Effectiveness of “Neither-Good-Nor-Bad” Information on User’s Trust in Agents in Presence of Numerous Options

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SUMMARY The effect of provision of “Neither-Good-Nor-Bad” (NGNB) information on the perceived trustworthiness of agents has been investigated in previous studies. The experimental results revealed several conditions under which the provision of NGB information works effectively to make users perceive greater trust of agents. However, the conditions in question were carried out in a situation in which a user is able to choose, with the agent’s advice, one of a limited number of options. In practical problems, we are often at a loss to choose because there are too many possible options and it is not easy to narrow them down. Furthermore, in the above-mentioned previous studies, it was easy to predict the size of profits that a user would obtain because its pattern was also limited. This prompted us, in this paper, to investigate the effect of provision of NGB information on the users’ trust of agents under conditions where it appears to the users that numerous options are available. Our experimental results reveal that an agent that reliably provides NGB information tends to gain greater user trust in a situation where it appears to the users that there are numerous options and their consequences, and it is not easy to predict the size of profits. However, in contradistinction to the previous studies, the results in this paper also reveal that stable provision of NGB information in the context of numerous options is less effective in a situation where it is harder to obtain larger profits.

key words: Human-Agent Interaction, “Neither-Good-Nor-Bad” information, trustworthiness of agents, numerous options

1. Introduction

Techniques for Human-Agent Interaction (HAI) are attracting increasing attention, and agent systems that assist daily activities by providing us with a variety of useful information are becoming especially widespread (e.g., Siri [1], Cortana [2], Alexa [3], and so on).

It is important for the long-term survival of such systems that agents gain sufficient trust from users. The best way to gain users’ trust is to continuously provide the most useful information. However, agents cannot always achieve this, mainly due to the limits of technology. Therefore, it is necessary to minimize users’ loss of trust in agents in cases when they fail to provide the correct information.

There have been several similar studies based on this point of view (e.g., [4]–[7]). However, most conventional studies assume that all information provided by agents is classified into just two categories: “correct” and “incorrect.” Correct information generates a profit for the users, while incorrect information generates a loss. Although there can be a range of sizes of profits (or losses) that correct (or incorrect) information generates for users in real situations, such moderate profits (or losses) are ignored in these previous studies.

On the other hand, Sakumoto et al. [8] and Yokoyama et al. [9] focused on these moderate profits. First, they defined three types of information provided by agents. The “best” information is defined as that which generates the maximum profit, the “worst” information is defined as that generating no profit, and “Neither-Good-Nor-Bad” (NGNB) information is defined as that which is not the best, but good enough to generate some profit for users. These definitions focus only on the size of profits generated by the information. They then investigated the effects of its provision on perceptions of trustworthiness of the agents. Their experimental results revealed several conditions under which the provision of NGB information works effectively to induce users to develop greater trust in agents. In short, a strategy in which the agent intentionally provides NGB information rather than the best information when it is hard to provide the best information (due to the limits of technology, problems of costs, and so on) will work under these conditions.

However, the previous studies have a drawback, in that all the experiments were carried out under the same conditions: a participant would choose one of three options using the agent’s advice. In practical problems, we are often at a loss to which to choose because there are too many possible options and it is not easy to narrow them down. Although this is exactly the kind of situation in which we will seek advice, the findings obtained from these previous studies may no longer apply under this situation. Furthermore, in their previous studies, the size of profits which a user could obtain was also limited to only three patterns. Such a condition may induce the user to become aware of how good the obtained profit was. From the viewpoint of the application of provision of NGB information to practical problems, these suppositions appear to be too limited.

Therefore, in this paper, we focus on a situation in which it appears to users that there are numerous possible options and their consequences, and investigate the effect of provision of NGB information on the users’ trust of agents in a given situation. The findings of this paper are expected to lead to a more useful principle when designing agent systems to assist users’ activities effectively in more practical situations.
2. Previous Studies

In this section, we first briefly review the previous studies [8], [9], on which this study is based and which we develop. We then point out their drawback.

