Proceedings of the 53rd Hawaii International Conference on System Sciences | 2020

Trusting a Humanoid Robot: Exploring Personality and Trusting Effects in a Human-robot Partnership

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Abstract

Research on trust between humans and machines has primarily investigated factors relating to environmental or system characteristics, largely neglecting individual differences that play an important role in human behavior and cognition. This study examines the role of the Big Five personality traits on trust in a partnership between a human user and a humanoid robot. A Wizard of Oz methodology was used in an experiment to simulate an artificially intelligent robot that could be leveraged as a partner to complete a life or death survival simulation. Eye-tracking was employed to measure system utilization and validated psychometric instruments were used to measure trust and personality traits. Results suggest that individuals scoring high on the openness personality trait may have greater trust in a humanoid robot partner than those with low scores in the openness personality dimension.

1. Introduction

In the film Prometheus, humans entrust their lives to an android robot who they collaborate with on an expedition to explore a faraway planet. With the rise of artificial intelligence, human-machine partnerships like this are no longer science fiction and are quickly becoming a reality of our modern time. These systems may take on many forms, anything from personal digital assistants like Siri to life-sized humanoid robotic assistants for the elderly [43]. The ability of these intelligent systems to process massive amounts of information and draw from countless sources of data already surpass the limits of human cognition. Consequently, collaborating with such intelligent machine partners necessitates trust be placed in them by their human counterparts. In this paper, we explore trust in a humanoid robot partner by individuals completing a life or death survival simulation.

As individuals collaborate with various intelligent systems, understanding factors relating to trust in these systems is critical. Information systems research has primarily investigated factors relating to the trust situation or characteristics of the computer system. The individual differences (such as personality type) that influence our behavior and shape our decisions have widely been neglected from past research on trust in human-robot partnerships. Additionally, a literature review of personality and human-robot interaction observed past work: narrowly focused on just a few personality traits, had contradictory findings between studies and lacked a coherent framework to guide research [29]. Therefore, our study has the following objective:

To explore the role of personality traits and trust in a partnership between humans and an intelligent system embodied as a humanoid robot.

To do this, we conducted an experiment involving 58 individuals collaborating with a robot partner to complete a series of critical decision-making simulations that involved perceived personal risk. Results suggest that the openness personality trait may be important to trust in an intelligent system embodied by a humanoid robot.

2. Background

In this section we provide a review of intelligent systems literature, a theoretical overview of trust and individual differences, and important background information relating to eye-tracking as a research method for measuring utilization of an intelligent system.

2.1. Intelligent Systems

An intelligent system can be defined as any system that perceives its environment and takes actions that maximize its chance of successfully

URI: https://hdl.handle.net/10125/63806
978-0-9981331-3-3

achieving prespecified goals [26]. Intelligent decision support systems are a specific type of intelligent systems used to aid humans in making complex decisions. Intelligent decision support systems are used widely throughout public and private industry and include applications in healthcare systems [40], systems for business and marketing [19], border security [36], and strategic military decision support systems [27]. These systems rely on artificial intelligence to evaluate context, situation, and input from various sources or sensors, in order to provide recommendations [24, 35]. Intelligent decision support systems are also based on expert systems, which are tools that incorporate the knowledge of experts into a system whose behavior is so sophisticated that it performs in a manner akin to a human expert [35]. While some intelligent systems have the capability of making decisions and act autonomously, a key distinguishing aspect of intelligent decision support systems is their design to alert a human user before action is taken.

The embodiment and interaction modality of intelligent systems can vary greatly. Embodiment includes both morphology and modality [16]. Morphology refers to the form an object or system takes. Intelligent systems can be presented to end users in a number of ways ranging from simple visual indicators to advanced anthropomorphic systems. In this work we conceptualize a humanoid robot as an intelligent system with an anthropomorphic or human like form.

Anthropomorphism is described by Epley, Waytz, and Cacioppo [5] as "the tendency to imbue the real or imagined behavior of nonhuman agents with characteristics, motivations, intentions, and emotions." Imbuing an intelligent system with anthropomorphic properties may impact a human user's perception of the system possessing a "mind." Consequently, anthropomorphizing may: 1) have perceived moral implications for the system itself, 2) suggest responsibility can be applied to the system, and 3) allow the system to have social influence on others [41]. In human-robot interaction studies, increases in a robot's humanness have been correlated to increased perceptions of intelligence, comfort and even trust [10, 39]. More broadly, research in intelligent systems has shown anthropomorphism can preserve trust in the face of systems with deteriorating reliability [38]. In summation, giving an intelligent system human like features may impact various perceptions and attitudes toward the robot, including trust.

