“I Believe AI Can Learn from the Error! Or Can It Not?”: The Effects of Implicit Theories of Artificial Intelligence on Trust Repair of the Intelligent Agent

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Abstract

After an intelligent agent makes an error, regaining lost trust is an important issue. In the process of trust repair, individuals’ underlying perception of the potential for improvement in an intelligent agent and the way an agent apologizes may influence the agent’s trust repair process. In this study, we investigated the influence of implicit theories of artificial intelligence and their apology style on trust repair after the trust violation. A 2 (implicit theory: Incremental vs. Entity) X 2 (apology attribution: Internal vs. External) between-subject design experiment was conducted (N = 150). Participants were asked to make 40 different decisions in a stock market investment game created for this study. Each time participants made an investment decision, an intelligent agent gave them a recommendation. The results show that trust was damaged less severely in the incremental rather than the entity theory condition and in the external rather than internal attribution apology condition after the trust violation. Trust was restored more strongly in the Entity-External condition than in the others. We discuss both theoretical and practical implications.

Keywords: Trust Repair, Artificial Intelligence, Implicit Theories, Apology Attribution, Anthropomorphism

1 Introduction

Trust is crucial for users to accept new technologies [1] but can be quite fragile [2–4]. Even a single failure can lead to a huge loss of trust in machines [5] and cause users to resist using them [2, 3]. For example, trust can be violated when a machine produces an error, triggers a problem, or functions in an unusual or unexpected way [6]. When the trust violation happens, proper

restorative actions must be executed to rebuild broken trust [7–10].

Recently, scholars have begun to investigate ways to repair trust after trust violation by intelligent agents such as robots and artificial intelligence (AI) agents [5, 11, 12] that are designed to interact with humans in a socially meaningful way.¹ Employing anthropomorphic cues can

¹When we refer to a “robot” in this article, it is confined to the robot with AI that designed to interact socially with

be helpful in repairing trust in machines [13–16]. Social practices in human relationships such as apology can also be applied to restore trust in an AI agent [6, 13, 16]. Individual differences such as prior experience and personality traits can influence the perception of AI [4]. For example, people who are extroverted and open to experience tend to have a positive attitude toward robots [17].

Individuals might hold different views about whether someone who makes a mistake can be trusted again. Some people might believe that the one who erred will behave the same way because humans never change, and others might think that one might not make the same mistake again because humans can improve. Indeed, interpersonal communication studies have shown that implicit theories (more colloquially, “mindsets”), which are an individual’s underlying assumptions regarding whether intelligence is fixed or changeable, can influence trust repair processes [18, 19].

While implicit theories are well-documented in human psychology, only a limited number of studies have shown how implicit theories affect how users perceive intelligent agents [20]. Hence, more research is needed to uncover the potential importance of implicit theories in human-AI interaction, as the findings on trust repair in the interpersonal communication literature may not apply to human-AI relationships. [21, 22].

Thus, this study aims to investigate how implicit theories influence the effectiveness of the trust repair tactics of an intelligent agent (in this case, various apology styles) and perception regarding the agent. In order to do this, this study draws largely on the literature on human psychology about apology and implicit theories. We conducted an experiment to see whether one’s implicit theory of artificial intelligence affects the outcomes of internal and external apology attribution on trust repair. The results highlight the importance of implicit theories of artificial intelligence in the trust repair and perception of intelligent agents.

humans. To avoid any confusion, we primarily used the term “intelligent agent.” However, when introducing previous literature, we use the terms “robot” and “AI agent” to provide specific and accurate information to reflect the studies on both human-robot interaction and human-AI interaction.

2 Literature Review

2.1 Implicit Theories and Intelligent Agents

Implicit theories (or mindsets) refer to the lay people’s theories about the malleability of characteristics and attributes related to intelligence [23–25], personality [26–28], morality [24, 29–31], emotion [32, 33], and so forth. In relation to the implicit theories of intelligence, there are two opposite theories: entity and incremental theory. *Entity theory (or fixed mindset)* is the belief that intelligence and personality traits are fixed and highly consistent in behavior [24]. Those who hold to entity theory (*entity theorists*) are quick to draw conclusions about people’s baseline characteristics and slow to change their beliefs even when new evidence becomes available [34]. On the other hand, *incremental theory (or growth mindset)* is the belief that intelligence and personality is changeable and behavior can vary, either over time or depending on the situation [24]. Those who hold to incremental theory (*incremental theorists*) are more likely to develop their views based on observations that are both congruent and incongruent to their beliefs [34].

Implicit theories have been shown to be influential in various areas such as education [35], sports [36, 37], health [38, 39], and marketing [40–42]. Until recently, however, implicit theories have received only limited attention in the Human-Computer Interaction (HCI) context except for a few studies that show that implicit theories also influence the perception of intelligent agents and technologies [4, 20, 43, 44] and that those who hold incremental theories are more ready to accept to innovative technologies [43, 44]. A recent study on human-robot interaction showed that entity theorists are more likely to feel anxious and uncomfortable about robots and less likely to evaluate the robots favorably than incremental theorists [4].

