.00	1.01
TW (n=120)	38.379	24	0.96	0.07	0.95
TK (n=120)	43.78	24	0.94	0.08	0.91
Specific Automation					
US (n=420)	112.199	24	0.96	0.09	0.94
TW (n=420)	103.708	24	0.96	0.09	0.94
TK (n=420)	45.689	24	0.99	0.05	0.99
Target finder (n=720)	131.015	24	0.97	0.08	0.95
Conflict detector (n=540)	91.639	24	0.98	0.07	0.97

Table 8 shows chi-square statistics ($\chi2$) and subjective goodness-of-fit indices for each of the cultures, as well as automated aids. The resulting comparative fit index (CFI) and Tucker-Lewis index (TLI) scores satisfied the suggested threshold values; however, two slight violations in the root mean square error of approximation (RMSEA) were observed in both the American and Taiwanese participants.

Table 9. Item loadings

General	Performance			Process			Context		
	Perform2	Perform3	Perform4	Process2	Process4	Process5	Context1	Context2	Context6
US	0.82	0.89	0.89	0.76	0.85	0.88	0.86	0.73	0.65
TW	0.81	0.81	0.65	0.77	0.80	0.75	0.87	0.79	0.60
TK	0.81	0.79	0.79	0.69	0.86	0.85	0.72	0.89	0.67
Specific	**Performance**			**Process**			**Purpose**		
	Perform2	Perform3	Perform4	Process3	Process4	Process5	Purpose3	Purpose4	Purpose5
US	0.80	0.87	0.83	0.76	0.86	*0.56*	0.74	0.84	0.86
TW	0.64	0.87	0.84	0.84	0.86	0.62	0.81	0.72	0.83
TK	0.84	0.84	0.82	0.77	0.76	0.75	0.69	0.80	0.87
Target finder	0.81	0.86	0.84	0.82	0.85	0.63	0.72	0.80	0.86
Conflict detector	0.74	0.83	0.81	0.73	0.84	0.71	0.69	0.83	0.84

The item loading matrix (Table 9) indicated that the items were good measures of the intended latent factors, in which only one loading item was below 0.60 (item process-5 in the specific cluster in the U.S. group: 0.56). Thus, we concluded that the proposed measurement model adequately fits the data for each culture.

Table 10. Structural weights

General Automation	**Performance**	**Process**	**Context**
US	0.57	0.58	0.84
TW	0.88	0.80	0.88
TK	0.74	0.56	0.85
Specific Automation	**Performance**	**Process**	**Purpose**
US	0.77	0.94	0.78
TW	0.86	0.86	0.86
TK	0.84	0.93	0.88

The results of structural weights (Table 10) indicate how the model constructs affect the overall level of trust in automation. The results of initial trust reveal that the context variable largely influences the overall levels of trust across three cultures, whereas similar weights are observed in the specific dimension.

10.3 MEASUREMENT INVARIANCE

Measurement invariance (MI) tests were performed to assure that the proposed constructs were measuring the same trait in all of the cultural groups. If the developed CTI scale succeeds at the MI tests, then the comparisons of the trust ratings across cultures were acceptable and yielded meaningful interpretations. The overview of invariance analysis results is shown in Appendix E, including the tested invariance model 1~12, the model description, and the corresponding fit statistical indices ($\chi 2$, degree of freedom, p-value, and CFI). Configural invariance (as in model

1) imposed no equality constraints, which evaluated whether the factors and patterns of the structure were similar across all groups; while measurement and structural invariance (as in model 2) focused on examining the loadings in the measurement and structural variables of the model were equivalent across the subgroups. The equal item-factor loading model (namely, configural invariance) served as a baseline model to compare the differences of the nested models (as in models 2 and 3).

10.3.1 Results for scale invariance analysis

To determine whether the items used in investigating general attitudes about automation had similar patterns on the corresponding factor loadings, the differences in $\chi 2$ and the degree of freedom between the baseline and nested models were examined. The results showed significant differences (p=.024) between the factor loading invariance (model 2) and baseline (model 1) models. By examining the loading values shown in Table 9, the item loading of performance_4 on the performance construct in the Taiwanese subgroup stood out, which was substantially lower than the other two subgroups (US:0.89, TW:0.65, TK:0.79). To identify whether this item alone accounted for the statistical variance, we measured whether the remaining eight items (exempting performance_4) had similar patterns and loadings on the corresponding factors across three cultures. The results (model 3) indicate that differences in the 8-item scale were not significant across cultures. The test of model 3 provided some evidence that performance_4 in the Taiwanese subgroup might be a major contributor to the failure of the invariance test of the measurement items across three subgroups. As a result, we measured whether the scale invariant existed in the U.S. and Turkish subgroups, with the Taiwanese group excluded. The results (models 4–6) indicate that the measurement model with all nine items passes both the factor loading and structural weights invariance tests in the American and Turkish cultural groups, which suggests that the instrument can effectively measure the differences in initial trust attitudes across cultures.

The aforementioned approaches were also applied to examine the items used to measure trust attitudes on specific uses of automation. The scale invariance was violated ($p=.020$) in model 8 and the possible problematic item (S_Process5) was excluded for further examination in model 9. The remaining 8-item structure (model 9) showed no statistical differences across three cultures, which suggested that S_Process5 was the main cause of the failure of the invariance test. Because the lowest loading value of S_Process5 was observed in the U.S. group (US:0.56, TW:0.62, TK:0.75), we therefore exempted the American data and conducted the scale invariance tests on both the Taiwanese and Turkish data (models 10–12). The results succeeded at both the factor loading and structural weights invariance tests and showed no statistical differences between the baseline (model 10) and nested models (model 12), which indicates that the developed scale was able to identify the differences between trust attitudes in the specific use of automation across cultures.

This is worth noting because the $\chi 2$ value is highly sensitive to the sample size and the significant results often reject the model that fits the data. Prior research (Cheung & Rensvold, 2002; Milfont, Duckitt, & Wagner, 2010) suggests that, from a practical perspective, it is more reasonable to base the invariance decision on a difference in comparative fit index (ΔCFI) rather on $\Delta\chi 2$ values (suggested value: $\Delta\chi 2 < 0.01$). The differences of CFI (ΔCFI) again confirmed that the developed scale is able to accurately measure the trust attitudes toward automation across cultures.

10.4 PREDICTIVE VALIDITY

To assess how well the CTI can predict system variables and the resulting trust attitudes, correlation analyses were performed to examine the relationship between the operators' level of trust and acceptance of the automated aids, in which a significant correlation between reliance behaviors on automation and trust scores on the scale would support the predictive validity of the developed CTI. For example, we might theorize that an operator who exhibited high reliance behaviors on system aids would rate a higher trust score in CTI than the ratings from an operator who is less inclined to follow the automated recommendations. Thus, if there was a change in an operator's reliance behaviors, the trust score in CTI should reflect those differences.

10.4.1 Cultural Effects on Trust in Target Finder between Reliability Conditions

Operators' reliance behaviors in payload tasks were measured by the ratio of following behaviors (i.e., accepted recommendations) to the total number of automated suggestions made by the target finder. Since appropriate levels of reliance are critical to human-automation interaction, to measure the appropriate use of automation, the overall following behaviors were further categorized into over-reliance, appropriate reliance, and under-reliance groups. Over-reliance was defined as when the autonomy (target finder) provided a false alarm and the operator believed that the recommendation was correct and submitted a Hit decision; in contrast, under-reliance was defined as an operator rejecting a correct suggestion and submitting a Safe decision instead. A higher ratio of appropriate reliance represented the operators appropriately calibrating their trust in automation.

10.4.2 Correlation for Trust Attitude and Reliance Behaviors on Target Finder among Three Cultures

Pearson correlation analysis (Table 11) for the results of reliance and trust ratings in target finder (average score was computed by the mean value of the three constructs) showed highly significant differences between specific trust and following as well as reliance behaviors, which suggested that the developed CTI could appropriately predict the relation between operators' reliance behaviors and trust attitude in automated aids under various system capabilities.

Table 11. Correlations for trust attitude and reliance behaviors on the target finder

*. Correlation is significant at the 0.05 level (2-tailed)

**. Correlation is significant at the 0.01 level (2-tailed)

	Average Specific Trust Finder (average score was computed by the mean value of the three constructs)	
Following Behaviors	Pearson correlation	.138**
	Significant difference	**.000**
Appropriate Reliance	Pearson correlation	.158**
	Significant difference	**.000**
Over-Reliance	Pearson correlation	-.140**
	Significant difference	**.000**
Under-Reliance	Pearson correlation	-.076*
	Significant difference	**.042**

Further analysis (Table 12) confirmed a positive correlation between following behaviors and trust ratings, and between appropriate reliance and trust values in the U.S. and Taiwanese populations. However, no significant difference was observed in the Turkish group, which suggests that system reliability may not be the most dominant factor that affects the relationship between trust and reliance in the Turkish population.

Table 12. Correlations for trust attitude and reliance behaviors in the target finder

*. Correlation is significant at the 0.05 level (2-tailed)

**. Correlation is significant at the 0.01 level (2-tailed)

Correlation Results		**Following Behaviors**	**Appropriate Reliance**	**Over-Reliance**	**Under-Reliance**
Trust *US* group	Pearson correlation	.176**	.120	-.065	.-130*
	Sig. (2-tailed)	**.006**	**.063**	.317	**.044**
Trust *TW* group	Pearson correlation	.193**	.207**	-.186**	-.081
	Sig. (2-tailed)	**.003**	**.001**	**.004**	.212
Trust *TK* group	Pearson correlation	.061	.061	-.103	.053
	Sig. (2-tailed)	.349	.345	.110	.410

10.4.3 Cultural Effects on Trust in Conflict Detector between System Transparency

An operator's reliance on navigation tasks was determined by the ratio of accepted new paths proposed by the conflict detector. Therefore, the analysis only included the path re-plan (PR) and path re-plan x highlight (PRHL) conditions. The results (Table 13) showed significant correlation in the PR condition but not in the PRHL condition, which revealed that while little SA was provided by the automation, the operator’s trust attitude significantly guided their reliance behaviors in the automated aids; however, when the transparency of the information increased, this relationship was not observed.

Table 13. Correlations for trust attitude and reliance behaviors in the conflict detector
**. Correlation is significant at the 0.01 level (2-tailed)

Num of Accepted Automated Waypoints in Conflict Detector		
Path Re-plan (PR)	Pearson correlation	.300**
	Significant difference	**.000**
Path Re-plan x Highlight (PRHL)	Pearson correlation	.092
	Significant difference	.218

10.4.4 Correlation for Trust Attitude and Reliance Behaviors on Conflict Detector among Three Cultures

Pearson correlation analysis (Table 14) for trust in conflict detectors and acceptance of proposed new paths in the PR condition showed significant differences in the American as well as the Turkish populations, but no significant difference was observed in the Taiwanese population.

Table 14. Correlations for trust attitude and reliance behaviors in the conflict detector
*. Correlation is significant at the 0.05 level (2-tailed)
**. Correlation is significant at the 0.01 level (2-tailed)

Correlation Results		**Path Re-plan (PR)**
Trust *US* group	Pearson correlation	.274*
	Sig. (2-tailed)	**.034**
Trust *TW* group	Pearson correlation	.171
	Sig. (2-tailed)	.193
Trust *TK* group	Pearson correlation	.442**
	Sig. (2-tailed)	**.000**

10.5 SUMMARY

Over various phases of statistical examinations, the final 18-item CTI satisfies the stringent (reliability and validity) tests, which suggests that the CTI is robust across national cultures and can be used to capture trust differences in both general and specific uses of automation. The final 18-item CTI is included in Appendix F, including the English, Chinese, and Turkish versions. Researchers should be cautious when using the items, as the general items measure participants' initial trust in automation and must be examined before the training or experimental sessions, while the specific items identify participants' trust attitude in a specific automated system and therefore should be used after experiencing the experimental sessions. In Appendix F, smartphones and GPS systems are assigned as the targeted systems for general and specific automation, respectively; however, researchers may switch these systems to work with their desired applications. To examine the trust ratings, the results of the invariance measurement indicate that CTI appears to be equivalent across cultures, which suggest that both the summed scale values and factor scores can be used to make comparisons between cultural samples on levels of trust in automation.

11.0 RESULTS OF THE TASK BASED EMPIRICAL STUDY

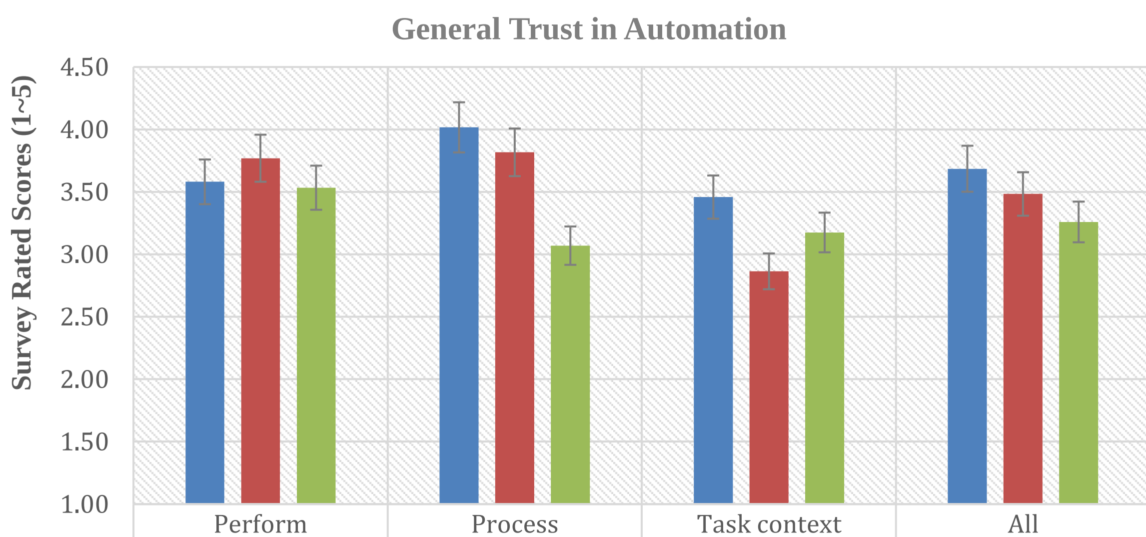
To evaluate the influences of cultural factors on trust in the specific use of automated systems under various conditions, the effects of system reliability for the target finder, automation transparency in the conflict detector, and perceived task loads were investigated. Data were analyzed using a mixed-model ANOVA analysis method with source reliability (high: 80% vs. low: 20%) in the target finder, automation transparency (control condition, path re-plan, highlight, and path re-plan x highlight) in the conflict detector, countries (U.S., Taiwan, and Turkey) as the between-subject factors, and task load (high vs. low) as the within-subject variable. While conducting multiple comparisons, the following results applied the Bonferroni correction for p<.05 rule to protect against Alpha inflation (i.e., family-wise error rate). In other words, a Type I error across the pairwise comparisons was adjusted to be less than a 5% chance, which was accomplished by dividing .05 by the number of comparisons.

11.1 SURVEY DATA: GENERAL TRUST

The analyses found significant cultural effects on initial levels of trust of automation in performance ($F_{2,357}$=2.969, p=.053), process ($F_{2,357}$=66.225, p<.001), and task context ($F_{2,357}$=18.697, p<.001). Post-hoc analysis revealed cultural effects on performance constructs

(TW>TK, *p*=.066), process dimensions (US>TW, *p*=.065; US>TK, *p*<.001; TW>TK, *p*<.001), and task context factors (US>TW, *p*<.001; US>TK, *p*=.011; TK>TW, *p*=.005).

To measure the overall effect, the average score was computed by the mean value of the three constructs ($F_{2,357}$=16.225, *p*<.001). T-tests revealed significant differences between the U.S. and Turkey (*p*<.001), the U.S. and Taiwan (*p*=.022), and Taiwan and Turkey (*p*=.009), in which the American participants had the highest score in general trust and the Turkish participants had the lowest, with the Taiwanese rates falling in between (Fig. 12).



