Decision-making with a Humanoid Robot Partner: Individual Differences Impacting Trust

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Abstract: Trust in human-machine teams, where humans partner with intelligent systems, is critical to effective collaboration and work success. Research in prior studies of trust in human-robot partnerships, has largely focused on three groups of trust antecedents: factors relating to the environment, the machine, and human individual differences. There is a dearth of research in this later area, despite wide recognition that individual differences play an important role in human behaviour and cognition. This paper draws on the psychological theory of trait activation and examines the role of human personality in trust in the relationships between humans and intelligent humanoid robots partnering to make critical decisions. We conducted an empirical study that looked to explore the role of the Big-Five personality traits on trust. Results suggest that the openness personality trait is a significant predictor of trust in a humanoid-robot partner, above and beyond the individual difference propensity trust. Individuals scoring high on the openness personality trait may have a greater trust in a humanoid robot partner than those with low scores in the openness personality dimension. Future studies should look to better understand the trait activating factors related to Openness in human machine trusting relationships.

1 INTRODUCTION

Advances in artificial intelligence promise a future of computing that will transform humans and machines' relationship, moving machines from tools to collaborative partners. This future has been referred to as the "cognitive computing" era and is characterized by intelligent systems, a class of systems that learn and interact naturally to perform knowledge work (Spohrer, J., and G. Banavar, 2015). These systems are designed to augment human expertise, amplify human intelligence, enhance productivity, and improve decision-making. These systems can be embodied as humanoid robots as a way of integrating them with human teammates. Trust in these systems is essential to collaborate effectively and fully realize the advantages of these new machine partners. Research has found trust to be a necessary ingredient for successful cooperation (Jones, G. R., and J. M. George, 1998), important in predicting human use and reliance on technology (Dzindolet, M. T., et al., 2003) and crucial to relationships in situations characterized by risk and uncertainty (Fukuyama, F., 1995; Luhmann, N., 1982). Despite recognizing the importance of trust, there is an incomplete understanding of trust, which adequately accounts for the relationship between the multitude of factors that contribute to trust in an a robot partner. Idiosyncratic patterns of trust has been observed across trust research in humans, machines, and other technology systems. This paper advances the theories of trust and unifies prior work by adopting existing approaches and theoretical frameworks from psychology literature and applying them to the Information Systems domain to better understand human trust humanoid robots.

It is generally recognized that three primary sources influence human trust in an intelligent machine: characteristics of the system (the robot being trusted), individual characteristics (the person who is trusting), and factors relating to the situation or environment where trust is being applied. In information systems literature, significant effort has been made to describe system characteristics and situational factors that contribute to trust. Relatively little attention has been devoted to understanding the

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role that personality traits and other individual differences play, despite numerous trust researchers recognizing their importance in trusting relationships involving both humans and machines (Billings, D. R., et al., 2012; Mayer, R. C., et al., 1995; Mcknight, D. H., et al., 2011). This paper focuses on how individual differences and personality traits relate to trust in humanoid-robot partners through the lens of Trait Activation Theory. This theory's application to the information systems domain provides a more complete picture of the factors that come together to predict trust.

Trait Activation Theory posits that situational cues uniquely act on an individual's personality to elicit behavioural and psychological responses characteristic of a personality type. In short, environmental factors "activate" or amplify personality trait expression. It follows that when interacting with a humanoid robot, situational cues activate characteristic personality responses, ultimately influencing an individual's perceptions and trust in the system. Trust in information systems has been operationalized both as a behaviour response as well as a quantifiable measure of a systems performance, process, and purpose. We posit that personality trait activation strongly impacts both behavioural and perceptual measures of trust in an intelligent system.

2 BACKGROUND

This section describes intelligent systems, previous research on trust, individual differences and trait activation theory.

2.1 Trust

Trust is a multi-dimensional construct that has proven quite difficult to conceptualize and define (McKnight, D. H., and N. L. Chervany, 2001). For this study we adopt a definition of trust that has been proposed by Madsen and Gregor (Madsen, M., and S. Gregor, 2000). 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).