These studies measured [4, 43, 44] or manipulated [20] participants’ implicit theories in regards to the self or the environment (e.g., do you think people can change?). However, implicit theories of intelligence may differ when thinking about one’s own intelligence (or the intelligence of human

beings in general) versus the intelligence of intelligent agents such as AI. Specifically, implicit theories about humans and intelligent agents should be distinguished because one could hold different beliefs about the changeability of intelligence in a human compared to an intelligent agent. For example, one could believe that humans can learn and develop by themselves but AI cannot improve without human intervention.

Whether the implicit theories of artificial intelligence influence the perception of the intelligent agent in a similar way to the influence of implicit theories about humans also needs to be studied. It is possible that implicit theories about an intelligent agent manifest differently from those about humans [21, 22]. Thus, our study specifically focuses on individuals' implicit theories of artificial intelligence and capabilities. This is unlike previous studies that have investigated implicit theories of human intelligence and ability to explain the perception of the intelligent agent.

2.2 Implicit Theories and Anthropomorphism

Implicit theories could also be related to the anthropomorphism of intelligent agents. Anthropomorphism is the perception of human characteristics in objects and their surroundings that are not human [45]. Anthropomorphism makes people think that non-human targets can do things that only humans can do [46, 47]. People are more likely to anthropomorphize non-human objects when they perceive that they have characteristics considered unique to humans [48]. For example, people are prone to treat intelligent agents as similar to humans when they have anthropomorphic cues such as a human-like face [49, 50], voice [49, 51], or exhibit behaviors such as apology [13, 16, 52].

Individuals' dispositional factors can also influence their degree of anthropomorphizing intelligent agents [53]. For example, lonely people are more likely to anthropomorphize intelligent agents [53], and people with a stronger need for control are also more inclined to seek explanations of a non-human object's actions, concentrating on anthropomorphic concepts like intentions and desires [53].

Likewise, the implicit theories that individuals hold might influence how they anthropomorphize intelligent agents. Implicit theories affect various

aspects of human perception [24, 28, 31], including their perception of robots [4] and other technologies [43, 44]. Incremental theorists believe that one's intelligence can develop over time [24]. When they perceive that robots are able to learn new abilities over time, individuals show more social responses to them and perceive that they are more lifelike [54] and intelligent [55]. This leads them to think that robots have a mind [48], which would result in anthropomorphism. Thus, incremental theorists may be more likely than entity theorists to perceive that robots and AIs are social creatures and attribute human-like features to computers.

Conversely entity theorists do not believe in the capacity to improve [24, 28]. Indeed, entity theory [24, 28] and people's heuristics on machines [16, 56–61] have in common that they both assume that the intelligence of humans and machines is reliable, consistent, and fixed. Thus, they may be less likely to perceive that intelligent agents are social creatures and less likely to anthropomorphize robots and AIs than incremental theorists.

2.3 Implicit Theories and Trust Repair

Implicit theories also affect individuals' trust evaluation and repair process [18, 19]. For example, incremental theorists are more likely to recover trust than entity theorists after a trust violation when the counterpart apologizes [19]. However, this does not imply that incremental theorists are necessarily more merciful than entity theorists. Although incremental theorists are more forgiving, they are also more sensitive than entity theorists to deception and likely to lower their trust after a trust violation. On the other hand, entity theorists are less sensitive to deception and prone to maintain their initial trust than incremental theorists [18]. As a result of these differences, individuals might respond differently to various types of apologies depending on the implicit theory they hold.

In human-human relationships, *apology* demonstrates regret for the trust violation by acknowledging responsibility [62, 63]. Apologies can be mainly classified into two categories in terms of attribution of apology: internal and external [62]. *Internal attribution apology* is the act of showing regret and acknowledging full

responsibility for one’s transgression [62]. People believe that those who accept full responsibility are more likely to improve in the future compared to those who try to avoid responsibility [62], so they are more likely to show favorable evaluations and expectation of a future relationship with them. However, it is also possible that an internal attribution apology may not be successful in recovering broken trust following the trust violation because it fundamentally acknowledges one’s blame [64–66]. An internal attribution apology that acknowledges full responsibility may be more likely to be accepted by incremental theorists after a trust violation because they assume that people can improve [24]. Thus, they may readily believe the promise of future improvement implied in an internal attribution apology [19]. On the other hand, entity theorists may not be likely to accept an apology that acknowledges the trust violation [19] because they do not believe that people can improve [24].

External attribution apology is the act of acknowledging only partial responsibility for one’s blame and ascribing remaining responsibility to external factors [62]. External attribution apology might be successful because people are less likely to blame those who excuse themselves with external factors [67, 68]. However, it also has risks in that those who make external excuses may be perceived as dishonest, egocentric, and incompetent [69]. An external attribution apology may be more likely to be favored by entity theorists because it gives them a reason not to adjust their first evaluation of the apologizer’s characteristics [18]. However, incremental theorists may not be likely to accept an external attribution apology because they are sensitive to the behaviors of others and quick to notice that they have been deceived [18]. Thus, they might think that someone who apologizes by giving external excuses is dishonest and deceitful.

A similar trust repair process can also occur in HCI. When the AI violates trust by making an error, causing a problem, or exhibiting an unexpected or inappropriate behavior, trust repair can be attempted as a responsive approach to restoring broken trust [6]. Intelligent agents can also apologize for their errors like humans do [6, 16]. Similar to a human’s apology, an intelligent agent’s apology can have either internal

attribution (e.g., blaming a process) or external attribution (e.g., blaming another party) [6]. The effectiveness of the intelligent agent’s apology can be influenced by various factors, such as using anthropomorphic features in the interface [13, 16]. For example, Kim and Song [13] found that an internal attribution apology is more successful for an agent with anthropomorphic cues, while an external attribution apology is more successful for an agent without anthropomorphic cues. However, no studies have showed how individuals’ implicit theories of artificial intelligence affect the trust repair process such as apology for intelligent agents.