	Perform	Process	Task context	All
U.S.	3.58	4.02	3.46	3.69
Taiwan	3.77	3.82	2.86	3.48
Turkey	3.53	3.07	3.18	3.26

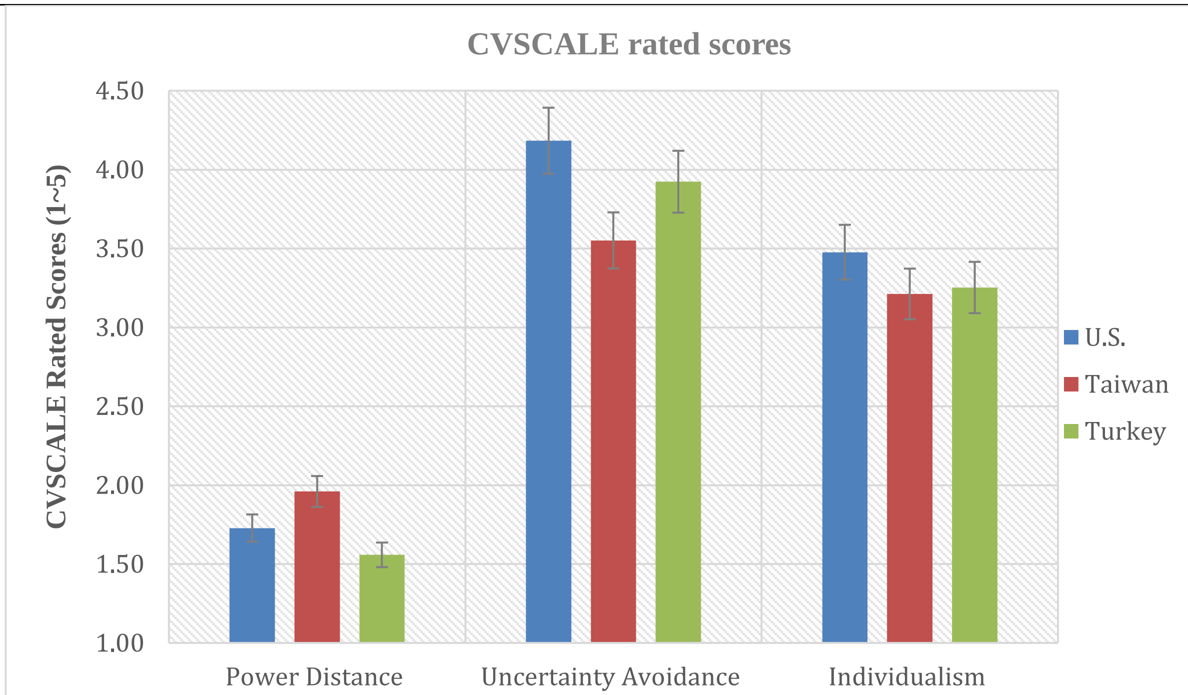
Figure 12. General levels of trust in automation among three cultures

11.2 CULTURAL VALUE SCALE

The results of the CVSCALE showed significant differences in all three cultural constructs, in which the American participants was higher in UA and IDV, and the Taiwanese participants was higher in PD (Table 15). The results also revealed the differences between Hofstede's original data, which was collected from IBM employees between 1967 and 1973, and our collected data, where the samples were drawn from student participants.

The results from Hofstede's original data suggested that the American participants had the lowest UA and that the Turkish participants had the highest PD score among these three countries. However, our data showed the reverse results, in which the American participants now had the highest score in UA and the Turkish participants had the lowest score in PD.

Table 15. CVSCALE rated scores



Measures	US	TW	TK	F-value, *p*-value	Post-hoc
Power distance (PD)	1.73	1.96	1.56	$F_{2,357}$=18.617 p<.001	TW>US (p=.002) TW>TK (p<.001) US>TK (p=.032)
Uncertainty avoidance (UA)	4.18	3.55	3.92	$F_{2,357}$=45.024 p<.001	US>TK (p<.001) US>TW (p<.001) TK>TW (p<.001)
Individualism (IDV)	3.48	3.21	3.25	$F_{2,357}$=5.162 p=.006	US>TK (p=.036) US>TW (p=.009) TK≈TW (N.S.)

11.3 CORRELATIONS FOR GENERAL TRUST ATTITUDE AND CULTURAL DIMENSIONS

Pearson correlation analysis (Table 16) for the cultural dimension and initial trust in automation showed significant differences between general levels of trust and UA, and between general levels of trust and IDV, which suggested that an individual's initial trust was positively correlated to both UA and IDV.

Table 16. Correlations for trust attitudes and cultural dimensions

General Trust		
Power distance (PD)	Pearson correlation	.052
	Significant difference	.325
Uncertainty avoidance (UA)	Pearson correlation	.128
	Significant difference	**.015**
Individualism (IDV)	Pearson correlation	.179
	Significant difference	**.001**

Further analysis confirmed a positive correlation between UA and general trust, and between IDV and general trust in the American participants; however, no significant difference was observed in the Taiwanese and Turkish participants (Table 17).

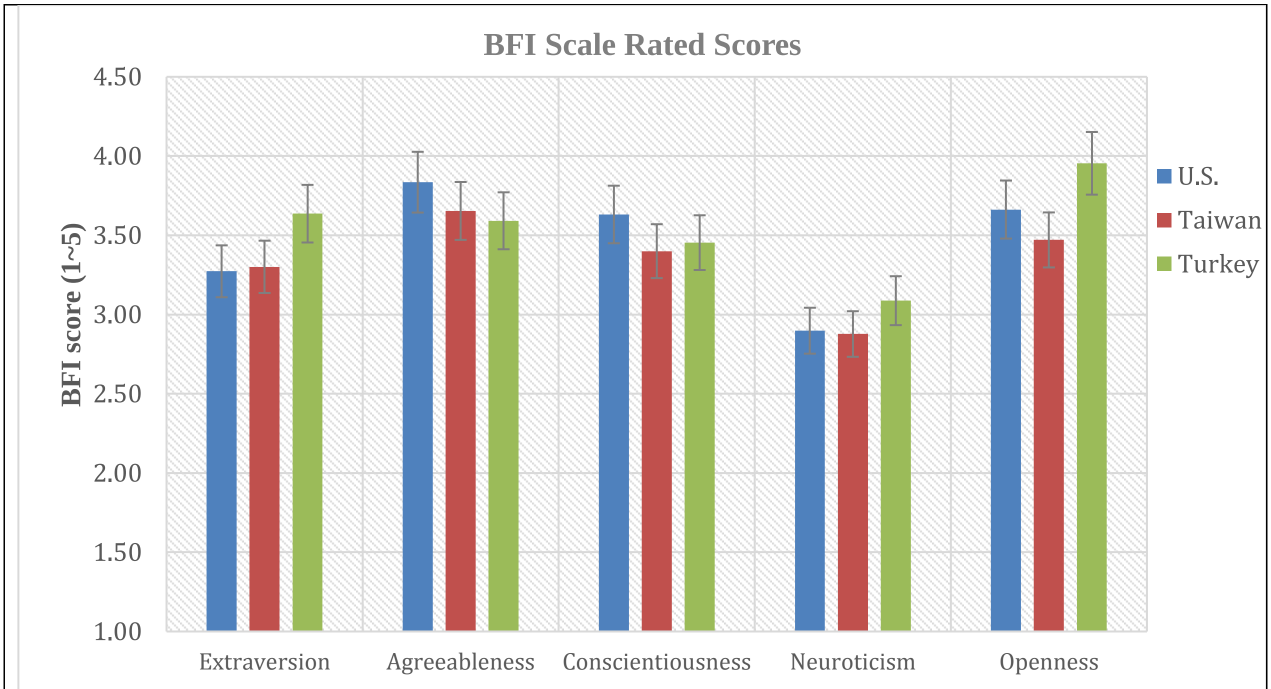
Table 17. Correlations for trust attitudes and cultural dimensions in the American, Taiwanese, and Turkish participants

Measures		**Trust**	**PD**	**UA**	**IDV**
Trust *US* group	Pearson correlation	1	.014	.212	.223
	Sig. (2-tailed)		.877	**.020**	**.014**
Trust *TW* group	Pearson correlation	1	-.119	-.076	.149
	Sig. (2-tailed)		.196	.408	.105
Trust *TK* group	Pearson correlation	1	.122	.122	.087
	Sig. (2-tailed)		.184	.183	.344

11.4 BIG FIVE INVENTORY

A big-five inventory (BFI) was used to measure differences in personality traits. An ANOVA analysis showed significant differences between participants in all five measures (Table 18): extraversion (**E**), agreeableness (**A**), conscientiousness (**C**), neuroticism (**N**), and openness (**O**).

Table 18. BFI scale rating comparisons



Measures	US	TW	TK	F-value, *p*-value	Post-hoc
Extraversion	3.27	3.30	3.64	$F_{2,357}$=9.489 *p*<.001	TK>TW (p<.001) TK>US (p=.001) TW≈US (N.S.)
Agreeableness	3.84	3.65	3.59	$F_{2,357}$=6.303 *p*=.002	US>TW (p=.034) US>TK (p=.002) TW≈TK (N.S.)
Conscientiousness	3.63	3.40	3.45	$F_{2,357}$=4.830 *p*=.009	US>TK (p=.070) US>TW (p=.010) TK≈TW (N.S.)
Neuroticism	2.90	2.88	3.09	$F_{2,357}$=3.012 *p*=.050	TK>TW (p=.080) US≈TK (N.S.) US≈TW (N.S.)
Openness	3.66	3.47	3.95	$F_{2,357}$=21.164 *p*<.001	TK>US (p<.001) TK>TW (p<.001) US>TW (p=.032)

11.5 CORRELATIONS FOR GENERAL TRUST AND PERSONALITY TRAITS

A Pearson correlation analysis showed that only two dimensions, agreeableness and conscientiousness, significantly correlated to an individual's initial level of trust. The results indicated that higher agreeableness or conscientiousness values in an individual's personality traits resulted in higher initial trust in automation, as shown in Table 19.

Table 19. Correlations for trust attitudes and personality traits

General Trust		
Extroversion (E)	Pearson correlation	.124
	Significant difference	**.019**
Agreeableness (A)	Pearson correlation	.215
	Significant difference	<**.001**
Conscientiousness (C)	Pearson correlation	.149
	Significant difference	**.005**
Neuroticism (N)	Pearson correlation	-.150
	Significant difference	**.004**
Openness (O)	Pearson correlation	-.044
	Significant difference	.400

Further analysis confirmed the correlation effects between the personality traits and general trust ratings in three selected countries (Table 20). The results showed positive correlations between extroversion and initial trust in the American as well as the Taiwanese participants, positive correlation between agreeableness and initial trust across all three cultures, and a positive correlation between conscientiousness and initial trust in the Taiwanese participants. A negative correlation was found between neuroticism and initial trust in the American, as well as in the Taiwanese participants.

Table 20. Correlations of trust attitudes and personality traits in the American, Taiwanese, and Turkish groups

Measures		**Trust**	**E**	**A**	**C**	**N**	**O**
Trust <u>*US*</u> group	Pearson correlation	1	.178	.155	.080	-.196	.109
	Sig. (2-tailed)		**.052**	**.091**	.385	**.032**	.237
Trust <u>*TW*</u> group	Pearson correlation	1	.345	.209	.226	-.158	.043
	Sig. (2-tailed)		**<.001**	**.022**	**.013**	**.086**	.638
Trust <u>*TK*</u> group	Pearson correlation	1	.098	.177	.065	-.034	-.124
	Sig. (2-tailed)		.286	**.053**	.480	.713	.177

11.6 SURVEY DATA: TRUST IN TARGET FINDER AND CONFLICT DETECTOR BETWEEN TASK LOADS

While increasing the task load (i.e., doubling the UAVs' travelling speed), no statistical difference was found on trust in the conflict detector between workload conditions. However, statistical differences were observed on trust in the target finder (Table 21), in which participants rated a higher trust in a high workload (HW) condition rather than in a low workload (LW) condition in performance, process, and overall trust.

Table 21. Trust in payload tasks between workload conditions

Payload Tasks: Trust in *Target Finder* between *Task Load* conditions			
Measures	**$F_{1,672}$**	***p*-value**	**Post-hoc**
S_Performance	3.831	.051	HW>LW
S_Process	2.748	.098	HW>LW
S_Purpose	0.710	.400	N.S.
Overall (average value)	3.089	.079	HW>LW

11.6.1 Survey data: cultural effects on trust in target finder between task load conditions

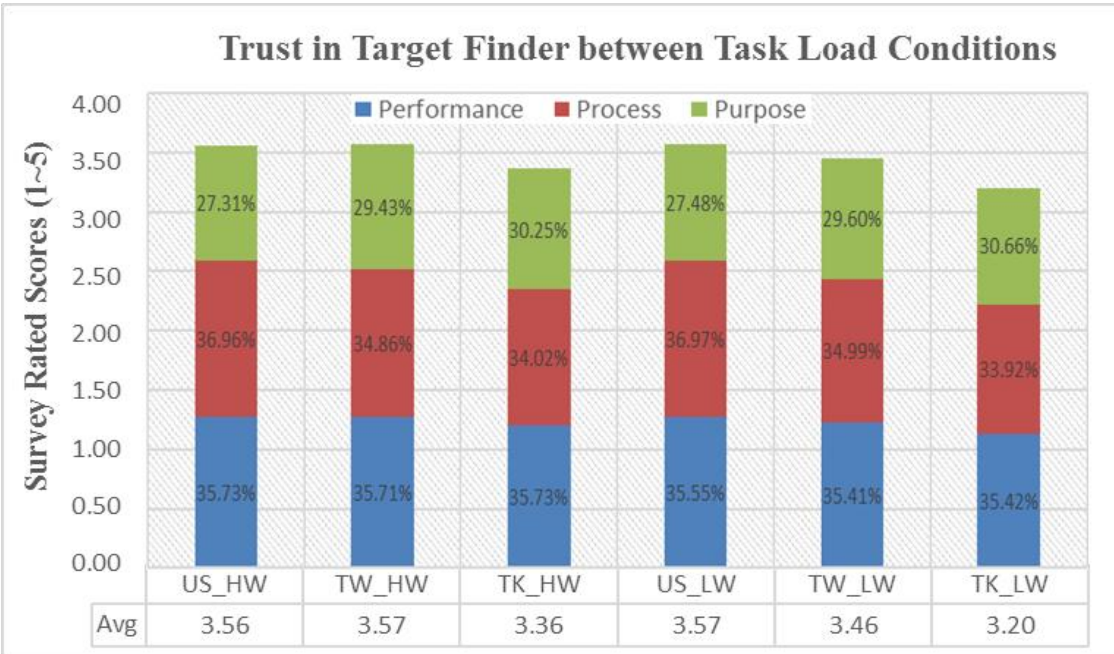


Figure 13. Average trust scores in target finder between task load conditions. Performance, process, and purpose constructs are each represented by their proportions in each bar in the chart

To identify the relationship between cultural contexts and task load conditions, two levels of task loads were examined for the target finder across cultures. The analysis (Fig. 13) found a main effect on overall trust values in the target finder under both HW ($F_{2,357}$=3.668, *p*=.027) and LW ($F_{2,357}$=9.339, *p*<.001). T-tests revealed similar trust attitudes in the American and Taiwanese participants, which were significantly higher than those of the Turkish participants in HW (US>TK, *p*=.066; TW>TK, *p*=.052) and LW (US>TK, *p*<.001; TW>TK, *p*=.012).

Further analysis showed that an increased task load affected participants' trust about the purpose of automation in the target finder ($F_{2,357}$=2.350, *p*=.097); in the HW condition, Taiwanese participants had higher levels of trust in the purpose factor than American participants (*p*=.095), while no difference was observed in the same construct in the LW condition. It is worth mentioning that significant differences were found between task load conditions in the Taiwanese (p=.045) and Turkish (p=.003) participants, in which higher trust was rated in a heavier task load; however, no statistical effect was observed in the American participants between task load conditions.

11.7 SURVEY DATA: TRUST IN TARGET FINDER BETWEEN RELIABILITY CONDITIONS

To examine the effects of source reliability on trust in automation, two reliability types, high (80%) and low (20%), were used in the target finder. Higher trust scores were rated as having a high reliability (HR) value greater than the low-reliability (LR) condition in the target detection system, and the comparisons are shown in Table 22.