2.1 Brief Review

Sakamoto et al. [8] defined three types of information provided by agents, as mentioned in the Introduction. The “best” information is defined as that which generates the maximum profit, the “worst” information is defined as that generating no profit, and “Neither-Good-Nor-Bad” (NGNB) information is defined as that which is not the best, but good enough to generate some profit for users. Next, they also defined two types of agents, which assist users by giving advice during a task. A “solid” agent is defined as one that reliably provides NGNB information. An “extreme” agent is defined as one that unreliably provides either the best or the worst information. They then compared these agents in terms of user trust by performing the following two experiments. In this paper, we follow these definitions of types of information and agents.

First, they carried out an experiment inspired by prospect theory [10], in which they focused on the effects of various scenarios, namely participants’ behavioral motivation. They set up three scenarios where the participants should, as far as possible, act “to gain profits,” “to avoid losses” and “to avoid the loss of already obtained profits.” The experimental results revealed that, in a scenario where users act to obtain profits, a solid agent that reliably provides NGNB information gains greater trust from the participants.

Second, they carried out an experiment inspired by assimilation-contrast theory [11], in which they focused on the effect of participants’ advance expectations of the agents. The participants were controlled such that they had either a higher or a lower expectation of the agents in advance. Their experimental results revealed that, when the users have a lower expectation of the agent, the solid agent was less trusted by the participants.

Yokoyama et al. [9] developed Sakamoto et al.’s study from the following two points of view; variation in the size of profits generated by the NGNB information, and disclosure or non-disclosure of the consequences of choices not taken.

First, they carried out an experiment to investigate the effects of the size of a small profit generated by NGNB information on the trustworthiness of the agents. In Sakamoto et al.’s experiment, the size of profits generated by the NGNB information was always fixed at 50% of the maximum. Furthermore, the probability that the extreme agent would generate the maximum profit was set at the same level. They set three conditions regarding the size of profits generated by the NGNB information: 20%, 50% and 80%. The experimental results revealed that the solid agent will gain higher user trust in a situation where it is harder to obtain larger profits and consequently the size of profits generated by the NGNB information is lower.

Second, they carried out an experiment to investigate the effects on perceived agent trustworthiness of disclosure or non-disclosure of the consequences of choices not made by the users. Although we are often unaware of such consequences and of what we should have done in practical situations, all the consequences including those of choices that they had not made were always disclosed to the users in Sakamoto et al.’s experiment. The experimental results revealed that the solid agent will gain more trust from users in a situation where the consequences of choices that they did not make are hidden from them.

2.2 Drawback

In the aforementioned previous studies [8], [9], the experimental participant was asked to perform several tasks using the agents’ advice. The structures of all these tasks were basically the same: the participant was asked to repeatedly choose one of three options to obtain better results. As one example, here we explain the “treasure hunt game,” which was employed in both [8] (as a scenario where users act “to gain profits”) and [9]. In this task, the participant was asked to choose one of the treasure chests and would obtain gold coins as their profit depending on their choice. One of the three chests contained 10 coins, one contained \( n \) coins and the third contained none. \( 0 < n < 10 \) and the value differs according to the condition of the size of profits. The agent told the participant which chest he or she should choose, but the participant did not have to obey this instruction. Figure 1 shows example screenshots of the “treasure hunt game.” (The Japanese-language version was used in the experiment.) These screenshots were under the “non-disclosure” condition in [9], where the results that the participants did not choose were not disclosed to them. Under this situation, if the agent recommends the chest containing 10 coins (or no coins), it will have provided the “best” (or “worst”) information. If it recommends the chest containing neither 10 nor zero coins, it will have provided the NGNB information.

However, as mentioned in the Introduction, we are more likely to face too many possible options for a problem that we encounter in practice than a limited number of options. Furthermore, the previous studies assumed that the size of profits which a user could obtain in the tasks was limited to only three patterns (e.g., 10 or \( n \) or 0 coins in the “treasure hunt game”). This assumption may induce the user to become aware of how good the obtained profit was. In practice, even the size of maximum profits can vary according to the situation at the time. The findings obtained from the previous studies [8], [9] may no longer hold under these wider conditions, so the suppositions mentioned above are too limited to permit the application of the provisions of NGNB information to practical problems.