Numerous definitions of trust exemplify the many different ways of conceptualizing the construct. In effort to bring clarity to the area of trust research, McKnight and Chervany (McKnight, D. H., and N. L. Chervany, 2001) 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 grouping groupings of the trustee characteristics: benevolence, integrity, competence, and predictability. They also identified seven conceptual type categories that include trusting: attitude, intention, belief, expectancy, behaviour, disposition, and institutional/structural. McKnight and Chervany then created an interdisciplinary model of conceptual trust types that included: 1) trusting intentions, 2) trust-related behaviour, 3) trusting beliefs, 4) Institution-based trust and 5) disposition to trust. We refer readers to the McKnight and Chervany paper (McKnight, D. H., and N. L. Chervany, 2001) 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 (Mcknight, D. H., et al., 2011) 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. (Mcknight, D. H., et al., 2011) 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 controversial endeavor. Generally speaking, there are two primary methods of measuring trust, behavioural measurement or self-report. In this study we focus on the latter. Jian et al. (Jian, J.-Y., et al., 2000) developed what is called the Empirically Derived Trust Measure (ED). The 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 reliable trust measure (Spain, R. D., et al., 2008). We will revisit trust measurement as it applies to our study in the methods section.

2.2 Individual Differences

Individual differences are the collection of traits, features, and behaviour 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 (Rotter, J. B., 1967) and personality traits such as openness, agreeableness or extraversion (Elson, J. S., D. Derrick, and G. Ligon, 2018). There is evidence to support that humans will treat machines as teammates (Groom, V., and C. Nass, 2007) and it also has been shown that these core personality traits affect team performance (Barrick, M. R., et al., 1998). 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 behaviour and include: openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability (Gosling, S. D., et al., 2003). Individual personality traits have been shown to be very stable over extended periods of time (McCrae, R. R., and O. P. John, 1992). Openness is a personality trait associated with intellectual curiosity coupled with a general disposition toward new experiences and adventure (Goldberg, L. R., 1992). Conscientiousness refers to an individual’s concern for detail, meeting planned goals, seeking achievement (Goldberg, L. R., 1992). Extraversion is an individual’s preferences for social interaction, stimulation, and desire to be with others (Goldberg, L. R., 1992). Agreeableness is the personality trait that indicates a person’s ability to work well with others, exhibiting high degree of trust and reserved temperament (Goldberg, L. R., 1992). Emotional stability describes the personality trait relating to the stability of an individual’s experience of emotion (Goldberg, L. R., 1992). We will discuss our method of measuring the Big Five personality traits in the methods section.

2.3 Trait Activation Theory

In psychology literature, trait activation theory has provided a framework to help understand why personality traits manifest themselves in only certain circumstances. Thus, one aim of the present effort is to introduce information systems researchers to this theoretical framework to understand the complex and often contradictory findings in the pursuit of scholarly work on human-computer interaction. Trait activation theory states that "the behavioural expression of a trait requires arousal of that trait by trait-relevant situational cues" (Tett, R. P., and H. A. Guterman, 2000). Sources of trait-relevant cues when interacting with intelligent systems will come from both perceptions of system characteristics or situational factors. These trait-relevant cues also serve as factors to inform user trust.

In the early stages of system use, minimal information will be available to inform trust. In such situations, authentic individual differences such as propensity to trust and the Big Five personality traits may be activated by initial perceptions of the system and early system interaction. While prior research has shown relationships between individual differences (propensity to trust, personality traits) and trust in human relationships, very little research has been conducted to understand how these individual differences will relate to early trust when a human collaborates with a novel intelligent system.

3 RESEARCH QUESTION

Prior trust research in the information systems domain suggests that individual differences may play a role in human trust in an intelligent system (Elson, J. S., et al., 2018). 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 (Tett, R. P., and D. D. Burnett, 2003). This is because in the absence of trait-relevant situational cues, individual behaviour 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:

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

4 METHOD

4.1 Sample

Participants were graduate and undergraduate students from a medium-sized Midwestern university. A total of 101 (58 females, 41 males, and two preferring not to identify) individuals were included in the analysis. They were recruited from a subject participant pool within the College of Business Administration. Thirty-three individuals were not included in the analysis because of incomplete data. Participants ages ranged from 19 to 24 years with a mean age of 23 years, a median age of 21 years, and mode of 21 years. Participation in this study was on a voluntary basis, however participation credit toward a course requirement was given to those who took part in the study.