Table 22. Trust in target finder between reliability conditions

Payload Tasks: Trust in *Target Finder* between *Reliability* conditions			
Measures	$\mathbf{F_{1,672}}$	***p*-value**	**Post hoc**
S_Performance	16.413	<.001	HR>LR
S_Process	15.329	<.001	HR>LR
S_Purpose	9.368	.002	HR>LR
Overall (average value)	19.089	<.001	HR>LR

11.7.1 Survey data: cultural effects on trust in target finder between reliability conditions

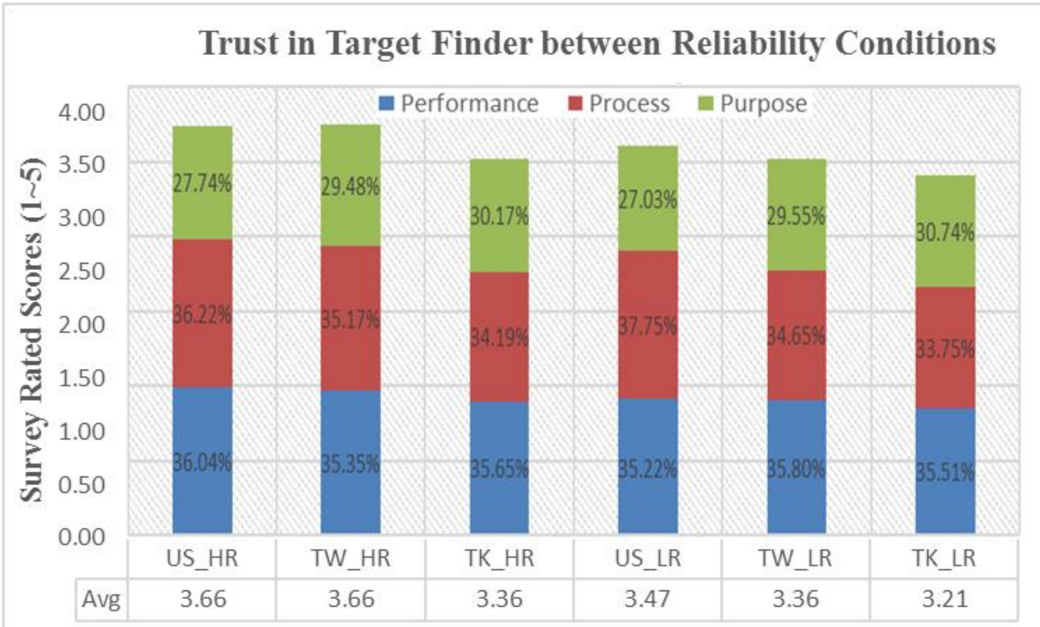


Figure 14. Average trust scores in target finder between system reliability conditions. Performance, process, and purpose constructs are represented by their proportions in each bar of the chart

Two levels of automation reliability were tested to investigate the relation between source reliability and cultural contexts (Fig. 14). The analysis revealed significant differences between the American and Turkish participants in both the HR (p=.001) and LR (p=.006) conditions, as well as a significant difference between Taiwanese and Turkish participants in the HR condition (p=.001). No statistical difference was observed between the American and Taiwanese participants. The results suggested that an increase in system reliability contributed to higher trust in autonomy. In general, participants from the American and Taiwanese cultures had similar levels of overall trust in the target finder, regardless of the reliability conditions, and Turkish participants again showed the least amount of trust in the automated aids.

11.8 SURVEY DATA: TRUST IN CONFLICT DETECTOR AMONG AUTO TRANSPARENCY

A conflict detector was designed to assist operators in identifying possible path conflicts between UAVs and to avoid hazardous areas by proposing alternative UAV paths. To determine how the system's overall transparency may affect the use of automation, three types of conflict detectors were manipulated: path re-plan (PR), highlight (HL), and path re-plan with highlight (PRHL).

The ANOVA analysis revealed a main effect for country ($F_{2,504}$=13.072, p<.001) and automation transparency ($F_{2,504}$=18.221, p<.001); however, no statistical difference was observed between workload conditions. The American and Taiwanese participants reached similar overall trust ratings in the conflict detector, and both overall ratings were significantly higher than those of the Turkish participants (US>TK, p=.002; TW>TK, p<.001).

The trust ratings of the conflict detector in different levels of automation transparency are included in Table 23, in which the highest trust was observed in the HL condition and the lowest score was found in the PR condition, with PRHL in the middle. T-tests showed that both HL and PRHL were significantly higher than the PR condition across all the comparisons. Little difference was observed between the HL and PRHL conditions in both performance and process constructs, and the effects were especially obvious in the purpose construct (HL>PRHL, p=.007).

Table 23. Trust in the conflict detector among automation transparency conditions

Navigation Tasks: Trust in ***Conflict Detector*** among ***Automation Transparency*** conditions			
Measures	**$F_{2,504}$**	***p*-value**	**Post hoc**
S_Performance	14.019	<.001	HL>PR (p<.001) PRHL>PR (p<.001) HL≈PRHL (N.S.)
S_Process	8.674	<.001	HL>PR (p<.001) PRHL>PR (p=.008) HL≈PRHL (N.S.)
S_Purpose	20.415	<.001	HL>PR (p<.001) PRHL>PR (p=.003) *HL>PRHL* (p=.007)
Overall (average value)	18.221	<.001	HL>PR (p<.001) PRHL>PR (p<.001) *HL>PRHL* (N.S.)

11.8.1 Survey data: cultural effects on trust in the conflict detector among auto transparency conditions

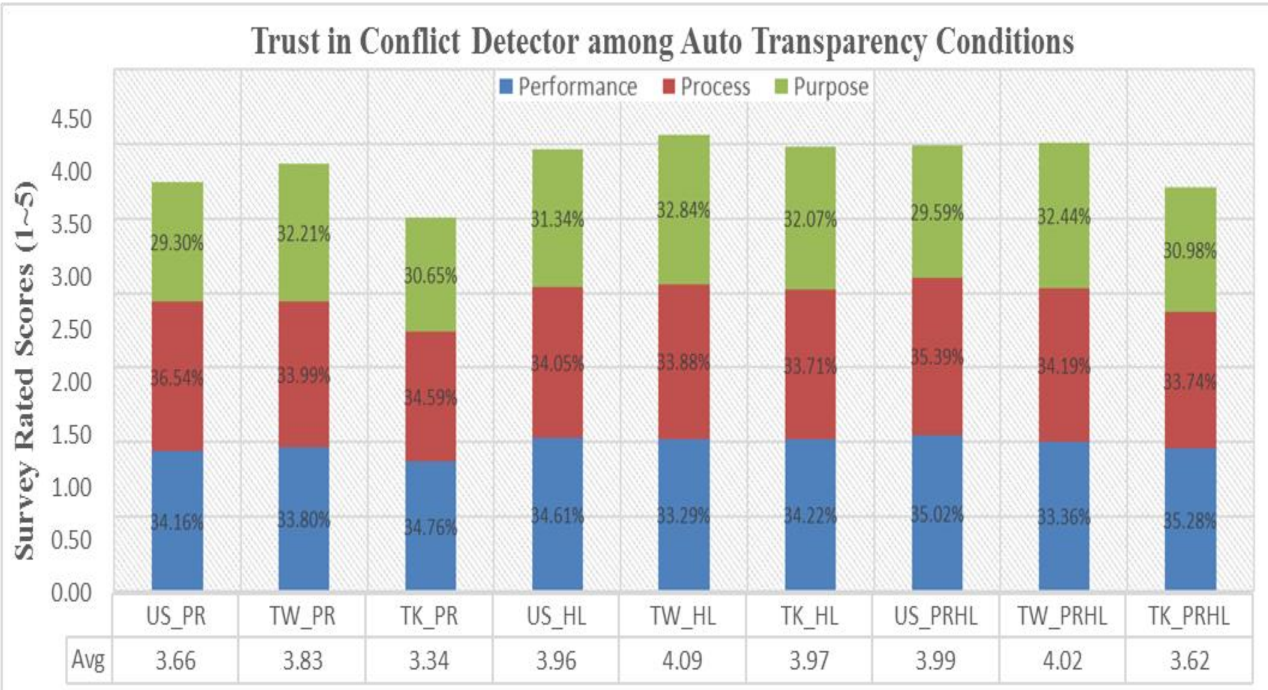


Figure 15. Average trust scores in the conflict detector between auto transparency conditions. Performance, process, and purpose constructs are represented by their proportions in each bar of the chart

Further analysis (Fig. 15) revealed significant cultural differences between the U.S. and Turkey and Taiwan and Turkey in both the PR (*p*=.064 and *p*=.001, respectively) and PRHL conditions (*p*=.002 and *p*=.001, respectively), while the trust rates in the American and Taiwanese participants were consistently higher than in the Turkish participants; however, no statistical difference was found in the HL condition between the three cultural groups.

Although similar levels of trust in the HL and PRHL conditions were found in the American and Taiwanese participants, it is worth mentioning that the trust scores between HL and

PRHL were significantly different in the Turkish participants, in which the HL was higher than PRHL (p=.002).

11.9 PERFORMANCE DATA: TARGET DETECTION IN PAYLOAD TASKS

The performance of payload tasks was examined by the number of targets detected. The ratio of target detection was computed by the number of correct target detections to the amount of engaged payload tasks. An ANOVA analysis showed that the task load ($F_{1,672}=6.084$, $p=.014$), reliability level ($F_{1,672}=14.359$, $p<.001$), and cultural factor ($F_{2,672}=21.518$, $p<.001$) significantly affected the number of hostile target detections (Fig. 16). The analysis also found a significant interaction between the task load and cultural groups ($F_{2,672}=7.128$, $p=.001$) and between the task load and reliability types ($F_{1,672}=21.335$, $p<.001$). T-tests showed revealed that American participants detected more targets than Turkish participants ($p<.001$), and Taiwanese participants detected more targets than Turkish participants ($p<.001$). No significant effect was found between American and Taiwanese participants.

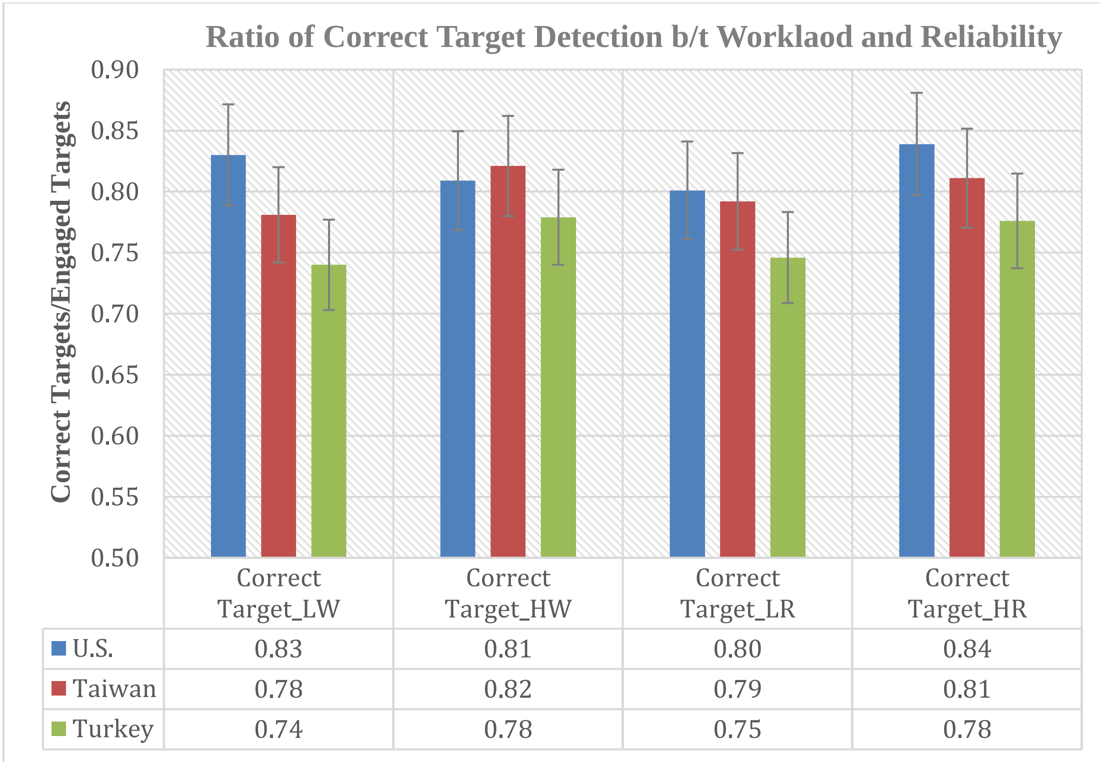


Figure 16. Ratio of correct target detection between workload and reliability conditions

To examine the effects of information uncertainty on performance in target detection tasks, the results were categorized by the level of uncertainties (Fig. 17). The analysis revealed significant cultural differences in non-alert ($F_{2,672}$=8.699, p<.001), warning ($F_{2,672}$=16.380, p<.001), and alarm ($F_{2,672}$=8.005, p<.001) conditions, as well as on the overall performance ($F_{2,672}$=21.518, p<.001).

Post-hoc results showed that American participants verified more targets than Taiwanese (p=.001) and Turkish (p=.002) participants in the non-alert group; a similar number of targets were detected by both American and Taiwanese participants in the rest of the conditions, which were significantly greater than Turkish participants in both warning (US>TK, p<.001; TW>TK, *p*<.001) and alarm (US>TK, *p*<.001, TW>TK, *p*=.011) groups, as well as overall comparisons (US>TK, *p*<.001; TW>TK, *p*<.001).

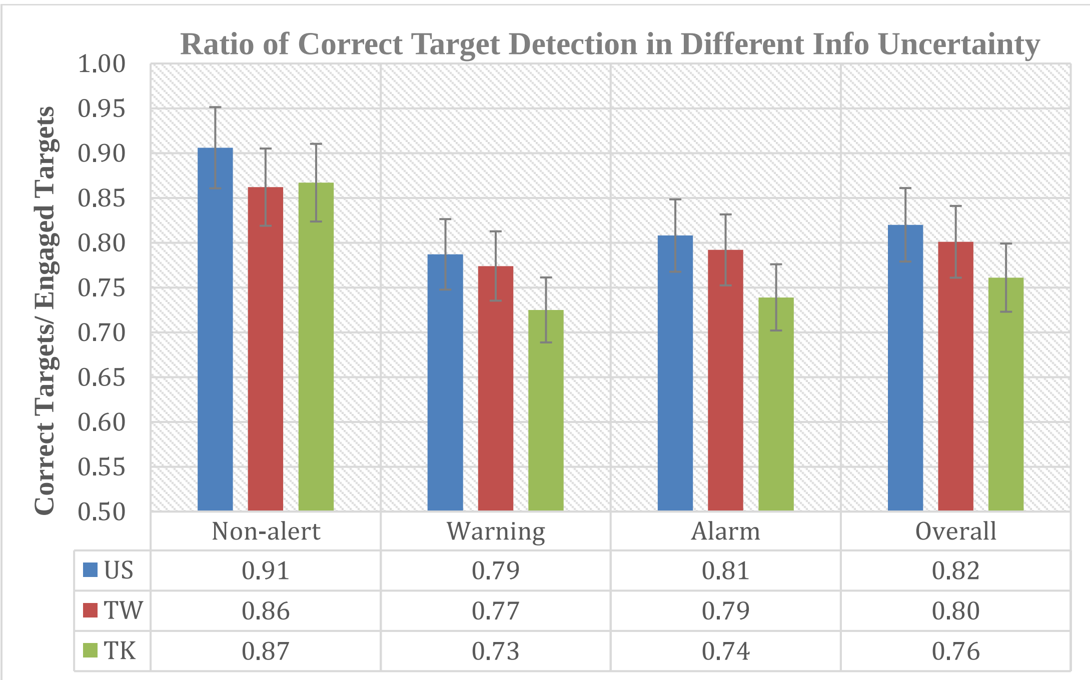


Figure 17. Ratio of correct target detection in different information uncertainty conditions

11.10 PERFORMANCE DATA: VEHICLE-VEHICLE AND VEHICLE-HAZARD DAMAGES IN NAVIGATION TASKS

Preventing UAV path conflicts and avoiding threat areas are vital to multi-UAV tasks, in which a failure to detect collisions might result from heavy task load or opaque system transparency. The

ANOVA analysis for vehicle-vehicle (V-V) damage (i.e., path conflicts) found a main effect for task loads ($F_{1,672}$=8.288, p=.004), auto transparency ($F_{3,672}$=15.925, p<.001), cultural variables ($F_{2,672}$=13.126, p<.001), and an interaction between task loads and auto transparency ($F_{3,672}$=3.214, p=.023), and is shown in Fig. 18. The results showed that an increasing task load led to a higher level of V-V damages. The lowest level of V-V damage was found in the PRHL approach, and not surprisingly, the highest level was found in the control condition, with no difference between the PR and the HL groups. Post-hoc analysis observed higher level of V-V damage with Turkish participants than with American (p<.001) and Taiwanese participants (p<.001), and no difference was found between the American and Taiwanese participants. To better measure the relationship between cultural factors and information transparency in navigation tasks, data were categorized based on their transparency types. While no difference was observed in the PRHL group, the analysis showed significant cultural differences in control ($F_{2,177}$=3.031, p=.051), PR ($F_{2,177}$=6.860, p=.001), and HL ($F_{2,177}$=4.821, p=.009) conditions in the V-V damage levels, in which significantly higher damage was found with Turkish participants than with American and Taiwanese participants in these three conditions.