Interaction modality, or the way in which a trustor interacts with a system is another aspect of a robot that may influence trust. Intelligent systems vary in their interaction modality and can range from simple graphical user interface to conversational voice control. A study in human computer trust showed that users were more trusting of a technology system when speaking to it compared to users who interacted primarily through typed responses [32]. The study suggests that speaking lowers the inhibitions of the trustor resulting in more indulgent choices and increased intent of information disclosure than interactions that utilize other non-verbal expression modalities.

2.2. Trust

Trust is a multi-dimensional construct that has proven quite difficult to conceptualize and define [22]. For this study we adopt a definition of trust that has been proposed by Madsen and Gregor [17]. They define trust as "the extent to which a user is confident in, and willing to act on the basis of the recommendations, actions, and the decisions of a computer-based tool or decision aid." In this definition, the human user is the "trustor" (the individual who is trusting) and the technology is the "trustee" (the object of trust).

There are numerous definitions of trust throughout literature exemplifying the many different ways of conceptualizing the construct. In effort to bring clarity to the area of trust research, McKnight and Chervany [22] created a typology of trust by reviewing sixty-five articles containing trust definitions and organized these by both trust reference (characteristics of the trustee) and by conceptual type. They identified four referent groupings of the trustee characteristics: benevolence, integrity, competence, and predictability. They also identified seven conceptual type categories that included trusting: attitude, intention, belief, expectancy, behavior, disposition, and institutional/structural. McKnight and Chervany then created an interdisciplinary model of conceptual trust types that included: 1) trusting intentions, 2) trust-related behavior, 3) trusting beliefs, 4) institution-based trust and 5) disposition to trust. We refer readers to the McKnight and Chervany paper [22] for additional information on trust and its classifications. In this work we focus on trusting beliefs.

Foundational work on trusting beliefs was conducted by Mayers, Davis, & Schoorman, and identified several elements which may at the heart of human-to-human trust including: 1) ability, 2) benevolence, and 3) integrity. Ability describes how capable or skilled a trustee is in carrying out a task in a domain specified by a trustor. Benevolence relates to a trustee having goals or intentions that benefit or align with a trustor. Finally, integrity relates to a trustor and trustee sharing a similar set of values and can be counted on to act in accordance with these shared beliefs. Building upon prior trust research, and recognizing the distinctions that exist between human to human and human to machine trust, McKnight et al. [21] identify three components of trusting beliefs that roughly align with those identified by Mayers, Davis & Schoorman: functionality, helpfulness, and reliability. Their work suggests that these elements of trust are evaluated either consciously or sub-consciously by technology users and help to form the trusting beliefs an individual has toward a technology.

In addition to understanding that there are different components underlying trusting beliefs, it is also important to acknowledge the temporal aspects of trust. McKnight et al. [21] describe trust with a specific technology as existing along a continuum starting with initial trust (formed with little to no experience with a technology) and moving on to knowledge based trust (formed over time and based on prior interaction with a technology). In this study we focus specifically on initial trusting beliefs.

Measuring trust has proved difficult and in some cases, a controversial endeavor. Generally speaking, there are two primary methods of measuring trust; behavioral measurement or self-report. In this study we focus on the latter. Jian et al. [12] developed what is called the Empirically Derived Trust Measure (ED). This scale assesses trust and distrust factors using 12 items and is best used for measuring initial trust in an information system. The ED has been utilized in a number of studies to measure trust and has been validated as a reliable trust measure [33]. We will revisit trust measurement as it applies to our study in the methods section.

2.3. Individual Differences

Individual differences are the collection of traits, features, and behavior that uniquely comprise the overall makeup of an individual. These differences are important for studying trust in human machine partnerships and include: propensity to trust [30] and personality traits such as agreeableness or extraversion [4]. There is evidence to support that humans will treat machines as teammates [9] and it also has been shown that these core personality traits affect team performance [1]. Therefore, it is important that individual personality characteristics be considered when looking at individual differences that could impact trust in human machine partnerships.

In psychology literature, the "Big-Five" personality traits have been studied as predictors of human behavior and include: openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability [8]. Individual personality traits have been shown to be very stable over extended periods of time [20]. Openness is a personality trait associated with intellectual curiosity coupled with a general disposition toward new experiences and adventure [7]. Conscientiousness refers to an individual's concern for detail, meeting planned goals, seeking achievement [7]. Extraversion is an individual's preferences for social interaction, stimulation, and desire to be with others [7]. Agreeableness is the personality trait that indicates a person's ability to work well with others, exhibiting high degree of trust and reserved temperament [7]. Emotional stability describes the personality trait relating to the stability of an individual's experience of emotion [7]. We will discuss our method of measuring the Big Five personality traits in the methods section.

