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Impact of Implicit Theories on the Intent to Use Performative AI and Advisory AI under asset management: An experimental study

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Abstract：

This study investigates what kind of people dislike (or prefer) performative and advisory AI under asset management to avoid "algorithm aversion," a behavior that causes humans to avoid AI. We focus on implicit theories, which is the beliefs about human abilities and properties, and we examine they affect preferences for "performative AI," which makes decisions on behalf of humans and "advisory AI," which provides support for human decision-making. Among implicit theories, entity theorists want to profit effortlessly and thus prefer to execute AIs that can do so, whereas incremental theorists would like to improve their abilities and thus prefer advisory AI.

To examine the hypotheses, we performed pre-registered two studies (total N = 770): a survey study without priming (study 1, N = 258) and a 2 × 1 between-participants experimental study with implicit-theories-priming treatments (study 2, N = 512). The results revealed that participants preferred advisory AI to performative AI. Incremental theorists have also established a preference for advisory AI over performative AI. Focusing on the users of AI, the current study demonstrates the importance

of the interrelationship between AI and humans and contributes to the realization of a society that coexists with AI.

1. Introduction

Today, the use of AI (Artificial Intelligence) is rapidly increasing in society. Its applications range from product sales forecasting (Fildes et al., 2009), to healthcare (Esmaeilzadeh et al., 2015; Inthorn et al., 2015), and informing management decisions (Prahl et al., 2013). However, Dietvorst et al. (2015, 2018) and Castelo et al. (2019) demonstrate that even if AI proves to be superior to humans, experimental participants prefer human support. This phenomenon is known as "algorithm aversion." Following Jussupow et al. (2020), we define algorithm aversion as "a biased evaluation of AI, manifested in negative behaviors and attitudes toward AI compared to human agents." Algorithm aversion is a phenomenon that should be avoided not only because it hinders productivity gains from AI adoption but also because it can lead to the loss of accurate predictions by AI (over humans). The importance of AI-based forecasting can be seen from studies that reveal that evidence-based AI forecasts are more accurate than human forecasts (Dawes, 1979; Dawes & Meehl, 1989; Schweitzer & Cachon, 2000; Highhouse, 2008).

This study focuses on two types of AI. One is a performative AI that takes independent actions by gathering information, making decisions, and performing them on behalf of humans, even making final decisions (Jussupow et al., 2020). The other is advisory AI which only supports humans and leaves the final decision to humans (Jussupow et al., 2020). This study investigates what kind of people dislike (or prefer) performative and advisory AI under asset management to avoid algorithm aversion. We focus on implicit theories, which are beliefs about the intelligence and nature of human beings (Dweck & Leggett, 1988). This theory is divided into the entity theory, which states that human qualities are fixed and do not change with effort, and the incremental theory, which states that human qualities are variable and can be improved with effort. From the review of much previous research, these beliefs are expected to influence humans' preference for performative and advisory AI. Therefore, we set three hypotheses: Participants prefer advisory AI more than performative AI (H1). Entity theorists use performative AI more than advisory AI (H2-1). Incremental theorists use advisory AI more than performative AI (H2-2).

To examine the hypotheses, we performed pre-registered two studies (total N = 770): a survey study without priming (study 1, N = 258) and a 2 × 1 between-participants experimental study with implicit-theories-priming treatments (study 2, N = 512). The results revealed that participants preferred advisory AI to performative AI. Incremental theorists have also established a preference for advisory AI over performative AI. Focusing on the users of AI, the current study demonstrates the importance of the interrelationship between AI and humans and contributes to the realization of a society that coexists with AI.

Our contributions to the research are threefold: First, we advocate the need for AI tailored to the individual characteristics of developers and managers. We contribute to the realization of a more productive society. Second, this unique research method, which directly compares two types of AI (performative and advisory), contributes to revealing new possibilities for algorithm aversion research. Third, this research, which focuses on AI users, will demonstrate the importance of research on the interrelationship between AI and humans in a wide range of academic fields, including psychology, ethics, and law, and promote the development of this theme.

The remainder of this paper is organized as follows: Section 2 describes previous studies and hypotheses. Section 3 describes the study design. Section 4 summarizes the results. Section 5 presents the discussion and future tasks.

2. Previous studies and hypotheses

2.1. Performative AI and advisory AI

This study focuses on two types of AI. One is a performative AI that takes independent actions by gathering information, making decisions, and performing them on behalf of humans, even making final decisions (Jussupow et al., 2020). The other is advisory AI which only supports humans and leaves the final decision to humans (Jussupow et al., 2020).

We summarize previous research on using these types of AI. Concerning performative AI, in Dietvorst et al.'s (2015) experiment, study participants applied bonuses to either their predictions or AI predictions. The results revealed that participants who saw the AI's performance were less likely to choose it. Additionally, Gogoll & Uhl (2018) and Bigman & Gray (2018) show that, when making moral judgments, participants in the experiment were not willing to defer to the AI instead of a human. On the other hand, concerning advisory AI, Logg et al. (2019) measured the extent to which participants would modify their expectations based on AI advice or human advice. The result indicated that participants responded more strongly to and revised their advice more when AI advised them. Dietvorst et al. (2018) and Bigman and Gray (2018) also suggest that AI use can be increased if humans can modify AI advice even slightly and if AI's role is limited to an advisory role. Several other studies have reported willingness to use advisory AI rather than human decision support (Gunaratne et al., 2018; Williams et al., 2018). However, as in Önkal et al. (2009), participants prefer humans to AI, even advisory AI.

