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The effect of shared investing strategy on trust in artificial intelligence

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Abstract

This study examined the determinants of trust in artificial intelligence (AI) in the area of asset management. Many studies of risk perception have found that value similarity determines trust in risk managers. Some studies have demonstrated that value similarity also influences trust in AI. AI is currently employed in a diverse range of domains, including asset management. However, little is known about the factors that influence trust in asset management-related AI. We developed an investment game and examined whether shared investing strategy with an AI advisor increased the participants' trust in the AI. In this study, questionnaire data were analyzed (n=101), and it was revealed that shared investing strategy had no significant effect on the participants' trust in AI. In addition, it had no effect on behavioral trust. Perceived ability had significantly positive effects on both subjective and behavioral trust. This paper also discusses the empirical implications of the findings.

Key Words: artificial intelligence, trust, value similarity, asset management

Introduction

The development of artificial intelligence (AI) is remarkable in diverse domains. Asset management is one of the most promising domains for AI application. Financial advisors with AI can more quickly provide their customers with asset management advice than those without AI (Komeichi & Nagaya, 2017). Then, what factors promote the practical application of AI in asset management? Many researchers have argued that trust plays an important role in implementing AI (Alaiad & Zhou, 2014; Benbasat & Wang, 2005; Lee & See, 2004). The next question, then, would be what determines trust in AI.

Earle & Cvetkovich (1995) proposed the salient value similarity (SVS) model, stating that people are more likely to trust in other people when they share each other's values. The SVS model has two key components: "salient values," meaning that specific values are important in a particular situation, and "value similarity," meaning that the trustor and trustee share salient values. Many studies on risk perception have shown that value similarity promotes trust in others and institutions (Nakayachi & Cvetkovich, 2010; Poortinga & Pidgeon, 2003; Siegrist, Cvetkovich, & Roth, 2000).

Additionally, several studies have found that value similarity determines trust in AI. Verberne, Ham, & Midden (2012) revealed that autonomous cars that shared the user's driving goals were more trustworthy than those that did not share such goals. Yokoi & Nakayachi (2018) found that shared policy of medical treatment enhanced participants' trust in AI. These findings suggest that value similarity increases trust not only in people and institutions, but also in AI. Although these studies measured subjective trust, they did not measure behavioral trust. In addition, they lacked the sources to discuss practical implications. We measured behavioral trust in addition to subjective trust for more significant practical implications.

This study examines the robustness of the findings that value similarity determines trust in AI in autonomous cars and medical care, and attempts to extend the generalizability of the findings to asset management. Subjective trust is measured to test generalizability, and behavioral trust is measured to discuss a practical implication. We operationally define value similarity as shared investing strategy, and hypothesize that individuals will trust more in AI when they share same investing strategy with the AI than when they do not. The participants in this study played an original investment game that we developed to test this hypothesis.

Method

Participants and Experimental Design

We identified the ideal sample size using G*power3.1 with α-error level of .05, desired power of .80, and η_p^2 of .073[1]. The results of the power analysis indicated a minimum sample size of 102 participants. As a result of our recruitment, one hundred and one students at a university in the Kansai region (26 males and 75 females; age M=20.2 years, SD=0.94 years) participated in the experiment. We manipulated shared investing strategy (two conditions: shared versus unshared) as a between-subjects factor. The dependent variable was trust in AI.

Investment Game

Participants played the investment game using a personal computer. They earned as many points as possible by investing points in companies that would start a new business. They first selected one investing strategy they strongly preferred from two options: large investment or small investment (Figure S1, see Online Appendix). We then allocated the participants randomly to one of two conditions: the shared condition with AI and the unshared condition with AI. In the former, the AI had a tendency to recommend the participant's preferred investing strategy, and in the latter the AI had a tendency to recommend the investing strategy that the participants did not prefer. Participants started with 50 points as the initial assets (Figure S2, see Online Appendix) and were then presented with descriptions about a target company. After reading the descriptions, they pushed a button to see the AI's recommended investing strategy. The participants then saw either the large investment (10 points) or the small investment (1 point) strategy and could choose one of the two; that is, they could go with the AI's recommendation or the other option. Next, the participants received information about whether the company's business succeeded or not after their decision. If the business succeeded, participants gained double the points they invested. If the business failed, in contrast, they lost the points that they invested. If participants invested 10 points and the business succeeded, then they gained 20 points; if participants invested 1 point and the business failed, then they lost only 1 point. We call these decision and outcome pairs good decisions. If participants invested 1 point and the business succeeded, then they gained only 2 points; if they invested 10 points and the business failed, they lost 10 points. We call these pairs bad decisions. In addition to the information about the result of the business, participants were presented with information about whether the AI's recommendation matched the participant's preferred investing strategy, and whether the investing strategy that the AI recommended was a good decision or not. The session for a participant consisted of ten trials.