4.2 Apparatus

The experimental task in this study was the Desert Survival Simulation, initially developed by Human Synergistics. This task was chosen as it had been previously utilized in numerous team studies and had performance data for several populations. Also, the specific survival situation involving the desert environment was specifically chosen as it would be an environment that was likely unfamiliar to participants from our sample population. This reduced the likelihood that individuals would possess expertise related to the simulation. Furthermore, the Desert Survival Simulation can be completed with relatively low workload as decisions can be considered one at a time and without time pressure. This attribute of the task helped to minimize the possibility that subjects would offload decision choices to their partner as a strategy to cope with high workload (Molloy, R., and R. Parasuraman, 1996). Finally, this survival simulation presented a situation with no clear-cut answer. To achieve the best score, individuals must carefully consider every decision they must make. The survival situation described a scenario where people had been stranded with only a small number of items that could be used to survive. The simulation's goal was to identify which of these items were the most essential and rank the items in order of their importance for survival.

A custom web application was used to conduct the survival task activity. The web application for the survival activity consisted of four primary interface screens that were accessed in sequential order: 1) an introductory screen, 2) an individual decision-making interface, 3) a collaborative interface, and 4) the final decision-making interface.

In this study, the intelligent system partner was the humanoid robot Pepper from SoftBank Robotics. The robot was programmed to respond to the participant questions about items from the survival scenario. Participants were told that their 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).

4.3 Procedure

Countermeasures were taken to discourage participants from completing the task without appropriately considering their answers. Participants were asked to provide written justification for why they had ranked their items and asked to provide their confidence for their ranking. Between steps, participants did not receive feedback regarding their performance or degree of success, so they did not know how they performed until being debriefed at the end of the study.

The experiment was conducted in a dedicated lab space with environmental controls to alleviate noise, light, and visual distractions. To avoid monomethod bias, participants completed an individual characteristics assessment prior to the experimentation day. 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 informed consent. Participants were made to believe that they were helping to evaluate a web application designed to walk users through a novel partner decision making process. Participants were also told that only individuals who achieved a passing score on the simulation activities would be awarded participation credit (in reality, all participants received credit for their participation). Participants then completed a study orientation and pre-survey in a private room. In this orientation presurvey, participants were shown an example of the web ranking interface and allowed 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 simulation. This question served as a manipulation check that ensured all participants in the analysis were aware of the risk associated with this experiment (the loss of participation credit).

Next, participants were directed to a second room, where they were introduced and seated across from their partner and given more information about the first survival simulation activity. 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.

Participants were reminded that they would be scored on their rankings and that failure to achieve a passing score (greater than 75% correct) would result in a loss of credit for this study. Participants were then automatically presented with the simulation instructions and left to work with their partner to achieve a solution.

4.4 Measures

The experiment utilized: measures of trust (before interaction and after the simulation), system utilization, perceived humanness of partner, perceived presence, the Big Five personality traits, propensity to trust, and propensity to anthropomorphize. In this study, we considered the following measures:

The Big Five Personality traits were measured using the Big Five Index (BFI), a psychometric instrument that measures Extraversion, Agreeableness, Openness to Experience, Conscientiousness, and Neuroticism (John, O. P., et al., 1991; John, O. P., et al., 2008). This questionnaire contains 44 items, each with a 5-point Likert scale that ask the participant to rate their agreement or disagreement with statements about their personality. Each item allowed for responses ranging from one to five, with one being strongly agree and five being strongly disagree. An example item for the measure of Extraversion was, "I am someone who is talkative." Scale reliabilities for each of the five personality measures resulted in Cronbach's alpha scores of .87 for Extraversion, .71 for agreeableness, .84 for conscientiousness, .79 for neuroticism, and .76 for openness.

Propensity to trust was assessed using the propensity to trust others measure developed by Ashleigh et al. (Ashleigh, M. J., et al., 2012). This 9-item measurement uses a 5-point Likert scale that asks the participant to rate their agreement or disagreement with statements about their attitudes toward others. An example question item is: "Other people are out to get as much as they can for themselves." Scale reliability for the measure resulted in a Cronbach's alpha score of .89.