In light of the above, humans may be more likely to use AI if they can participate in decision-making and if decision rights are retained. Therefore, when comparing performative and advisory AI, we hypothesize that humans will prefer to use the latter. However, to the best of our knowledge, while there are some studies that ask participants to use more compared to AI or humans (Rühr et al., 2019), few studies ask the same participants which they would prefer to use more, a performative or an advisory AI. Therefore, we use the latter experimental design to conduct a test on the intention to use each AI. The difference between performative and advisory AI is important when considering algorithm aversion. By comparing performative and advisory AIs, this study provides suggestions on what types of AIs humans dislike and how to avoid algorithm aversion.

As predicted from a review of previous studies, advisory AIs are expected to be used more than performative AIs. We, therefore, formulate the following hypothesis:

H1: Participants use advisory AI more than performative AI.

2.2. Implicit theories

Furthermore, we focus on implicit theories and show that this belief influences humans' preference for performative and advisory AIs. Implicit theory of intelligence is a belief about the intelligence and nature of human beings, and a concept mainly used in the educational field. This theory is divided into the entity theory, which states that human qualities are fixed and do not change with effort, and the incremental theory, which states that human qualities are variable and can be improved with effort. implicit theories are originally examined to identify differences in student performance in learning (Dweck & Leggett, 1988; Dweck & Yeager, 2019). For example, Stipek and Gralinski (1996) demonstrate that students' beliefs about intelligence predict their academic performance. In addition, Hong et al. (1999) find that when experimental participants tackled an exam and received negative feedback, incremental theorists were more likely to receive remediation to improve exam performance than entity theorists. Initially, this discussion of “intelligence” dominated, but it is extended to broader ideas as it becomes clear that implicit theories play an important role in how we make judgments about others (Dweck et al., 1995; Levy et al., 2001; Plaks, 2017) and that implicit theories is a key factor in the way we judge others (Dweck & Yeager, 2019). Thus, there are various types of scales measuring implicit theories, depending on their purpose (e.g., Dweck et al., 1995; Levy & Dweck, 1998; Hong et al., 1999).

The implicit theories have been applied in a wide range of domains, not only concerning people. For example, Rai and Lin’s (2019) experiment on financial decision-making finds that entity theorists prefer risk-averse investments, whereas incremental theorists prefer risk-taking investments. Sharifi and Palmeira (2017) also compare the degree of difficulty with which each theory favors the use of technological products and the difficulty of using these. The results reveal that entity theorists chose technological products that were easy to use because of their propensity to believe that being effortful is incompetent (Dweck & Master, 2008), while incremental theorists chose technological products that were difficult to use owing to their propensity to place value on increasing their competence (Dweck, 1986).

Findings suggest that the characteristics of each implicit theory lead to different attitudes toward robots. Allan et al. (2022) establish that entity theorists exhibit more anxiety toward robots than incremental theorists. Han et al. (2020) also find that different theories respond differently to the advertising messages of travel agencies. Entity theorists preferred firms described as “this is your servant,” while incremental theorists preferred firms described as “this is your partner.” Because entity theorists are risk averse (Rai & Lin, 2019) and have the desire to profit effortlessly (Dweck & Leggett, 1988; Elliott & Dweck, 1988), and because incremental theorists believe it is important to enhance their abilities (Dweck & Leggett, 1988), which we believe led to these results. The present study adds to these findings.

Based on the above, we predict that, depending on the characteristics, the entity theorists will be more inclined to use servant AI, that is, a performative AI that makes decisions on their behalf, and the incremental theorists will be more inclined to use partner AI, that is, an advisory AI in which its role is only to advise and not to hinder their improvement. We, therefore, formulate the following hypotheses.

H2-1: Entity theorists use performative AI more than advice AI.

H2-2: Incremental theorists use advisory AI more than performative AI.

3. Study design

To examine the hypotheses, we performed two studies: Study 1, in which we mainly examined H1, was a survey study without priming (N = 258). Study 2, in which we mainly examined H2, was a 2 × 1 between-participants-design experiment with priming (N = 512). Both studies were pre-registered.

3.1. Study 1 (Survey)

3.1.1. Participants

After approval by the Institutional Review Board, we pre-registered for the experiment in AsPredicted (https://aspredicted.org/, Pre-registered No.104435). The pre-registration information is available at https://aspredicted.org/~c5MX6He6p8. We collected data using Google Forms on Amazon's MTurk platform, which has been shown to collect samples efficiently and obtain data of a comparable quality to laboratory experiments (Goodman & Paolacci, 2017). Participants were required to be U.S. residents, complete at least 100 Human Intelligence Tasks (HITs, MTurk's task unit), and have a HITs approval rate of at least 95% to participate in the experiment. Participants were paid $2.00 above the U.S. minimum wage ($7.25 per hour).

