Comparison of human trust in an AI system, a human, and a social robot as a task partner

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Abstract
This study investigated trust in a social robot compared with that in an AI system and a human as a task partner in consideration of four types of trust: initial trust (trust before a task), early trust (trust in the beginning of a task), trust decline due to a partner’s errors, and trust recovery due to a partner’s performance recovery. We conducted an online experiment using calculation and emotion recognition tasks where participants answered after referring to the answers of an AI, human, or robot partner. During the experiment, the participants rated their levels of trust in their partners. As a result, trust in a social robot was basically neither similar to that in the AI nor in the human and settled between them. The results are discussed in consideration of the previous studies.

Keywords: Trust; social robot; AI system; interpersonal trust

Introduction
Trusts in AI systems and humans
In recent years, artificial intelligence (AI) systems have been entering all aspects of life. In the future, many human activities are expected to be performed with AI systems. Human activities undertaken with automated AI systems, such as visual recognition systems, self-driving cars, and cleaning robots, have been considered a form of cooperation with a partner rather than with a tool (e.g., Paris Salas, & Cannon-Bowers, 2000). Successful cooperation between human users and systems requires users to appropriately adjust their reliance on the systems, such as by delegating tasks to the systems or getting advice or answers from them (Lee & See, 2004). Over-reliance on these systems might cause fatal errors or accidents, whereas under-reliance could cause the human workload to be excessive (e.g., Parasuraman & Riley, 1997). In the field of human factors, trust has been considered a fundamental parameter in deciding the level of reliance in human-system cooperation (Lee & See, 2004).

Regarding the characteristics of human trust in automated AI systems, trust is generally formed on the basis of the performance of a system, such as its accuracy and reliability (Madhavan & Wiegmann, 2007). People are first inclined to form very high trust, leading to over-reliance; however, trust decreases extremely due to system errors, leading to under-reliance. This occurs because people have a schema, called the “perfect automation schema,” that the systems always perform perfectly without errors (Dzindolet, Pierce, Beck, & Dawe, 2002).

Contrary to trust in automated AI systems, in the field of psychology, interpersonal trust is defined as “expectation of goodwill and benign intent” (Yamagishi & Yamagishi, 1994). In human-human cooperation, trust in a human partner is generally formed on the basis of their knowledge and experience, such as their expertise (Madhavan & Wiegmann, 2007). People first form general trust in others based on default expectations of their trustworthiness, and people gradually develop trust through cooperation (Yamagishi & Yamagishi, 1994).

Some studies experimentally compared the reliance on a system and a human partner as guided by trust and showed that since a human partner is assumed to make errors and a system partner is not, trust in a human partner does not fall due to human errors as much as due to system errors (Dzindolet et al., 2002). Moreover, although trust in a system partner is strongly correlated to the reliance on the system, trust in a human partner is not correlated to reliance (Lewandowsky, Mund, & Tan, 2000; Maehigashi, Miwa, & Kojima, 2018).

Trust in social robots
The development of social robots has progressed recently. They are designed to have physicality and to interact and communicate with people in an interpersonal manner. In the future, social robots are expected to be widely used in social environments (Breazeal, 2003) and at home (Kidd & Breazeal, 2008). In human-robot cooperation, people develop trust in robot partners, and the trust affects their willingness to accept information produced by the robot partners (Hancock, Billings, Schaefer, & Chen, 2011). Therefore, trust is also considered to be an important factor in human-robot interaction. However, there are only a few studies on the characteristics of human trust in a robot partner compared with trust in an AI system and human partner.

Hertz and Wiese (2019) experimentally compared reliance guided by trust in the answer given by a computer-system, a human, or a social-robot partner by using calculation and emotion recognition tasks. As a result, they found that reliance was stronger for the computer-system and robot partners in the calculation task, but it was stronger for the human partner in the emotion recognition task. On the basis of the results, they discussed the possibility that their participants trusted their partners because of their analytical ability, which machines have greater of, in the calculation task and because of their partners’ expertise shaped through.
knowledge and experience, which humans have greater of, in the emotion recognition task.