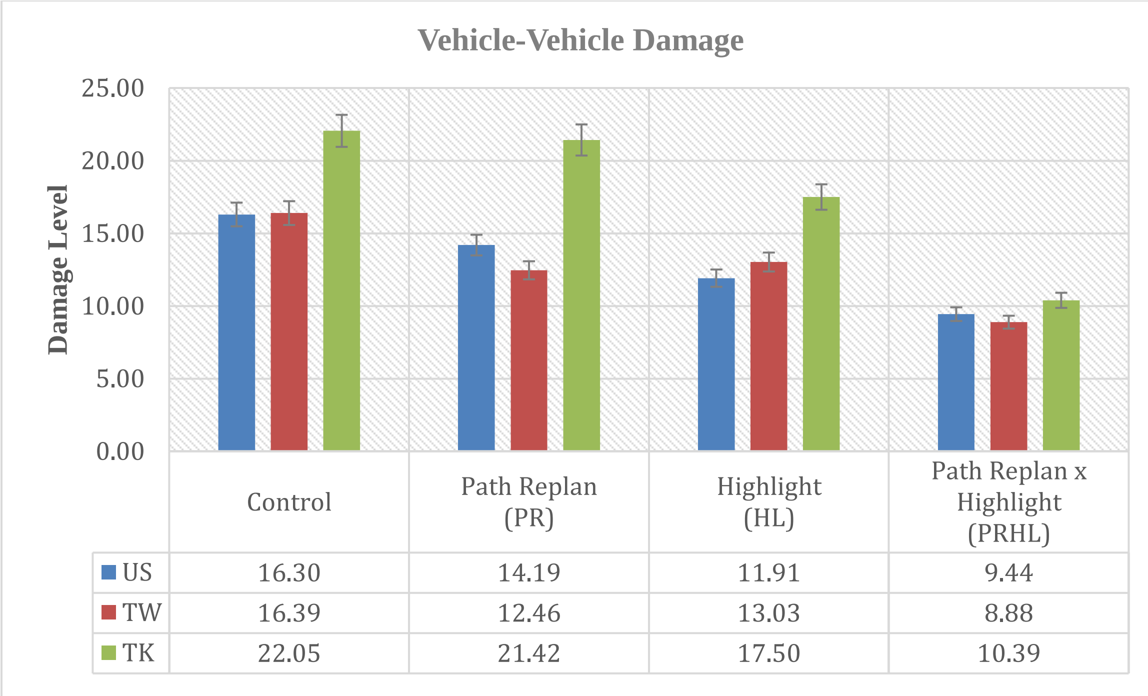


Figure 18. Vehicle-to-vehicle damage levels between auto transparency conditions

The related measure of vehicle-hazard (V-H) damage (i.e., threat areas) revealed significant differences in task load ($F_{1,672}$=21.366, *p*<.001), auto transparency ($F_{3,672}$=75.703, *p*<.001), and country ($F_{2,672}$=5.768, *p*=.003). Significant differences were also found for the interactions between task loads and system transparency ($F_{3,672}$=196.628, *p*<.001), as shown in Fig. 19. Higher levels of V-H damage were found in the LW than in the HW conditions. The lowest level of V-H damage was found in the control condition, while the highest values were found in the HL approach, with higher levels of damage in the PRHL condition than in the PR condition.

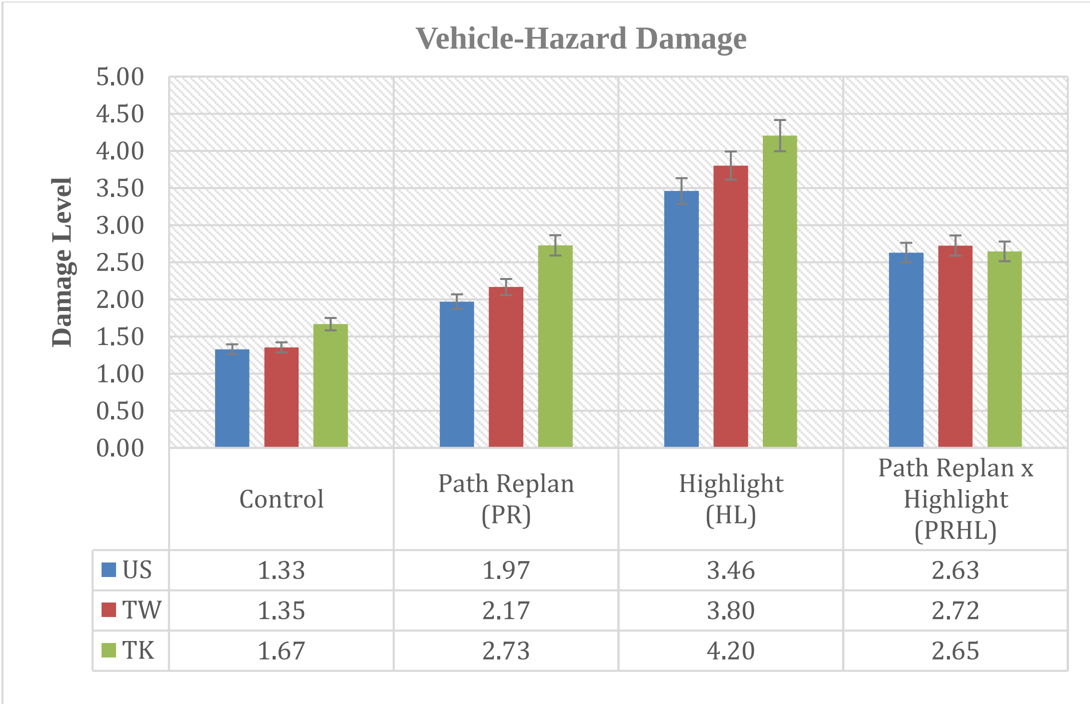


Figure 19. Levels of vehicle-to-hazard damage between auto transparency conditions

11.11 BEHAVIORAL DATA: CHECKING BEHAVIORS IN PAYLOAD TASKS

While participants enjoyed the automated assistance (target finder) in payload tasks, before accepting or rejecting the automated suggestions, the participants could verify the provided aids by selecting "check" mode to see a picture with better resolution in order to further identify the target's existence and the accuracy of the provided recommendation. The results of these checking behaviors are shown in Table 24. Post-hoc analysis found significant cultural differences between American and Turkish participants (p=.018) and between Taiwanese and Turkish participants (p<.001).

Table 24. Checking behaviors in payload tasks across experimental conditions

Checking Behaviors	F- value	*p*-value	Post-hoc
Country	$F_{2,672}$= 7.855	<.001	US≈TW (N.S.) US>TK (*p*=.018) TW>TK (*p*<.001)
Auto Transparency	$F_{3,672}$= 5.669	.001	PR>HL (*p*=.057) Control>HL (*p*=.001) Control>PRHL (*p*=.022)

11.11.1 Behavioral data: checking behaviors in payload tasks between information uncertainties

To examine the effects of operators' uncertainty avoidance, a likelihood alarm system (LAS) was used to generate three types of colored cues (Fig. 8) to provide information about the likelihood of critical events to direct operator attention to the necessary events, in which alarm conditions (a red border) had a high likelihood of indicating the target and non-alert conditions (a green border) indicated a low possibility that the target was included in the image, with warning conditions (yellow highlights) showing higher levels of uncertainty and informing the operator that the assigned target might or might not be present.

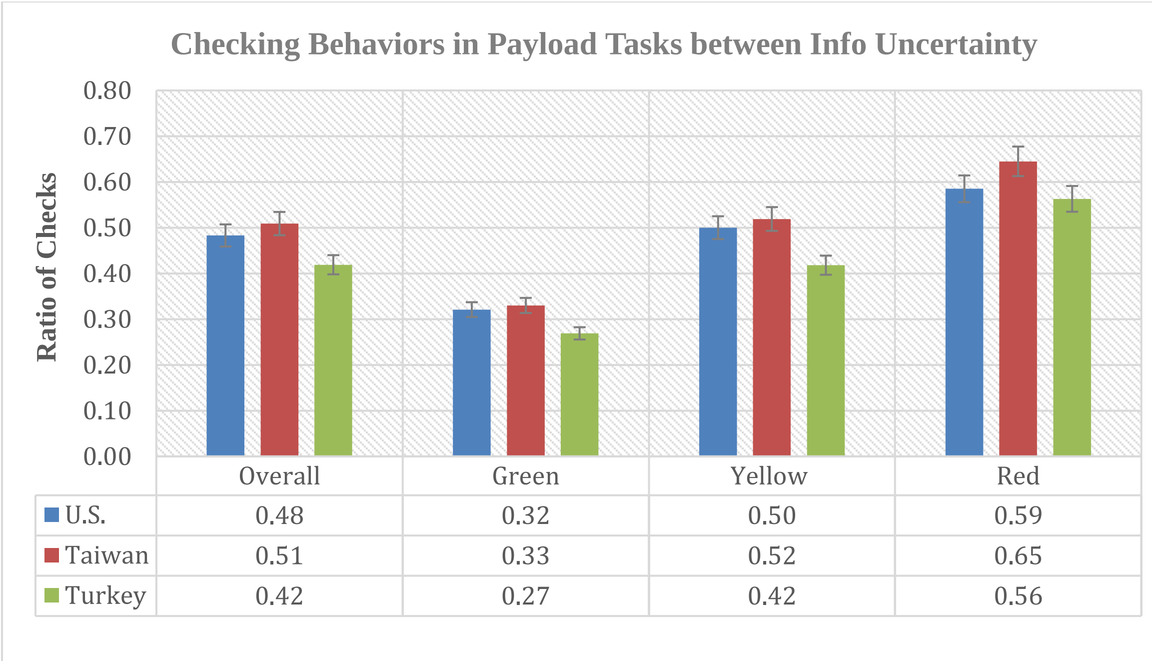
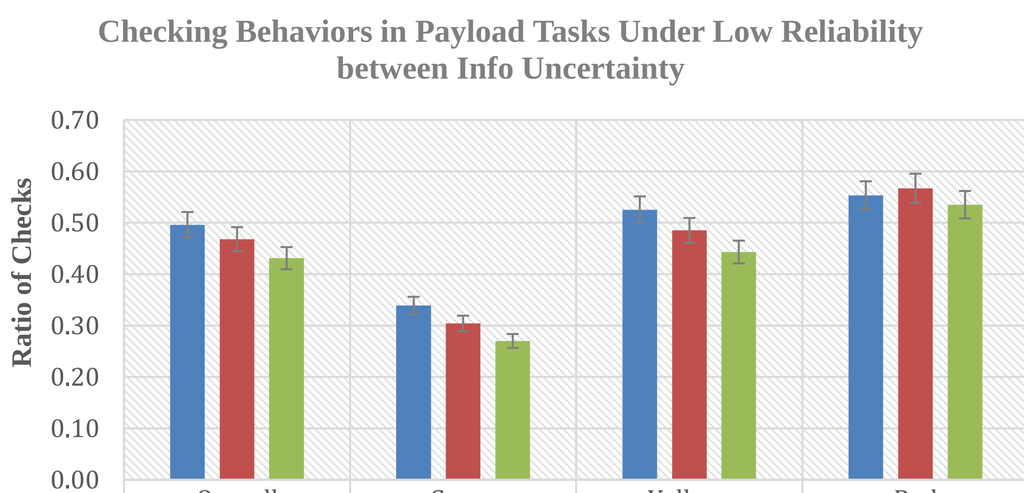


Figure 20. Checking behaviors in payload tasks between information uncertainty conditions

The ratio of checks was calculated by dividing the number of checks in each of the colored cluster by the overall amount of checks. Statistical differences were found in the overall comparison ($F_{2,672}$=7.855, p<.001), as well as in three colored cue conditions (Red: $F_{2,672}$=4.205, p=.015; Green: $F_{2,672}$=3.099, p=.046; Yellow: $F_{2,672}$=9.141, p<.001), as shown in Fig. 20. The results also indicated that the number of checks in the alarm condition (i.e., red border) were significantly higher than in the warning condition (i.e., yellow highlights), p<.001, as well as the non-alert (i.e., green highlights), p<.001, condition, and that the checking pattern in the warning situation was higher than in the non-alert (p<.001) condition. Post-hoc analysis showed that the American and Taiwanese participants had significantly higher checking behaviors than the Turkish participants in both the (yellow) warning condition (US>TK, p=.003; TW>TK, p<.001) and the overall conditions (US>TK, p=.018; TW>TK, p<.001). In addition, the Taiwanese participants had more frequently checked patterns than Turkish participants in both the non-alert (p=.065) and alarm conditions (p=.016).

11.11.2 Behavioral data: number of checks in payload tasks between reliability conditions and information uncertainty

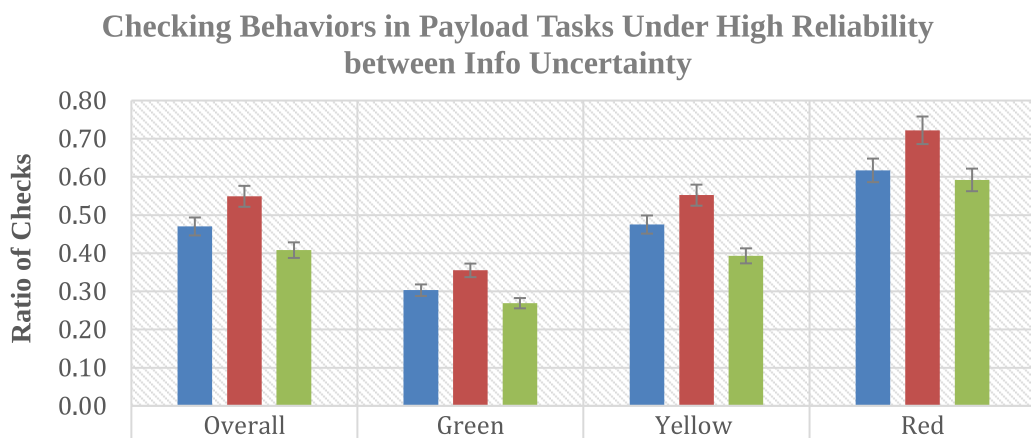
Source reliability may drastically influence operators' checking behaviors. To examine the possibility, we measured the number of checks between reliability types and the overall level of information uncertainty. In the low-reliability condition, the ANOVA analysis showed no significant cultural differences (Fig. 21); however, the T-test revealed a marginal difference between the American and Turkish cultures in the (yellow color) warning condition (p=.071).



	Overall	Green	Yellow	Red
U.S.	0.50	0.34	0.53	0.55
Taiwan	0.47	0.30	0.49	0.57
Turkey	0.43	0.27	0.44	0.54

Figure 21. Checking behaviors in payload tasks under low reliability between information uncertainty conditions

In the high-reliability condition, the ANOVA analysis (Fig. 22) showed a significant cultural effect across all the comparisons (Red: $F_{2,336}=6.224$, $p=.002$; Green: $F_{2,336}=2.627$, $p=.074$; Yellow: $F_{2,336}=10.393$, $p<.001$; Overall: $F_{2,336}=9.730$, $p<.001$). The results showed that Taiwanese participants exhibited significant higher checking patterns than those of the other two cultures (including overall checking behaviors as well as across three different levels of information uncertainty), and that the fewest checking behaviors were observed in the Turkish participants, with the American participants falling in between.