We recruited 258 participants using MTurk. We did a power analysis beforehand and calculated this sample size using the failure rates (about 50% of the sample) of the manipulation checks in the pilot experiments conducted before the implementation. 258 participants completed the questionnaire, and 49 failed the operation check. Our final sample size for analyzed data was 207. The remaining participants had the following characteristics: 68.9% male, mean age 35.5 years, 87.1% Caucasian, 4.3% Asian, 1.9% Hispanic, 3.3% African-American, and 3.3% Native American; We conducted the survey in August 2022.

3.1.2. Procedures

Participants gave their consent to participate in the experiment and read a scenario in which they would entrust their asset management to a "robo-advisor." This scenario was modified from Zhang et al. (2021). This setting was used because both performative and advisory AIs exist as services in real-life asset management situations. Participants were told that robo-advisors can be used for asset management, and they responded regarding the extent to which they would like to use two types of the robo-advisors: "performative-type" and "advisory-type" robo-advisors. Performative-type can manage assets on behalf of participants, while advisory-type proposes optimal investment plans to participants, who can then manage their assets based on these proposals. The latter proposes the best investment plan for the participant, and the participant can manage their assets based on the proposal. The extent to which participants wanted to use each robo-advisor was measured on a 6-point Likert scale. Participants were also told that there was no difference in the ability to make suggestions and the cost of using each. They then answered items such as age and gender, completed the experiment, and received their rewards at a later date. Participants were tested via a questionnaire to determine if they understood the scenario and answered the questions carefully. Answers were used to check the operation.

3.1.3. Measurement

Intention to Use AI: Questions were based on Zhang et al. (2021). Participants responded on a 6-point scale (1=not at all willing to use, 6=very willing to use) to indicate their intention to use a performative and an advisory robo-advisor.

Implicit theories Scores: Participants' implicit theories scores were measured using Levy and Dweck's (1997) eight-item scale. Participants responded on a six-point scale (1 = strongly disagree, 6 = strongly agree) regarding the extent to which they agreed with four items representing entity theory ideas and four items representing incremental theory ideas. The latter four were reversal items and were averaged together with entity theory items. Higher scores reflect the idea of entity theory.

Other Variables: Years of education were measured by the number of years participants had attended an educational institution: Up to 15 years, 16-19 years, and 20+ years. Participants were also asked if they had majored in a computer-related field. For interest in technology, we followed Neyer et al. (2012). Financial literacy and risks related to financing were measured following Zhang et al. (2021).

Perception of control over one's assets based on Rühr et al. (2019). Experience with robo-advisors was measured following Zhang et al. (2021), and the risk of using robo-advisors was measured based on Featherman and Pavlou (2003). Cognitive and affective trust in robo-advisors was measured based on Komiak and Benbasat (2006). To test the hypotheses in more detail, the respondents were asked to indicate their willingness to manage their assets with ease and to improve their asset management skills.

3.2. Study 2 (experiment)

3.2.1. Participants

Study 2 was conducted to ascertain the intention to use a robo-advisor with implicit theories priming. We used a 2 × 1 between-participants design. Specifically, we manipulated the participants' implicit theories priming (entity or incremental). Participants were randomly assigned to one of the following two conditions: (1) Entity theory priming condition, in which the participants are primed as the entity theorists. (2) Incremental theory priming condition, in which the participants are primed as the incremental theorists.

After approval by the Institutional Review Board, we pre-registered for the experiment in AsPredicted (https://aspredicted.org/, Pre-registered No.104434). We collected data using Google Forms on Amazon's MTurk platform. The procedure was the same as in Study 1. Participants were required to live in the U.S., complete at least 100 HITs, and have a HITs approval rate of at least 95%. Participants were paid $2.00 above the U.S. minimum wage ($7.25 per hour).

We recruited 512 participants using MTurk. We did a power analysis beforehand and calculated this sample size using the failure rates (about 50% of the sample) of the manipulation checks in the pilot experiments conducted before the implementation. In the entity theory priming condition, 256 participants completed the questionnaire, and 81 failed the operation check. In the incremental theory priming condition, 256 participants completed the questionnaire, and 127 failed the operation check. Our final sample size for analyzed data was 304 (175 in the entity theory priming condition, 129 in the incremental theory priming condition).

In the entity theory priming condition, the remaining participants (N = 175) had the following characteristics: 65.1% male, mean age 35.7 years, 80.0% Caucasian, 12.0% Asian, 2.3% Hispanic, 4.6% African-American, and 1.1 other. In the incremental theory priming condition, remaining participants (N = 129) had the following characteristics: 65.1% male, mean age 37.0 years, 82.9% Caucasian, 6.2% Asian, 3.1% Hispanic, 7.0% African-American, and 0.8% other. We conducted the survey in August 2022.