Various studies have been conducted in the area of personality and human robot interaction. A review of these studies found that most researchers focused on the extraversion personality trait [29]. Not only have extraverts been found to be more comfortable with robots in their personal space [6], but in some studies extraversion is linked to increased levels of trust [10]. Other studies in human robot interaction have been conducted and have not observed these same findings. Without a foundational framework in this area, confusion can arise when apparent contradictions are reported. For example extraversion has been observed to have no correlation with trust in some cases [31].

2.4. Eye-tracking

Eye-tracking involves the detection of eye movements and the measurement of its anatomical components so they can be recorded in parallel to stimuli and provide objective insight into intangible latent constructs. Foundational to eye-tracking is the gaze point, a fundamental unit that underlies many other eye-tracking measures. A gaze point represents a single raw sample captured by an eye-tracker and can be mapped to a visual stimuli to indicate where an individual is looking at any given point in time.

A series of gaze points occurring within a close proximity to one another and within a predefined temporal threshold is called a fixation [28]. Variations in how these fixations occur give rise to common eye-tracking measures such as "fixation duration" (how long eye-gaze is fixed on a specific location of a stimuli) [37] and "number of fixations" (how many fixation events happened within a specified area on the stimuli) [25].

Attention is an example of an intangible latent construct measured by eye-tracking. Attention refers to the increased mental effort undertaken by an individual toward a specific stimuli, thought, or activity [15]. Fixations have been shown to correlate with user attentiveness, a link that is well supported in eye-tracking research [3]. When utilizing eye-tracking with computer screens, it is common for eye-tracking researchers to specify specific regions, called areas of interest (AOIs), and measure fixation events occurring within those regions. To do this, the number of fixations occurring within the coordinate plots of an AOI are recorded and counted. From these fixation counts, one can obtain insight into the amount of attention paid to that specific area on the screen. For a more comprehensive review of eye tracking and a list of eye-tracking measures, we refer to Holmqvist et al. [11]. We will return to the topic of measuring attention in our methods section.

3. Theory and Research Questions

Prior trust research in the information systems domain suggests that individual differences may play a role in human trust in an intelligent system [4]. Sparse research into embodied intelligent systems makes it difficult to hypothesize specific relationships between individual personality types and trust in an intelligent system with a humanoid appearance. Trait activation theory suggests that when individuals are working in novel, ambiguous situations an individual's personality traits will be expressed [34]. This is because in the absence of trait-relevant situational cues, individual behavior defaults back to activity associated with core personality traits. It is therefore reasonable to expect personality traits to play a role in trust in a novel partnership with an embodied intelligent system. We therefore pose the following research question:

RQ1: What is the relationship between the Big Five personality traits and trust in a humanoid robot?

A study of personality and trust in a humanoid robot would be incomplete without consideration of the actual interaction or utilization of the machine partner. While intelligent systems may present solutions or recommendations in a way that suggests rationality, intelligence, autonomy, and environmental perception [42], it is not known whether human collaborators will utilize this information and partner with the intelligent system or simply act independently and ignore the intelligent system. McKnight et al. [21] suggest that trust is influenced and formed with experience. In a situation where working with an intelligent system is optional, it is unknown if individuals will utilize suggested solutions developed by the system and if such utilization will impact trust. We therefore suggest a second research question:

RQ2: What, if any relationship exists between utilization of an intelligent system and trust?

We have developed the following research model to explore the relationship between individual personality traits, utilization, and trust.

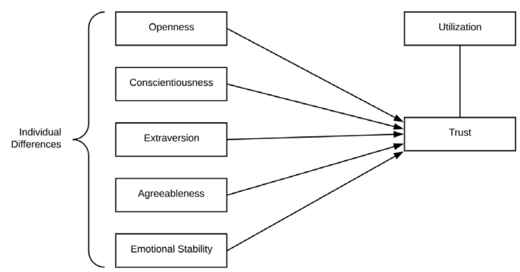

Figure 1. Conceptual Model

4. Method

4.1 Sample

Participants were graduate and undergraduate students from a medium sized Midwestern university. A total of 58 subjects were recruited from a subject participant pool and compensated with course credit. Data collection occurred over a period of two months. Participants ages ranged from 19 to 24 years with the average age 21.69 years, median age of 21 years, and mode of 21 years.

4.2 Experimental Task & Apparatus

The experimental tasks utilized in this study included the "Desert and Reef Survival Simulations" originally developed by Human Synergistics. These tasks were chosen because they had been previously utilized in numerous studies and had performance data for a number of populations. In addition, the specific survival situations involving desert and reef environments were specifically chosen as they would be environments that were likely unfamiliar to participants from our sample population.