	Overall	Green	Yellow	Red
U.S.	0.47	0.30	0.48	0.62
Taiwan	0.55	0.36	0.55	0.72
Turkey	0.41	0.27	0.39	0.59

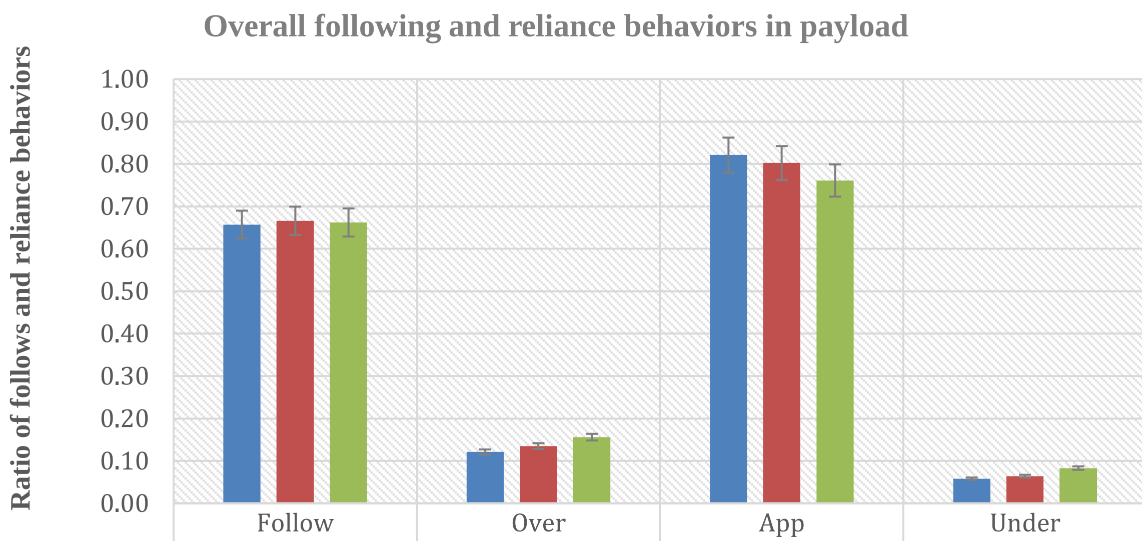
Figure 22. Checking behaviors in payload tasks between information uncertainty conditions

11.12 BEHAVIORAL DATA: RELIANCE IN PAYLOAD TASKS

Operators' reliance behaviors in payload tasks were measured by the ratio of following behaviors (namely, the number of accepted recommendations) to the total number of automated suggestions made by the target finder. The analysis revealed a main effect on the task load ($F_{1,672}=33.965$,

$p<.001$) and reliability ($F_{1,672}=2236.715$, $p<.001$), in which operators followed significantly more target aids in the LW condition than in the HW condition, as well as in the HR condition rather than in the LR conditions (Fig. 23).

Appropriate levels of reliance are critical to human-automation interaction. To measure the appropriate use of automation, the overall following behaviors were further categorized into over-reliance, appropriate reliance, and under-reliance groups. Over-reliance was defined as when the autonomy (target finder) provided a false alarm, but the operator believed that the recommendation was correct and submitted a Hit decision; whereas under-reliance was defined as an operator rejecting a correct suggestion and submitting a Safe decision. A higher ratio of appropriate reliance represented the operators appropriately calibrating their trust in automation. The results revealed substantial cultural effects on over-reliance ($F_{2,672}=11.015$, $p<.001$), appropriate reliance ($F_{2,672}=21.911$, $p<.001$), and under-reliance ($F_{2,672}=16.806$, $p<.001$) comparisons. Higher over-reliance (TK>US, $p<.001$; TK>TW, $p=.012$) and under-reliance (TK>US, $p<.001$; TK>TW, $p<.001$) behaviors were observed in Turkish participants. In addition, both the American and Taiwanese participants exhibited better levels of reliance than the Turkish participants (US>TK, $p<.001$; TW>TK, $p<.001$); however, no statistical difference was found between American and Taiwanese participants.



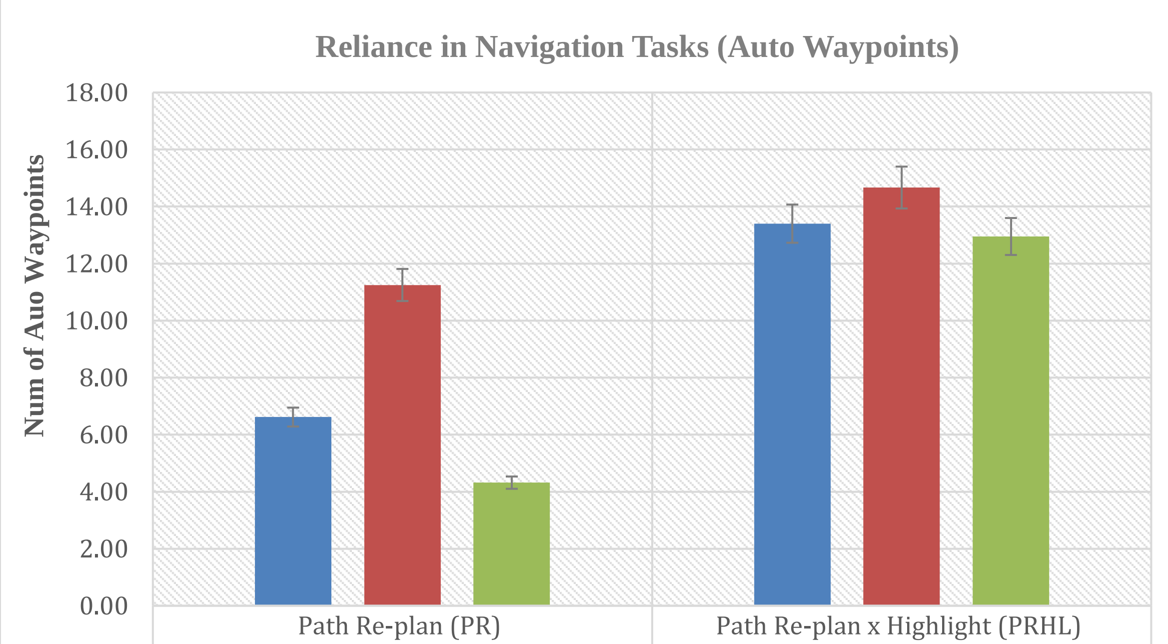
	Follow	Over	App	Under
U.S.	0.66	0.12	0.82	0.06
Taiwan	0.67	0.14	0.80	0.06
Turkey	0.66	0.16	0.76	0.08

Figure 23. Following and over-/appropriate/under-reliance behaviors in payload tasks

11.13 BEHAVIORAL DATA: RELIANCE IN NAVIGATION TASKS

An operator's reliance on navigation tasks were determined by the ratio of accepted new paths proposed by the conflict detector. Therefore, the analysis only included path re-plan (PR) and path re-plan x highlight (PRHL) conditions (Fig. 24). The results showed a main effect on the task load (HW>LW, $F_{1,336}$=4.602, p=.033), reliability (LR>HR, $F_{1,336}$=5.090, p=.025), auto transparency (PRHL>PR, $F_{1,336}$=32.384, p<.001), and country ($F_{2,336}$=5.350, p=.005). Post-hoc analysis showed that the Taiwanese participants had the highest reliance on the automated recommendations made by the conflict detector in navigation tasks (TW>US, p=.089; TW>TK, p=.004), but that no significant difference was observed between the American and Turkish participants.

Increasing information transparency may encourage operators to rely more on autonomy. Further analysis showed a cultural effect on the PR condition ($F_{2,168}$=8.109, *p*<.001) but not on the PRHL condition, in which the Taiwanese participants accepted significantly more proposed new paths in the PR approach than the American participants (*p*=.027) and the Turkish participants (*p*<.001); no difference was observed between the American and Turkish participants. In addition, the number of manual waypoints revealed that the American participants added more waypoints than Turkish participants (*p*=.094) in the PR condition, and issued higher number of manual waypoints than Taiwanese participants (*p*=.009) as well as Turkish participants (*p*<.001) in the PRHL condition.



	Path Re-plan (PR)	Path Re-plan x Highlight (PRHL)
U.S.	6.62	13.40
Taiwan	11.25	14.67
Turkey	4.32	12.95

Figure 24. Number of accepted auto waypoints in path re-plan and path re-plan x highlight conditions

11.14 BEHAVIORAL DATA: BEHAVIORS AFTER EXPERIENCING THE FIRST FAILURE IN PAYLOAD TASKS

Prior research suggested that operators may stop using automation after a failure happens. To measure this effect, we examined the resulting following and reliance behaviors in payload tasks after an operator experiences their first automation failure (Fig. 25).

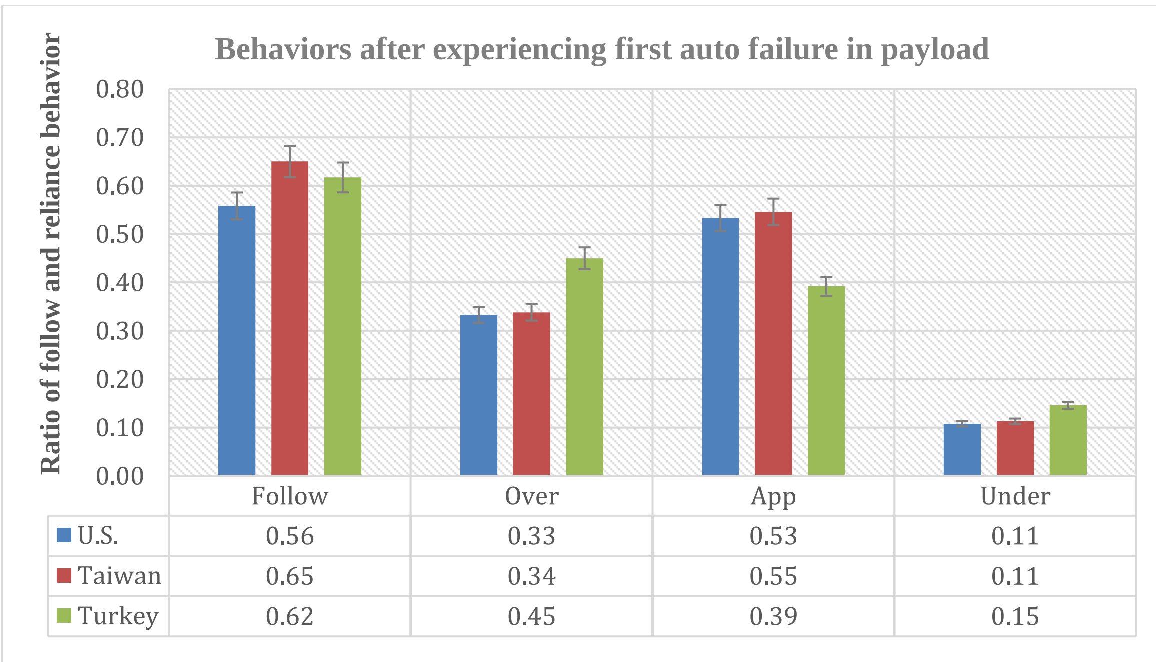


Figure 25. Following and reliance behaviors after experiencing the first auto failure in payload tasks

The ANOVA analysis found a marginal cultural effect in following behaviors ($F_{2,672}$=2.509, *p*=.082), and T-tests revealed that Taiwanese participants had significantly higher following rates than the American participants (*p*=.082) after experiencing the first failure. Significant cultural differences were observed in over-reliance ($F_{2,672}$=7.113, *p*=.001) and appropriate-reliance ($F_{2,672}$=8.359, *p*<.001), in which Turkish participants had significantly higher over-reliance (TK>US, *p*=.003; TK>TW, *p*=.004) and lower appropriate reliance (US>TK,

p=.002; TW>TK, p=.001) than the American and Taiwanese participants. However, no difference was observed in the under-reliance comparisons.

11.15 BEHAVIORAL DATA: BEHAVIORS AFTER EXPERIENCING FAILURES IN PAYLOAD TASKS

To further investigate operators' reliance on automation after automation failures, we examined the overall following and reliance behaviors in the context of the payload tasks (Fig. 26). Although no statistical cultural difference was found for the overall following rates after experiencing system failures, significant cultural effects were found in appropriate reliance ($F_{2,672}$=8.272, p<.001) and under-reliance ($F_{2,672}$=8.594, p<.001), while a marginal difference was found in over-reliance ($F_{2,672}$=2.795, p=.062). Post-hoc analysis showed that the Taiwanese participants better calibrated their reliance than American and Turkish participants after system failures (TW>US, p=.040; TW>TK, p<.001). T-tests also observed higher levels of under-reliance between the Turkish participants and the other two cultures (TK>US, p=.001; TK>TW, p=.002).

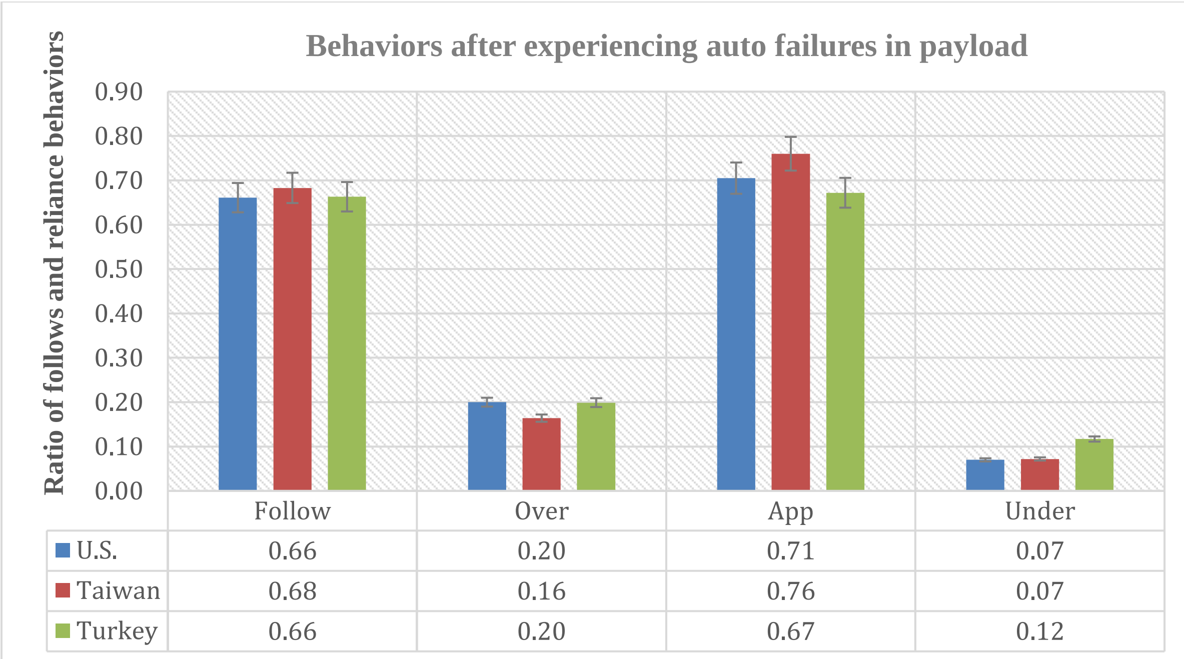


Figure 26. Following and reliance behaviors after experiencing auto failures in payload tasks

12.0 DISCUSSION

The present study investigated the impact of cultural factors and personality traits on trust in automation, in which theoretically guided experiments were conducted in the U.S., Taiwan and Turkey, and 120 student participants were recruited in each of the countries (in total, 360 responses were collected). Participants' trust attitudes were measured by our developed cultural trust instrument (CTI), personality traits were categorized by big five inventory (BFI), cultural values were identified by CVSCALE, and the resulting reliance was examined through operators' interactive behaviors in RESCHU, a multi-UAV air traffic control system, under various experimental tasks and scenarios.

12.1 GENERAL TRUST

According to cultural syndromes, an individual from a dignity culture (e.g., America) has a higher level of general trust, whereas an individual from an honor culture (e.g., Turkey) has a lower level of initial trust. Our first hypothesis assumed that *individuals from dignity cultures are more likely to have higher levels of initial trust in automation than those from both honor and face cultures*. These cultural effects were confirmed, in which Turkish participants had the lowest trust scores in general attitude toward automation and the American participants had the highest initial trust scores in their general attitude toward automation, with those participants from a face culture (namely, Taiwan) in between. The findings revealed that American participants had the strongest faith in automated systems optimizing outcomes, whereas Turkish participants held opposite views on the use of automation. Interestingly, it was observed that Taiwanese participants had the highest trust ratings in the performance factor, but the lowest ratings in the task context construct. This showed that an individual from a face culture may believe that automation can significantly increase task performance, but that automation might be unable to satisfy all needs in a variety of diverse situations.

12.2 EFFECTS OF PERSONALITY TRAITS AND CVSCALE

Evaluations of the inter-relational aspects of personality and general trust showed that an individual with high trait of extraversion, agreeableness, or conscientiousness had increased trust in automation, whereas an increased trait of neuroticism lessened the initial trust ratings.

