Personal Influences on Dynamic Trust Formation in Human-Agent Interaction

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ABSTRACT

The development of automated technologies in our daily life has transformed the role of human operators from a controller to a teammate who shares control with automated agents. However, this ‘teammate’ relationship between humans and automation raises an important but challenging research question regarding the formation of human-agent trust. Considering that the formation of human-agent trust is a dynamic and sophisticated process involving human factors, this study conducted a two-phase online experiment to examine personal influences on users’ trust propensity and their trust formation in human-agent interactions. Our findings revealed distinctive personal influences on dispositional trust and the formation of human-agent trust at different stages. We found that users who exhibit higher trust propensities in humans also develop higher trust toward automated agents in initial stages. This study, as the first of its kind, not only fills the gap of knowledge about personal influences on human-agent trust, but also offers opportunities to enhance the future design of automated agent systems.

Author Keywords

Human-agent collaboration; decision-aids automation; psychological factors; user interaction design.

ACM Classification Keywords

H.1.2 User/Machine systems: Human Factors; J.4 Social and Behavioral Sciences: Psychology.

INTRODUCTION

Today’s rapidly developing computing and artificial intelligence technologies make automated systems ‘smarter’ and ‘more intelligent.’ As a result, they are able to assist human operators in performing complex and critical daily tasks. For instance, robotic surgery allows doctors to perform compound procedures with more control and

precision; the military aircraft cockpit automated system assists pilots in decision-making, navigation, and route planning; the self-driving car helps decrease drivers’ cognitive load and human errors. These applications of intelligent automated agent systems have fundamentally changed the relationship between humans and automation. The role of human operators has transformed from a main controller to a teammate sharing control with automated agents [32]. However, when automated agents become more like a ‘partners’ rather than just tools [14], how humans calibrate appropriate trust relations while interacting with intelligent agent systems becomes an important but challenging question.

Previous research has indicated that increasing the human features of automation could enhance users’ trust and reliance on automation, thus further improving their task performance [56,41,43,26,6,9]. However, increasing human features in automated agents can lead to the misuse of automated systems due to misplaced trust. Misplaced trust in agent systems can result in disastrous consequences. For example, pilots’ excessive trust in automated systems can increase the risks of aviation accidents [36,57]. Furthermore, the recent case of a self-driving Tesla car resulting in a fatal accident in May 2016 may have been due to the driver’s excessive trust in and reliance on the autopilot system [60]. Conversely, inappropriate distrust can lead to disuse of agent systems as well. Therefore, supporting human operators in forming and calibrating appropriate trust levels in automated agents is critical and essential for preventing either the misuse or disuse of agent systems [25].

The formation of human-agent trust, similar to that of human-human trust, is a dynamic process influenced by numerous factors, such as human factors, the performance of automated systems, and the environment [18,25,52]. Nevertheless, the majority of studies on human-agent interactions focus on how the reliability, dependability, and predictability of automated systems influence trust formation [1,3,7,10,32,33,40,48,50,55,61]. We still have a very limited understanding of how humans actually perceive and develop trust in automated agents, as well as how personal factors impact that trust formation. Human trust is a complicated process that varies across individuals. Personal variance in trust formation also makes human-

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agent trust even more difficult to analyze and predict. Therefore, investigating the effect of personal differences on the formation of human-agent trust is indispensable, especially for future designs of human-agent interaction. Since very few empirical studies focus on personal influences on the formation of human-agent trust [18,52], in this study, we conducted an online experiment to examine three types of personal influences on human-automation trust formation, including dispositional trust, decision-making style and attachment style. This study, to the best of our knowledge, is the first empirical study investigating personal influences on human-agent trust.

The rest of this paper is organized as follows. In Background and Research Aims, we focus on reviewing the theoretical framework of human-automation trust, address the gaps in this field, and propose the aims of this study. In Study Design we describe our experiment and our participants' demographics. We then present and discuss our findings about personal influences on human-agent trust, acknowledge study limitations, and draw further conclusions.

BACKGROUND AND RESEARCH AIMS

Researchers in the field of human factors have applied the understanding of human-human trust to the formation of human-agent trust because users have a tendency to apply interpersonal interaction to interactions with automated machines or systems [37,38]. For instance, human-like features of an automated agent, such as politeness, humanoid faces, or speech, have been proven to increase users' trust and reliance on automated agents, which in turn further enhanced their performance in given tasks [43,41,56]. Also, users are more likely to prefer an automated agent that can learn, identify, and react to personality differences [27]. In general, prior research has evidenced that, similar to human-human trust, the development of human-agent trust can be based on performance, process, and purpose of the automated agent [18]. However, the formation of human-agent trust is still dissimilar from human-human trust formation in significant ways [31].