The "Desert and Reef Survival Situations" described scenarios where people had been stranded with only a limited number of items that could be used to survive. The goal of the simulations was to identify which of these items were most essential and rank the items in order of their importance for survival. For each survival simulation participants would make two rankings, an individual ranking and then a final ranking that was made with consideration of solutions and input from a partner. After generating a ranking solution individually, participants were allowed to view their partner's solution and converse with their partner to better understand the reasoning behind the partner solution. Participants were told that their final ranking would be compared against a solution developed by military survival experts. Participants were also informed that they would need to rank 75% or more of their items correctly (as compared to the expert's ranking) or they would not receive participation credit for the study.

A custom web application was used to conduct the survival task activities. The web application utilized the Django web framework and was written primarily in Python and Java-Script. All of the actions and inputs of the participants were logged by the web application and associated with an anonymous participant identification number.

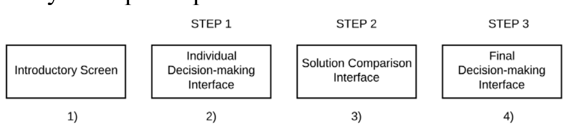

Figure 2. Web Interface Screen Flow

The web application for each survival activity consisted of four primary interface screens that were accessed in sequential order (reference Figure 2): 1) an introductory screen, 2) an individual decision-making interface, 3) a collaborative interface, and 4) the final decision-making interface. On the introductory screen, the web application first presented users with a login and then advanced to display directions and the scenario description for the survival scenario. This was followed by the individual decision-making interface (Step 1) that presented a randomized list of items to be ordered according to their importance to the survival situation. At this point in time, individuals believed that they and their partner were working independently to develop an optimal solution. After submitting their individual solutions, the web application would display an animated dialogue that stated "waiting for your partner." This was added to emphasize the partner was working to generate a solution. This was followed by the solution comparison interface (Step 2) pictured in Figure 2. Finally, participants utilized the final decision-making interface which involved a reference area on the left (showing their individual and partner rankings) as well as a work area on the right displaying the original randomized list of items.

Countermeasures were taken to discourage participants from completing the task without giving appropriate consideration to their answers. In both Step 1 and Step 3, participants were asked to provide written justification for why they had ranked their items and also asked to provide their confidence for their ranking.

The embodied intelligent system partner in this study was a humanoid robot programmed to respond to the participant questions about items from the survival scenarios. Information about each of the items was taken from the explanations from the survival simulation solutions manual developed by survival experts. While the robot partner was capable of responding to participant questions without intervention, we disabled this functionality after pilot testing revealed that mistakes could sometimes occur preventing a natural interaction. We decided to utilize a "Wizard of Oz" methodology for data collection and manually activate the partner's spoken responses to questions. In order to minimize the set of potential questions asked of the partner, we informed participants that they were only allowed to ask about a single item at a time. We developed a series of custom responses to answer questions that were out of these bounds and redirect participants to ask questions that were about the items.

4.3 Procedure

The experiment was conducted in a dedicated lab space with environmental controls to alleviate noise, light, and visual distractions. Figure 3 illustrates the experimental procedure. Prior to the experimentation day, participants completed an individual characteristics assessment. Participants returned to the lab on a different day to complete the experiment described in this study. Upon arrival on the second day, participants first completed an IRB mandated

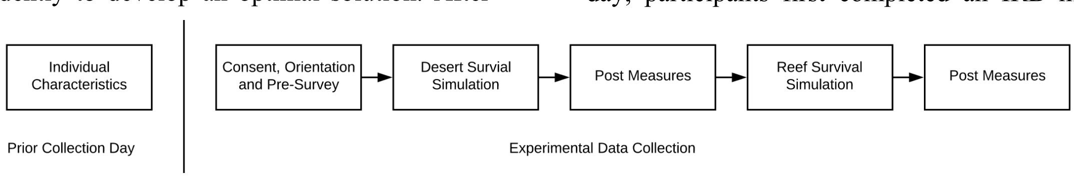

Figure 3. Experimental Procedure

informed consent. Participants were made to believe that they were helping to evaluate a web application designed to aid decision making. At this time, participants were also told that only individuals who achieved a passing score on the simulation activites would be awarded participation credit (in reality all participants received credit for their participation). Participants then completed a study orientation and pre-survey. In this orientation presurvey, participants were shown an example interface and given an opportunity to perform a ranking of items. The pre-survey included a question that asked what would happen if participants did not achieve a passing score on the survival simulations. This question had a forced validation that ensured all participants were aware of the risk associated with this experiment (the loss of participation credit).