CVSCALE was used to measure the cultural values along Hofstede's cultural dimensions at the individual level. The mismatch between Hofstede's original data and our collected data may be due to differences in an individual's background, including age, education, and gender differences (Chien, Semnani-azad, Lewis, & Sycara, 2014).

Since automation is increasingly being used in all aspects of our daily life (e.g., smartphones), this finding could significantly change beliefs about the use of automation. The correlation analysis suggested that an individual will tend to rely on automated assistance when uncertainty is increased, especially in American populations (Table 17, UA in the American participants). As predicted by the cultural syndromes theory, as IDV increased, so did an initial willingness to trust in automation (Table 17, IDV in the American participants).

12.3 EFFECTS OF TASK LOAD

Increasing task load demanded more cognitive resources and required the operators to allocate more attention to the navigation tasks, which led to fewer resources being available for payload tasks. Although increases in UAV travelling speeds directly affected operators' perceived workload in navigation tasks, the checking patterns in payload tasks were not influenced by the differences in task load conditions (as shown in results section 11.11). In other words, the *ratio* of checking behaviors remained the same between the HW and LW groups. Interestingly, the task load conditions had little effect on the level of trust in the conflict detector, but largely influenced the level of trust in the target detector, in which higher trust ratings in the target finder was found in the high task load group. Research (Hoff & Bashir, 2015) concluded that (sub)tasks can be influential, but that the effects largely depended on the degree of interference with the task demand. For example, Phillips and Madhavan (2011) found the subtasks actually increased trust in automated applications, whereas Lees and Lee (2007) concluded that the distracted variable caused few effects on trust in their collision warning system.

This indirect relationship could have resulted because little attention was reserved for the aided suggestions from the target finder, which may have caused the operators to fail to scrutinize the correctness of automation estimations. However, as a similar checking ratio was observed in both task load conditions, this was not the case for our data. While increased UAV travelling speeds led to a higher number of target engagements as well as checking behaviors, the additional interaction time that is required may facilitate human-automation collaboration processes and contribute to better trust in automation. Since more enemy targets were found in the HW condition, another potential cause for the higher degree of trust in heavy task-load scenarios could be explained by the positive feedback. Research concludes that feedback greatly altered the level of trust in intelligent systems (Hancock et al., 2011). The testbed system RESCHU indicated the accumulated feedback from interaction, which provides an opportunity for the operators to improve system performance, as well as calibrate trust. As an increased number of targets are detected in HW, the provided feedback might greatly enhance an operator's trust in automated aids.

With respect to the task load differences, we hypothesized that *(Hypothesis-12) operators will accept more automated recommendations or exhibit fewer checking behaviors on automation while perceiving high workload conditions*. These effects have been partially confirmed, in which increased task load contributed a higher reliance to the navigation tasks (as shown in results section 11.13), but indicated a reversed result for the payload tasks (as shown in results section 11.12). In other words, operators had strong reliance in the target finder in low task-load situations. Both the American and Taiwanese participants had higher trust ratings in the target finder than Turkish participants, regardless of workload conditions (as shown in results section 11.6). In addition, both Taiwanese and Turkish participants had higher levels of trust in the target finder in HW than in LW conditions, but this effect was not observed in American participants. Recent studies suggested that face (e.g., Taiwan) and honor (e.g., Turkey) cultures are closely related, which may provide an explanation for the non-significant difference (Aslani et al., 2013; Aslani et al., 2016). Another potential reason may result from an insufficient amount of increased task load. Since participants from dignity cultures achieved the best performance on both payload and navigation tasks, the assigned task load conditions may fail to adequately increase the workload for the American participants. Therefore, the changes to UAV speed failed to exert similar influences on participants from dignity cultures, which led to little difference in the trust ratings between task load conditions.

12.4 EFFECTS OF SOURCE RELIABILITY

With increased reliability, as expected, participants verified more hostile targets, as well as rated higher trust scores in the automated aids (target finder), which suggests that the operators were able to differentiate changes in the source reliability conditions. With respect to cultural differences (as shown in results section 11.7), both American and Taiwanese participants reached similar levels of overall trust in the target finder in both high reliability (HR) and low reliability (LR) conditions, and the scores were much higher than those of Turkish participants across reliability conditions. Therefore, our hypothesis, *(Hypothesis-3) honor culture operators will take longer interaction times than operators from dignity and face cultures to develop equal degrees of trust*, was confirmed.

As in *(Hypothesis-7) the trust of face culture operators will be relatively more influenced by information about the purpose of automation than honor or dignity culture operators*, the differences in system reliability may greatly affect the operators' perceived purpose of automation. However, this hypothesis was not supported, in which increased source reliability failed to strengthen the Taiwanese participants' trust attitudes in the designed purpose of automation, rather than the other two cultures.

To validate the aided suggestions in payload tasks, participants were able to check the pictures before accepting or rejecting the recommendations, in which the checking patterns could fluctuate according to the source reliability. The most frequent checking pattern was observed in the alarm condition and the lowest was in the non-alert condition, with the warning condition in between, which suggests that information uncertainty greatly affected operators' reliance and resultant checking behaviors (as shown in results section 11.11). American and Taiwanese participants had higher checking patterns than the Turkish participants, including the results of overall checks, as well as in the warning conditions. Although the results showed little difference on the number of checks between reliability types, distinguishable cultural effects were found in the frequency of checking behaviors, in which American and Taiwanese participants were more inclined to verify the pictures than Turkish participants. This finding partially confirmed *Hypothesis-13, honor and face culture operators will exhibit more vigilance and more monitoring behavior than operators from dignity cultures*. The results revealed that participants from dignity (U.S.) and face (Taiwan) cultures were more vigilant and had higher monitoring behaviors.

The observed checking patterns represented operators' reliance on automation. American operators detected an identical number of targets to Taiwanese operators with fewer checks, which indicates that a higher number of checks might not necessarily guarantee better performance in payload tasks. The results (as shown in section 11.12) also revealed that American participants were significantly better in calibrating their trust in the target finder than participants from the other two cultures, whereas higher over-reliance and under-reliance behaviors were found in Turkish participants rather than in American and Taiwanese participants. Based on the results of trust ratings and checking patterns, as compared with Turkish participants, American and Taiwanese participants had higher levels of trust and a higher number of checks, which indicated a positive relationship between these two factors, as a higher number of checks contributes to a greater level of trust in automated assistance. The findings revealed that participants developed trust in the provided automation through the checking processes, which suggested that the motivation behind the checks was users' suspicions of the aided recommendations, rather than an inherent distrust of the autonomy itself.

As the effects of trust were observed, humans either switched away from autonomy or ignored the aids when reliability dropped (Desai et al., 2012). While experiencing a payload task failure, either from accepting an incorrect suggestion (over-reliance) or rejecting a correct aid (under-reliance), Taiwanese participants tended to follow the next recommendations after the first failure, while American participants had the lowest tendencies to accept the following suggestions; however, no statistical difference was observed between Taiwanese and Turkish participants or American and Turkish participants. This finding confirms *Hypothesis-8, unreliable automation will lower ratings of trust of operators from all cultures (both low- and high-PD) operators, but face culture operators will be more likely to continue relying on automation*, and partially confirms *Hypothesis-6, face culture operators will recover their trust in automation after failure more quickly than honor and dignity culture operators*. Honor culture operators were generally slowest in recovering trust. The results concluded that participants from face cultures relied on the automated suggestions when they first encountered a payload task failure; in contrast, operators from dignity cultures followed their own decisions and went against the aided information. Due to little experience with faulty automation, as well as placing a low value on individualism, the (resulting) insufficient self-confidence guided face culture operators to follow the provided aided information, instead of their own decisions. However, the difference found between Taiwanese and Turkish cultures was not significant.

However, as a consequence of exposure to faulty automation, after gaining a fair amount of experience on the unreliable automated system by committing payload task failures, operators' overall restored reliance showed little difference among the three cultures (as shown in results section 11.15). The first assumption of *Hypothesis-5, honor operators will either disuse or take longer to regain trust after a failure occurs and may not recover trust to the original* *level (miscalibrate), as compared with face and dignity operators*. *The dynamic relation between use and trust may magnify these effects*, was denied, in which the regaining trust patterns showed negligible differences between these three cultures. However, a mixed phenomenon between trust attitude and the use of automation was observed in Turkish participants, in which the level of trust attitude failed to influence the reliance behaviors. This finding confirmed part of *Hypothesis-5, the dynamic relation between use and trust may magnify these effects*.

12.5 EFFECTS OF AUTOMATION TRANSPARENCY

Research shows that information transparency greatly affected perceived difficulty in autonomy, while increasing system transparency contributed to better trust in automation (Lyons et al., 2016; Martelaro et al., 2016). Three types of conflict detectors were designed in our study to support operators in identifying UAV path conflicts and avoiding threat areas. The path re-plan (PR) condition, which proposed alternative paths with little SA, had the lowest trust scores, while the highlight (HL) approach, which highlighted possible collisions on the map and required the operators to manually add waypoints to solve hazardous situations, was rated as having the highest level of trust, with the integrated method of path re-plan with highlight (PRHL) reaching the middle level of trust. These results (as shown in section 11.8) greatly suggested that increased automation transparency contributed to higher levels of trust in autonomy.

With respect to system transparency, there should be little difference between the HL and PRHL conditions. Trust ratings showed non-significant differences in these two conditions for American and Taiwanese operators; however, Turkish participants had higher levels of trust in the HL than in the PRHL condition. As the HL method included the human-automation shared control mechanism, this type of interaction allowed operators to have a longer interaction time to facilitate human-machine collaboration. Since participants from honor cultures generally have lower levels of trust and require better knowledge of automation to develop trust, the shared control interaction was especially beneficial to the participants from honor cultures. This finding confirmed *Hypothesis-11, Honor operators will require greater support of trust from knowledge of process and/or purpose than dignity and face cultures, and will be prone to disuse.* In addition, the American and Taiwanese participants had similar levels of trust in the PR and PRHL conditions, which were higher than those of the Turkish participants; however, no difference was observed in the HL conditions across all participants. The results concluded that allowing both operators and automation to play an active role and share responsibility for the tasks could not only effectively enhance human trust, but could also reduce the cultural differences in reliance behaviors.

The lowest level of vehicle-vehicle (V-V) damage was found in the PRHL approach (as shown in section 11.10), and not surprisingly, the highest was found in the control condition, with little difference between the PR and HL groups. If an operator strictly followed the proposed new paths and applied them to the UAVs, there should be negligible variance between the PR and PRHL conditions and they should, at least, should outperform the HL condition, which provided no suggestions for new paths. However, the performance disparity again emphasized the importance of automation transparency, which led to profound effects on operators' reliance behaviors.

A higher reliance on the conflict detector (i.e., an operator accepted more proposed new paths) was observed in the PRHL condition, rather than in the PR condition (as shown in section

11.13). The results suggest that the American and Turkish participants were less likely to comply with automation when little SA was available. With limited information about automation, Taiwanese PR participants had higher reliance than either the American or Turkish participants. This confirms *Hypothesis-9, Face culture operators will trust and exhibit automation bias and accept recommendations even if their basis is not well understood, while dignity and honor culture operators will be less likely to trust or accept recommendations on this basis.* However, the cultural effect was not found in the PRHL group, which leads to an opposite view on *Hypothesis-10, Dignity and honor culture operators will be less likely to comply with high LOA than face culture operators, who, as a result, will be more likely to exhibit complacency and automation bias. There will be no difference in the use of low LOA*. The results of trust ratings and reliance patterns showed that the Taiwanese participants had the highest reliance behaviors, with similar trust scores as American participants. This joint finding confirmed *Hypothesis-2, if using automation was encouraged by the user's organization, face culture operators will have higher ratings of trust and reliance than those from honor and dignity cultures*.

Prior studies suggested that when self-confidence was higher than trust in automation, manual commands would be used to control the system (Moray et al., 2000). Although a similar amount of proposed new paths was adopted across three cultures in the PRHL condition, the number of manual waypoints in the navigation tasks revealed that American participants issued more waypoints than the participants from the other two cultures. The result partially confirmed *Hypothesis-4, operators from dignity and honor cultures will be more self-confident and therefore are less likely to rely on or ignore the automation than face culture operators*. Operators from dignity cultures exhibited more self-confidence (as shown by a higher number of manual waypoints) than those from face and honor cultures; however, the reliance on automation remained the same across three cultures, rather than ignoring the recommended paths.

13.0 CONCLUSIONS

Trust is conceived as an intervening variable between user intention and actions that involve reliance on automation. To improve human-automation interaction, there is a need to study factors that would aid in determining how users from different cultures will adopt and use technology. The overall goal of this research is to study both theoretically and empirically the effect of cultural and individual contexts on trust antecedents, trust establishment, trust dissolution after the occurrence of faults, and trust restoration in human interaction with automation. To examine how trust mediates human-automation relationships across cultures, we developed a cross-cultural trust instrument to examine trust factors as well as its antecedents, and conducted theoretically guided large sample empirical studies in the U.S., Taiwan, and Turkey to identify the influence of cultural dynamics in various aspects of trust in automation.

This work provides several significant contributions. First, the developed trust sensitivity task, which incorporates a variety of task types and scenarios identified from the review of trust in automation literature, allows researchers to effectively examine the variances of trust in automation and determine whether these effects are universal or specific to a specific culture. Second, the developed instrument provides a reliable measure to examine trust in automation across cultures. Third, the studies (cultural trust instrument) investigated not only the effect of system performance, as with most studies in the literature on trust in automation, but also the process and task context. Fourth, this is the first set of studies that examine cultural factors based on the characteristics of the three major cultural syndromes, along with Hofstede's cultural dimensions. Fifth, to the best of our knowledge, our experiments are the first to study the dynamics of trust in automation across cultures. These contributions provide critical implications and insights for enhancing human trust in intelligent automation systems across cultures.

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APPENDIX A: STUDIES RELATED TO TRUST IN AUTOMATION

System-related factors: source reliability				
Study	**Trust Constructs**	**Purpose**	**Method**	**Finding**
(Visser & Parasuraman, 2011). Adaptive aiding of human-robot teaming effects of imperfect automation on performance, trust, and workload.	Self-confidence	Examined the effects of system reliability and adaptive automation on human-robot performance with different levels of task load	Participants performed target verification tasks with an aided target recognition system at various levels of reliability or different types of automation (static or adaptive). Adaptive automation was invoked in the context of the mission, rather than on users' performance.	Higher trust and self-confidence ratings were found in adaptive automation, rather than in the conventional static automation approaches.
(Chen et al., 2011). Effects of unreliable automation and individual differences on supervisory control of multiple ground robots.	Reliance Deceptive	Examined the effects of unreliable automation types and levels (60% or 90%) on the performance of robotics operators	Participants detected target appearances and planned new paths to avoid hostile areas. An imperfect automated path planner was used to recommend route revisions for the robots.	Higher trust was rated in the false alarm than in the miss-prone conditions. Participants also perceived the false alarm conditions to be more deceptive than the miss-prone conditions. Less reliance was rated in the low reliability condition.
(Desai et al., 2012). Effects of changing reliability on trust of robot systems.	Distrust Regain trust	Examined how changes in autonomy reliability affect trust and use of automation	Participants drove a robot to search for victims and were asked to freely choose one of two provided robot autonomy scenarios: either the robot	The timing of reliability drops result in different trusting behaviors, especially when decreases in reliability occurred in the middle of or

			ignored a user's inputs and followed the predesigned paths, or the participants could control and overwrite the robot's movements. Timing of automation failures was manipulated.	later on in the tasks. Operators switched away from autonomy (distrust) during a reliability drop much faster than returning to autonomy (regain trust) after a reliability increase.
(Salem, Lakatos, Amirabdollahian, & Dautenhahn, 2015). Would You Trust a (Faulty) Robot? Effects of Error, Task Type and Personality on Human-Robot Cooperation and Trust	Reliance Compliance	Examined how the faulty robot behaviors influenced human choices and willingness to cooperate with the robot by following its unusual requests.	Participants received requests from the robot and decided whether to perform the requested tasks. Two types of robot reliability (correct or faulty) were applied to execute user responses. The robot also sent unusual requests to the operators to examine user trust in automation.	Faulty automation affected operators' perception of system reliability and trustworthiness; however, compliance with the robot's faulty requests depended on the cause of lasting damage by doing so.
System-related factors: automation faults (false-alarm prone vs. miss-prone)				
(Dixon & Wickens, 2006). Automation reliability in unmanned aerial vehicle control: A reliance-compliance model of automation dependence in high workload	Compliance Reliance	Examined the effects of automation false alarms and miss prones, as related to human compliance and reliance, respectively	Imperfect auditory auto-alerts were provided for possible system failures. Participants were instructed to cross-checking with the raw data, in order to skip the warning (false alarm) or catch the failure (miss prone).	Compliance and reliance were independent of each other, in which compliance was affected by false alarms, while reliance was influenced by miss prones.
(Dixon et al., 2007). On the Independence of Compliance and Reliance: Are Automation False Alarms Worse Than Misses	Compliance Reliance	Examined the influence of automation failures on operator compliance and reliance in order to clarify the independence between these two factors.	Participants were asked to monitor system failures with unreliable automated aids (false alarms or misses). Regardless of whether a failure actually occurred or was detected, participants were allowed to make only one un-retractable response during each trial.	False alarms correlated with operator compliance and reliance, whereas miss prones appeared to affect reliance only.