3.2.2. Procedures

Participants read the same scenarios and answered the same questions as Study 1. Before reading the scenario in which asset management is entrusted to a robo-advisor, they were primed with either the entity theory idea or the incremental theory idea of implicit theories. Priming was performed. The rationale for priming implicit theories with sentences is that, like other schemas and beliefs, such theories can be viewed as situation-level constructs that are stable over time and temporarily accessible (Franiuk et al., 2004; Hoyt et al., 2012). Thus, after reading a persuasive text on the entity or incremental theory, participants are led to adopt that particular mode of thinking (Hong et al., 1999). To encourage participants to read the texts carefully, we asked them to summarize them, state the rationale they found most persuasive, and finally take a fill-in-the-blanks quiz on the texts. The answers to the quiz were used to check the participants' manipulations, and those who answered even one question incorrectly were excluded from the analysis. The same procedure as in Study 1 was then followed. The measurement of the variables was the same as in Study 1.

4. Results

Descriptive statistics for each experiment are shown as Table 1 and Table 2.

(Table 1 and 2 about here.)

Gender was treated as 0=female and 1=male. Years of education (Education) were quantified as 0=Up to 15 years, 1=16-19 years, and 2=20+ years. The major computer was analyzed as 0=No, 1=Yes. The financial literacy score was assigned a number between 0 and 3 depending on the number of correct answers to questions that tested financial knowledge. The analysis was conducted using R (version 4.0.3).

4.1. The results of Study 1.

In study 1(a survey without priming), we compared the intention to use the performative-type AI with that to use the advisory-type AI. Since the data on usage intention did not follow a normal distribution, a Wilcoxon rank sum test was performed. Table 3 shows the results that the usage intention of the latter was statistically significantly higher than that of the former at the 10% level ($Z = 1.675$, $p=0.094$).

(Table 3 about here.)

Regression analysis was also conducted to confirm the implicit theories scores and the intention to use AI (Table 4). Multicollinearity was judged to be not problematic because there were no correlation coefficients above 0.8 and none of the variance inflation factors (VIF) values, a measure for determining collinearity, were below 4.0 for any of the variables. In addition, the calculated standard errors are robust to heterogeneous variance. Both the regression model to use the performative AI as the dependent variable and that to use the advice AI as the dependent variable were significant ($F(1,15)=9.317$, $p<0.001$, degrees of freedom adjusted $R2=0.375$; $F(1,15)=8.108$, $p<0.001$, degrees of freedom adjusted $R2=0.339$, respectively. The implicit theories score had no significant effect on either the intention to use performative or advisory AI ($B=0.188$, $p=0.296$; $B=0.033$, $p=0.833$).

(Table 4 about here.)

Thus, Study 1 reveals that the intention to use advisory AI was statistically significantly higher than that to use performative AI. The result supports H1.

Study 1 also reveals that the implicit theories score had no significant effect on either performative or advisory AI intention to use AI. The result does not support H2.

4.2. The results of Study 2

To check whether the priming of the entity and incremental theory worked for the participants, firstly, we compared the implicit theories scores for each condition of the questionnaire. Because the data did not follow a normal distribution, we performed a Wilcoxon rank sum test. The result revealed no significant difference in implicit theories scores between the entity theory priming condition and the incremental theory priming condition ($Z=1.432$, $p=0.152$). Secondly, on the other hand, the implicit theories score in the incremental theory condition was significantly smaller than the median implicit theories score of 3.5 in study 1 (survey without priming) (Wilcoxon rank sum test results, Z=2.184, p=0.029), which can be interpreted as priming was at work concerning the incremental theory priming condition.

Within the same primed group, we compared the intention to use performative and advisory AI. Table 5 shows the result.

(Table 5 about here.)

Because neither data followed a normal distribution, we performed a Wilcoxon signed-rank test. In the entity theory priming condition, there was no significant difference in the intention to use each AI (Z=0.939, p=0.348). In the incremental theory priming condition, on the other hand, there was a significant difference in the intention (Z=2.425, p=0.015). The results suggest that there was a significant difference in the intention to use each AI under the incremental theory priming condition. We also tested whether there was a difference in the intention to use the performative or the advising AI between the conditions using a Wilcoxon rank sum test. The results found no significant difference in both (Z=1.343, p=0.179; Z=0.011, p=0.991).

Regression analysis was performed to confirm the implicit theories scores and intention to use AI. Table 6 shows the result.

(Table 6 about here.)

Multicollinearity was judged not problematic because there were no correlation coefficients above 0.8 and none of the variables had a VIF value below 3.0, which is an indicator for determining collinearity. In addition, the calculated standard errors were robust to heterogeneous variance. Both the regression models (performative or advising AI as the dependent variable) were significant ($F(1,16)=8.105$, $p<0.001$, degrees of freedom adjusted $R2=0.274$; $F(1,16)=5.264$, $p<0.001$, degrees of freedom adjusted $R2=0.185$)). implicit theories scores had no significant effect on either intention to use performative or advisory AI ($B=-0.057$, $p=0.517$; $B=0.105$, $p=0.105$). The willingness to manage assets effortlessly had a significant effect on the intention to use the performative AI ($B=0.186$, $p=0.022$), and the willingness to improve asset management skills had a significant effect on the intention to use the advising AI ($B=0.165$, $p=0.039$).

Study 2 revealed that the intention to use advisory AI was higher than that to use performative AI in the incremental theory priming condition. Thus, in study 2, H2-2 was supported, although H2-1 was not supported.

Study 2 also shows that willingness to manage assets had a significant effect on the intention to use performative AI, and willingness to improve asset management skills had a significant effect on the intention to use advisory AI.