2.4 Current Study

The current study investigates the impact of implicit theories of artificial intelligence and various apology attributions on the perception of intelligent agents and their trust-repair mechanism. Previous studies have shown that holding an incremental theory about human intelligence helps to shape more favorable evaluations of robots than holding an entity theory [4, 20, 70]. However, holding implicit theories about intelligent agents and holding implicit theories about humans could have varying effects on the perception of intelligent agents [21, 22]. Thus, our study focuses on the implicit theories of artificial intelligence rather than human intelligence in investigating their influence on the perception of intelligent agents.

Implicit theories of artificial intelligence can have several influences on the perception of the agent. First, incremental theorists may be more likely to perceive the agent to be intelligent [55] and treat it as a social being [54]. Perceived animacy and intelligence can make individuals think that the agent has a mind [48] and thus may lead to higher anthropomorphism. Second, implicit theories may influence the agent’s trust repair process. Individuals who hold an incremental theory may believe that the agent could change and develop over time, so they are likely to believe in the future improvement suggested by an internal attribution apology more easily than entity theorists. In contrast, incremental theorists would be more sensitive than entity theorists to potentially deceitful and dishonest information implied in an external attribution apology. Thus, trust repair

for incremental theorists would be more efficient when the agent apologizes with internal attribution compared to when the agent apologizes with external attribution.

However, individuals who hold entity theory, may consider the agent less likely to change, and thus may not believe the message of future improvement implied in an internal attribution apology. They are also likely to consider that excuses in the external attribution apology are valid and choose not to change their initial evaluation of the agent. Hence, an external attribution apology would be more effective than an internal one.

Based on the above discussion, the following hypotheses are proposed:

- H1. Incremental theorists, compared to entity theorists, will show a higher level of a) likeability and b) intention to use toward the intelligent agent.
- H2. Incremental theorists, compared to entity theorists, will show a higher level of a) perceived intelligence, b) animacy, and c) anthropomorphism toward the intelligence agent.
- H3. Implicit theories of artificial intelligence will play a moderating role in the relationship between trust repair and the different attributions of apology (i.e., internal vs. external).
 - H3a. Among entity theorists, trust repair would be more effective when the agent apologizes with an external rather than an internal attribution.
 - H3b. Among incremental theorists, trust repair would be more effective when the agent apologizes with an internal rather than an external attribution.

3 Method

3.1 Experimental Design

The experiment was a 2 X 2 between-subjects design using manipulations of implicit theories of artificial intelligence (Entity vs. Incremental theory) and attributes of the apology (Internal vs. External attribution apology) as independent variables. We randomly assigned participants to one of four experimental conditions: Entity-Internal, Entity-External, Incremental-Internal and Incremental-External.

3.2 Participants

In total, 205 participants were recruited from the notice board of an university website in South Korea and completed the study via Pavlovia, an online experiment platform provided by Open Science Tools Ltd. The study adhered to the 1964 Declaration of Ethical Standards of Helsinki and was granted ethical approval by the university's Institutional Review Board. Before participating in the study, all participants signed an informed consent form.

Before starting the main experiment, as part of the manipulation of implicit theories, we primed participants by giving information sheets describing either incremental theory or entity theory of AI depending on the condition they were assigned to (see manipulation section for more details). At the end of the experiment, a question that asks them to recall the argument from the information sheet was administered as a manipulation check. Forty-five participants (22%) failed to recall the argument provided at the beginning of the experiment. In addition, 10 individuals who were either younger than 14 years old ($Q1 - 1.5 \text{ IQR}$) or older than 33 years old ($Q3 + 1.5 \text{ IQR}$) were eliminated as age is one of the important demographic factors that can influence attitude toward AI; compared to younger adults, older ones are less likely to trust the AI application [71, 72]. After these exclusions, 150 participants were included in the analysis (for Entity-Internal, $n = 37$; Entity-External, $n = 38$; Incremental-Internal, $n = 37$; Incremental-External, $n = 38$). The ages ranged from 19 to 32 years ($M = 23.35$, $SD = 2.81$); 53% ($n = 85$) were female, 42% ($n = 68$) were male, and 4% ($n = 7$) preferred not to identify their gender. Regarding experience with investing in stocks, 30% ($n = 45$) had no experience at all, 47% ($n = 71$) had occasional experience, and 22% ($n = 34$) often invested in stocks. The participants received 3,000 Korean won (approximately US \$ 2.50) for participating in the study and extra incentives of 1436 won (US \$ 1.30; $SD = 284$ won [US \$ 0.30]), on average, were provided depending on the individuals' performance on the task.