Human-agent trust versus human-human trust

One of the main differences between human-agent trust and human-human trust is the developing process. The beginning of human-human trust formation is based on the predictability of a trustee's actions [47], and then, as interpersonal relationships evolve, trustee integrity and benevolence become critical bases for trust [25]. On the other hand, the initial formation of human-agent trust is based on positive beliefs in unfamiliar automated systems [4,12,32]. As the number of interactions with automation increases, elements of system performance, such as dependability and reliability, become the main determinants for trust [32]. Therefore, trust formation in human-agent interactions involves various factors that need to be understood from an interdisciplinary perspective.

Formation of human-agent trust

One interdisciplinary approach to comprehending multifactorial influences on human-agent trust is the three-layered framework Hoff and Bashir [18] proposed. In the three-layered framework, three types of trust components exist before and during human-automation interaction, including dispositional trust, situational trust, and learned trust. As the framework describes, before interacting with automated systems, individuals initially have their own overall trust propensity toward humans and/or automated systems. This long-term trust propensity is termed "dispositional trust," which can be affected by different personal attributes, such as age, gender, and personality. Next, users develop their situational trust based on a given internal context and external environment. Prior to interacting with an automated system, users' preexisting knowledge about that system helps users develop their initial learned trust toward the automated agent. Then, when initiating interactions with the system, users will form their dynamic learned trust, which can further impact their reliance on the system. With continuous interaction with the system, the performance and design features of the system could further affect the dynamic learned trust.

Personal influences: empirical gaps in human-agent trust

As the three-layered framework [18] suggests, personal differences have great impacts on the formation of human-agent trust. Previous studies have also identified personal influences on users' trust in and reliance on automated systems [15,18,52]. Although the human element is often highlighted as important in the literature, personal factors are still often overlooked or relegated to a minor focus in human-agent trust research [15,52]. Many personal factors still have not been empirically tested and validated. In addition, an important but missing piece of knowledge in previous work is the role of personal factors in the dynamic formation of human-agent trust.

Based on prior work, we identified two chief empirical gaps in contemporary research. First, very few studies include and examine the influence of personal factors on users' dispositional trust in both humans and automation while also taking into account human-human interpersonal trust. Dispositional trust represents an individual's general propensity to trust automation and/or humans across various contexts and circumstances [18]. Several studies have found that individuals with higher dispositional trust tend to place higher trust in automated systems [2,33,45]. However, these studies did not specify whether dispositional trust in automation and dispositional trust in humans would have similar effects on human-agent trust. Also, empirical studies have not fully investigated the discrepancy between dispositional trust in automation and dispositional trust in humans [31]. Whether personal factors have similar effects on both dispositional trust in automation and in humans remains unclear. Thus, our first

research aim was to investigate personal influences on dispositional trust in automation and humans.

Previous studies have indicated several significant personal effects on users' trust toward automated systems, including dispositional trust [2,33,45], personality traits [33,34,49,58], age [11,16,21,42,51], gender [39,59], and culture/ethnicity [19,28,29,53]. However, as far as we know, no empirical research has investigated how personal factors affect dynamic formation of human-agent trust. Therefore, the second aim of this study was to investigate personal influences on dynamic trust formation in human-agent interactions.

Considering the similarities between human-human trust and human-automation trust, instead of examining previously addressed factors, we propose to investigate two other personal factors that are important in human-human trust: decision-making style and attachment style. According to prior research, trust plays an important role in people's interpersonal decision-making practices [13,24]. However, very few studies examine whether individuals' decision-making style affects their trust formation in automated agents. One's personal decision-making style is a 'habit-based personality' defined as 'the learned, habitual response pattern exhibited by an individual when confronted with a decision situation' [54]. That is, each individual shows a habitual pattern in decision-making contexts. Since the formation of human-agent trust involves a series of decision-making processes, we hypothesize that users' personal decision-making style may have effects on both of their dispositional trust and the trust formation in automated agents. Our hypotheses are addressed below:

H1a: Users' decision-making style will affect their dispositional trust in automation.