The results of their study show that trust in a social robot is more similar to trust in an AI system than trust in a human. However, since people’s cooperative behaviors toward their human partners do not always depend on trust (Mayer, Davis, & Schoorman, 1995), reliance on a human partner is not assured to be guided by trust. Therefore, this study directly investigates subjective trust, considering a partner’s performance change as in the previous studies on automated AI systems (e.g., Lewandowsky et al., 2000), which investigated initial trust (trust before a task), early trust (trust in the beginning of a task), trust decline due to a partner’s errors, and trust recovery due to a partner’s performance recovery.

Research question and hypotheses
This study aims to investigate the characteristics of trust in social robots by comparing trust in AI systems and humans in consideration of the above four types of trust. The research question is this study is as follows.

RQ: Is trust in a social robot similar to that in an AI system or in a human?

A social robot is a machine that consists of AI systems. Therefore, people might form and change trust in a social robot in a similar way toward an AI system as shown in Hertz and Wiese (2019). However, social robots have anthropomorphic physicality and do multiple kinds of tasks as individual agents like humans. Interaction with such a robot prompts greater anthropomorphism in the machine (Kiesler, Powers, Fussell, & Torrey, 2008). Therefore, people might form and change trust in a social robot in a similar way toward humans.

Moreover, people perceive mind (Broadbent et al., 2013) and intentionality (Levin, Killingsworth, Saylor, Gordon, & Kawamura, 2013) in a robot with anthropomorphic physicality more than in a machine without it and less than in a human (Gray, Gray, & Wenger, 2007; Levin et al., 2013). Therefore, in line with human perception of mind and intentionality, people might form and change trust in a social robot in a way neither similar to an AI system or human. The hypotheses in this study are as follows, and the hypotheses were tested for each type of trust: initial trust, early trust, trust decline, and trust recovery.

H1: trust in a social robot is similar to that in an AI system.
H2: trust in a social robot is similar to that in a human.
H3: trust in a social robot is neither similar to that in an AI system or a human.

Experiment
Method
Experimental design The experiment had a two-factor between-participants design. The factors were the task (calculation and emotion recognition tasks) and the partner (AI, human, and robot partners).

Participants An a priori G*Power analysis revealed that 26 participants in each condition were needed at least for a medium effect size (\(f = 0.25\)) with a power of 0.80 and alpha of 0.05 (Faul, 2007) in this experimental design. On the basis of this analysis and in consideration of the possibility that some participants would act or perform irregularly, a total of 258 participants (190 male, 68 female) were recruited through a cloud-sourcing service provided by Yahoo! Japan. Their ages ranged from 21 to 76 years old (M = 47.24; SD = 10.49). They were randomly assigned to one of six conditions. As a result, in the calculation task, there were 44 participants in the AI, 42 in the human, and 45 in the robot conditions. Also, in the emotion recognition task, there were 45 participants in the AI, 41 in the human, and 41 in the robot conditions.

Procedure First, the participants gave informed consent and read the task procedure. Next, the task partner was introduced with one of the pictures in Figure 1 depending on the experimental condition. In the AI and robot conditions, the AI system and social robot were explained to have computational functions in the calculation task or emotional recognition functions in the emotion recognition task and would work with the participants in real time. In the human condition, the partner was introduced as an experimental collaborator who had previously answered identical problems that would be given in the experiment. As the AI partner, a picture with a command prompt showing randomized numbers was displayed (Figure 1a). As the robot partner, a picture of Parlo (Fujisoft Inc.) was displayed (Figure 1c).

After that, the participants first performed 10 calculation or emotion recognition problems by themselves without a partner. After that, they performed 36 calculation or emotion recognition problems with one of the partners. In the calculation task, participants mentally calculated two-digit addition problems with carry up and subtraction problems with carry down. In the emotion recognition task, participants chose which of five emotions (anger, disgust, surprise, sadness, and fear) was expressed in pictures of human facial expressions using AffectNet (Mollahosseini, Hasan, & Mahoor, 2017).

The task procedures are shown in Figure 2. (1) A cross was displayed at the center of the screen for 0.5 seconds, (2) a calculation problem or a picture of a facial expression was presented for 5 seconds, (3) the task partner took 3 seconds to answer the problems, (4) the partner’s answer was displayed, and (4) the participant’s answer was entered with a numeric keypad by the participants. While the task partner...
was answering problems and the partner’s answer was displayed, one of the pictures in Figure 1 was displayed depending on the experimental condition.