5. Discussion and conclusions

We measured entity and incremental theorists’ intention to use AI to clarify what kind of people dislike (or prefer) AI under asset management. We discuss the results, limitations, and future perspectives below.

First, we predicted that participants would prefer advisory AI over performative AI (H1), and the result of study 1 supports H1. This is the same result as in previous studies and more robustly indicates that humans generally have a preference for AIs that give them advice.

Next, we predicted that among implicit theories, entity theorists would prefer performative AIs (H2-1) and incremental theorists would prefer advisory AIs (H2-2). The result of study 2 supports H2-2, although H2-1 was not supported.

There are two possible reasons that H2-1 was not supported. First, the participants may not have accepted the thinking style of the entity theory. The fixed mindset of entity theory (e.g., people do not change at any given moment) is likely to be socially undesirable (Hang et al., 2019), and because participants' implicit theories was not fully manipulated, participants proceeded to the scene in a normal state, unbiased toward either thinking style, we infer that this was the case. Therefore, we think that when participants responded to implicit theories scores, they avoided making socially undesirable entity theory choices.

Second, there may not be a significant relationship between implicit theories scores and beliefs about asset management. Regarding the regression analysis results indicating a significant relationship between beliefs about asset management and intention to use AI, we think that this is because people use AIs that are consistent with their beliefs. Even though advisory AIs are preferred, the existence of different types of AIs would be of some significance. In the real world, especially in investment situations, people face situations in which they have to choose between performative- and advisory-type AIs. We think that we will choose an AI that is in line with our original beliefs about asset management and our objectives at the time, and we will do things to our advantage.

This study has some limitations. This study was conducted in an online environment, whereas previous research was conducted in a face-to-face setting. We think that this difference in the experimental environment prevented priming, which was successful in the previous study. However, we were concerned about the impact of this difference in the experimental environment on our results; therefore, we carefully designed our priming and devised our priming strategy. For example, we created a fill-in-the-blank question, which had not been used in previous studies, and set strict criteria for selecting data to be excluded. Even with these innovations, we were unable to manipulate the implicit theories sufficiently. However, since studies using priming in online experiments are rare, we think that our study is valuable from this perspective.

This study suggests three future research directions. The first is related to the priming mentioned in the limitations and is to create an environment similar to that of previous studies through laboratory experiments and conducting a follow-up study. To make the findings more robust, we think that it is necessary to confirm the results when priming is sufficient. The second point was the priming. We used priming in study 2, but future research should also use the implicit theoretical values that participants originally possess. Although priming was intentionally used, a broader range of methods should be used to approach algorithm aversion. The third point concerns the scenario scene setting. The setting was asset management, but it would be interesting and meaningful to check participants' AI choices in a medical situation. Currently, AI is being introduced in medical diagnosis and prescribing, and doctors may shortly be able to choose whether to let AI diagnose their patients' symptoms completely or to receive advice. We were only able to observe the participants' intention to use AI in one situation, so we believe that we can better grasp the reality by assuming and verifying numerous situations.

Many human–robot interaction (HRI) studies support social science findings (e.g., Cominelli et al., 2021; Gillath et al., 2021). While most AI research focuses on improving prediction accuracy and developing situation-specific AI, HRI research that focuses on the individual characteristics of humans and the users of AI is also important. However, regarding the easy application of social science theories to the relationship between AI and humans, de Graaf et al. (2016) and Damholdt et al. (2020) indicate that "accept without question that the basic propositions of social science are necessarily applicable to social robotics and HRI research is erroneous." Therefore, we argue it is important to not only explain "which types of people dislike (or prefer) AI" only based on previous research, but also to examine this question using experiment.

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Appendix 1: Survey & experimental Scenarios

The following are the instructions that were presented to the participants in our experiments. In study 2, participants are randomly assigned to only one of the two conditions and read only one scenario. The different parts of each scenario are underlined and italicized according to the conditions of the experiment. Footnotes are also underlined and italicized.

Page 1 Introduction

I pledge to answer this survey honestly. (Yes or No)

First, this is a reading comprehension test of a scientific text. Read the following passage and summarize the theme of the article in one sentence. Also, state the evidence you thought was the most convincing.

*Please make sure to answer properly as you will be eligible for a credit!

Page 2 with priming of the implicit theories

〈*entity theory condition*〉

Knowles spent the last decade tracing identical twins who were raised apart. According to his results, up to 88 percent of a person's disposition is due to genetic factors. About 10 percent of disposition seems to be determined during the first three years of life. This means that disposition may be increased or decreased by only about 2 percent during most of a person's life.

Q. Summarize the theme of the article in one sentence.

Q. State the evidence you thought was the most convincing.

Q. This is a fill-in-the-blank question for the sentence above. Select the appropriate words or numbers to complete the sentence.

Knowles spent the last decade tracing identical twins who were raised apart. According to his results, up to [A] percent of a person's disposition is due to [B]. About 10 percent of disposition seems to be determined during the first [C] of life. This means that disposition may be increased or decreased by only about [D] percent during most of a person's life.