H1b: Users' decision-making style will affect their dispositional trust in humans.

H2: Users' decision-making style will affect their trust formation in the automated agent.

Furthermore, research in the field of interpersonal trust has suggested that an individual's attachment style impacts one's trust formation in interpersonal relationships. According to attachment theory, each individual develops mental models of self and other that affect their patterns of support seeking and support giving in adult relationships [62]. These mental models become stable traits over time, which constitute one's attachment style [62]. An individual who has an avoidant or anxiety attachment style in interpersonal relationships tends to be distrustful of others [8,22] or to develop lower levels of trust toward others. Therefore, we hypothesize that users with avoidant and/or anxious attachment style will exhibit lower dispositional trust in both automation and humans. Also, this type of interpersonal attachment style may influence personal attachment to automation, which in turn can affect users' trust toward automation. We hypothesize that users with

avoidant and/or anxious attachment style will form lower trust toward automated agent.

H3a-1: Users with avoidant attachment style will exhibit lower dispositional trust in automation.

H3a-2: Users with anxious attachment style will exhibit lower dispositional trust in automation.

H3b-1: Users with avoidant attachment style will exhibit lower dispositional trust in humans.

H3b-2: Users with anxious attachment style will exhibit lower dispositional trust in humans.

H4a: Users with avoidant attachment style will form lower trust toward the automated agent.

H4b: Users with anxious attachment style will form lower trust toward the automated agent.

Prior research has also indicated that individuals with higher dispositional trust tend to develop higher trust in automated agent systems [2,33,45]. Hence, we hypothesize that users with higher dispositional trust in automation and in humans will develop higher trust toward the automated agent.

H5a: Users with higher dispositional trust in automation will form higher trust toward the automated agent.

H5b: Users with higher dispositional trust in humans will form higher trust toward the automated agent.

To the best of our knowledge, there is no empirical study investigating how people's dispositional trust, decision-making style and attachment style directly impact dynamic trust formation during human-automation interaction. In order to fill this gap in knowledge, we conducted an experimental study to investigate personal influences on users' dispositional trust toward both humans and automation, and on their trust formation during interactions with automation. We will assess three types of personal factors, including: 1) dispositional trust, 2) decision-making style, and 3) attachment style.

STUDY DESIGN

In this study, we conducted a two-phase online experiment. To imitate the use of automation in the real world, we applied a microworld-task approach that allows researchers to implement experimental control in real-life settings [25,33]. We designed a simulated airport passenger-screening task and asked participants to collaborate with an automated agent system. In phase 1, we assessed participants' personal factors. In phase 2, participants were first provided training for the experimental task and then asked to perform the task. Participants' trust formation toward the automated agent was gauged during phase 2. This study was approved by the Institutional Review Board. We next explain the details and process of our experiment.

Simulated Scenario: Airport Passenger-Screening Task

We employed an airport passenger-screening security task as our experimental scenario, which is familiar to most people and a high-stakes task. In the experiment, participants were asked to play a role as an airport security agent for the Transportation Security Administration (TSA). Their mission was to scrutinize passengers for dangerous items. The passenger-screening task was simulated via a screen interface with X-ray images of passengers. These images may have contained weapons, vague objects, or no items (see Figure 2). Participants were asked to inspect each image as accurately as possible and select whether they would “search” the person (if they believed the passenger held a dangerous item) or “pass” the person (if they believed the passenger held no dangerous items). Participants were told to work with an automated agent system, called the Automated Security Officer (ASO, see Figure 3), which performed security scans and provided a recommendation for each passenger.

Figure 2. Examples of simulated X-ray image of passenger

Figure 3. Introduction of Experiment and Automated Security Officer (ASO)

The benefit of using an airport security task is that first, most people are familiar with the context of airport security screening, and therefore should be able to learn the task with little training. Second, it is a high-stakes task in which participants face intensive demands on their time and cognitive resources. For example, although preventing dangerous items from entering the airport and aircrafts is

the top priority of airport security screeners, excessively exhaustive searches can cause long lines, missed flights, and customer dissatisfaction. Therefore, as an airport security screener, participants need to balance the demands of accuracy and speed, which is very akin to the challenges users of automated technology encounter in real life [33]. Next we illustrate the process of our online experiment.