Next, participants were directed to a second room (refer to figure 4) where they were introduced and seated across from their partner, calibrated for eye-tracking, and given more information about the first survival simulation activity. The calibration process required participants to focus on nine dots positioned with three rows of dots across the top, middle, and bottom of the screen. This process was repeated until the participants acquired an "excellent calibration" (average distance of measured gaze from the target $\mu(x,y) \leq 20$ pixels). The participants were told that the partner had access to a database of various survival items, their usefulness in past survival situations, and would use this database to help generate a real time solution.

Figure 4. Experiment Setup

Participants were told that the partner would develop solutions in real time and would not have access to the solutions developed by the survival experts (in reality the solutions presented as the partner solutions were the optimal solution developed by the survival experts). Participants were reminded that they would be scored on their rankings and that failure to achieve passing score would result in a loss of credit for this study. Participants were then automatically presented the instructions for the simulation and left to work with their partner to achieve a solution.

After completing the first survival simulation, participants rang a doorbell to inform the study proctor they were finished. Participants then left the room and completed an assessment that measured trust and perceptions of their partner after the first activity.

Participants were then directed back to the room where they worked with their partner to complete the first survival simulation. At this time, participants were once again calibrated for eye-tracking and began the second survival simulation.

After completing the second survival simulation, participants rang the doorbell again and were escorted to another room to complete a final assessment that asked about their experience and perceptions of their partner in the second survival simulation. At this point they were debriefed and thanked for their participation.

4.4 Measures

The experiment utilized: measures of trust (before interaction as well as after the first and second simulation), system utilization, performance, perceived reliability, confidence, perceived humanness of partner, perceived presence, the Big Five personality traits, propensity to trust, and propensity to anthropomorphize. In this paper, we considered only the following measures:

Trust was assessed using the Empirically Derived (ED) scale developed by Jian et al [12]. The 12 item instrument conceptualizes trust as being comprised of two factors (trust & distrust). The trust factors of the scale include confidence, security, integrity, dependability, reliability, trust and familiarity. The distrust factors include deceptiveness, underhandedness, suspiciousness, wariness, and harm. Example question items include: "I am wary of my partner" and "I am confident in my partner."

The Big Five Personality traits were measured using the Big Five Index, a 44-item instrument that measures extraversion, agreeableness, openness to experience, conscientiousness, and neuroticism [13,

Table 1. Correlations Between Individual Personality Scores, Utilization and Trust

	Mean	SD	1	2	3	4	5	6	7
1. Trust in Partner	3.80	0.41	1	.396**	.048	-.114	.097	-.191	.338*
2. Utilization	101.95	126.96		1	-.283*	-.164	-.054	-.126	-.142
3. Extraversion	2.81	0.69			1	.238	.024	-.104	.399**
4. Agreeableness	2.35	0.55				1	.329*	-.341**	.308*
5. Conscientiousness	2.45	0.57					1	-.404**	-.011
6. Neuroticism	3.11	0.63						1	-.207
7. Openness	2.41	0.45							1

**Correlation is significant at the 0.01 level.
*Correlation is significant at the 0.05 level.

14]. Scale reliabilities for each of the five personality measures resulted in Cronbach's alpha scores of .88 for extraversion, .79 for agreeableness, .82 for conscientiousness, .79 for neuroticism, and .69 for openness. An example item for the measure of extraversion was, "I am someone who is talkative." Each item allowed for responses ranging from one to five, with one being strongly agree and five being strongly disagree.

Utilization of the partner's generated solution was measured using eye-tracking. Figure 5 shows an example eye-tracking gaze path over the partner solutions space in "Step 2" of the survival simulation activity. A Tobii X-60 eye-tracking device was used to measure the number of fixations that occurred within the partner solution space in Step 2 of the desert survival simulation. We utilized a duration dispersion based fixation algorithm which consider a fixation to be a collection of one or more gaze points occurring within a 1 degree radius for a minimum of 100 ms and having 50% or more samples.

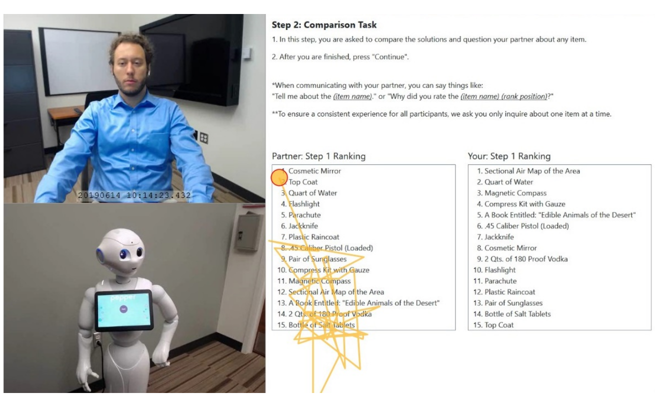

Figure 5. Eye-tracking for the Partner Solutions in the Comparison Task

5. Results

The central focus for this study was to investigate the role of individual personality traits and trust in the partner for the desert survival simulation. While we collected data for the reef survival simulation, we did not analyze that data for the present study. Correlations for all of the Big Five, utilization and trust were performed and can be found in Table 1.