Moreover, in this experiment, the partner’s performance was manipulated to test the hypotheses. Each task contained 36 problems, and they were divided into 3 trials with 12 problems for each trial. The first trial was a correct trial where the partner gave all correct answers. The next trial was an error trial where the partner gave all incorrect answers. The last trial was a recovery trial where the partner gave all correct answers.

Before the start of each task and after each of four problems, participants were asked “how much is your partner trustworthy?” and were required to rate their trust level in their partners on a 7-point scale (1: Extremely untrustworthy, 2: Not very trustworthy, 3: Slightly untrustworthy, 4: Neither trustworthy or untrustworthy, 5: Slightly trustworthy, 6: Very trustworthy, and 7: Extremely trustworthy). In addition, following the trust rating, participants also rated the accuracy of their partners (1: Extremely inaccurate - 7: Extremely accurate) and impressions of their partners (1: Extremely unlikable - 7: Extremely likable) on 7-point scales.

Furthermore, in the emotion recognition task, a picture was selected in a randomized order from a set of 10 facial expressions for each emotion. In the calculation task, the calculation problems were randomly generated each time.

Results
First, to confirm the analysis of the data, on the basis of the a priori G*Power analysis, we selected the data of the first 26 participants in each condition to avoid Type I and II errors in the following statistical analyses. Second, we searched for irregular data related to the accuracy rate, that is, the rate at which the participants answered correctly, without and with the partner in 2SD above or below the mean in each condition, and we eliminated the irregular data of the participants in each condition. We repeated the first and second procedure until 26 participants were secured for each condition.

Accuracy rate
First, as a task analysis, we conducted a 2 (task: calculation and emotion recognition) × 3 (partner: AI, human, and robot) × 2 (task situation: with and without partner) ANOVA on the accuracy rate in each task (Figure 3).

As a result, there was no two-way interaction ($F(2, 150) = 0.36, p = .70, \eta^2_p < .01$). Moreover, there was an interaction between the task and the task situation factors ($F(1, 150) = 26.32, p < .001, \eta^2_p = .15$). A significant simple main effect was found on the task situation factor, showing that, in the emotion recognition task, the accuracy rate was higher with the partner than without it ($F(1, 75) = 27.80, p < .001, \eta^2_p = .27$); however, in the calculation task, there was no such difference ($F(1, 75) = 0.01, p = .91, \eta^2_p < .01$). Also, there was no significant interactions between the task and the partner factors ($F(2, 150) = 1.52, p = .22, \eta^2_p = .02$) and between the partner and the task situation factors ($F(1, 150) = 0.59, p = .56, \eta^2_p = .01$). Furthermore, there were significant main effects on the task factor ($F(1, 150) = 27.80, p < .001, \eta^2_p = .15$). However, there was no main effect on the partner factor ($F(2, 150) = 2.16, p = .12, \eta^2_p = .03$). A post-hoc G*Power analysis with an alpha of .05 revealed that the two-way ANOVA with the present sample size ($N = 156$) obtained
between the human and robot conditions (by the task type, and in contrast, the trust rating in the human condition was not. On that point, trust in the robot partner had similar characteristics to that in the AI partner.

**Initial trust** In the following analyses, we conducted a 2 (task: calculation and emotion recognition) × 3 (partner: AI, human, robot) ANOVA on all the dependent variables to test the hypotheses. First, we conducted an analysis on initial trust, that is, the trust rating for each condition before each task (Figure 4a).

As a result, there was a significant interaction ($F(2, 150) = 4.21, p < .05, \eta^2_p = .05$). There was a significant simple main effect on the partner condition in the calculation task ($F(2, 150) = 5.59, p < .01, \eta^2_p = .07$), showing that the trust rating in the AI condition was higher than that in the human condition ($t(150) = 3.38, p < .001, r = .27$). However, there was no significant difference in the trust ratings between the AI and robot conditions ($t(150) = 1.97, p = .05, r = .16$) and between the human and robot conditions ($t(150) = 1.41, p = .16, r = .11$). Moreover, there were significant simple main effects on the task factor in the AI and robot conditions, showing that the trust ratings for the AI and robot partners in the calculation task were higher than those in the emotion recognition task (AI condition: $F(1, 150) = 16.68, p < .001, \eta^2_p = .10$; robot condition: $F(1, 150) = 9.60, p < .01, \eta^2_p = .06$). In addition, there was a significant main effect on the task factor ($F(1, 150) = 17.87, p < .001, \eta^2_p = .11$). Also, there was no significant main effect on the partner factor ($F(2, 150) = 2.78, p = .07, \eta^2_p = .04$).