Phase 1: online questionnaire for evaluating personal factors

In phase 1, participants were asked to complete an online questionnaire gauging their personal attributes, including dispositional trust, personality traits, decision-making style, attachment style, and demographics. In order to avoid priming effects and biasing of participants' responses in phase 2, we waited 48 hours before asking the same participants to complete phase 2 of the experiment. Research has shown that memory of new information declines an average of 70% in 24 hours [23]. This amount of delay between the two phases could decrease participants' memory retention and the connection between phase 1 questionnaires to phase 2 tasks. After 48 hours of phase 1, participants were invited to phase 2 of the study via email with an online link to the experiment.

Phase 2: online experiment for assessing the formation of trust toward the ASO

In phase 2, participants were instructed to screen passengers in a simulated security checkpoint. The goal of this simulated task is to inspect if passengers need to be searched or passed. As exhibited in Figure 2, passengers may bring nothing, vague items, or obvious weapons. Based on this information, participants need to make an assessment for each passenger.

Before the experiment, participants had to complete a short training session that instructed them about what their main tasks were (passenger screening), what to look for (weapons or sharp objects), how to search or pass a passenger, and how to work with the ASO and the scoring system. During the training, participants had to go through three trials. This training was designed to assure that participants were clear on what was expected of them.

Once starting the task, participants had 10 seconds to view an X-ray image of a passenger and make an initial decision about whether to search or pass the passenger. After the participant completed the initial assessment, the ASO showed up and provided a second opinion on whether to search or pass the passenger. Then, participants had another 10 seconds to decide if they would like to keep or change their initial assessment. Participants went through two blocks of experiments. In the first block, participants completed 10 trials. In the second block, participants completed 20 trials. After each block, participants answered questions about their degree of trust toward the ASO, trust toward self, and their self-perceived accuracy of their performance.

Experimental design

In order to assess the dynamic formation of trust toward the ASO, we designed a 2 (Agreement with the ASO: Low versus High) x 2 (Agreement with the ASO: Decreasing versus Increasing) between-subject experiment. We manipulated participants' working experience with the ASO by varying the degree of agreement on the vague objects between participants and the ASO. The purpose of this manipulation was to test if the degree of the ASO's agreement influenced trust formation in the ASO. However, we want to note that since we focused this paper on personal influences on trust formation, we will not emphasize analyzing or interpreting the influence of agreement rate on trust formation. We will present the analysis of agreement rate in subsequent papers.

As exhibited in Table 1, in the first block of trials, the high agreement group experienced agreements with the ASO on 80% of the passengers carrying vague objects, and the low agreement group experienced agreements with the ASO on 60% of the passengers carrying vague objects. For the participants who initially experienced high agreements with the ASO in the first block, half of them experienced increasing agreements with the ASO in the second block (on 90% of passengers carrying vague objects) and the other half of them experienced decreasing agreements with the ASO in the second block (on 70% of passengers carrying vague objects). Similarly, for the participants who were assigned to the low agreement group, half of them experienced increasing agreements with the ASO in the second block (on 70% of passengers carrying vague objects) and the other half of them experienced decreasing agreements with the ASO in the second block (on only 50% of passengers carrying vague objects).

	Block 1: % of agreement	Block 2: Change of agreement
Condition 1 (N=38)	High (80%)	Increase 10%
Condition 2 (N=39)		Decrease 10%
Condition 3 (N=39)	Low (60%)	Increase 10%
Condition 4 (N=40)		Decrease 10%

Table 1. 2x2 between-subjects factorial experiment design

We randomly assigned participants to each of the four conditions in counterbalance order. Each participant experienced the same levels of agreement rate within each condition.

Participants

One hundred and fifty-six participants were recruited via Amazon Mechanical Turk, 60 of whom were female. Our participants were comprised of a wide range of age groups. 43.6% of participants were younger than 30 years old, 50.7% were between 30 to 60 years old, and 5.8% were older than 60 years old. For education, 21.2% of participants held a high school degree, 55.1% completed

college, and 23.7% earned advanced degrees. Most participants (N=126) were from the United States; 29 participants were from India and 1 participant was from Sri Lanka. Participants were given \$2 US dollars for their participation after completing the study.