Significant correlations among the key variables of interest and trust included openness scores (r = .34, $p < .05$) and utilization (r = .40, $p < .01$). Higher openness scores are associated with higher scores of partner trust. Similarly, higher scores in utilization are associated with higher scores of partner trust. We performed a regression analysis on these variables to determine the amount of variance each accounted for in partner trust.

The regression of trust on openness scores and utilization was significant, $F(2,51) = 11.11$, $p < .01$, $R^2 = .30$, indicating that together openness scores and utilization were significant predictors of partner trust. The multiple regression equation generated by this model showed that predicted trust = .363 * openness + .001 * utilization + 2.763. This means that for every one unit increase in openness scores, there would be an expected increase in predicted trust of .363, holding utilization constant. Additionally, this means that for every one unit increase in utilization, there would be an expected increase in predicted trust of .001, holding openness scores constant. Additionally, if both openness and utilization scores were zero, the predicted trust score would be 2.76.

Together, the independent variables utilization and openness scores accounted for 30.4% of the variation in partner trust. Openness was a significant positive predictor of partner trust, above and beyond utilization, β = .39, B = 0.36, $t(51) = 3.27$, p = .002, 95% CI [0.14, 0.59], such that greater openness would predict greater trust. Utilization was a significant positive predictor of partner trust, above and beyond openness, β = .44, B = 0.001, $t(51)$ = 3.73, p < .001, 95% CI [0.001, 0.002], such that greater utilization would predict greater trust.

Figure 6 illustrates a fixation based heat map of an individual with high trust on the partner solution displayed in Step 2 in the comparison task screen. The heat map shows that for the individual trusting their partner, a great amount of attention was paid to the partner solution.

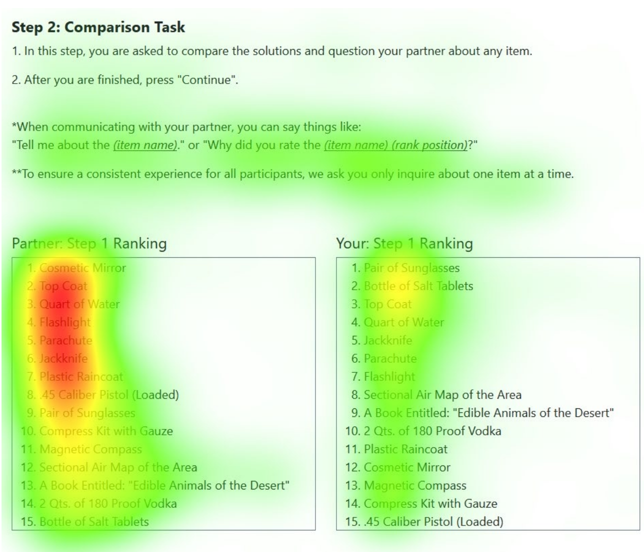

Figure 6. Heat Map for Solution Comparison Task by an Individual with High Partner Trust

6. Discussion

To summarize the results of this present effort, we found that there was a significant positive correlation between openness scores and trust. Prior research in the IS field identified emotional stability, extraversion, and agreeableness as being personality types important to trust in human-computer partnerships [4, 29]. We did not observe these personality facets to be significant factors in trust of a humanoid robot partner, and instead found the openness personality dimension to be important. This is a significant finding and could have implications for deploying humanoid robots in a number of real-world situations where trust in the robot is important. While our findings were exploratory and additional research needs to be conducted in this area, a potential implication for human robot partnerships would be to hire or select individuals scoring high in openness for collaborative work with humanoid robots.

Possibly, a reason for the openness personality trait being a significant predictor of trust may be related to the novelty of working with the humanoid robot. The openness personality trait is associated with intellectual curiosity coupled with a general disposition toward new experiences and adventure [7]. Most participants reported never interacting with a humanoid robot before this experience. Future work should explore if this novelty factor endures over time for individuals high in openness.

Our analysis also indicated that attention to partner solutions (utilization) had a relationship to partner trust. While correlations between these two variables have been investigated before [2, 23], our study is one of the first to find correlations when measuring utilization through eye-tracking. The relationship between utilization and trust is unique as utilization is both an outcome of trust and a factor that influences whether or not to trust [18]. Future studies should look to better understanding the relationship between trust and utilization over time and at various levels of experience with a machine partner.