Therefore, in this paper, we employ a task that eliminates the above-mentioned drawback and investigate the ef-
fect of provision of NGNB information on the users’ trust of agents. (Details of the task we employ are described in Sect. 3.2.1.) In the task, we also employ the following settings because the previous results have shown that the provision of NGNB information works more effectively under these conditions.

- A scenario where users need to act to obtain profits as far as possible.
- A situation where the consequences of choices that they did not make are concealed from them.
- No advance control of users’ expectations of agents.

3. Experiment

In this section, we carry out an experiment to investigate the effects of provision of NGNB information on users’ trust of agents in a situation in which it appears to users that there are numerous options and their consequences.

3.1 Hypotheses

The results of a previous study [9] have shown that users prefer a solid agent that is guaranteed to generate some profit rather than an extreme agent that occasionally generates maximum profits under the following two situations.

- A situation where it is harder to obtain larger profits, and consequently the size of profits generated by the NGNB information is lower.
- A situation where the consequences of choices that the users did not make are concealed from them. In other words, how good the profits generated by the agent were is hard to know.

It appears likely that the numerous options and unpredictable size of profits assumed in this paper will strengthen the characteristic of the situation mentioned above. We can infer from these that the user will attach more importance to a solid agent that generates small but stable profits.

We therefore formulated the following two hypotheses and carried out an experiment to verify them.

**Hypothesis 1:** A solid agent that provides NGNB information reliably will be highly trusted in situations where it appears to users that there are numerous options and the profits obtained as a result of a choice are hard to predict.

**Hypothesis 2:** In addition to Hypothesis 1, a solid agent that provides NGNB information reliably will be better trusted in a situation where it is harder to obtain larger profits and consequently the size of profits generated by the NGNB information will be lower.

3.2 Method

3.2.1 Experimental Task

In this paper, we employ an “insect hunt game” as an experimental task. Although this game has basically the same structure as the “treasure hunt game,” it is designed to remove the constraint of a limited number of options as described in Sect. 2.2.

In the “insect hunt game,” participants are asked to choose a place against a background image of a forest (excluding the message windows) by clicking an arbitrary pixel, and will obtain points as profits according to the kind of the insect that they capture in the place they have chosen. Figure 2 shows example screenshots. (The Japanese-language version was used in the experiment.) The agent suggests the participants as to which place they should choose to capture a high-score insect, but the participants do not have to obey this instruction. The agent’s prediction is shown as a circle in the image, as seen in the upper image in Fig. 2. If the agent recommends a place with the highest-score (or the lowest-score) insect at the scene, it will have provided the “best” (or “worst”) information. If it recommends a place where there is neither the highest-score nor the lowest-score insect, it will have provided NGNB information. The task consists of twenty trials: the participants will choose 20 times, and the agent will also give advice 20 times during the task.

This task is designed such that the participants appear to have numerous options (as many as there are pixels in the background image) and their consequences. However, these “numerous options” are just pretenses. We in fact internally limit the points which they can obtain to only three patterns, the same as in the “treasure hunt game,” making it possible to compare the results in this paper with those of the previous papers. The three patterns of the points that the participants could obtain correspond to the best, the NGNB and the worst information.
The type of information that the agent provides and the consequent points that the participants who follow the agent’s advice will obtain are internally predetermined for each trial. (Details are described in Sect. 3.2.2.) If the participants do not follow the agent’s advice, they will obtain one of the two other predetermined points according to the place they choose. There are thus three categories of points for each trial.

In the task, the scenarios (daytime, evening and night) and corresponding background images change every five trials. Along with that, the pattern of the size of points generated by the best and the NGNB information also changes. (Only the worst point is always set to zero.) Furthermore, the number of points varies even in the same scenario. By these settings, we expect that the users believe as if the system is working stochastically. However, the points are in fact internally predetermined as described above. These are all done to make profit attainment hard for the participants to predict and not to reveal to the participants that their patterns are limited.

### 3.2.2 Experimental Conditions

In this experiment, we set the following two conditions regarding agents.

**Solid Agent:** This agent provides mainly NGNB information, and occasionally the best and worst information during the task.

**Extreme Agent:** This agent provides only either the best or worst information during the task. It never provides NGNB information. The ratio of the best information to the worst depends on the conditions determining size of profits as described below.