3.3 Task

An investment game [13, 73] was adopted and modified for this experiment using PsychoJS-2020.1 [74]. The participants started with a fund of 1000 points and had to acquire as many points as possible by investing points in companies whose stock price would most likely rise in the year to come. The game consisted of five rounds of eight investment choices each for a total of 40 investment choices. Participants had to choose one of two options between a large investment (100 points) or a small investment (10 points) based on the given company information, which included the type of industry, number of employees, year of founding, headquarters location, revenue, and operating profit. When the company turned out to be successful, participants earned double the amount they invested. When the company failed, they had to surrender the points they had invested. The success and the failure in business were entirely hypothetical and predetermined by the researchers (See Figure 1).

The game featured an AI advisor algorithm to help the participants make decisions. When participants made an investment with a company, the AI made recommendations which participants could adopt or not. After each round, the number of suggestions that participants adhered to was shown with the total earned points and the possible earnings if the participant had strictly followed the AI's recommendation.

The success and failure of the investments were predetermined in such a way that all the participants would experience trust violation in Round 3, the middle of five rounds, following the procedure described in a previous study [13]. In Rounds 1 and 2, the AI provided seven good and one bad decision out of eight (87.5 % accuracy); this was high enough for users to trust the AI's advice. However, in Round 3, the AI presented only two good and six bad suggestions out of eight (25% accuracy), which was low enough for users to experience trust violation. Right after the trust violation, the AI showed an apology message. Then the AI again provided highly accurate suggestions: seven good and one bad. In total, the AI presented 30 good decisions and 10 bad decisions out of 40 recommendations (75% accuracy). Following the experiments, participants were asked to complete the main questionnaire.

3.4 Manipulation of Implicit Theories of Artificial Intelligence

In order to manipulate the implicit theory of an intelligent agent, two different pieces of information about AI algorithms were given before starting the investment game to introduce either the entity or incremental theory depending on the condition. The content of the information was based on the adopted version of Chiu et al. [28]'s induction. Before starting the main experiment, participants read a short text introducing either the entity or incremental theory depending on the condition. The entity version explains that the performance of machine learning algorithms is fixed and cannot be changed, while the incremental version states that the performance of machine learning algorithms is not fixed and can be changed. Each view was given with rationales and examples buttressing the argument. For example, the entity version information was,

- In a talk at the International Conference on Artificial Intelligence held online last January, Dr. George Medin argued that “Although machine learning models could sometimes outperform (or underperform) compared to expectations, they cannot be improved more than a certain level even with good feedback.” He introduced an example: “Even if we use good data, the Linear Model cannot outperform the Support Vector Machine, and the Support Vector Machine cannot outperform the Artificial Neural Network”, insisting that “Thus, in most of the Machine Learning algorithms, their performances are fixed and cannot be changed.”

The incremental version was,

- In a talk at the International Conference on Artificial Intelligence held online last January, Dr. George Medin argued that “Machine learning models could sometimes outperform or underperform compared to expectations and they can be improved more than a certain level with good feedback.” He introduced an example: “If we use good data, the Linear Model can outperform the Support Vector Machine, and the Support Vector Machine can outperform the Artificial Neural Network”, insisting that “Thus, in most of the machine learning

algorithms, their performances are not fixed and can be changed.”

As the experiment was conducted online, these information sheets were created with much care to ensure that participants would not fail to read or understand them. For example, only one or two sentences were shown on each sheet, along with an image explaining the sentence’s meaning. In addition, the phrase containing the claim about the implicit theories of the artificial intelligence was boldfaced. The button to proceed to the next page appeared three seconds after showing the information to give participants the time to read it.

3.5 Manipulation of Apology Attribution

In all condition, the agent apologized for the negative consequences of the investment. Then, depending on the condition, the agent provided the explanation for the error using either an internal or external attribution. In the internal condition, the intelligent agent took full responsibility for the trust violation:

- I am sorry. As the final return on the algorithm’s suggestion was XXX points, the investment was not successful. The failure was caused by the algorithm’s limitations. There was a limitation to the algorithm’s ability because the algorithm couldn’t get enough data to predict the growth pattern of a company. The results of this round will be reflected in the algorithm and used to improve the algorithm’s suggestion.

The intelligent agent in the external condition acknowledged only part of the responsibility and attributed the rest to the influence of external abnormality in the stock market:

- I am sorry. As the final return on the algorithm’s suggestion was XXX points, the investment was not successful. The failure was caused by an abnormal business environment rather than the algorithm’s limitations. There was an abnormal pattern of corporate growth that was impossible to predict in the data the algorithm obtained. The results of this round will be reflected in the algorithm and used to improve the algorithm’s suggestion.

3.6 Measures

In measuring trust, two different methods were used: cognitive and behavioral trust. *Cognitive trust* was measured by directly asking participants to answer to what extent they trusted the agent in each round using a 7-point Likert scale [75–77]. To examine the development of trust over time, the change rate of cognitive trust was calculated. Since there were five rounds of investment and the trust violation occurred in Round 3, we defined *initial cognitive trust* as cognitive trust in Round 1, *post-violation cognitive trust* as cognitive trust in Round 3, and *final cognitive trust* as cognitive trust in Round 5, the final round. *Cognitive trust damage* was defined as a rate of change in cognitive trust from Round 1 to 3. Note that the apology occurred right before measuring cognitive trust in Round 3, thus trust damage measured in this study might reflect the early stage of trust repair. Finally, *cognitive trust repair* was defined as a rate of change in cognitive trust from Round 3 to 5.