Q. What is the word or number that applies to A? *(Answer: 88)*

Q. What is the word or number that applies to B? *(Answer: genetic factors)*

Q. What is the word or number that applies to C? *(Answer: three years)*

Q. What is the word or number that applies to D? *(Answer: 2)*

〈incremental theory condition〉

Knowles spent the last decade tracing identical twins who were raised apart. According to his results, up to 88 percent of a person's disposition is due to environmental factors. In an extreme case, a young girl adopted by a college professor and his wife entered the school and engaged in volunteer activities. The genetically identical twin was raised by the real mother, who was a prostitute. This girl was a delinquent and never went to school.

Q. Summarize the theme of the article in one sentence.

Q. State the evidence you thought was the most convincing.

Q. This is a fill-in-the-blank question for the sentence above. Select the appropriate words or numbers to complete the sentence.

Knowles spent the last decade tracing identical twins who were raised apart. According to his results, up to [A] percent of a person's disposition is due to [B]. In an extreme case, a young girl adopted by a college professor and his wife entered the school and engaged in [C]. The genetically identical twin was raised by the real mother, who was a prostitute. This girl was [D] and never went to school.

Q. What is the word or number that applies to A? *(Answer: 88)*

Q. What is the word or number that applies to B? *(Answer: environmental factors)*

Q. What is the word or number that applies to C? *(Answer: volunteer activities)*

Q. What is the word or number that applies to D? *(Answer: a delinquent)*

Page 3. Scenario about asset management and the assessment

Please read the following passage and answer the questions.

You just inherited $100,000 from your relatives. You decide to invest all the money.

You are thinking about using the online service of "Performative Robo-advisor" or "Advisory Robo-advisor" that is offered by a financial services firm in your area. After collecting information about you through an online survey, both Robo-advisors can use an algorithm to automatically develop your investment policy statement and asset allocation strategies that are appropriate for your goals and risk tolerance with no human intervention.

“Performative Robo-advisor” manages your assets on your behalf based on the investment policy statement and asset allocation strategies. You can fully entrust the management of your assets to the Robo-advisor.

“Advisory Robo-advisor” recommends the investment policy statement and asset allocation strategies to you. You can manage your assets on your own based on the recommendations.

The quality of the investment policy statement and asset allocation strategy as prepared by “Performative Robo-advisor” is the same as the quality of the investment policy statement and asset allocation strategy as prepared by “Advisory Robo-advisor”.

The financial cost is the same whether you use “Performative Robo-advisor” or “Advisory Robo-advisor”.

Q. Choose 'Yes' if the following statement is correct or 'No' if it is incorrect.

・ If you use ‘Advisory Robo-advisor’, you can manage your assets yourself based on the recommendations of the Robo-advisor.

・ If you use ‘Performative Robo-advisor’, the Robo-advisor manages your assets for you.

・ Both ‘Advisory Robo-advisors’ and ‘Performative Robo-advisors’ create investment strategies of the same quality.

Q. How likely would you use 'Performative Robo-advisor' for your financial planning? (I don't want to use it at all: 1 ~ I would like to use it very much: 6)

Q. How likely would you use 'Advisory Robo-advisor' for your financial planning? (I don't want to use it at all: 1 ~ I would like to use it very much: 6)

Page 4. Questions about implicit theories

Please select the number of the following questions that apply to your opinion. (1 = strongly disagree, 2 = disagree, 3 = mostly disagree, 4 = mostly agree, 5 = agree, 6 = strongly agree)

Q. The kind of person someone is, is something basic about them, and it can't be changed very much

Q. People can do things differently, but the important parts of who they are can't really be changed

Q. Everyone is a certain kind of person, and there is not much that they can do to really change that.

Q. Select 5 for this question.

Q. As much as I hate to admit it, you can't teach an old dog new tricks. People can't really change their deepest attributes.

Q. Everyone, no matter who they are, can significantly change their basic characteristics.

Q. People can substantially change the kind of person they are.

Q. No matter what kind of a person someone is, they can always change very much.

Q. People can change even their most basic qualities.

Page 5. Questions about participants' demographic data

Q. How old are you?

Q. What is your gender?

Q. How long have you been in education?

Q. Have you majored or are you majoring in computer-related content (computer science, information systems, telecommunications management, etc.)?

Q. I am very interested in new technological developments. (1 = Strongly disagree;6 = Strongly agree)

Q. I take immediate pleasure in new technological developments. (1 = Strongly disagree;6 = Strongly agree)

Q. I am always interested in using the latest technological devices. (1 = Strongly disagree;6 = Strongly agree)

Q. Whenever I have the opportunity, I use much more technical products than I do now. (1 = Strongly disagree;6 = Strongly agree)

Q. How much risk are you willing to take when you save or make investments? (1 = not willing to take any financial risk, 6 = take substantial financial risk expecting to earn substantial returns)

Q. I want to make asset management easy. (1 = Strongly disagree;6 = Strongly agree)

Q. I want to improve my asset management skills. (1 = Strongly disagree;6 = Strongly agree)

Q. There are many things you can do to get the best value for your money.

Q. With enough effort, you can get very good value for the money you invest.

Q. Select 1 for this question.

By actively participating in the asset management process, you can have a substantial impact on your own asset development. In the long run, you can take responsibility for getting the best value for your money. What are your thoughts on Robo-advisor services in general?