These agent conditions are exactly the same as those in the previous studies. Since the participants are asked to perform relative evaluation between two types of agents as will be described in Sect. 3.3, these conditions are set as a within-participants factor.

We also set three conditions regarding size of profits generated by the NGNB information, 20%, 50% and 80%, as a between-participants factor. These conditions are also the same as those in the previous studies. The ratios for each condition also represent the percentages of the number of provisions of the best information by the extreme agent during the task. Table 1 shows the number of provisions of information by the agents during the task for each combination of agent and size of profits. Table 2 shows the predetermined points that the participants will obtain for each condition. The three values of each cell denote the points that correspond to the best, the NGNB and the worst information, respectively. The values in Tables 1 and 2 are set to make the expected profits that the participants would realize by following all the advice in the same way for the solid and extreme agents. We can therefore compare the trustworthiness of the agents regardless of any differences in their performance.

### Table 1 Number of Provisions of Information by Agents

| Conditions | Number of Provisions |
|------------|----------------------|
|            | Best    | NGNB    | Worst  | Total  |
| 20%        | Solid   | 2       | 15     | 3      | 20     |
|            | Extreme | 5       | 0      | 15     | 20     |
| 50%        | Solid   | 2       | 16     | 2      | 20     |
|            | Extreme | 10      | 0      | 10     | 20     |
| 80%        | Solid   | 3       | 15     | 2      | 20     |
|            | Extreme | 15      | 0      | 5      | 20     |

### Table 2 Points for Each Set of Conditions

| Trial | Scene | Conditions |
|-------|-------|------------|
|       |       | 20% | 50% | 80% |
| 1     | Daytime #1 | 15 – 3 – 0 | 15 – 8 – 0 | 15 – 12 – 0 |
| 2     |       | 20 – 4 – 0 | 13 – 7 – 0 | 13 – 10 – 0 |
| 3     |       | 14 – 3 – 0 | 20 – 10 – 0 | 14 – 18 – 0 |
| 4     |       | 18 – 4 – 0 | 18 – 9 – 0 | 20 – 16 – 0 |
| 5     |       | 13 – 3 – 0 | 14 – 7 – 0 | 14 – 11 – 0 |
| 6     | Daytime #2 | 10 – 2 – 0 | 9 – 5 – 0 | 9 – 7 – 0 |
| 7     |       | 9 – 2 – 0 | 10 – 5 – 0 | 9 – 7 – 0 |
| 8     |       | 6 – 1 – 0 | 6 – 3 – 0 | 10 – 8 – 0 |
| 9     |       | 10 – 2 – 0 | 9 – 5 – 0 | 6 – 5 – 0 |
| 10    |       | 7 – 1 – 0 | 10 – 5 – 0 | 10 – 8 – 0 |
| 11    | Evening | 28 – 6 – 0 | 28 – 14 – 0 | 28 – 22 – 0 |
| 12    |       | 25 – 5 – 0 | 25 – 13 – 0 | 25 – 20 – 0 |
| 13    |       | 30 – 6 – 0 | 22 – 11 – 0 | 22 – 18 – 0 |
| 14    |       | 23 – 5 – 0 | 30 – 15 – 0 | 30 – 24 – 0 |
| 15    |       | 29 – 6 – 0 | 28 – 14 – 0 | 23 – 18 – 0 |
| 16    | Night | 38 – 8 – 0 | 34 – 17 – 0 | 34 – 27 – 0 |
| 17    |       | 32 – 6 – 0 | 38 – 19 – 0 | 38 – 30 – 0 |
| 18    |       | 34 – 7 – 0 | 32 – 16 – 0 | 32 – 26 – 0 |
| 19    |       | 36 – 7 – 0 | 36 – 18 – 0 | 36 – 29 – 0 |
| 20    |       | 40 – 8 – 0 | 40 – 20 – 0 | 40 – 32 – 0 |
This agent is excellent.

Which agent would you want to ask for advice if you played

I think I spend more time shopping and choosing products

I want to play other games with this agent.

Whenever I choose a product, I try to choose the best one.

I always collect information on new products, the latest

I feel tired when with this agent.

I closely follow my favorite things such as TV stars, singers,

This agent’s advice led to a good result.

This agent is useless.