Second, we computed behavioral trust, also known as compliance. *Behavioral trust* was defined as how many times the participant complied with the suggestion proposed by the AI agent [78]. Since the trust was violated at the end of Round 3, after measuring the behavioral trust in Round 3 and before Round 4, we defined *initial behavioral trust* as behavioral trust in Round 1, *post-violation behavioral trust* as behavioral trust in Round 4, and *final behavioral trust* as behavioral trust in Round 5. We did not calculate the rate of change in behavioral trust because there was a divide by zero problem since some of the participants did not comply with the agent at all in specific rounds.

In addition to trust, diverse perceptions of intelligent agents were measured including anthropomorphism, animacy, perceived intelligence, likeability, and intention to use. We adopted 7-point Likert scale scales of anthropomorphism ($\alpha = 0.74$) using three items (e.g., machine-like — human-like, unconscious — conscious, and artificial — lifelike), animacy ($\alpha = 0.75$) using five items (e.g., stagnant — lively), perceived intelligence ($\alpha = 0.87$) using five items (e.g., incompetent — competent), likeability ($\alpha = 0.77$) using five items (e.g., dislike — like) in the Godspeed Questionnaire Series [79, 80]. Intention to use (α

= 0.87) was measured asking three questions: “If there is an AI system similar to this, I want to use it”, “If there is an AI system similar to this, I would recommend it to my friend”, and “If there is an AI system similar to this, I have the intention to use it.” Answers were measured on a 7-point Likert scale from Strongly disagree (1) to Strongly agree (7).

Perceived malleability of an intelligent agent was measured by asking participants to choose between opposite arguments “Machine learning algorithms’ performances are not fixed and can be changed” or “Machine learning algorithms’ performances are fixed and cannot be changed.” The purpose of this question was to check whether the participants’ implicit theory of artificial intelligence was appropriately manipulated. A higher score indicates that people think artificial intelligence is not fixed and can be improved.

Finally, participants reported previous stock investment experience on a 7-point scale from Never (1) to Very Frequently (7).

4 Results

4.1 Manipulation Check

We conducted a manipulation check by comparing the perceived malleability of AI between incremental and entity theory conditions using Welch’s two-sample t-test. As expected, participants who held incremental theory considered machine learning algorithms to be significantly more malleable and able to be changed than did participants with the entity theory ($M = 6.01$, $SD = 0.15$ vs. $M = 4.69$, $SE = 0.15$), $t(108) = 6.26$, $p < 0.001$ $d = 1.02$.

4.2 Hypothesis Testing

4.2.1 Perception of Intelligent Agent

H1 expected that the perception of an intelligent agent would be more favorable among incremental theorists than entity theorists. To test this, Type III ANOVA was conducted.

The analysis of likeability (H1a) demonstrated a significant main effect of implicit theories of artificial intelligence, $F(1,146) = 4.05$, $p = 0.046$, $\eta_p^2 = 0.027$. The result showed that the level of likeability was significantly higher in incremental than entity theory ($M = 4.29$, $SE = 0.10$ vs. $M = 4.02$, $SE = 0.10$).

The result for intention to use (H1b) also presented a significant main effect of implicit theories of artificial intelligence, $F(1,146) = 5.33$, $p = 0.022$, $\eta_p^2 = 0.035$. The result showed that the level of likeability was significantly higher in incremental than entity theory ($M = 4.99$, $SE = 0.16$ vs. $M = 4.46$, $SE = 0.16$), $p = 0.02$. Overall, the results showed that incremental theorists showed more likeability (H1a) and intention to use (H1b) than entity theorists, which supported H1.

4.2.2 Anthropomorphism and Related Variables

H2 predicted that incremental theorists would demonstrate higher animacy, perceived intelligence, and anthropomorphism than entity theorists. To test this, Type III ANOVA was conducted.

The result for perceived intelligence (H2a) showed a significant main effect of implicit theories of artificial intelligence, $F(1,146) = 4.36$, $p = 0.04$, $\eta_p^2 = 0.029$. The analysis showed that the level of perceived intelligence was significantly higher in incremental than entity theories ($M = 4.64$, $SE = 0.12$ vs. $M = 4.28$, $SE = 0.12$). In terms of animacy (H2b) and anthropomorphism (H2c), however, there were no significant main effects of implicit theories of artificial intelligence (H2b: $F[1,146] = 0.84$, $p = 0.36$, $\eta_p^2 = 0.006$; H2c: $F[1,146] = 1.43$, $p = 0.23$, $\eta_p^2 = 0.010$).

Overall, the results showed that the participants who held an incremental theory showed higher perceived intelligence (H2a) than entity theorists, but this was not the case for animacy (H2b) and anthropomorphism (H2b). Thus, H2 was only partially supported.

4.2.3 Cognitive Trust

H3 predicted an interaction effect such that trust will be recovered more efficiently when the agent uses external rather than internal attribution apologies with entity theorists and internal rather than external attribution apologies with incremental theorists. To test the hypothesis in terms of cognitive trust, Type III Analysis of Covariance (ANCOVA) was conducted to compare initial cognitive trust, cognitive trust damage, post-violation cognitive trust, cognitive trust repair, and final cognitive trust. Previous stock investment experience served as a covariate across the analysis.

The results for initial cognitive trust showed no significant main effects of implicit theories about artificial intelligence in the initial trust, $F[1,145] = 0.18$, $p = 0.67$, $\eta_p^2 = 0.001$. We did not analyze the main effects of apology type nor the interaction effect because trust violation had not yet occurred and thus the agent did not apologize.