Trust was assessed using a modified version of the Empirically Derived (ED) scale developed by Jian et al (Jian, J.-Y., et al., 2000). The 12-item instrument conceptualizes trust as being comprised of two factors (trust & distrust). The scale's trust factors include confidence, security, integrity, dependability, reliability, trust, and familiarity. The distrust factors include deceptiveness, underhandedness, suspiciousness, wariness, and harm. Original items were worded about a "system." Items were reworded to reference a generic "partner." Example question items include: "I am wary of my partner" and "I am confident in my partner." Scale reliability for the measure resulted in a Cronbach's alpha scores of .83.

5 RESULTS

Descriptive statistics for the continuous variables trust, propensity to trust, Conscientiousness, Neuroticism, Extraversion, Agreeableness, Openness, analytic cognition, affective cognition (see Table 1).

Table 1: Descriptive Statistics for Continuous Variables.

Variables	N	Mean	Std. Deviation	Variance	Minimum	Maximum
Trust	97	3.82	0.43	0.19	3.00	5.00
Propensity to Trust	97	3.87	1.05	1.11	1.11	6.44
Conscientiousness	97	3.74	0.61	0.37	1.33	5.00
Neuroticism	97	2.94	0.62	0.39	1.63	4.25
Extraversion	97	3.10	0.74	0.55	1.63	5.00
Agreeableness	97	3.72	0.51	0.26	2.44	4.67
Openness	97	3.50	0.53	0.28	2.10	4.80

A correlation analysis was performed to identify the individual differences that were significantly correlated with trust. Next, a hierarchical regression analysis was performed to test the relationship between analytical cognitive processes, affective cognitive processes, and trust, including key individual differences as covariates.

Results of a correlation analysis showed that only two individual differences variables under consideration were significantly correlated with trust in the humanoid robot partner: Openness (r = -.276, p = .003) and propensity to trust (r =.168, p =.050). The remaining individual difference variables were not significantly correlated with trust: Extraversion (r = -.043, p = .339), Agreeableness (r = .044, p = .335), Conscientiousness (r = .018, p = .429), and

Table 2: Correlations Among Continuous Variables.

Variables	1	2	3	4	5	6	7
1. Trust	-						
2. Propensity to Trust	.17*	-					
3. Conscientiousness	.02	.22*	-				
4. Neuroticism	-.09	-.34**	-.28**	-			
5. Extraversion	-.04	.29**	.11	-.30**	-		
6. Agreeableness	0.04	.39**	.34**	-.34**	.08	-	
7. Openness	-.28**	0.15	.08	-.17*	.32**	.21*	-

Table 3: Hierarchical Multiple Regression of Trust on Propensity to Trust and Openness.

Model	*b*	*SE*	*t*	β	*F*	R^2	Δ*F*	ΔR^2	95% CI
1. Intercept	3.55	0.17	21.37**		2.78	0.03			[3.22, 3.88]
Propensity to Trust	0.07	0.04	1.67	0.17					[-0.01, 0.15]
2. Intercept	4.36	0.30	14.51**		6.52*	0.12	10.00	0.09	[3.76, 4.96]
Propensity to Trust	0.09	0.04	2.21*	0.22					[0.01, 0.17]
Openness	-0.25	0.08	-3.16*	-0.31					[-0.41, -0.09]

Neuroticism (r = -.091, p = .186). Correlations among each of the variables are presented in Table 2. Considering these results, only the significantly correlated individual difference variables were retained for the final regression.

The correlation analysis revealed that only two individual differences, propensity to trust and openness, were significantly correlated to trust. Therefore, the other personality traits were not included in the final regression analysis. We performed a hierarchical multiple regression analysis with trust on openness and propensity to trust. The variable propensity to trust was entered into the first block and openness into the second block. The results are summarized in Table 3.

In the first block, propensity to trust was added, the model was predicted trust on propensity to trust. The regression of predicted trust on propensity to trust was not significant, $F(1, 95) = 2.76, p = .099, R^2 = .028$, indicating that propensity to trust was not a significant predictor of trust. Variance in propensity to trust accounted for 3% of the variance in trust. Propensity to trust was not a significant predictor of trust, β = .17, B = .07, $t(95) = 1.67$, $p = .099$, 95% CI [-0.01, 0.15], indicating that greater propensity to trust did not predict greater trust. For more information, refer to Table 3.