Measurement

For the online questionnaire distributed in phase 1, several measurements were employed to measure participants' personal attributes, including dispositional trust, decision-making style, attachment style, personality traits, self-esteem, and demographics. We assessed two types of dispositional trust: one in automation and one in humans. Since there is no standardized measurement for dispositional trust in automation, we adopted 12 items from Singh et al. [57] to measure dispositional trust in automation, which is the most appropriate measurement available to assess people's trust propensity in automation. We adopted 8 items from Mayer and Davis [35] to measure dispositional trust in humans. For decision-making style, we employed the General Decision Making Style scale developed by Scott and Bruce [54]. We used the Relationship Scale Questionnaire [20] for assessing attachment style. For personality traits, we used Big Five Inventory [30] and the Rosenberg Self-Esteem Scale [17] to measure self-esteem. Participants were asked to answer questions on a 5-point scale (strongly disagree: strongly agree). Note that in this study, we focused our analyses particularly on dispositional trust, decision-making style, and attachment style. For phase 2, we adopted 6 items from Merritt's trust scale [44] to assess participants' self-reported trust toward the ASO during the experiment.

Trust Terminology

Since we examined different types of trust, we would like to clarify the terminology and concept of the types of trust referred to in this study.

- **Dispositional trust in humans and in automation** is an individual's overall, long-term trust propensity toward humans and automation in across different contexts and situations, which is evaluated before the experiment.
- **Primary trust toward the ASO** is the initial development of trust toward the ASO, assessed after the experiment's first block of tasks.
- **Secondary trust toward the ASO** is the variation of trust toward the ASO after two blocks of trials, meaning that we measured trust after Block-1 and then we measured it again after two blocks of the trials. Therefore, secondary trust toward the ASO is computed by subtracting Block-1 trust from Block-2 trust. The assessment of secondary trust can shed light on how users may adjust their trust toward the ASO after some interactions with the agent. The equation for secondary trust is exhibited below.

$$\text{Secondary_trust} = \text{Trust}_{\text{block2}} - \text{Trust}_{\text{block1}}$$

We will use the above terminology of trust in the following sections. We next illustrate our analyses and results of the online experiment.

RESULTS

Personal influences on dispositional trust

Our first research question investigated whether personal factors have different effects on users' dispositional trust in automation and humans by multiple regression analysis. As shown in model 1 (see Table 2), the only significantly positive predictor of dispositional trust in automation is rational decision-making style. This suggests that participants who preferred to make decisions in a rational way also showed more trust propensities in automation. There is no significant effect of attachment style on dispositional trust in automation. Hence, our hypothesis H1a is partially supported and both H3a-1 and H3a-2 are rejected.

Furthermore, we found that spontaneous decision-making style is a positive predictor of dispositional trust in humans. This result indicates that participants who made decisions in a more spontaneous manner also exhibited higher dispositional trust in humans. Also, participants who showed higher relational avoidance tended to have lower dispositional trust in humans. Thus, our hypothesis H1b is partially supported. The hypothesis H3b-1 is supported but H3b-2 is rejected. These findings suggest that personal attributes have diverse effects on different types of dispositional trust. Hence, both of our hypotheses H1 and H3 are partially supported.

Personal influences on dynamic trust formation toward automated agent

We examined three types of personal influence on the formation of human-agent trust, including: 1) dispositional

trust, 2) decision-making style, and 3) attachment style. Multiple regression analysis was adopted to examine which personal factors have predictable influences on the formation of primary and secondary trust toward the ASO. Considering the possible effects of experimental design, we also included the ASO agreement in the analyses. We next present the influence of personal factors on primary trust, followed by their influence on secondary trust.

Personal influences on primary trust toward the ASO

In model 3 we examined the effect of four types of predictors on primary trust toward the ASO, including 1) the degree of ASO agreement rate in Block-1, 2) dispositional trust in automation and in humans, 3) decision-making style, and 4) attachment style. The model indicates that there was a collective significant effect between personal factors and primary trust toward the ASO, ($F(10, 148) = 6.83, p < .001, R^2 = .14$).

Our results show that spontaneous ($b = .27, t = 2.30, p = .023$) and rational ($b = .38, t = 2.68, p = .008$) styles have significantly positive effects on primary trust. This suggests that participants who tended to make decisions in a more spontaneous and rational way also developed higher primary trust in the ASO agent. Nevertheless, there are no significant effects of the degree of ASO agreement and attachment style on primary trust. We also found that dispositional trust in humans has significantly positive effects on primary trust ($b = .42, t = 2.95, p = .004$). This may suggest that users who exhibit higher dispositional trust in humans tend to develop higher primary trust toward automated agents than those who exhibit lower dispositional trust in humans.