I will pursue things while there is still a chance of obtaining

Which agent provides greater satisfaction?

I can trust this agent.

Which agent provides a better result?

When I make a decision, I will consider all the options.

I will follow this agent’s advice.

This agent’s mistakes are unacceptable.

I want to play other games with this agent.

I feel tired when with this agent.

I want to ask this agent to give me advice if I play the same
game again.

Table 3 Questionnaire on Agent Trustworthiness

| Q1 | This agent is excellent. |
|----|--------------------------|
| Q2 | This agent’s advice led to a good result. |
| Q3 | This agent is useless.* |
| Q4 | I am satisfied with this agent. |
| Q5 | I will follow this agent’s advice. |
| Q6 | This agent’s mistakes are unacceptable.* |
| Q7 | I can trust this agent. |
| Q8 | I want to play other games with this agent. |
| Q9 | I feel tired when with this agent.* |
| Q10| I want to ask this agent to give me advice if I play the same game again. |

Table 4 Questionnaire on Relative Trustworthiness between Agents

| Q1 | Which agent provides a better result? |
|----|-------------------------------------|
| Q2 | Which agent provides greater satisfaction? |
| Q3 | Which agent would you want to ask for advice if you played the same game again? |

Table 5 Questionnaire on Maximization Scale

| Q1 | I will pursue things while there is still a chance of obtaining them. |
|----|-------------------------------------------------------------------|
| Q2 | When I make a decision, I will consider all the options. |
| Q3 | I think I spend more time shopping and choosing products than other people. |
| Q4 | I always collect information on new products, the latest health trends, etc. |
| Q5 | I closely follow my favorite things such as TV stars, singers, etc. |
| Q6 | Even when I plan to buy only one item, I often compare products at many stores. |
| Q7 | I tend to become extremely enthusiastic and immersed in any hobby. |
| Q8 | Whenever I choose a product, I try to choose the best one. |

3.3 Questionnaires

In the experiment, the participants were asked to complete three different questionnaires. These are exactly the same as those in the previous study [9].

Table 3 shows a questionnaire on agent trustworthiness. After the task, the participants are asked to state how strongly they agree with each sentence on a 7-point scale. A higher value means that they agreed with the sentences more strongly. We define the mean value of the answers to all the questions as an evaluation score of agent trustworthiness.

Table 4 shows a questionnaire on relative trustworthiness between the solid and extreme agents. The participants are asked to compare the two agents from each viewpoint described in the question and evaluate them numerically in a range of −3 to +3 at the end of the experiment. A positive score means that the solid agent is more trustworthy, and a negative score means the opposite. We define the mean score of the answers to all the questions as an evaluation score of the relative trustworthiness of the agents.

Table 5 shows a questionnaire on the participants’ personalities. This questionnaire is the Japanese version of the “Maximization Scale” proposed by Isobe et al. [12]. (The original version was proposed by Schwartz et al. [13].) The participants are asked at the end of the experiment to state on a 5-point scale how strongly they agree with each sentence. We define the summation of the answers to all the questions as the maximization score. The higher the maximization score, the more likely the participant is to pursue optimal results.

3.4 Procedure

Thirty-six college students (30 males and 6 females) participated in this experiment. Their ages ranged from 19 to 22 years. They were randomly assigned to one of three conditions as regards size of profits, namely 20%, 50% and 80%. Twelve participants were therefore assigned to each condition.

First, the participants were asked to perform the task with one of the agents under an assigned condition. They were then asked to complete the agent trustworthiness questionnaire shown in Table 3. Next, they were asked to perform the task again with the other agent and complete the questionnaire again. Finally, they were asked to complete the questionnaires on the relative trustworthiness of the two types of agents shown in Table 4 and on the Maximization Scale shown in Table 5.

3.5 Results

Figure 3 shows evaluation scores (mean values for all participants) for perception of agent trustworthiness for each condition of size of profits. The error bars denote the standard error. The statistical difference was determined using a two-sided paired t-test. The trustworthiness score of the solid agent was statistically higher than that of the extreme agent under the 50% condition, 4.57, p < .001, g = 1.87) and the 80% condition (t(11) = 3.62, p < .01, g = 1.48) conditions, where g denotes the effect size (Hedges’ g). On the other hand, there was no significant difference under the 20% condition (t(11) = 0.91, n.s.).