(Chen, 2009). Concurrent Performance of Military Tasks and Robotics Tasks: Effects of Automation Unreliability and Individual Differences	Self-confidence Reliance	Examined how an unreliable target recognition system (false alarms or misses) affected operators' perceived workload and performance on the automated and concurrent tasks.	Participants performed hostile target detection tasks, as well as robotic control tasks. An unreliable aided target recognition system was used to assist operators in locating targets.	Self-confidence is a critical factor in moderating trust in and reliance on automation. The relation between self-confidence and reliance is also affected by an operator's ability in attentional control.
(Rovira & Parasuraman, 2010). Transitioning to Future Air Traffic Management: Effects of Imperfect Automation on Controller Attention and Performance.	Self-confidence	Examined the influences of imperfect automation (false alarm vs. miss) on operator performance and attention allocation.	Participants were instructed to perform air traffic control tasks with an automated conflict probe tool on four different levels (manual, reliable automation, miss, and false alarm).	Operators reported higher self-confidence in performing the tasks without the automation when they were supported with unreliable automation, as compared to reliable automation.
(Bahner, Hüper, & Manzey, 2008). Misuse of automated decision aids: Complacency, automation bias and the impact of training experience.	Complacency Automation Bias	Examined automation misuse with regard to complacency and automation bias in interacting with decision automation.	Operators were asked to supervisory control a process control system. An automated diagnosis system was provided to alert for possible system faults. Operators may access all relevant information about the state of the systems to verify fault diagnoses.	Commission errors were associated with inappropriate level of complacency, which reflected in insufficient verifications of the proposed decisions. Exposing participants to automation failures during training session effectively decreased their complacency
System-related factors: automation transparency				
Study	**Trust Constructs**	**Purpose**	**Method**	**Finding**
(Manzey et al., 2008). Performance consequences of automated aids in supervisory control: The impact of function allocation.	Reliance	Examined the positive and negative performance consequences in the use of automated decision aids.	Participants were instructed to operate a life-support system, including monitoring various system parameters and fixing system faults, if any. An automated detection system was used to diagnose system faults and provide solutions, in which the operators can	The number of system parameters accessed did not necessarily contribute to the commission of errors. Instead of a complete lack of verification, the brevity of attention allocation in cross-checking behaviors may be the cause of commission errors.

			veto proposed recommendations after checking the relevant system variables.	
(Martelaro et al., 2016). Designing HRI to Encourage More Trust, Disclosure, and Companionship	Vulnerability Expressivity	Examined the effect of increased agent transparency (expressivity and vulnerability of a robot) on trust in intelligent agents.	Participants were guided by a robot through a circuit-building task. The robot's vulnerability and expressivity were manipulated, in which operators perceived that different content came from the robot during the assisting processes.	Vulnerability was associated with higher trust and companionship, whereas expressivity increased disclosure.
(Wang et al., 2016). Trust Calibration within a Human-Robot Team: Comparing Automatically Generated Explanations	Compliance	Examined how different automatically generated system explanations impact on trust (with probability, no probability, and no explanation).	Participants received reports from robots and then decided whether to trust the findings (safe vs. dangerous). Three types of information uncertainty were provided (explanation containing a probabilistic assessment; explanation with non-numeric information about the report; or no explanation).	Higher trust was found in a system that provided more explanations (both probabilistic and non-numeric information). However, compliance was not affected by the explanation.
(Lyons et al., 2016). Engineering Trust in Complex Automated Systems	Reliance	Examined how information transparency affected the use of automated recommendations.	Participants performed path-planning tasks with the aids from different types of automated planners. Three levels of automation transparency were provided (control, probability of success, and logic behind the statement).	The highest trust was found in the logic condition (providing the logic behind the risk statements) and the lowest was found in the control condition, which suggested that automated recommendations should be accompanied by the logic form.
System-related factors: level of automation (decision aids)				
Study	**Trust Constructs**	**Purpose**	**Method**	**Finding**

(Rovira et al., 2007). Effects of imperfect automation on decision making in a simulated command and control task	Reliance Distrust	Examined the relation between unreliable automation and different types of decision support systems	Participants were instructed to perform enemy-friendly engagement selection tasks. To identify the most dangerous enemy targets, varieties of decision automations with different prioritizing mechanisms were used.	Highly reliable yet imperfect automation led to greater detrimental effects when failures happened. Prioritizing tasks in decision automation effectively increased the operators' levels of trust; however, the variance of automation reliability did not affect their trust ratings.
(Merritt & Ilgen, 2008). Not all trust is created equal: Dispositional and history-based trust in human-automation interactions	Competence Responsibility Dependability	Examined the effects of individual differences between the examination of trust and automation use.	Participants were instructed to visually search for weapons in X-ray images of luggage with the aid of an automatic weapon detector that provided recommendations.	When the machine characteristics (competence, responsibility, predictability, and dependability) were high, participants with a high propensity to trust had higher levels of post-task trust than participants with initial trust; in contrast, when the machine functioned less well, the relationship was reversed, in which high initial trust participants rated lower post-task levels of trust than the high initial trust group.
(Miller & Perkins, 2010). Development of metrics for trust in automation.	Competence Dependability Consistency Confidence	Developed a five-factor metric (competence, predictability, dependability, consistency, and confidence) to model trust in an automated decision system.	Participants performed path-planning tasks. The operators had to choose either to adopt the automated suggested route, or to create a manual path under time constraint and different risk conditions.	Competence, predictability, dependability, consistency, and confidence factors were all highly correlated to human trust in automation.
(Lyons & Stokes, 2012). Human-human reliance in the context of automation	Reliance Automation Bias	Examined the reliance on conflicting information sources between human aids and automated tools.	Participants were instructed to choose the safest route for convoy tasks under different risk conditions. Two types of decision-making tools (human aids vs. automated planner) were included, and the levels of conflict information (low to high) between the two sources were manipulated.	Automation bias was observed, in which lower reliance was placed on human aids when receiving conflicting information between human and automated aids. Automation bias was increased as risk increased (i.e., higher reliance was found on automation than human aids in higher risk conditions).

(Phillips & Madhavan, 2013). The role of affective valence and task uncertainty in human-automation interaction	Confidence Mood	Examined the interaction between information uncertainty, received mood, and aided target detector in terms of impact on confidence and trust in automation.	Participants received and rated positive or negative pictures before the visual search tasks. An imperfect automated target detector was used to indicate the foe's presence or absence.	Participants with a positive mood were more susceptible to the automated suggestions, and were more confident than those with a negative mood when using the automation.

APPENDIX B: TRUST INSTRUMENT DEVELOPMENT: ROOT CONSTRUCTS AND DEFINITIONS

Empirically Derived (ED)	**Constructs**	**Definitions**
ED incorporates a three-phase experiment, comprised of a word elicitation study, a questionnaire study, and a paired comparison study; and was performed to empirically develop a scale to measure trust between people and automated systems. Twelve items falling into two factors (trust and distrust), are incorporated in the instrument. All the items are selected for our test.	Trust	The *trust* factor comprises seven main items: confidence, security, integrity, dependability, reliability, trust, and familiarity.
	Distrust	The *distrust* factor comprises five main items: deceptiveness, underhandedness, suspiciousness, wariness, and harm.

Human-Computer Trust (HCT)	**Constructs**	**Definitions***
HCT scale is designed to examine trust in intelligence systems (a taxi dispatch system was used in their study). HCT instrument comprises 25 items (five constructs, each with five items to reflect the concept). All the items are adapted to our test. *All definitions are from (Madsen & Gregor, 2000).	Perceived Reliability	"Reliability of the system, in the usual sense of repeated, consistent functioning."
	Perceived Technical Competence	"A system is perceived to perform tasks accurately and correctly based on the information that is input."
	Perceived Understandability	"A human supervisor or observer can form a mental model and predict future system behavior."
	Faith	"A user has faith in the future ability of the system to perform even in situations in which it is untried."

	Personal Attachment	"A user finds using a system agreeable and it suits her taste."
SHAPE Automation Trust Index (SATI)	**Constructs**	**Definitions***
SATI measures human trust in automated systems in controlling air traffic management tasks. The scale measures controller's trust twice, pre- and post-adoption use, in order to obtain human feedback and sensitively examine any fluctuations in trust. The first part comprises four questions and the second part consists of eight sections. Sixteen items within seven constructs were chosen for inclusion in the test. *All definitions are from (Goillau & Kelly, 2003).	Reliability	"The extent to which you can rely on the machine to consistently support the tasks."
	Accuracy	"Accuracy of machine in supporting successful completion of tasks."
	Understanding	"The extent to which the machines' decision on when and how to intervene and support the task requires assessment, knowledge, and understanding of the task."
	Faith	"The extent to which you believe that the machine will be able to intervene and support the tasks in other system states in the future."
	Liking	"The extent to which you can anticipate and expect the machine to support the tasks."
	Familiarity	"The extent to which you have confidence in the machines' decision on when and how to intervene and support the task."
	Robustness	"The extent to which you can count on the machine to provide the appropriate support to the tasks."

Culture-Technology Fit (CTF)	Constructs	Definitions*
CTF investigates the trustworthy relationship between cultural contexts and post-adoption beliefs in the use of the mobile Internet. CTF includes 30 items within 10 factors (three items for each). The cultural profiles (uncertainty avoidance and individualism) were selected for our test. *All definitions are from (Lee et al., 2007).	Uncertainty Avoidance	"The extent to which the members of a culture feel threatened by uncertain or unknown situations."
	Individualism	"Individualism represents a preference for a loosely knit social framework in which people are expected to take care of themselves and to look after their own interests."
International Comparison of Technology Adoption (ICTA)	**Constructs**	**Definitions***
The ICTA compared the usage intention of information technologies across different cultural contexts. The UTAUT instrument (Venkatesh et al., 2003) was selected to examine the cultural effects. The survey comprised fourteen items within five factors, of which eleven items within four factors were chosen for our test. *All definitions are from (Venkatesh et al., 2003).	Performance expectancy	"An individual believes that using the system will help him or her to attain gains in job performance."
	Effort expectancy	"The degree of ease associated with the use of the system."
	Social influence	"The degree to which an individual perceives that important others believe she should use the new system."
	Facilitating conditions	"The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system."
Online Trust Beliefs (OTB)	**Constructs**	**Definitions**
OTB examined the moderating role of uncertainty avoidance in online trust beliefs between subjective norms and the integrity & ability dimensions. OTB adopted sixteen	Uncertainty Avoidance	"Uncertainty avoidance is the level of risk accepted by the individual. This dimension examines the extent to which one feels threatened by ambiguous situations." (Srite & Karahanna, 2006)

items within six factors from (Srite & Karahanna, 2006) and (Limayem, Khalifa, &Frini, 2000), of which twelve items within five constructs were selected for inclusion in our test.	Subjective Norms	"Social factors that are likely to influence the online shopping intentions/behavior." (Limayem et al., 2000)
	Benevolence	"The belief that the trusted party, while hoping to make a profit, wants to do good to the customer." (Hwang & Lee, 2012)
	Integrity	"A trusted party adheres to accepted rules of conduct, such as honesty and keeping promises." (Hwang & Lee, 2012)
	Intention	"The behavioral intent of a buyer to precede the act of purchasing." (Hwang & Lee, 2012)
Technological Adoptiveness Scale (TAS)	**Constructs**	**Definitions**
TAS is a twelve-item measure that examines a person's relative openness to adopting and using new technology. Nine items were chosen for inclusion in our test.	General Technology-Adoptiveness	The attitude of openness in adopting any technology that has been released recently and is unfamiliar to a user.
Trust in Specific Technology (TIST)	**Constructs**	**Definitions***
TIST examines different kinds of trust across contexts and technologies, from specific (e.g., Excel or spreadsheet	Specific Technology-Reliability	"The belief that the specific technology will consistently operate properly."

products) to general uses of automated tools. The scale comprises 26 items within seven factors, of which nineteen items within six constructs are adapted to our test. *All definitions are from (Mcknight & Carter, 2011).	Specific Technology-Functionality	“The belief that the specific technology has the capability, functionality, or features to do for one what one needs to be done.”
	Situational Normality-Technology	“One feels comfortable when one uses the general type of technology of which a specific technology may be an instance.”
	Structural Assurance-Technology	“One believes structural conditions like guarantees, contracts, support, or other safeguards exist in the general type of technology that make success likely.”
	Faith in General Technology	“One assumes technologies are usually consistent, reliable, functional, and provide the help needed.”
	Trusting Stance-General Technology	“One presumes that one will achieve better outcomes by assuming the technology can be relied on.”
Individual Reaction to Computing Technology (IRCT)	**Constructs**	**Definitions**
IRCT measures the users' reactions to computing technology. IRCT includes 34 items within six factors, of which one construct was adopted for our test.	Performance Outcome	"Performance-related outcomes are those associated with improvements in job performance (efficiency and effectiveness) associated with using computers."
Uses of a Specific Web Site (USWS)	**Constructs**	**Definitions**
USWS investigates the relational and psychological factors that affect users' propensities to stick with a website. USWS includes 37 items within eight factors, of which one construct was adopted.	Communication Quality	"Communication quality refers to the timely sharing of meaningful information between Web site and users by means of formal and informal channels."

Decision-making in Electronic Commerce (DEC)	**Constructs**	**Definitions**
DEC examines users' trust-based decision-based process with regard to online purchasing decisions. DEC includes 49 items within eleven factors, of which two factors were adopted in our study.	Information Quality	"Information quality refers to a consumer's general perception of the accuracy and completeness of Website information as it relates to products and transactions."
	Presence of a third-party seal	"The Presence of a Third-Party Seal (TPS) refers to an assurance of an Internet vendor provided by a third-party certifying body such as a bank, accountant, consumer union, or computer company."
Appraisal System on Trust for Management (ASTM)	**Constructs**	**Definitions**
ASTM examines the relationship between trust and perceptions of the appraisal system. ASTM comprises seven factors and 41 items, of which one factor was included in our study.	Benevolence	"Benevolence is the extent to which a trustee is believed to want to do good to the trustor, aside from an egocentric profit motive."
Trust in Specific Technology (TIST)	**Constructs**	**Definitions**
TIST investigates trust across a variety of contexts and technologies. TIST includes 26 items within seven factors, of which one construct was included in our study.	Specific Technology-Helpfulness	"The belief that the specific technology provides adequate and responsive help for users."
Trust Measures for E-commerce (TME)	**Constructs**	**Definitions**
TME investigates trust in e-commerce in multidimensional contexts. TME includes 59 items within nineteen factors, of which three constructs were included in our study.	Trusting Beliefs-Competence	"Trusting beliefs means the confident truster perception that the trustee has attributes that are beneficial to the truster; Competence (is defined as the) ability of the trustee to do what the truster needs."

	Trusting Intentions-Willingness to Depend	"Trusting intentions means the truster is securely willing to depend, or intends to depend, on the trustee; Willingness to depend (is defined as the) volitional preparedness to make oneself vulnerable to the trustee."
	Trusting Intentions-Subjective Probability of Depending	"The perceived likelihood that one will depend on the other."
Adopting an Information Technology Innovation (AITI)	**Constructs**	**Definitions**
AITI measures the users' adoption with regard to information technology innovation. AITI comprises 26 items within seven factors, of which one dimension was included in our study.	Ease of Use	"The degree to which an individual believes that using a particular system would be free of physical and mental effort."
Understanding Information Technology Usage (UITU)	**Constructs**	**Definitions**
UITU measures users' intentions on the use of information technology. UIUT includes seven factors and 35 items, of which two factors were included in our study.	Perceived Behavioral Control	"Perceived Behavioral Control reflects beliefs regarding access to the resources and opportunities needed to perform a behavior, or alternatively, to the internal and external factors that may impede performance of the behavior. "
	Compatibility	"Compatibility is the degree to which the innovation fits with the potential adopter's existing values, previous experiences and current needs."
Personal Computing (PC)	**Constructs**	**Definitions**

PC investigates the factors that affect the use of personal computer technology. PC comprises 30 items within seven dimensions, of which one construct was included in our study.	Facilitating Conditions	Facilitating Conditions are defined as the "objective factors, out there in the environment, that several judges or observers can agree make an act easy to do."
Technology Acceptance and Usage Behavior (TAUB)	**Constructs**	**Definitions**
TAUB measures user reactions and usage behaviors when interacting with new information systems. The survey comprised twelve items within four factors, of which one dimension was included in our study.	Perceived Ease of Use	"Perceived ease of use is defined as the degree to which a person believes that using a technology will be free from effort."