To analyze cognitive trust damage, cognitive trust from Round 1 was controlled as a baseline for each individual. There was a significant main effect of implicit theories of artificial intelligence ($F[1,144] = 6.06$, $p = 0.02$, $\eta_p^2 = 0.032$) and apology type ($F[1,144] = 4.65$, $p = 0.03$, $\eta_p^2 = 0.024$). In particular, there was a significant difference between implicit theories as trust damage was smaller in incremental than entity theory ($M = -13\%$, $SE = 5\%$ vs. $M = -29\%$, $SE = 5\%$) after the trust violation. The results also revealed that trust damage was significantly less in the external than internal attribution apology ($M = -14\%$, $SE = 5\%$ vs. $M = -28\%$, $SE = 5\%$) after the trust violation. However, there was no significant interaction between implicit theories and apology attributions, $F(1,144) = 1.33$, $p = 0.25$, $\eta_p^2 = 0.006$.

The result of post-violation cognitive trust demonstrated a significant main effect of implicit theories of artificial intelligence, $F(1,145) = 4.93$, $p = 0.03$, $\eta_p^2 = 0.032$. Specifically, post-violation cognitive trust was kept significantly higher in incremental than entity theory ($M = 3.53$, $SE = 0.17$ vs. $M = 3.01$, $SE = 0.17$). However, there was no significant main effect of apology type ($F[1,145] = 1.73$, $p = 0.19$, $\eta_p^2 = 0.011$) nor an interaction effect between implicit theories and apology type ($F[1,145] = 0.67$, $p = 0.41$, $\eta_p^2 = 0.004$).

To analyze cognitive trust repair, cognitive trust for Round 3 was controlled as a baseline. The result of trust repair revealed a significant interaction effect between implicit theories of artificial intelligence and apology type, $F(1,144) = 6.27$, $p = 0.01$, $\eta_p^2 = 0.024$. The post-hoc test of Duncan's MRT showed that the cognitive trust repair in Entity-External ($M = 111\%$, $SE = 16\%$) was significantly higher than in Entity-Internal ($M = 42\%$, $SE = 16\%$, $p = 0.0379$) and Incremental-External ($M = 77\%$, $SE = 16\%$, $p = 0.008$) conditions. However, there was no significant difference between Entity-External and Incremental-Internal

($M = 86\%$, $SE = 16\%$, $p = 0.127$) conditions. Neither the main effect of apology type ($F[1,144] = 3.56$, $p = 0.06$, $\eta_p^2 = 0.014$) nor implicit theories ($F[1,144] = 0.12$, $p = 0.73$, $\eta_p^2 = 0.000$) were significant.

The result for final cognitive trust did not show any significant results. The interaction effect between implicit theories of artificial intelligence and apology types was not significant, $F(1,145) = 3.05$, $p = 0.08$, $\eta_p^2 = 0.020$. The main effect of apology type was not significant, $F[1,145] = 3.84$, $p = 0.052$, $\eta_p^2 = 0.025$. The main effect of implicit theories was also not significant, $F(1,145) = 0.95$, $p = 0.33$, $\eta_p^2 = 0.006$.

In total, the results showed that cognitive trust was damaged less when participants were primed with incremental than entity theory and the agent apologized with external than internal attribution, although the effect of apology type was not shown in post-violation cognitive trust. The results also showed that trust was repaired better in the Entity-External and less in the Entity-Internal condition, although trust repair in the Entity-External was no higher than trust repair in the Incremental-Internal condition. These findings partially support H1a, but not H1b (see Figure 2).

4.2.4 Behavioral Trust

To test H3 in terms of behavioral trust, we conducted a Type III ANOVA and compared behavioral trust in Round 1 to view initial trust, behavioral trust in Round 4 to view how trust was damaged after the trust violation, and behavioral trust in Round 5 to view the trust recovery.

The result for initial behavioral trust showed no significant main effect of implicit theories of artificial intelligence, $F(1,145) = 1.17$, $p = 0.28$. The result for post-violation behavioral trust showed no significant interaction effect ($F[1,145] = 0.28$, $p = 0.61$, $\eta_p^2 = 0.002$) nor significant main effect of implicit theories ($F[1,145] = 1.01$, $p = 0.32$, $\eta_p^2 = 0.007$) and apology type ($F[1,145] = 1.95$, $p = 0.17$, $\eta_p^2 = 0.012$). The result for final behavioral trust also demonstrated that the interaction effect ($F[1,145] = 1.53$, $p = 0.22$, $\eta_p^2 = 0.010$) and the main effect of implicit theories ($F[1,145] = 0.73$, $p = 0.40$, $\eta_p^2 = 0.005$) and apology type ($F[1,145] = 1.36$, $p = 0.25$, $\eta_p^2 = 0.008$) was not significant. Overall, the results showed that there are no significant differences in

behavioral trust between conditions, which did not support H3.

5 Discussion

The current study explored how implicit theories about AI affect the agent's trust repair process depending on different attributions of apology.