Q. How familiar are you with a Robo-advising service? (1 = Never heard about it; 6 = I am currently using it).

Q. On the whole, considering all sorts of factors combined, how risky would you say it would be to sign up for and use a Robo-advisor? (1 = Not risky at all; 6 = very risky)

Using a Robo-advisor is risky. (1 = Strongly disagree;6 = Strongly agree)

Using a Robo-advisor exposes you to overall risk.(1 = Strongly disagree;6 = Strongly agree)

A Robo-advisor must have a good knowledge of financial planning. (1 = Strongly disagree; 6 = Strongly agree)

A Robo-advisor must be a real expert in financial planning.(1 = Strongly disagree; 6 = Strongly agree)

A Robo-advisor must be unbiased. (1 = Strongly disagree; 6 = Strongly agree)

A Robo-advisor must be honest. (1 = Strongly disagree; 6 = Strongly agree)

Select 5 for this question.

You should feel secure about relying on a Robo-advisor. (1 = Strongly disagree; 6 = Strongly agree)

You should feel comfortable about relying on a Robo-advisor. (1 = Strongly disagree; 6 = Strongly agree)

You should feel content about relying on a Robot-advisor. (1 = Strongly disagree; 6 = Strongly agree)

Q. Did you know anything about the survey before you answered this question?

Page 5. Final page

That's all for the survey. Thank you for your cooperation.

This study examines that beliefs about human disposition influence the use of algorithms. At the beginning of the survey, we asked you to read a passage that manipulates your beliefs about human disposition. We then measured the degree to which you would prefer to use which type of AI more.

Table 1 Descriptive Statistics (Study 1)

	Study 1 (n = 209)			
	mean	SD	min	Max
Intent to use "Performative AI"	4.517	1.275	1	6
Intent to use "Advisory AI"	4.713	1.053	1	6
Implicit theory score (α = 0.7)	3.326	0.725	1	5.5
Age	35.54	10.52	22	67
Gender	0.689	0.464	0	1
Education	0.837	0.548	0	2
Major computer	0.818	0.387	0	1
Interest tech score (α = 0.84)	4.697	0.892	1.5	6
Financial literacy score	1.321	1.108	0	3
Financial risk tolerance	4.431	1.171	1	6
Desire to manage assets with ease	4.651	0.96	1	6
Desire to improve asset management skills	4.684	1.09	1	6
Control perception (α = 0.78)	4.711	0.777	1.75	6
Robo-advisor familiarity	4.215	1.443	1	6
Robo-advisor risk tolerance (α = 0.74)	4.25	0.97	1	6
Cognitive trust (α = 0.65)	4.713	0.829	2	6
Emotional trust (α = 0.72)	4.593	0.853	1.333	6

Table 2. Descriptive Statistics (Study 2)

	Entity condition (n = 175)				Incremental condition (n = 129)			
	mean	SD	min	Max	mean	SD	min	Max
Intent to use "Performative AI"	4.423	1.358	1	6	4.225	1.382	1	6
Intent to use "Advisory AI"	4.56	1.211	1	6	4.612	1.041	1	6
Implicit theory score (α = 0.89)	3.476	1.102	1	6	3.263	1.068	1	6
Age	35.74	10.14	23	71	36.99	10.19	20	69
Gender	0.655	0.475	0	1	0.651	0.478	0	1
Education	0.72	0.574	0	2	0.853	0.486	0	2
Major computer	0.617	0.487	0	1	0.744	0.438	0	1
Interest tech score (α = 0.82)	4.713	0.839	1.75	6	4.733	0.807	2.25	6
Financial literacy score	1.869	1.129	0	3	1.806	1.126	0	3
Financial risk tolerance	4.149	1.199	2	6	4.093	1.247	1	6
Desire to manage assets with ease	4.886	0.982	1	6	4.705	0.896	1	6
Desire to improve asset management skills	4.903	1.07	1	6	4.76	1.029	1	6
Control perception (α = 0.75)	4.859	0.684	3	6	4.787	0.704	2.5	6
Robo-advisor familiarity	3.669	1.506	1	6	3.938	1.396	1	6

Robo-advisor risk tolerance (α = 0.83)	3.91	1.063	1	6	3.966	1.092	1	6
Cognitive trust (α = 0.71)	4.886	0.872	2.333	6	4.837	0.809	2.667	6
Emotional trust (α = 0.83)	4.587	0.967	1	6	4.442	1.107	1	6

Table 3. Wilcoxon's Rank Sum Test (Study 1)

Study1 Wilcoxon signed-rank test (Wilcoxon rank sum test)

	Z	r (effect size)
Performative AI - Advisory AI	1.675†	0.082
		† p<0.10

Table 4. Regression Analysis (Study 1)