APPENDIX C: CONVERGENT VALIDITY

FACTOR LOADINGS, KMO VALUES, AND TOTAL VARIANCE EXPLAINED IN SPECIFIC AUTOMATION

Pattern Matrix- General Automation					
Construct	***Item***	***Group***	***Performance***	***Process***	***Context***
Performance	Using a smart phone increases my effectiveness on my jobs.	All	**0.810**	-0.006	0.232
		US	**0.817**	0.052	0.236
		TW	**0.811**	0.209	0.212
		TK	**0.814**	0.008	0.134
	Using a smart phone will improve my output quality.	All	**0.831**	0.175	0.111
		US	**0.892**	0.078	0.034
		TW	**0.814**	0.117	0.255
		TK	**0.788**	0.200	0.117
	Using a smart phone will increase my chances of achieving a higher level of performance.	All	**0.820**	0.224	0.148
		US	**0.887**	0.057	0.202
		TW	**0.650**	0.392	0.233
		TK	**0.793**	0.207	0.229
Process	The information that a smart phone provides is of high quality.	All	0.228	**0.785**	0.096
		US	0.143	**0.762**	0.154
		TW	0.272	**0.774**	0.115
		TK	0.253	**0.689**	0.226
	A smart phone provides sufficient information.	All	0.033	**0.839**	0.215
		US	0.015	**0.845**	0.175
		TW	0.038	**0.802**	0.292
		TK	0.052	**0.861**	0.106
	I am satisfied with the information that a smart phone provides.	All	0.118	**0.873**	0.098
		US	0.021	**0.876**	0.112
		TW	0.313	**0.751**	0.149
		TK	0.116	**0.850**	0.132

Context	I prefer to use a smart phone to make decisions under high workload situations.	All	0.034	0.161	**0.828**
		US	0.059	0.028	**0.855**
		TW	0.121	0.222	**0.869**
		TK	0.260	0.182	**0.721**
	Using a smart phone helps me to expend less effort to accomplish tasks.	All	0.144	0.123	**0.842**
		US	0.311	0.215	**0.729**
		TW	0.216	0.205	**0.787**
		TK	-0.011	0.106	**0.888**
	Using a smart phone helps me accomplish tasks with lower risk.	All	0.354	0.242	**0.650**
		US	0.144	0.288	**0.654**
		TW	0.350	0.388	**0.601**
		TK	0.339	0.186	**0.674**
KMO (suggested threshold: 0.7)		All	0.808		
		US	0.761		
		TW	0.850		
		TK	0.768		
Total Variance Explained (suggested threshold: 60)		All	71.839		
		US	71.682		
		TW	70.876		
		TK	68.897		

Pattern Matrix- Specific Automation

Construct	***Item***	***Group***	***S_Performance***	***S_Process***	***S_Purpose***
S_Performance	GPS improves my performance.	All	**0.810**	0.293	0.231
		US	**0.801**	0.377	0.173
		TW	**0.768**	0.217	0.261
		TK	**0.864**	0.217	0.279
	GPS enables me to accomplish tasks more quickly.	All	**0.861**	0.178	0.233
		US	**0.906**	0.105	0.151
		TW	**0.823**	0.226	0.215
		TK	**0.837**	0.233	0.303
	GPS increases my productivity.	All	**0.836**	0.220	0.282
		US	**0.850**	0.204	0.275
		TW	**0.839**	0.185	0.243
		TK	**0.817**	0.264	0.302
S_Process	My interaction with GPS is clear and understandable.	All	0.201	**0.824**	0.189
		US	0.168	**0.799**	0.211
		TW	0.139	**0.852**	0.207
		TK	0.232	**0.794**	0.244

	GPS is user-friendly.	All	0.256	**0.851**	0.072
		US	0.194	**0.846**	0.004
		TW	0.219	**0.869**	0.097
		TK	0.383	**0.715**	0.248
	GPS uses appropriate methods to reach decisions.	All	0.300	**0.631**	0.390
		US	0.214	**0.518**	0.513
		TW	0.361	**0.632**	0.321
		TK	0.363	**0.703**	0.325
S_Purpose	I am confident about the performance of GPS.	All	0.250	0.350	**0.718**
		US	0.279	0.335	**0.702**
		TW	0.260	0.246	**0.775**
		TK	0.215	0.385	**0.752**
	When an emergent issue or problem arises, I would feel comfortable depending on the information provided by GPS.	All	0.241	0.207	**0.801**
		US	0.272	0.070	**0.835**
		TW	0.253	0.375	**0.699**
		TK	0.208	0.330	**0.781**
	I can always rely on GPS to ensure my performance.	All	0.158	0.038	**0.857**
		US	0.074	0.041	**0.858**
		TW	0.215	0.045	**0.826**
		TK	0.250	0.119	**0.859**
KMO (suggested threshold: 0.7)		All	0.882		
		US	0.850		
		TW	0.872		
		TK	0.912		
Total Variance Explained (suggested threshold: 60)		All	76.026		
		US	75.046		
		TW	73.996		
		TK	78.633		

APPENDIX D: DISCRIMINANT VALIDITY

Diagonal elements (the values in parentheses) are the square root of the shared variance between the constructs and their measures; off-diagonal elements are correlations between constructs

General **Automation**						
ALL *(N=360)*	**CR**	**Mean**	**SD**	**Perform**	**Process**	**Context**
Perform	0.81	3.63	0.80	*(0.76)*		
Process	0.82	3.63	0.79	0.40	*(0.78)*	
Context	0.75	3.17	0.79	0.53	0.49	*(0.71)*
US *(N=120)*	**CR**	**Mean**	**SD**	**Perform**	**Process**	**Context**
Perform	0.86	3.58	0.86	*(0.82)*		
Process	0.81	4.02	0.65	0.17	*(0.77)*	
Context	0.71	3.46	0.76	0.52	0.48	*(0.67)*
TW *(N=120)*	**CR**	**Mean**	**SD**	**Perform**	**Process**	**Context**
Perform	0.79	3.77	0.77	*(0.74)*		
Process	0.77	3.82	0.58	0.71	*(0.73)*	
Context	0.79	2.86	0.74	0.77	0.69	*(0.74)*
TK *(N=120)*	**CR**	**Mean**	**SD**	**Perform**	**Process**	**Context**
Perform	0.78	3.53	0.75	*(0.74)*		
Process	0.78	3.07	0.77	0.45	*(0.74)*	
Context	0.73	3.18	0.76	0.61	0.52	*(0.68)*

Specific Automation						
ALL *(N=1260)*	**CR**	**Mean**	**SD**	**S_Perform**	**S_Process**	**S_Purpose**
S_Perform	0.88	3.80	0.81	*(0.85)*		
S_Process	0.81	3.79	0.74	0.76	*(0.77)*	
S_Purpose	0.84	3.26	0.89	0.70	0.74	*(0.80)*
US *(N=420)*	**CR**	**Mean**	**SD**	**S_Perform**	**S_Process**	**S_Purpose**
S_Perform	0.89	3.90	0.89	*(0.85)*		
S_Process	0.75	4.02	0.69	0.76	*(0.71)*	
S_Purpose	0.84	3.17	0.95	0.67	0.71	*(0.80)*
TW *(N=420)*	**CR**	**Mean**	**SD**	**S_Perform**	**S_Process**	**S_Purpose**
S_Perform	0.84	3.85	0.75	*(0.80)*		
S_Process	0.82	3.84	0.71	0.70	*(0.78)*	
S_Purpose	0.84	3.44	0.87	0.75	0.76	*(0.80)*
TK *(N=420)*	**CR**	**Mean**	**SD**	**S_Perform**	**S_Process**	**S_Purpose**
S_Perform	0.91	3.63	0.78	*(0.88)*		
S_Process	0.84	3.51	0.73	0.80	*(0.80)*	
S_Purpose	0.86	3.18	0.82	0.69	0.83	*(0.82)*

APPENDIX E: MEASUREMENT INVARIANCE

FIT INDICES FOR INVARIANCE TESTS (SUGGESTIVE THRESHOLD VALUES: ∆CFI < 0.01)

General automation								
Model	**Model Description**	χ^2	**($\Delta\chi^2$)**	**df**	**∆df**	**p-value**	**CFI**	**∆CFI**
Three groups: US, Taiwan, and Turkey								
1	Configural model (equal pattern)	104.951	_	72	_	_	0.971	_
2	Factor Loading Invariance	128.474	23.523	84	12	0.024	0.961	-0.01
3	Factor Loading Invariance above except *Performance_4* free	113.574	8.623	82	10	0.568	0.972	0.001
Two groups: US and Turkey								
4	Configural model (equal pattern)	66.572	_	48	_	_	0.974	_
5	Factor Loading Invariance	73.557	6.985	54	6	0.322	0.973	0.001
6	Factor Loading and Structural Weights Invariance	82.453	15.881	60	12	0.197	0.969	0.005

Specific automation								
Model	**Model Description**	**χ^2**	**($\Delta\chi^2$)**	**df**	**Δdf**	**p-value**	**CFI**	**ΔCFI**
7	Configural model (equal pattern)	261.596	_	72	_	_	0.971	_
8	Factor Loading Invariance	285.586	23.991	84	12	0.020	0.969	0.002
9	Factor Loading Invariance above except *S_Process5* free	279.905	18.309	82	10	0.050	0.970	0.001
Two groups: Taiwan and Turkey								
10	Configural model (equal pattern)	149.397	_	48	_	_	0.978	_
11	Factor Loading Invariance	151.878	2.482	54	6	0.871	0.979	0.001
12	Factor Loading and Structural Weights Invariance	163.786	14.389	56	8	0.072	0.976	0.002

APPENDIX F.1: ITEMS OF THE CULTURAL TRUST INSTRUMENT (ENGLISH VERSION)

Culture Trust Instrument (English Version)							
Dimension	***Survey Items***	**Disagree strongly**	**Disagree**	**Neither agree nor disagree**	**Agree**	**Agree strongly**
General Automation Performance Expectancy	Using a smart phone increases my effectiveness on my jobs.	1	2	3	4	5
	Using a smart phone will improve my output quality.	1	2	3	4	5
	Using a smart phone will increase my chances of achieving a higher level of performance.	1	2	3	4	5
General Automation Process Transparency	The information that a smart phone provides is of high quality.	1	2	3	4	5
	A smart phone provides sufficient information.	1	2	3	4	5
	I am satisfied with the information that a smart phone provides.	1	2	3	4	5
General Automation Cultural-Technological Context	I prefer to use a smart phone to make decisions under high workload situations.	1	2	3	4	5
	Using a smart phone helps me to expend less effort to accomplish tasks.	1	2	3	4	5
	Using a smart phone helps me accomplish tasks with lower risk.	1	2	3	4	5

<u>Specific</u> Automation Performance Expectancy	GPS improves my performance.	1	2	3	4	5
	GPS enables me to accomplish tasks more quickly.	1	2	3	4	5
	GPS increases my productivity.	1	2	3	4	5
<u>Specific</u> Automation Process Transparency	My interaction with GPS is clearly understandable.	1	2	3	4	5
	GPS is user-friendly.	1	2	3	4	5
	GPS uses appropriate methods to reach decisions.	1	2	3	4	5
<u>Specific</u> Automation Purpose Influence	I am confident about the performance of GPS.	1	2	3	4	5
	When an emergent issue or problem arises, I would feel comfortable depending on the information provided by GPS.	1	2	3	4	5
	I can always rely on GPS to ensure my performance.	1	2	3	4	5

APPENDIX F.2: ITEMS OF THE CULTURAL TRUST INSTRUMENT (CHINESE VERSION)

Culture Trust Instrument (Chinese Version)						
Dimension	***Survey Items***	**非常不同意**	**不同意**	**中立**	**同意**	**非常同意**
General Automation Performance Expectancy	使用智慧型手機能增加我工作上的效能	1	2	3	4	5
	使用智慧型手機時，我的成果品質將會有所改善	1	2	3	4	5
	使用智慧型手機將有機會提高我的工作表現	1	2	3	4	5
General Automation Process Transparency	智慧型手機所提供的資訊品質很高	1	2	3	4	5
	智慧型手機能提供充足的資訊	1	2	3	4	5
	我對於智慧型手機所提供的資訊感到滿意	1	2	3	4	5
General Automation Cultural-Technological Context	當工作量(workload)大的時候，我更傾向使用智慧型手機去作決策	1	2	3	4	5
	使用智慧型手機可以幫助我以較少的精力去完成工作	1	2	3	4	5

	使用智慧型手機能幫助我在較低的風險下完成工作(task)	1	2	3	4	5
<u>Specific</u> Automation Performance Expectancy	衛星定位系統(GPS)能改進我的表現	1	2	3	4	5
	衛星定位系統(GPS)能使我更快地完成工作	1	2	3	4	5
	衛星定位系統(GPS)能提升我的生產力	1	2	3	4	5
<u>Specific</u> Automation Process Transparency	我與衛星定位系統(GPS)的互動過程(interaction)是清晰易懂的	1	2	3	4	5
	衛星定位系統(GPS)的設計是人性化(user-friendly)的	1	2	3	4	5
	衛星定位系統(GPS)能運用適當的方式做出決策	1	2	3	4	5
<u>Specific</u> Automation Purpose Influence	我對衛星定位系統(GPS)的表現有信心	1	2	3	4	5
	當有緊急事件發生時，我能依賴衛星定位系統(GPS)所提供的資訊	1	2	3	4	5
	我總是可以依賴衛星定位系統(GPS)來確保我的表現	1	2	3	4	5

APPENDIX F.3: ITEMS OF THE CULTURAL TRUST INSTRUMENT (TURKISH VERSION)

Culture Trust Instrument (Turkish Version)						
Dimension	***Survey Items***	**Tamamen Katılmıyorum**	**Katılmıyorum**	**Ne katılıyorum ne katılmıyorum**	**Katılıyorum**	**Tamamen katılıyorum**
General Automation Performance Expectancy	Cep telefonu kullanmam işlerimdeki etkinliğimi artıracaktır.	1	2	3	4	5
	Cep telefonu kullanmam işle ilgili çıktılarımın kalitesini artıracaktır.	1	2	3	4	5
	Cep telefonu kullanmam daha yüksek düzeyde iş performansı çıkarma şansımı artıracaktır.	1	2	3	4	5
General Automation Process Transparency	Cep telefonun sağladığı bilgi yüksek kalitededir.	1	2	3	4	5
	Cep telefonu yeterli bilgi sağlar.	1	2	3	4	5
	Cep telefonumun sağladığı bilgi benim için yeterlidir.	1	2	3	4	5
General Automation Cultural-Technological Context	Çok yoğun işim olduğu zamanlarda karar almada cep telefonu kullanmayı tercih ederim.	1	2	3	4	5
	Cep telefonu kullanımım, daha az emek vererek işleri tamamlamamda yardımcı olur.	1	2	3	4	5

	Cep telefonu kullanarak işleri tamamlamak daha az risk içerir.	1	2	3	4	5
Specific Automation Performance Expectancy	GPS benim performansımı artırır.	1	2	3	4	5
	GPS işleri daha hızlı şekilde tamamlamamı sağlar.	1	2	3	4	5
	GPS verimliliğimi artırır.	1	2	3	4	5
Specific Automation Process Transparency	Benim GPS'le etkileşimim net şekilde anlaşılabilir.	1	2	3	4	5
	GPS kullanıcı-dostudur.	1	2	3	4	5
	GPS kararlara ulaşmak için uygun yöntemleri kullanır.	1	2	3	4	5
Specific Automation Purpose Influence	GPS'in performansına güvenirim.	1	2	3	4	5
	Acil bir durum veya problem oluştuğunda, GPS'ten elde ettiğim bilgiye güvenirim.	1	2	3	4	5
	Her zaman performansımı korumak için GPS bilgisine güvenebilirim.	1	2	3	4	5