The results revealed that the trust rating of the calculation task was higher in the AI than in the human condition, and however, there was neither a difference in the trust ratings between the AI and the robot conditions or between the human and the robot conditions. Therefore, H3 was supported for initial trust in the calculation task. However, the trust ratings in the AI and robot conditions were affected by the task type, and in contrast, the trust rating in the human condition was not. On that point, trust in the robot partner had similar characteristics to that in the AI partner.

**Early trust** Next, we conducted an analysis on early trust, that is, the trust rating for each condition of the correct trial (Figure 4b). As a result, there was no significant interaction ($F(2, 150) = 0.23, p = .79, \eta^2_p < .01$). Moreover, there was a significant main effect on the partner factor ($F(2, 150) = 3.80, p < .05, \eta^2_p = .05$). The results of multiple comparisons with Ryan’s method showed that the trust rating in the AI condition was higher than that in the human condition ($t(150) = 2.73, p < .01, r = .22$). However, there was no significant difference in the trust ratings between the AI and robot conditions ($t(150) = 1.71, p = .09, r = .14$) and between the human and robot conditions ($t(150) = 1.01, p = .31, r = .08$). Furthermore, there was a significant main effect on the task factor ($F(1, 150) = 28.56, p < .001, \eta^2_p = .16$). The results indicated that the trust rating was higher in the AI than in the human condition, and however, no difference was found in the trust ratings between the AI and the robot conditions and between the human and the robot conditions. Therefore, H3 was supported for early trust.

**Trust decline** To compare declines in trust due to a partner’s errors, we calculated the difference value between the last trust rating in the correct trial and the first rating in the error trial for each participant and conducted an analysis on the difference value. Figure 5 shows the mean difference value for each condition.

As a result, there was no significant interaction ($F(2, 150) = 1.60, p = .21, \eta^2_p = .02$). Moreover, there was a significant main effect on the partner factor ($F(2, 150) = 3.07, p < .05, \eta^2_p = .04$). The results of multiple comparisons with Ryan’s method showed that the difference value for the AI condition was lower than that for the human condition ($t(150) = 2.47, p < .05, r = .20$). However, there was no significant difference in the trust ratings between the AI and robot conditions ($t(150) = 1.02, p = .31, r = .08$) and between the human and robot conditions ($t(150) = 1.44, p = .15, r = .12$). Furthermore, there was a significant main effect on the task factor ($F(1, 150) = 110.53, p < .001, \eta^2_p = .42$).

The results revealed that the difference value was greater in the AI than in the human condition, and however, there was neither a difference in the difference values between the AI and the robot conditions or between the human and the robot conditions. Therefore, H3 was supported for trust decline.

In addition, we conducted the analysis on the trust rating...
in the error trial (Figure 4c). As a result, there was no significant interaction \((F(2, 150) = 1.52, \, p = .22, \, \eta^2_p = .02)\). There was a significant main effect on the task factor \((F(1, 150) = 123.12, \, p < .001, \, \eta^2_p = .45)\). However, there was no significant main effect on the partner factor \((F(2, 150) = 2.42, \, p = .09, \, \eta^2_p = .03)\).

**Trust recovery** To compare trust recovery due to a partner’s performance recovery, we calculated the difference value between the last trust rating in the error trial and the first rating in the error trial for each participant and conducted an analysis on the difference value. As a result, there was no significant interaction \((F(2, 150) = 0.69, \, p = .50, \, \eta^2_p = .01)\). Moreover, there was a significant main effect on the task factor, showing that the difference value was greater in the calculation task than in the emotion recognition task \((F(1, 150) = 59.42, \, p < .001, \, \eta^2_p = .28)\). Furthermore, there was no significant main effect on the partner factor \((F(2, 150) = 2.90, \, p = .06, \, \eta^2_p = .04)\). The results showed that there was no difference in the difference value among the partner conditions, and therefore, none of the hypotheses were supported for trust recovery.