In the second block, openness was added; the model was predicted trust on propensity to trust and openness. The multiple regression of predicted trust on propensity to trust and openness was significant, $F(2,94) = 6.52$, $p < .05$, $R^2 = .122$, indicating that together propensity to trust and openness were significant predictors of trust. Variance in propensity to trust and openness accounted for 12% of the variance in trust. The increment in R^2 was significant $\Delta R^2 = .09$, $\Delta F = 10.00$, $p < .05$. That is, the unique contribution to the variance accounted for in trust by openness was significant. The increment in the multiple coefficients of determination indicates that the variance in openness accounted for an additional 9% of the variance for trust above and beyond propensity to trust. In this model, propensity to trust was significant predictor of trust, β = .22, B = .09, $t(94) = 2.21$, $p = .030$, 95% CI [0.01, 0.17], indicating that greater propensity to trust predicted more trust above and beyond Openness.

Openness was a significant predictor of trust, β = -.31, B = -.25, $t(94) = -3.16$, $p = .002$, 95% CI [-0.41, -0.10], indicating that greater Openness predict less trust above and beyond propensity to trust. For more information, refer to Table 3.

6 DISCUSSION

A key finding from this study was that under these experimental conditions, individual personality traits were found to be more predictive of trust in an intelligent system than the individual difference propensity to trust. This is a significant finding as historical precedent (Rotter, J. B., 1967) and recent meta-analysis of trust research in intelligent systems (Schaefer, K. E., et al., 2016) has observed the later (trust propensity) as the primary individual difference considered.

Openness was found to be correlated with trust. In the hierarchical regression, Openness remained a significant predictor of trust above and beyond propensity to trust. Greater Openness predicted less trust, a finding that viewed through the lens of trait activation theory may have related to the delayed collaboration between human and intelligent system serving as situationally relevant cue. In this example, the delayed collaborative nature of the task may have served as a trait releaser which facilitated behaviour characteristic of individuals scoring high in Openness. Individuals scoring high in Openness may act in ways that relate to confirmation bias. For example, a recent study showed that individuals engaging in activity related to confirmation bias in different online groups, shared a similar personality profile which included scoring high in Openness (Bessi, A., 2016). The confirmation bias relates to the tendency to seek out information that confirms existing beliefs (Nickerson, R. S., 1998). It was observed that the beliefs of the intelligent system varied greatly from those of most participants, as evidenced in poor individual scores. While additional analysis is needed, it is possible that individuals scoring high in Openness (characteristically seeking decision confirming information) rejected partner suggestions as being erroneous, leading to decreased trust.

The following example shows how system design could apply to these findings. An embodied intelligent system used by individuals who score high on the Openness personality trait may want to make recommendations from the onset of a decision-making task to avoid independent solution generation which could lead to situations where confirmation bias may come into play.

For systems that have or are already being deployed, these results are also practical and can inform management and training decisions. For example, individuals scoring high in openness can be identified and taught to realize the importance of considering system information when making decisions and encouraged to critically evaluate their original decisions.

7 LIMITATIONS AND FUTURE RESEARCH

This research focused on exploring the relationship between individual characteristics and early trust in intelligent systems. Like all empirical work, there exist several limitations that need to be addressed.

The use of controlled laboratory experiments is widely recognized as a limitation of information systems research. Results from lab studies may not generalize to individuals and systems in the real world. Future studies should be conducted that look to test for the relationships found in this study explicitly.

Future studies will need to be conducted to look at the relationships and trait-relevant cues related to the openness personality dimension. Experiments need to be conducted to target the activation of specific personality traits by manipulating trust factors from each of the three-factor groupings. Future work will want to look at factors such as etiquette with initial greetings and politeness encoded in system behaviour and interaction responses. Finally, continued work is needed in the area of system embodiment and the impact that various morphologies and modalities have on system use, trust, and trust outcomes.

8 CONCLUSIONS

The results reported here suggest that when interacting with a humanoid robot partner, the openness personality trait is a significant predictor of trust above and beyond the individual difference propensity to trust. Continuing to develop and refine the proposed framework of early trust in intelligent systems is critical to ensuring the success of future human-machine collaborations.

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