The AI in both the shared and unshared conditions were programed to make good decisions six times, meaning that the AI's quality about the investment was equally controlled between the conditions[2]. The AI in the shared condition recommended the strategy that participants preferred eight times: five of which would result in a good decision and three of which would result in a bad decision. It also recommended the strategy that the participants did not prefer

1) The effect size (η_p^2) was the average of effect sizes found by Verberne et al. (2012) and Yokoi & Nakayachi (2018).

2) In the preliminary experiment, we programed the AI to make good decision seven times. But the rate of trust in the questionnaire and the number of entrusting AI were largely high in both conditions (ceiling effect). Conversely, if the AI made a good decision five times, participants would suspect that the AI's good decisions were just luck, resulting in a low rate of trust in both the conditions (floor effect). We therefore programed the AI to make a good decision six times to prevent the ceiling and floor effects.

twice, where one would result in a good decision and the other would result in a bad decision. The AI in the unshared condition, on the other hand, recommended the strategy that participants did not prefer eight times and the participant's preferred strategy twice. The decision quality was the same as in the shared condition. Tables S1 and S2 illustrate the progress of the games for each condition respectively (see Online Appendix).

Participants performed an additional task (Figure S3, see Online Appendix) after finishing the ten trials. In this task, participants were instructed to invest an additional fifteen times and asked how many times they entrust the decision about investment to the AI. The game ended after deciding the number of entrusting the AI.

Measures

We used a questionnaire to measure the perceived value similarity as a manipulation check, with trust in AI as the dependent variable and perceived ability and integrity as covariates (Table S3, see Online Appendix), referring to items in Benbasat & Wang (2005) and Yokoi & Nakayachi (2018). A five-point Likert scale was used for all items in the questionnaire with a scale ranging from "1=do not agree at all" to "5=strongly agree." We recorded the number times participants entrusted AI in the fifteen additional investments as a behavioral measure of trust.

Procedure

After entering the experiment room, the experimenter explained the experiment briefly to the participants and that they would receive a gift card (JPY 500) as a reward for participating in the experiment and cash as an additional reward. They then signed the consent form. The experimenter explained the exact rules of the investment game, and explained that the additional cash reward would depend on their performance in the investment game. The instruction aimed to make participants aware that entrusting AI could influence their interests. After finishing the game, participants were asked to complete the questionnaire. Finally, they were thanked, given their rewards, and debriefed.

Results

We excluded the responses of one participant who crudely answered the questions, leaving the responses of one hundred participants for analysis. Table 1 shows the descriptive statistics by condition.

Manipulation check

The results of t-test revealed that participants in the shared condition had a significantly higher evaluation of perceived value similarity than in the unshared condition ($t(98)=5.615$, $p<.001$). This result indicated that our manipulation of shared investing strategy was successful[3].

The number of entrusting AI in the additional task

The effect of shared investment strategy on the number of entrusting AI was tested using the General Linear Model (GLM) procedure. We assumed that the dependent variables followed a binomial distribution because it was discrete and its maximum value was 15. The explanatory variables were shared investing strategy, perceived ability, and perceived integrity. A dummy variable was used for shared investing strategy, coded as follows: 1=the shared condition and 0=the unshared condition. The results of the analysis showed that shared investing strategy did not have a significant effect on the number of entrusting AI (Table 2). Perceived ability

Table 1　Descriptive statistics

	N	Trust	Value similarity	Ability	Integrity	The number of entrusting
Shared	49	3.27 (0.78)	3.01 (0.73)	3.10 (0.85)	3.48 (0.69)	8.96 (3.83)
Unshared	51	2.85 (0.67)	2.29 (0.55)	2.74 (0.65)	3.16 (0.63)	8.69 (4.50)

Values in brackets indicate standard deviations.

3) Although the manipulation check found a significant difference in the rate of perceived similarity between the two conditions, the rate in the shared condition was midpoint in the five-point Likert scale (3.01). Future research should resolve the problem of why the score of perceived similarity in the shared condition did not increase.

Table 2 Results of the binomial logistic regression analysis predicting the number of entrusting AI with additional investment

	Estimate	SE	95%CI	*Z*-value	*P*-value
Intercept	−0.44	0.28	−1.00～0.12	−1.55	0.122
Shared strategy	−0.02	0.11	−0.24～0.19	−0.20	0.839
Perceived ability	0.29	0.08	0.14～0.44	3.72	<.001
Perceived integrity	−0.01	0.09	−0.18～0.16	−0.11	0.910

significantly affected the number of entrusting AI, but perceived integrity did not.