5.1 Implicit Theories of Artificial Intelligence and Perception of the Intelligent Agent

Our results showed that participants who hold incremental theory were more likely to have a favorable perception of an AI agent when it tries to repair broken trust. Incremental theorists liked the agent more and had a higher intention to use compared to entity theorists. This result is in line with previous findings showing that participants who hold incremental theory are more likely to favor robots and other technologies and have higher intention to use them than individuals with entity theory [4, 43, 44].

5.2 Implicit Theories of Artificial Intelligence and Anthropomorphism

The findings suggest that believing in the intelligent agent's ability to learn and develop is not enough to elicit anthropomorphism in participants. Although incremental theorists are more likely to perceive higher intelligence in the agent than entity theorists, animacy and anthropomorphism did not show differences between people with the entity and incremental theories of artificial intelligence.

The result of higher perceived intelligence by incremental theorists is in line with previous findings that individuals tend to consider the AI agent to be more intelligent when they believe in the AI's capability of improvement and development over time [55]. However, the incremental theory did not lead to higher animacy despite previous findings that perceiving developmental capacity facilitates lifelikeness [54]. The insignificant results for animacy might be due to the absence of embodiment in our experiment. The concept of animacy is primarily based on studies with an embodied robot [79, 80]. However, the agent in this study

was not embodied and had no anthropomorphic cues such as face or voice. Thus, we recommend that future researchers should test if the positive effect of implicit theories of artificial intelligence on trust repair is amplified when anthropomorphic cues are present or the agent is embodied.

5.3 Implicit Theories of Artificial Intelligence and Trust in Intelligent Agents

We initially hypothesized that the effectiveness of different attributions of apology on the trust repair of intelligent agents would be moderated by implicit theories of artificial intelligence. Thus, we expected that entity theorists would recover trust in machines more when they apologize with external attribution than with internal attribution based on the belief that machines cannot change (i.e., automation bias). We also expected that incremental theorists would recover trust in the intelligent agent more when they interact with an agent that apologizes with internal attribution than with one that apologizes with external attribution based on the belief that the intelligent agent's performance can develop as it learns from its mistakes.

However, our results only partially supported the interaction hypothesis. In terms of trust damage, there was no interaction effect between implicit theories of artificial intelligence and attributions of apology. There were main effects of implicit theories and attributions of apology; cognitive trust was damaged less when the participant held incremental than entity theory and in the external attribution apology rather than internal attribution apology condition. In terms of trust repair, there was an interaction effect between implicit theories of artificial intelligence and attributions of apology. However, only entity theorists showed different levels of trust repair in their responses to varied apology attributions, contrary to our hypothesis.

5.3.1 Trust Damage

The results for trust damage were generally in line with previous studies. The results demonstrated that cognitive trust was damaged less in incremental theorists than entity theorists after trust violation. These results are in accordance with

the literature on trust repair in interhuman relationships, which shows that trust declines less for individuals with incremental theory than those with entity theory after the trust violation [19].

The results also showed that cognitive trust was damaged less when the intelligent agent used an external attribution apology than when it used an internal attribution apology. These results are in line with the findings of Kim and Song [13] that trust in intelligent agents is damaged less when the agent apologizes with an external than an internal attribution.

5.3.2 Trust Repair

The results also indicated that cognitive trust repair was stronger for the agent that apologized with external attribution than for the agent that apologized with internal attribution in interactions with entity theorists. However, incremental theorists did not show different levels of trust repair in response to the different apology attributions. These results suggest that the effectiveness of trust repair was determined by the attribution of the apology for entity theorists, but not for incremental theorists.

The reason for this might be because laypeople belief about AI agents [16, 60, 61] and entity theory [24] share common characteristics. Any message about future improvement implied in an internal attribution apology may not seem persuasive to participants who held an entity theory of AI because they believe that AI is consistent in its performances [24, 58–61], while external attribution served as a reasonable explanation for the error in the AI agent [13].

Notably the trust repair was stronger for entity theorists than for incremental theorists when they interacted with an agent that apologized with external attribution. This might be because entity theorists are quicker to judge the agent's trust and more likely to pertain their first impression than incremental theorists [34]. They might believe that the excuses in the external attribution seemed plausible, decide not to alter their initial evaluation, and restore trust more efficiently.

We initially expected that the incremental theorists' trust repair would be stronger for agents that apologized with internal attribution than for agents that apologized with external attribution. We postulated this because incremental

theorists would accept the potential for future improvement implied in an internal attribution apology [19] based on the belief that the intelligent agent's performance can improve as it learns from errors [24].

However, the results indicate that incremental theorists do not favor the internal attribution apology over the external one. There might be several reasons for this. First, people may have thought that the subject of potential for future development was not the algorithm, but the developer or company behind the algorithm. Participants may have assumed that human intervention would be needed for the AI to improve. However, this study did not ask whether they assumed there were other actors than the AI agents such as the developer or company behind the algorithm. Thus, future researchers should also investigate whether individuals recognize the role of developer or company as well as the algorithm.

Second, incremental theorists may not think that the machine can take responsibility. Although it is important for individuals to believe in the promise of future improvement to accept an internal attribution apology, another important premise of embracing an internal attribution apology is whether the transgressor is capable of taking responsibility. Indeed, internal attribution apology is the act of taking full responsibility for the trust violation [62]. However, this study did not measure whether individuals believe that the machine is capable of taking responsibility. Thus, future researchers should examine whether individuals perceive that humans and machines have different levels of ability to take responsibility.