In addition, we conducted the analysis on the trust rating in the recovery trial (Figure 4d). As a result, there was no significant interaction \((F(2, 150) = 0.84, \, p = .43, \, \eta^2_p = .01)\). Moreover, there was neither significant main effect on the task factor \((F(1, 150) = 1.18, \, p = .28, \, \eta^2_p = .01)\) nor on the partner factor \((F(2, 150) = 1.72, \, p = .18, \, \eta^2_p = .02)\).

**Correlational analysis** To make sure of the relationship between the trust rating and the reliance rate, that is, the rate at which participants answered in line with their partners, we performed correlational analyses based on the individual mean trust rating and reliance rate in the correct, error, and recovery trials. Table 1 shows the results of the correlational analyses for each condition. A post-hoc G*Power analysis with an alpha of .05 revealed that the correlational analysis with the present sample size \((N = 52)\) obtained a power of .98 for detecting a high effect size \((f = .50)\), showing satisfactory statistical power.

As a result, in the calculation task, there were significant correlations in the AI conditions of the correct and recovery trials. However, no significant correlations were found in the human condition. A difference in the relationship between the trust rating and reliance rate for the AI and human partners was found as shown in the previous studies (Llewandowsky et al., 2000; Maehigashi et al., 2018). Moreover, there was a significant correlation in the robot condition for the correct trial; however, no such correlations were found in the error and recovery trials. This result shows the possibility that trust in the robot partner was formed differently from the human partner in the correct trial and differently from the AI partner in the recovery trial. Furthermore, in the emotion recognition task, there were significant correlations in all the conditions of all the trials. These results showed the possibility that the participants might have no choice but to trust and rely on their partners since the emotion recognition task was very difficult for them to do by themselves.

In addition, there were significant correlations between the mean overall trust and accuracy ratings in all the conditions of the calculation task \((rs > .44, \, ps < .05)\) and the emotion recognition task \((rs > .85, \, ps < .001)\). Also, there were significant correlations between the mean overall trust and impression ratings in all the conditions of the calculation task \((rs > .57, \, ps < .01)\) and the emotion recognition task \((rs > .82, \, ps < .001)\).

**Discussion**

This study investigated the characteristics of trust in social robots by comparing trust in AI systems and humans in consideration of four types of trust. As a result, the participants in this study formed trust in a robot in a way neither similar toward an AI system or human before the tasks and in the beginning of the tasks. Also, the participants changed trust in the robot in a way that was neither similar to that in the AI system or the human due to the partners’ errors. Therefore, H3 (trust in a social robot is neither similar to that in an AI system or a human) was supported for three types of trust.

First, a difference in trust in the AI and human partner was confirmed as shown in the previous study (Dzindolet et al., 2002), that is, the initial trust of the calculation task and the early trusts of the both tasks in the AI partner were higher.
than the human partner, and also, the trust declines of the both tasks in the AI partner were greater than the human partner. However, the initial trust of the emotion recognition task in the AI partner was not higher than the human partner. This might be because, in the emotion recognition task of this experiment, the AI system was explained as having emotional recognition functions. Therefore, the participants might have been skeptical about the functions before the task and accepted the functions according to the task performance.

Next, Hertz and Wiese (2019) experimentally showed that objective reliance on a social robot is more similar to reliance on a computer system than that on a human. Their experiment was conducted based on the assumption that objective reliance was guided by trust. However, since reliance on a human partner is not assured to be guided by trust, this study directly investigated subjective trust. Therefore, because of the difference in the measurement scale, the results of this experiment were considered to differ from those in the previous study.