Questionnaire measurement of trust

We conducted an analysis of covariance (ANCOVA) with trust in AI as the dependent variable, shared investing strategy as the independent variable, and perceived ability and perceived integrity as covariates. The results showed that the effect of shared investing strategy on trust in AI was not significant ($F(1, 99)=3.731$, $p=.056$, $\eta_p^2=.037$). Perceived ability had a significantly positive effect on trust in AI ($F(1, 99)=10.601$, $p=.002$, $\eta_p^2=.099$), but perceived integrity did not ($F(1, 99)=.223$, $p=.480$, $\eta_p^2=.005$).

Discussion

This study examines the robustness of the findings that value similarity determines trust in AI in the context of asset management. The results did not support the hypothesis.

The results of the questionnaire are not in line with findings from several prior studies (Verberne et al, 2012; Yokoi & Nakayachi, 2018) and fail to extend the generalizability of the effect of value similarity on trust in AI to the context of asset management. The effect of shared investing strategy was marginally significant. However, the size of the effect was small, leaving a possibility that shared investing strategy slightly enhances trust in AI. The results of the test for behavioral trust did not support our hypothesis, in addition to that of subjective trust. Shared investment strategy may not have a large effect on the adoption of AI in asset management because it had a small effect on subjective trust and did not have a significant effect on behavioral trust. If it does not influence adoption, AI should be programmed to recommend the best strategy for earning money, regardless of the sharing strategy with the trustor.

Why did shared strategy with AI not increase the trust score in the questionnaire and the number of entrusting AI? The two ad-hoc interpretations might be as follows. First, the most important goal for participants and the AI was to earn as many points as possible. The investment strategy was just a means to achieve this goal. Therefore, sharing the strategy was not a very important value for the participants. Even in the unshared condition, they shared the most salient values in the game. Accordingly, trust in AI might not differ between the two conditions. Yokoi & Nakayachi (2018) examined a policy of medical treatment to cure a disease, and their results also suggested that shared policy had a small effect. However, Verberne et al. (2012) focused on driving goals, and their results suggested that shared driving goal had a large effect. These findings indicated that the goal promotes trust in AI more than the means does. Second, the AI's ability for investment might be a strong determinant of trust. In both conditions, the AI made a good decision six times. Perceived ability had significant effect on both subjective trust and behavioral trust. Because ability largely influenced trust in AI and the AI's ability was equally controlled between the two conditions, the effect of shared investing strategy might not be significant.

It is important to mention the limitations of this study. The sample consisted of undergraduate students, who probably have less investing experience. Less-experienced investors will probably have different levels of trust in AI than will more experienced inventors. Future research should explore the effect of investing experience on trust in AI.

References

Alaiad, A., & Zhou, L. (2014). The determinants of home healthcare robots adoption: An empirical investigation. *International Journal of Medical Informatics*, **83**, 825–840.

Benbasat, I., & Wang, W. (2005). Trust in and adoption of online recommendation agents. *Journal of the Association for Information Systems*, **6**, 72–101.

Earle, T. C., & Cvetkovich, G. T. (1995). *Social Trust: Toward a Cosmopolitan Society*. Westport, CT: Praeger Press.

Johnson, B. B. (1999). Exploring dimensionality in the origins of hazard-related trust. *Journal of Risk Research*, **2**, 325–354.

Komeichi, M., & Nagaya, Y. (2017). *Complete Knowledge of Artificial Intelligence* (In Japanese, translated by the author of this article). Tokyo: Nikkei Publishing Inc.

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

Inoue, S., & Une, M. *Institute For Monetary And Economic Studies Bank Of Japan*.

Nakayachi, K., & Cvetkovich, G. (2010). Public trust in government concerning tobacco control in Japan. *Risk Analysis*, **30**, 143–152.

Siegrist, M., Cvetkovich, G., & Roth, C. (2000). Salient value similarity, social trust, and risk/benefit perception. *Risk Analysis*, **20**, 353–362.

Tadapaneni, N. R. (2019). Artificial Intelligence in Finance and Investments. *International Journal of Innovative Research in Science, Engineering and Technology.*

Poortinga, W., & Pidgeon, N. F. (2003). Exploring the dimensionality of trust in risk regulation. *Risk Analysis*, **23**, 961–972.

Yokoi, R., & Nakayachi, K. (2018). The effects of shared policy of medical treatment on trust in artificial intelligence. *Japanese Journal of Social Psychology*, **34**, 16–25.

Verberne, F. M., Ham, J., & Midden, C. J. (2012). Trust in smart systems sharing driving goals and giving information to increase trustworthiness and acceptability of smart systems in cars. *Human Factors*, **54**, 799–810.