	Performative AI					Advisory AI				
	B	St. Error	Beta	t	p	B	St. Error	Beta	t	p
(Intercept)	1.158	0.936	-	1.237	0.218	0.135	0.651	-	0.207	0.836
Implicit theory score	0.188	0.179	0.107	1.048	0.296	0.033	0.156	0.023	0.211	0.833
Age	-0.009	0.008	-0.07	-1.097	0.274	0.011	0.006	0.107	1.799	0.074
Gender (0:female; male:1)	-0.097	0.162	-0.035	-0.599	0.55	0.277	0.128	0.122	2.168	0.031
Education	-0.195	0.131	-0.084	-1.484	0.14	0.047	0.123	0.024	0.379	0.705
Major computer (0:No; 1:Yes)	-0.086	0.431	-0.026	-0.199	0.842	-0.135	0.271	-0.05	-0.498	0.619
Interest tech score	-0.202	0.214	-0.141	-0.943	0.347	0.706	0.137	0.598	5.159	0.000
Financial literacy score	-0.164	0.091	-0.143	-1.799	0.074	0.088	0.068	0.093	1.295	0.197
Financial risk tolerance	0.265	0.141	0.244	1.885	0.061	-0.003	0.094	-0.004	-0.037	0.971
Desire to manage assets with ease	0.051	0.092	0.038	0.55	0.583	0.129	0.085	0.118	1.516	0.131
Desire to improve asset management skills	0.027	0.116	0.023	0.235	0.814	-0.066	0.091	-0.069	-0.731	0.465
Control perception	0.243	0.186	0.148	1.309	0.192	0.044	0.133	0.032	0.329	0.743
Robo-advisor familiarity	0.229	0.103	0.259	2.225	0.027	0.009	0.071	0.012	0.123	0.902
Robo-advisor risk tolerance	-0.088	0.115	-0.067	-0.767	0.444	0.105	0.084	0.097	1.251	0.212
Cognitive trust	-0.245	0.141	-0.159	-1.734	0.085	-0.027	0.128	0.021	-0.212	0.832
Emotional trust	0.518	0.151	0.347	3.432	0.001	-0.066	0.102	-0.053	-0.647	0.519

	N: 209; F: 9.317**; Adjusted R-squared: 0.375	N: 209; F: 8.108**; Adjusted R-squared: 0.339
		** p<0.01; * p<0.05; † p<0.1

Table 5. Wilcoxon rank sum test (Study 2)

Study2 Wilcoxon rank sum test						
Condition	Intent to use		Condition	Intent to use	Z	r (effect size)
Entity	Performative AI	vs.	Entity	Advisory AI	0.939 n.s.	0.071
Incremental	Performative AI	vs.	Incremental	Advisory AI	2.425*	0.214
Entity	Performative AI	vs.	Incremental	Performative AI	1.343 n.s.	0.077
Entity	Advisory AI	vs.	Incremental	Advisory AI	0.011 n.s.	0.001
						*p<0.05

Table 6 Regression Analysis (Study 2)

	Performative AI					Study2 Advisory AI				
Dependent variable	The degree with the intention to use Performative AI					The degree with the intention to use Advisory AI				
	B	St. Error	Beta	t	p	B	St. Error	Beta	t	p
(Intercept)	1.685	0.747	-	2.257	0.025	0.925	0.594	-	1.557	0.12
Implicit theory score	-0.057	0.087	-0.045	-0.648	0.517	0.105	0.064	0.1	1.626	0.105
Age	0.001	0.008	0.007	0.121	0.904	-0.007	0.007	-0.066	-1.094	0.275
Gender (0:female; male:1)	-0.257	0.14	-0.089	-1.84	0.067	-0.295	0.123	-0.123	-2.406	0.017
Education	-0.181	0.137	-0.071	-1.318	0.189	0.261	0.107	0.124	2.435	0.016
Major computer (0:No; 1:Yes)	0.43	0.224	0.148	1.919	0.056	-0.08	0.19	-0.033	-0.422	0.673
Interest tech score	0.265	0.122	0.16	2.181	0.030	0.07	0.098	0.051	0.715	0.475
Financial literacy score	-0.137	0.067	-0.113	-2.055	0.041	-0.07	0.069	-0.069	-1.02	0.309
Financial risk tolerance	0.259	0.08	0.231	3.238	0.001	-0.024	0.068	0.025	-0.351	0.726
Desire to manage assets with ease	0.186	0.081	0.129	2.297	0.022	0.073	0.083	0.061	0.885	0.377
Desire to improve asset management skills	0.006	0.081	0.005	0.075	0.94	0.165	0.079	0.152	2.077	0.039
Control perception	-0.091	0.154	-0.046	-0.593	0.554	0.292	0.128	0.177	2.282	0.023
Robo-advisor familiarity	0.073	0.063	0.078	1.165	0.245	0.055	0.056	0.07	0.978	0.329
Robo-advisor risk tolerance	-0.18	0.092	-0.141	-1.953	0.052	0.165	0.065	0.156	2.54	0.011
Cognitive trust	0.018	0.114	0.011	0.158	0.875	-0.123	0.1	-0.091	-1.234	0.218

Emotional trust	0.153	0.097	0.115	1.577	0.116	0.146	0.088	0.132	1.652	0.1
Conditions (0:entity; 1:incremental)	-0.191	0.14	-0.069	-1.37	0.172	0.089	0.117	0.039	0.765	0.445
	N=304; F: 8.105**; Adjusted R-squared: 0.274					N=304; F: 5.264**; Adjusted R-squared: 0.185				
						** p<0.01; * p<0.05; † p<0.1				