Figure 4 shows evaluation scores (mean values for all participants) of relative trustworthiness for the solid and extreme agents under each condition of size of profits. The error bars denote the standard error. The statistical difference
Fig. 4 Relative Trustworthiness of Agents

Table 6 Correlation Coefficients between Maximization Scale and Trustworthiness

| Condition | Solid | Extreme | Relative |
|-----------|-------|---------|----------|
| 20%       | 0.65  | -0.52   | -0.15    |
| 50%       | 0.22  | 0.44    | -0.22    |
| 80%       | 0.43  | -0.15   | 0.18     |

from zero was determined using a two-sided $t$-test. There were significant differences under the 50% ($t(11) = 8.88$, $p < .001$, $g = 3.07$) and the 80% ($t(11) = 2.91$, $p < .05$, $g = 0.47$) conditions. There was no significant difference under the 20% condition ($t(11) = 1.45$, n.s.).

Figures 5 (a), (b) and (c) show the rates of participants who followed the agent’s advice at intervals of five trials under the 20%, 50% and 80% conditions, respectively. The statistical difference was determined using Pearson’s chi-squared test. There was a significant difference only for 16–20 trials under the 50% condition ($χ^2(1, N = 120) = 15.55$, $p < .001$).

Finally, Table 6 shows the correlation coefficients between the maximization score and the evaluation scores of the trustworthiness of the solid agent, those of the extreme agent, and those of relative trustworthiness under each condition.

4. Discussion

4.1 Verification of Hypothesis 1

First, based on the experimental results, we verify Hypothesis 1 described in Sect. 3.1.

We can see from Figs. 3 and 4 that, under the 50% and 80% conditions, the perceived trustworthiness of the solid agent is significantly higher than that of the extreme agent, and the relative trustworthiness has a positive value, namely the solid agent is rated higher than the extreme agent again. Furthermore, we can also see from Fig. 5 (b) and (c) that the rate of participants who followed the solid agent’s advice increases over 16–20 trials. (There is a notably significant difference under the 50% condition.) Therefore, it is considered that, under both the 50% and the 80% conditions, the solid agent is more trustworthy than the extreme agent. Furthermore, even under the 20% condition, the tendency is similar to that under the other two conditions, although the significant difference disappears.

These results support Hypothesis 1 described in Sect. 3.1, namely that “a solid agent that provides NGNB information reliably will be highly trusted in a situation where it appears to users that there are numerous options and the profits obtained as a result of choice are hard to predict.” We can therefore conclude that a strategy in which the agent intentionally provides NGNB information rather than the best information will be effective even in situations with numerous options and when it is not easy to predict the consequent profits.

4.2 Verification of Hypothesis 2

Next, we verify Hypothesis 2 based on the experimental results.

As mentioned in Sect. 4.1, we can see from Figs. 3, 4 and 5 that the trustworthiness of the solid agent is evaluated as being significantly higher than that of the extreme agent under the 50% and 80% conditions, while the significant difference disappears under the 20% condition.
For further investigation, we rearranged the data in Fig. 3 from a different viewpoint, namely the differences in the trustworthiness scores among the conditions as regards the sizes of profits for each agent. Figure 6 shows the results. For the solid agent, the overall difference was determined by analysis of variance. A significant difference was found (F(2,33) = 7.50, p < .01, ̂ω² = 0.27), where ̂ω² denotes the effect size. Tukey’s test found significant differences between the 20% and 50% conditions (p < .05, g = 1.04), and between the 20% and 80% conditions (p < .01, g = 1.40). Therefore, the solid agents gain significantly lower trust for lower sizes of profits, in other words, in situations where it is harder to obtain large profits.

These results do not support Hypothesis 2 described in Sect. 3.1. As mentioned in Sects. 2.1 and 3.1, the previous study by Yokoyama et al. [9] has reported that the solid agent will gain higher user trust in situations in which it is harder to obtain larger profits, and consequently the size of profits generated by the NGNB information is lower. In more concrete terms, the trustworthiness of the solid agent is significantly higher than that of the extreme agent, but only under the 20% condition. Yokoyama et al. [9] has reported that the significant difference disappears under the 50% condition, and the pattern reverses for the 80% condition. This paper, however, gives exactly the opposite results.

