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How Does the Difference Between Users' Expectations and Perceptions About a Robotic Agent Affect Their Behavior?

An Adaptation Gap Concept for Determining Whether Interactions Between Users and Agents Are Going Well or Not

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Abstract We assumed that the difference between the users' expectations regarding the functions of an agent and the function that they actually perceived would significantly affect their behavior toward the agent. We then defined this differences as the adaptation gap and experimentally investigated how the adaptation gap signs affected the acceptance rate indicating how many of the agent's suggestions the participants accepted as their behaviors toward the agent. The results showed that the participants with positive adaptation gap signs had a significantly higher acceptance rate than those with negative ones. This led us to conclude that the adaptation gap signs significantly affected the participants' behavior toward agents in the way that we expected, and that comprehending these signs will become indispensable for designing interaction between users and agents.

Keywords Adaptation gap · User expectations and perceptions · User behavior toward agents

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1 Introduction

Various interactive agents such as robotic agents [1, 2] and embodied conversational agents (ECA) [3, 4] have recently been developed to assist us with our daily tasks. Researchers in the human-computer interaction (HCI) and human-robot interaction (HRI) communities are working particularly hard to create such interactive agents. In these fields, the issue of "how the users' mental models of an agent formed before the interaction affect their subsequent interaction with it" is especially focused on [5–7]. Users form a mental model about an agent based on its appearance, its behaviors, and their own preferences, and this model they create has a significant effect on the way they interact with the agent. For example, when a user encounters a dog-like robot, he or she expects dog-like behavior from it [8] and naturally speaks to it using commands and other utterances intended for a real dog, such as "sit," "lie down," and "fetch." However, the user would not act this way toward a cat-like robot.

Several previous studies have focused on the effect of users' mental models about an agent on their ensuing interactions [9]. For example, Matsumoto et al. [10] proposed a "minimal design policy" for designing interactive agents and concluded that the agent's appearance should be minimized in its use of anthropomorphic features to ensure that users do not over or underestimate an agent's competency level. This minimal design policy was applied to the development of Muu [11], an interactive robot, and Talking Eye [12], a life-like agent. Kiesler [13] argued that the design of an agent should include a process that anticipates a user's mental model on the basis of the common ground theory [14]; that is, individuals engaged in conversation must share knowledge (common ground) in order to be understood and to have a meaningful exchange. In particular, she

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stated that an agent should be designed in such a way that a user could easily estimate his or her common ground with it.

The above design policies or "road maps" were quite effective for designers, especially at the beginning of an interaction, because they could determine whether or not a user would actually start interacting with a given agent. However, these approaches cannot anticipate cases in which an agent expresses certain behaviors that completely deviate from the user's mental model. For example, imagine that a user meets a humanoid robot that looks very much like a real human being. The user would then intuitively form a mental model of the robot, expecting fluent human-like speech, dialogue, and dexterous limb motions [15]. However, if this particular robot could only express machine-like speech and halting limb motions that completely deviate from the user's mental model, he or she will immediately become disappointed with the robot because of its unexpected behavior. The user would then probably stop or lose interest in interacting with it.

2 Adaptation Gap Hypothesis

To comprehend this undesirable situation in the hope of avoiding it, we assumed that the difference between the users' expectations regarding the function of the agent and the actual function they perceive would significantly affect their subsequent behavior. This difference, which we call the adaptation gap (AG) [16–18], can be defined as $AG = F_{after} - F_{before}$. Here, F_{after} is the function that a user perceives in the agent and F_{before} is the function that the user expected. We assume that this AG has the following two properties (Fig. 1).

- $AG < 0\,(F_{after} < F_{before})$: When the users' expected function of an agent exceeds their perceived function of the agent, there is a negative adaptation gap. In this case, most people become disappointed by the agent and do not trust the robot's output.
- $AG > 0\,(F_{after} > F_{before})$: When the users' perceived function of an agent exceeds their expected function of the agent, there is a positive adaptation gap. In this case, most people are not disappointed by the agent and do trust the robot's output.

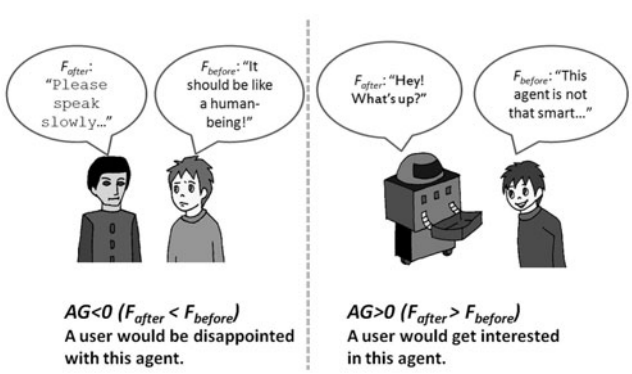

Fig. 1 Intuitive concept of adaptation gap

3 Differences Between our Former and the Present Study

In our previous study, we experimentally investigated how the positive or negative signs of adaptation gap (AG signs) affect the users' final impressions of an agent during user-agent interaction [18]. The results of this previous study showed that positive or negative AG signs and subjective impressions of agents before the experiment (I_{before} in Fig. 2) significantly affected the user's final impressions of the agents (I_{after} in Fig. 2). Specifically, the participants who showed positive AG signs and negative impressions of the agents before the experiment (I_{before}) ended up having significantly positive impressions of the agents (I_{after}), whereas the participants who showed negative AG signs and positive impressions of the agents before the experiment ended up having significantly negative impressions after. Therefore, not only the AG signs but also the users' impressions before the experiment had a significant effect on the users' final impressions. While this information is useful, we failed to observe the pure effects of the adaptation gap on the users' impressions about agents and their subsequent behavior toward them.