Personal influences on secondary trust toward the ASO

For the formation of secondary trust in the ASO, it would

Predictors	Model 1: Automation		Model 2: Humans	
	<i>B</i> (SE)	<i>t</i>	<i>B</i> (SE)	<i>t</i>
Intercept	31.08 (3.96)	7.86 ($p < .001$)	3.27 (0.40)	8.19 ($p < .001$)
Decision-making style				
Spontaneous	-0.29 (0.64)	-0.45 ($p = .656$)	0.18 (0.07)	2.71 ($p = .007$)
Avoidance	0.31 (0.48)	0.63 ($p = .528$)	0.06 (0.05)	1.31 ($p = .192$)
Intuitive	0.14 (0.52)	0.27 ($p = .791$)	-0.08 (0.05)	-1.56 ($p = .120$)
Dependence	-0.54 (0.59)	-0.92 ($p = .359$)	0.11 (0.06)	1.76 ($p = .081$)
Rational	4.25 (0.74)	5.74 ($p < .001$)	-0.05 (0.08)	-0.62 ($p = .536$)
Attachment style				
Avoidance	-0.03 (0.08)	-0.42 ($p = .676$)	-0.03 (0.01)	-4.26 ($p < .001$)
Anxiety	-0.09 (0.10)	-0.90 ($p = .368$)	-0.07 (0.01)	-0.77 ($p = .440$)
Adjusted R^2	.21		.20	
F-value	$F(7, 148) = 6.83$ ($p < .001$)		$F(7, 148) = 6.49$ ($p < .001$)	

Table 2. Estimated parameters of multiple regression models for dispositional trust in automation and humans

not only be affected by the initial rate of the ASO agreement, but also by the dynamic change of the ASO agreement (e.g., the increasing or decreasing rate). Additionally, participants' secondary trust would develop based on their primary trust in the ASO. Therefore, it was important to consider these three factors in the model while testing personal influences.

In model 4, six types of predictors for secondary trust toward the ASO were tested, including 1) the degree in Block-1 (high versus low), 2) the change (increase versus decrease) of ASO agreement rate in Block-2, 3) primary trust toward the ASO, 4) dispositional trust in automation and in humans, 5) decision-making style and 6) attachment style. According to the model, there was a collective significant effect of these five types of predictors on secondary trust toward the ASO ($F(12,143)=3.88, p<.001, R^2=.18$).

Our results show that there is no significant effect of the ASO agreement rate and the change of the agreement rate on secondary trust in the ASO. However, we found that the degree of primary trust in the ASO has a significantly negative effect on secondary trust ($b=-.39, t=-5.24, p<.001$). To clarify the effect of primary trust, we further conducted a two-way ANCOVA to test the interaction effect between the ASO agreement and primary trust on secondary trust. Yet the result shows no significant interaction effect on

secondary trust. This suggests that participants who developed lower primary trust toward the ASO in Block-1 tended to increase their trust in Block-2. In other words, participants tended to adjust their trust after more interactions with the ASO. Furthermore, the results show no personal effects on secondary trust in the ASO, which may suggest that personal factors do not affect users' trust adjustment toward the automated agent within the context of this study.

Overall, we found that only users' decision-making style has significant effects on their primary trust toward the automated agent. Hypothesis H2 is thus partially supported. In addition, our results show no significant effect of attachment style on both primary and secondary trust. Therefore, both hypotheses H4a and H4b are rejected. For the effect of dispositional trust, we found that only dispositional trust in humans has a significant effect on primary trust. Thus, hypothesis H5a is rejected and H5b is partially supported.

DISCUSSION

This study investigated personal influences on human-agent trust via a simulated airline passenger-screening task in which participants worked with the automated agent ASO. Table 3 exhibits the hypotheses and findings of this study.

Types of trust	Personal influences	Hypotheses	Findings
Dispositional trust in automation and humans	Decision-making style	H1a: Users' decision-making style will have effects on their dispositional trust in automation.	Partially supported
		H1b: Users' decision-making style will have effects on their dispositional trust in humans.	Partially supported
	Attachment style	H3a-1: Users with avoidant attachment style will exhibit lower dispositional trust in automation.	Rejected
		H3a-2: Users with anxious attachment style will exhibit lower dispositional trust in automation.	Rejected
		H3b-1: Users with avoidant attachment style will exhibit lower dispositional trust in humans.	Supported
		H3b-2: Users with anxious attachment style will exhibit lower dispositional trust in humans.	Rejected
Trust in the automated agent	Decision-making style	H2: Users' decision-making style will affect their trust formation in the automated agent.	Partially supported
	Attachment style	H4a: Users with avoidant attachment style will form lower trust toward the automated agent.	Rejected
		H4b: Users with anxious attachment style will form lower trust toward the automated agent.	Rejected
	Dispositional trust	H5a: Users with higher dispositional trust in automation will form higher trust toward the automated agent.	Rejected
		H5b: Users with higher dispositional trust in automation will form higher trust toward the automated agent.	Partially supported