We can assume that this is due to the change in the experimental task. Note that we introduced a change of scenario at intervals of five trials and the variation in the size of profits even under the same scenario to make the profits that the participants obtain would be hard to predict, as shown in Table 2. The values shown in Table 2 were set to create variation in the size of profits: the values in themselves have no meaning. However, under the 20% condition in this paper, the maximum difference between the points obtained from the best information and that from NGNB information was set to 32, which was seemingly large. Conversely, in the previous study [9], the difference in the profits was set to a maximum of only eight. Therefore, the solid agent may lose user trust when the profits obtained by following its advice are seemingly much smaller than those obtained by not following the advice, even if it brings reliable profits.

On the other hand, it is unlikely that the small difference between the profits from the best and those from NGNB information is directly linked to the trustworthiness of the agent. We can see from Fig. 3 that the maximum significant difference in the scores for trustworthiness between the solid and the extreme agents appeared under the 50% condition, rather than the 80% condition. Furthermore, we can see from Fig. 4 that the maximum score for relative trustworthiness again appeared under the 50% condition. We therefore conclude that a balance between the number of times that users realize profits due to the agent’s information and the seeming difference between the profits from the best information and that from NGNB information has a powerful influence on trust in the agent in scenarios where the users act to achieve profits.

To summarize, in a situation where it appears to the users that there are numerous options and it is not easy to predict the consequent profits, the reliable provision of NGNB information will work effectively to minimize users’ loss of trust in the agents when the profits generated by that information do not significantly diverge from the maximum profit. It is therefore important to determine how accurately we can estimate the maximum profit in advance to be able to apply the provision of NGNB information to practical problems in the presence of numerous options.

4.3 Influence of Participants’ Personalities

Third, we discuss the influence of the participants’ personalities on trust in the agent.

We can see from Table 6 that there was a relatively strong negative correlation between the participant’s maximization score and the trustworthiness of both agents under the 20% condition. On the other hand, the correlations under the other conditions were weak. From these results, we can say that the influence of the participants’ personalities is strengthened by the situation where it is harder to obtain large profits.

It is possible that this tendency is one of the causes of the result discussed in Sect. 4.2. We should further investigate the relation between these results.

4.4 Limitation of Findings

Finally, we discuss the limitation of findings obtained in this paper.

As mentioned in Sects. 3.2.1 and 3.2.2, the task employed in this paper was designed such that the participants appear to have numerous options. However, these “numerous options” were in fact just pretenses. The consequent profits were internally limited to only three patterns and predetermined. Furthermore, the “worst” profit was always fixed at zero as shown in Table 2. These were all done for making it possible to compare the results with those of the previous papers.

Of course, there cannot be such constraints in practical problems. Although it is considered that the users believed as if there really were numerous options, the constraints cannot be denied that those may have affected the results. Therefore, the scope of findings obtained in this paper may
be limited by the above-mentioned constraints. Further investigation on this point is required in the future.

5. Conclusion

In this paper, we investigated the effect of provision of NGNB information on the users’ trust of agents when faced with numerous options. The experimental results support our hypothesis that an agent that reliably provides NGNB information tends to gain greater user trust under conditions where there are numerous options and the size of profits is not easy to predict. However, appearing to contradict the previous study’s result, the experimental results in this paper also revealed that the stable provision of NGNB information will be less effective in a situation where it is harder to obtain larger profits.

The results shown in this study are anticipated to expand the range of application of provision of NGNB information to the solution of practical problems, in that they can assist with the formulation of useful principles when designing agent systems to gain higher user trust over the long term.

As future work, we need to conduct further studies to expand the findings obtained in this paper and reveal in more detail the conditions under which the provision of NGNB information by an agent works more effectively to gain user trust. In particular, we should investigate the inconsistency between the results in this paper and those in the previous study [9]. Although the setting of values of profits in themselves had no particular significance in this paper, the size of the perceived difference between the values of profits may have played an important role in perception of the trustworthiness of agents, as discussed in Sect. 4.2. In future, we should conduct experiments with a variety of settings of these values.

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