Risk and uncertainty are essential components for trust. A lack of real and meaningful risk has been a severe limitation in prior trust studies as the risk often has been either simulated or lacked real world consequence. An important aspect of this study was the inclusion of real individual risk (loss of participation credit) to the human participants who engaged in the survival tasks.

The study we have presented is not without its own set of limitations. First, participants interacted with only one humanoid robot as their partner. Future studies would want to look at how other system embodiments with varying degrees of humanness and interaction modalities would impact the interaction. Second, we only examined trust at one point in time. Levels of trust could be studied at various points during the interaction as trust could change throughout the interaction. Finally, this study was conducted in a controlled laboratory setting and like many experiments, application of findings to the real world should be considered in this light.

7. Conclusion

Our findings suggest that, under the conditions of this study, individuals scoring high in openness may be more trusting of humanoid robots than individuals low in openness.

8. References

[1] Barrick, M.R., G.L. Stewart, M.J. Neubert, and M.K. Mount, "Relating member ability and personality to work-team processes and team effectiveness.", *Journal of Applied Psychology 83*(3), 1998, pp. 377–391.

[2] Bisantz, A.M., and Y. Seong, "Assessment of operator trust in and utilization of automated decision-aids under different framing conditions", *International Journal of Industrial Ergonomics 28*(2), 2001, pp. 85–97.

[3] Corbetta, M., "Frontoparietal cortical networks for directing attention and the eye to visual locations: Identical, independent, or overlapping neural systems?", *Proceedings of the National Academy of Sciences 95*(3), 1998, pp. 831–838.

[4] Elson, J.S., D. Derrick, and G. Ligon, "Examining Trust and Reliance in Collaborations between Humans and Automated Agents", 2018.

[5] Epley, N., A. Waytz, and J.T. Cacioppo, "On seeing human: A three-factor theory of anthropomorphism", *Psychological Review 114*(4), 2007, pp. 864–886.

[6] Gockley, R., and M.J. MatariĆ, "Encouraging physical therapy compliance with a hands-off mobile robot", *Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction*, ACM (2006), 150–155.

[7] Goldberg, L.R., "The Development of Markers for the Big-Five Factor Structure.", *Psychological assessment 4*(1), 1992, pp. 26.

[8] Gosling, S.D., P.J. Rentfrow, and W.B. Swann, "A very brief measure of the Big-Five personality domains", *Journal of Research in Personality 37*, 2003, pp. 504–528.

[9] Groom, V., and C. Nass, "Can robots be teammates?: Benchmarks in human–robot teams", *Interaction Studies 8*(3), 2007, pp. 483–500.

[10] Haring, K.S., Y. Matsumoto, and K. Watanabe, "How do people perceive and trust a lifelike robot", *Proceedings of the world congress on engineering and computer science*, (2013).

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

[12] Jian, J.-Y., A.M. Bisantz, and C.G. Drury, "Foundations for an empirically determined scale of trust in automated systems", *International Journal of Cognitive Ergonomics 4*(1), 2000, pp. 53–71.

[13] John, O.P., E.M. Donahue, and R.L. Kentle, *The Big Five inventory—Versions 4a and 54*, Berkeley, CA: University of California, Berkeley, Institute of Personality and Social Research, 1991.

[14] John, O.P., L.P. Naumann, and C.J. Soto, "Paradigm Shift to the Integrative Big Five Trait Taxonomy", *Handbook of Personality: Theory and Research 3*, 2008, pp. 114–158.

[15] Kahneman, D., *Attention and effort*, Prentice-Hall, Englewood Cliffs, N.J, 1973.

[16] Li, J., "The benefit of being physically present: A survey of experimental works comparing copresent robots, telepresent robots and virtual agents", *International Journal of Human-Computer Studies 77*, 2015, pp. 23–37.

[17] Madsen, M., and S. Gregor, "Measuring human-computer trust", *11th australasian conference on information systems*, Citeseer (2000), 6–8.

[18] Masalonis, A.J., and R. Parasuraman, "Trust as a Construct for Evaluation of Automated Aids: Past and Future Theory and Research", *Proceedings of the Human Factors and Ergonomics Society Annual Meeting 43*(3), 1999, pp. 184–187.

[19] Matsatsinis, N.F., and Y. Siskos, *Intelligent Support Systems for Marketing Decisions*, Springer Science & Business Media, 2012.

[20] McCrae, R.R., and O.P. John, "An introduction to the five-factor model and its applications", *Journal of personality 60*, 1992.