Table 3. Overview of hypotheses and findings

In terms of dispositional trust, we hypothesized that users' decision-making style and attachment style would have impacts on their dispositional trust in automation and humans (Table 3). We found that participants who displayed rational decision-making styles also showed higher levels of trust in automation. A possible explanation is that users with rational decision-making styles may consider automation as operating in a logical manner, which corresponds to their propensities and further increases their trust in the automated agent. Nevertheless, the results show no significant effects in attachment style on dispositional trust in automation. For dispositional trust in humans, participants who had spontaneous decision-making styles displayed higher dispositional trust in humans. Spontaneous decision-makers have a sense of immediacy and a desire to complete a decision as soon as possible [54], which may further drive them to place higher dispositional trust in humans. Also, corroborating prior research [8,22], participants who had avoidant attachment styles showed lower dispositional trust in humans. Overall, our findings suggest that personal factors place dissimilar effects on dispositional trust in automation and humans.

We further assessed personal influences on the dynamic formation in human-agent trust. We found three personal factors that have positive effects on participants' primary trust in the automated agent: dispositional trust in humans, rational decision-making style, and spontaneous decision-making style. These findings first suggest that users with higher dispositional trust in humans may be more likely to see an automated agent as human, and that, consequently, they will place higher primary trust in an automated agent. Second, users with rational decision-making styles may perceive automated agents as performing logical functions, which increases their primary trust. For users with spontaneous decision-making styles, the desire to proceed swiftly through decision-making processes may drive them to place higher primary trust in an automated agent. Note that the positive association between dispositional trust in humans and spontaneous decision-making style may also imply that users with spontaneous decision-making tendencies may initially perceive an automated agent as human.

Interestingly, when it comes to secondary trust in automated agents, the only impactful factor is primary trust. Personal factors do not significantly influence the formation of secondary trust. We found that participants who formed higher primary trust in the automated agent tended to decrease their level of secondary trust. These results indicate that without personal influences, users may use the baseline of primary trust to calibrate their secondary trust in the automated agent after more interactions with it. However, it remains unclear what factors influence users' decisions on their trust calibration, which needs further investigation.

In general, our findings evidence that two types of personal factors—dispositional trust and decision-making style—have effects on dynamic human-agent trust formation. However, attachment style is not an influential factor in the formation of human-agent trust.

LIMITATIONS

In this study we acknowledge that our findings about personal influences on human-agent trust may only apply to the specific sample and contexts of this study. We recommend future studies to recruit more diverse samples and to compare personal influences across different contexts. In addition, our adopted measurement scale for dispositional trust in automation might have influenced our results. We suggest that future studies test multiple measurements of dispositional trust in automation and compare the results. Furthermore, our participants only interacted with the automated agent in a short-time period, which may be different from daily long-term usage of automated agents. It may be difficult for us to infer whether users will perform the same results in a long-term interaction with an automated agent. We suggest future studies to design a context that can observe personal effects on the formation of human-agent trust in a long-time period.

CONCLUSION

In this experimental study we investigated personal influences on users' dispositional trust and dynamic formation of human-automation trust. This work, as the first of its kind, not only fills the gap of knowledge about personal influences on human-agent trust but also can be utilized to enhance the design of automated agent systems. One of the key design challenges in human-agent trust is how to assist users in calibrating appropriate trust levels in the system throughout repeated interactions. Since the formation of trust is different and varied across individuals, we think that understanding patterns of personal influences on trust formation based on decision-making and attachment characteristics can be valuable for the design of trust calibration. For instance, we can employ the identified pattern of personal influences to develop trust persona, which can be used to design a mechanism for trust calibration. While there is still much to be done, our work reveals interesting phenomena and provides insight into how personal factors influence human-agent trust. This study will help inform better approaches for the future design of human-agent interaction and collaboration.

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