Moreover, the results of this experiment showed that trust in a social robot is neither similar to that in an AI system or a human. Mind perception theory indicates that people perceive mind along with dimensions of experience (the capacity to feel and to sense) and agency (the capacity to do, to plan, and to exert self-control) (Gray et al. 2007; Gray & Wenger, 2012). In particular, in regard to the agency dimension, social robots with anthropomorphic physicality were perceived to have higher agency than those without it (Broadbent et al., 2013); however, they were perceived to not have as much agency as humans (Gray et al. 2007). An identical pattern was also confirmed for the human perception of intentionality (Levin et al., 2013). Because a social robot has anthropomorphic physicality, people might perceive the robot differently from an AI system and a human as a task partner and form trust in the robot differently from that in an AI system and a human.

Furthermore, although people perceive less mind and intentionality in AI systems and robots than in humans, Dzindolet et al. (2002) experimentally showed that people do not assume error possibilities for automated AI systems, and do, however, assume them for humans. There is a possibility that the robot with anthropomorphic physicality prompted the participants to assume a few error possibilities for it, and as a result, they might have developed trust differently from trust in an AI system and a human.

References

Breazeal, C. (2003). Toward sociable robots. *Robotics and Autonomous Systems*, 42(3-4), 167-175.

Broadbent, E., Kumar, V., Li, X., Sollers, J., Stafford, R. Q., MacDonald, B. A., & Wegner, D. M. (2013). Robots with display screens: A robot with a more humanlike face display is perceived to have more mind and a better personality. *PloS One*, 8(8), Article e72589.

Dzindolet, M. T., Pierce, L. G., Beck, H. P., & Dawe, L. A. (2002). The perceived utility of human and automated aids in a visual detection task. *Human Factors*, 44(1), 79-94.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39(2), 175–191.

Gray, H., Gray, K., & Wenger, D. M. (2007). Dimensions of mind perception. *Science*, 315(5812), 619.

Gray, K., & Wegner, D. M. (2012). Feeling robots and human zombies: Mind perception and the uncanny valley. *Cognition*, 125(1), 125–130.

Hancock, P. A., Billings, D. R., Schaefer, K. E., & Chen, J. Y. C. (2011). A Meta-Analysis of Factors Affecting Trust in Human-Robot Interaction. *Human Factors*, 53(5), 517-527.

Hertz, N., & Wiese, E. (2019). Good advice is beyond all price, but what if it comes from a machine? *Journal of Experimental Psychology: Applied*, 25(3), 386-395.

Kidd, C. D., & Breazeal, C. (2008). Robots at home: Understanding long-term human-robot interaction. *2008 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 22-26.

Kiesler, S., Powers, A., Fussell, S. R., & Torrey, C. (2008). Anthropomorphic interactions with a robot and robot–like agent. *Social Cognition*, 26(2), 169-181.

Lee, J. D., & See, A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors*, 46(1), 50–80.

Levin, D. T., Killingsworth, S. S., Saylor, M. M., Gordon, S. M., & Kawamura, K. (2013). Tests of concepts about different kinds of minds: Predictions about the behavior of computers, robots, and people. *Human-Computer Interaction*, 28(2), 161-191.

Lewandowsky, S., Mundy, M., & Tan, G. P. A. (2000). The dynamics of trust: Comparing humans to automation. *Journal of Experimental Psychology: Applied*, 6(2), 104–123.

Madhavan, P., & Wiegmann, D. A. (2007). Similarities and differences between human–human and human–automation trust: An integrative review. *Theoretical Issues in Ergonomics Science*, 8(4), 277-301.

Maehighashi, A., Miwa, K., & Kojima, K. (2018). Delegation of a task to a partner in cooperation with a human partner and with a system partner. *Proceedings of the 40th Annual Meeting of the Cognitive Science Society*, 726-731.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management*, 20(3), 709-734.

Mollahasseini, A., Hasan, B., & Mahoor, M. H. (2017). AffectNet: A database for facial expression, valence, and arousal computing in the wild. *IEEE Transactions on Affective Computing*, 10(1), 18-31.

Parasuraman, R., & Riley, V. (1997). Humans and automation: use, misuse, disuse, abuse. *Human Factors*, 39(2), 230–253.

Paris, C. R., Salas, E., & Cannon-Bowers, J. A. (2000). Teamwork in multi-person systems: A review and analysis. *Ergonomics*, 43(8), 1052–1075.

Yamagishi, T., & Yamagishi, M. (1994). Trust and commitment in the United States and Japan. *Motivation and Emotion*, 18(2), 129-166.