[21] Mcknight, D.H., M. Carter, J.B. Thatcher, and P.F. Clay, "Trust in a specific technology: An investigation of its components and measures", *ACM Transactions on Management Information Systems 2*(2), 2011, pp. 1–25.

[22] McKnight, D.H., and N.L. Chervany, "Trust and distrust definitions: One bite at a time", In *Trust in Cyber-societies*. Springer, 2001, 27–54.

[23] Moray, N., T. Inagaki, and M. Itoh, "Adaptive Automation, Trust, and Self-Confidence in Fault Management of Time-Critical Tasks", 2000, pp. 16.

[24] Nunamaker, J.F., D.C. Derrick, A.C. Elkins, J.K. Burgoon, and M.W. Patton, "Embodied Conversational Agent-Based Kiosk for Automated Interviewing", *Journal of Management Information Systems 28*(1), 2011, pp. 17–49.

[25] Poole, A., and L.J. Ball, “Eye tracking in HCI and usability research”, *Encyclopedia of human computer interaction 1*, 2006, pp. 211–219.

[26] Poole, D.L., A.K. Mackworth, and R. Goebel, *Computational intelligence: a logical approach*, Oxford University Press New York, 1998.

[27] Rasch, R., A. Kott, and K.D. Forbus, “Incorporating Ai into Military Decision Making: An Experiment”, *IEEE Intelligent Systems 18*(4), 2003, pp. 18–26.

[28] Recarte, M.A., and L.M. Nunes, “Effects of verbal and spatial-imagery tasks on eye fixations while driving.”, *Journal of experimental psychology: Applied 6*(1), 2000, pp. 31.

[29] Robert, L., “Personality in the human robot interaction literature: A review and brief critique”, *Robert, LP (2018). Personality in the Human Robot Interaction Literature: A Review and Brief Critique, Proceedings of the 24th Americas Conference on Information Systems, Aug*, (2018), 16–18.

[30] Rotter, J.B., “A new scale for the measurement of interpersonal trust”, *Journal of Personality 35*(4), 1967, pp. 651–665.

[31] Salem, M., G. Lakatos, F. Amirabdollahian, and K. Dautenhahn, “Would you trust a (faulty) robot?: Effects of error, task type and personality on human-robot cooperation and trust”, *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, ACM (2015), 141–148.

[32] Schroeder, J., and M. Schroeder, “Trusting in Machines: How Mode of Interaction Affects Willingness to Share Personal Information with Machines”, (2018).

[33] Spain, R.D., E.A. Bustamante, and J.P. Bliss, “Towards an empirically developed scale for system trust: Take two”, *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, SAGE Publications Sage CA: Los Angeles, CA (2008), 1335–1339.

[34] Tett, R.P., and D.D. Burnett, “A personality trait-based interactionist model of job performance.”, *Journal of Applied psychology 88*(3), 2003, pp. 500.

[35] Turban, E., J.E. Aronson, and T.-P. Liang, *Decision Support Systems and Intelligent Systems*, Prentice Hall, 2004.

[36] Twyman, N.W., J.G. Proudfoot, R.M. Schuetzler, A.C. Elkins, and D.C. Derrick, “Robustness of multiple indicators in automated screening systems for deception detection”, *Journal of Management Information Systems 32*(4), 2015, pp. 215–245.

[37] Unema, P.J., S. Pannasch, M. Joos, and B.M. Velichkovsky, “Time course of information processing during scene perception: The relationship between saccade amplitude and fixation duration”, *Visual cognition 12*(3), 2005, pp. 473–494.

[38] de Visser, E.J., S.S. Monfort, R. McKendrick, et al., “Almost human: Anthropomorphism increases trust resilience in cognitive agents.”, *Journal of Experimental Psychology: Applied 22*(3), 2016, pp. 331–349.

[39] Walters, M.L., K.L. Koay, D.S. Syrdal, and K. Dautenhahn, “Preferences and Perceptions of Robot Appearance and Embodiment in Human-Robot Interaction Trials.”, 2009, pp. 8.

[40] Warren, J., G. Beliakov, and B. van der Zwaag, “Fuzzy logic in clinical practice decision support systems”, *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences*, (2000), 10 pp.-.

[41] Waytz, A., J. Cacioppo, and N. Epley, “Who Sees Human? The Stability and Importance of Individual Differences in Anthropomorphism”, *Perspectives on psychological science : a journal of the Association for Psychological Science 5*(3), 2014, pp. 219–232.

[42] Wooldridge, M., N.R. Jennings, and others, “Intelligent agents: Theory and practice”, *Knowledge engineering review 10*(2), 1995, pp. 115–152.

[43] “Projet ROMEO”, *Projet ROMEO*. https://projetromeo.com/