5.4 Implications

Our study has some theoretical implications. First, it contributes to broadening the extant literature on interhuman communication in the HCI context. Our study is one of the first to investigate the effect of implicit theories in this context. Previous studies have shown that the implicit theory about the self and human intelligence influences the perception of the AI agents such as robot anxiety and evaluation [4, 20]. However, our study showed that not just implicit theories of the self but also implicit theories of artificial intelligence affect the perceptions of AI such as likability and intention to use. The results also showed that

implicit theories influence the trust repair process of the AI agents, which has not been explored previous.

To our knowledge, this is the first study to show that implicit theories influence the trust repair of an AI agent as well as in human relationships [18, 19]. Our study suggest that an incremental theory generally has positive effects on the trust repair strategy (i.e., apology) of the agent as shown in the human-human relationship literature [19]. This study also demonstrates that entity theorists recovered trust more when they interacted with the agent that apologized with an external attribution than in other situations. This finding is specific to the HCI context and is not shown in the previous human-human relationship literature [18, 19].

Second, our study revealed that an individual's preexisting perception of machines and technologies should be considered when studying HCI. The recent advances in AI and ML have made them more likely to adapt and develop themselves by learning from errors [81, 82]. Individuals familiar with these recent technologies are likely to think that AI can learn and develop. However, not all people have this understanding of the state-of-art technology. Previous literature on automation bias and machine heuristics shows that people generally believe that machines are more consistent and reliable than humans [58–61] but are more resistant to change [16]. Thus, individuals not familiar with AI and ML technologies might believe that AI agents cannot learn from mistakes. This implies that it may be necessary to consider individuals' preexisting beliefs and thoughts about intelligent agents as important moderators or intervening variables when studying the interaction between humans and intelligent agents.

Our study also has some practical implications for designing an intelligent agent. The results show that it is important for designers to consider the way their product or service is introduced. Simply introducing the service differently can made users have a different perception of intelligent agents. In our study, we found that introducing AI agents as able to improve made users credit and like the agent more and eventually have greater intention to use the service.

Our findings also show that it is better to design intelligent agents to prevent negative consequences of trust violation by the agent by using

apology strategies that mitigate its blame rather than acknowledge it. However, caution is needed because an intelligent agent that diminishes its responsibility can be seen as deceptive, dishonest, or even incompetent [69].

5.5 Limitations and Future Studies

The primary limitation of this study is that inducing implicit theories had an unbalanced result for some of the participants in the entity theory condition. While only 6% (5 participants out of 85) in the incremental condition failed to recall the statement in the manipulation essay, 33% (40 out of 105) in the entity theory condition did so. Although the precise factor in the entity theory condition that made participants fail to pass the manipulation test is unclear, it would be reasonable to expect that individuals, in general, tend to have an incremental belief toward AI. We postulate that some individuals' incremental beliefs were sufficiently strong, such that it was not changed easily by our experimental manipulation. Another possibility is related to the technical terms. The script provided to the participants used many technical terms (e.g., Linear Model, Support Vector Machine, and Artificial Neural Network) to manipulate the implicit theories of artificial intelligence. It is possible that some participants did not understand this language on a technical level.

Furthermore, we did not measure participants' preexisting implicit theories of artificial intelligence as a disposition. Rather, we primed specific implicit theories of artificial intelligence as a manipulation. Past research has repeatedly demonstrated that experimentally induced implicit theories yield a similar effect to those seen in self-reported chronic orientation [83–85]. More crucially, inducing implicit theories allows researchers to analyze their causative role and to rule out the idea that the results could be explained by variables other than observed levels of entity or incremental theory endorsement [40, 41]. However, using the self-reported chronic implicit theories scale allows researchers to examine the relationship between the variables in a more ecologically valid way [83–85]. Thus, future researchers would need to reproduce the current observations by measuring implicit theories as personal dispositions. This could also help

validate the robustness of the current finding in a more natural setting.

6 Conclusion

This study demonstrated that having an incremental theory enhances the intelligent agent's trust repair and the favorable perception of intelligent agents compared to an entity theory, and trust recovers to a greater extent when agents apologize with external rather than internal attribution. The study also showed that trust was repaired best when participants who held entity theory received an apology with external attribution. The findings showed that the effect of implicit theories of artificial intelligence on trust repair shown in the human-human interaction literature is also applicable in the HCI context. Our study is one of the first attempts to explore the influence of implicit theories of artificial intelligence on trust repair by AI agents. We hope that future researchers will further investigate the effect of implicit theories on various contexts of HCI.

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Declarations

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics approval

The authors declare that this study was approved by the Institutional Review Board at the affiliated university and was performed in accordance with the 1964 Declaration of Ethical Standards of

Helsinki. Informed consent was obtained from all the participants engaged in the study.

Data availability

All data generated or analyzed during this study are available via the Open Science Framework repository, <https://osf.io/fym4x/>

Authors' contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Taenyun Kim. The first draft of the manuscript was written by Taenyun Kim. Hayeon Song reviewed and edited the original manuscript. All authors read and approved the final manuscript.

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Seoul (2021)

Fig. 1 An overview of the experimental procedure and manipulation of the experiment

Fig. 2 Main Results. (A) Cognitive trust over Rounds, (B) Cognitive Trust Change and (C) Perception of AI. ENT: Entity theory. INCR: Incremental theory. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.