In terms of the above results, the relationship between the independent variables and the dependent variables was

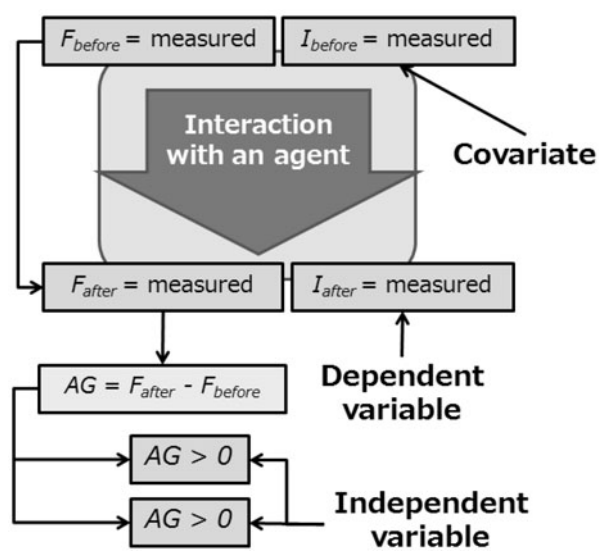

Fig. 2 Relationship between independent and dependent variables in our previous experiment [18]

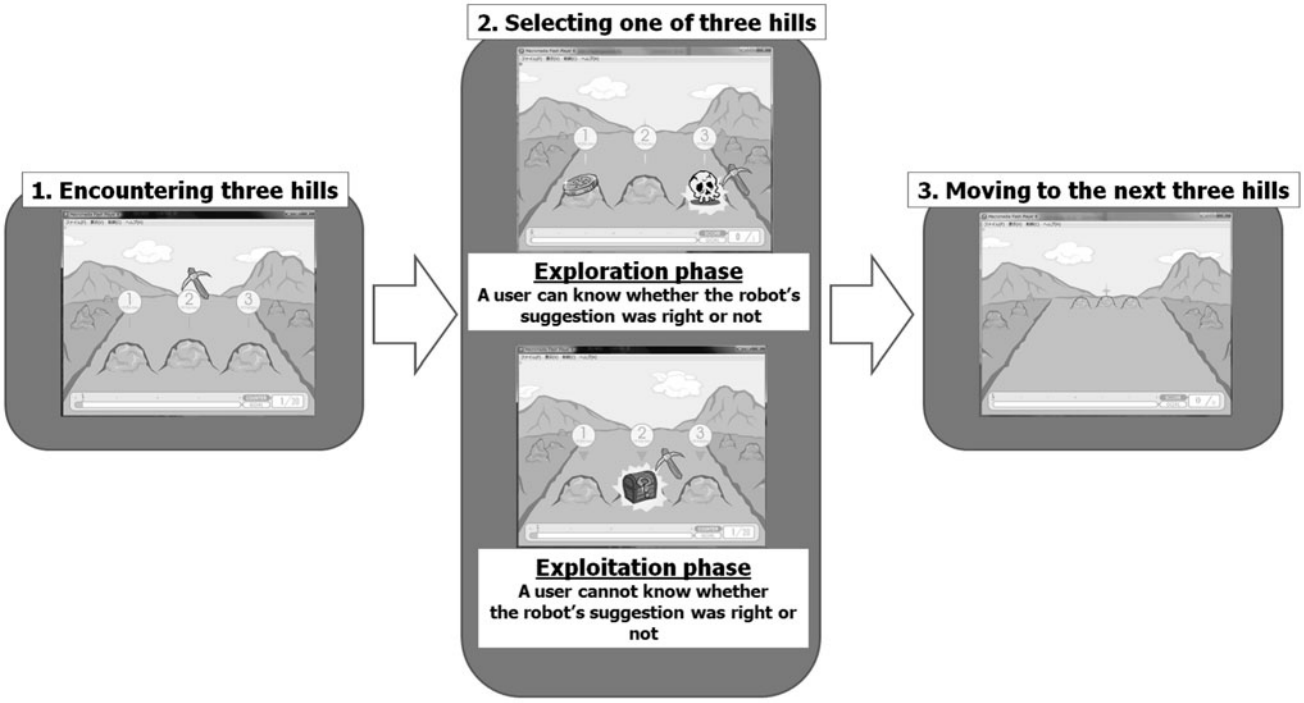

Fig. 3 Treasure hunting video game

complicated, and we had to use a covariate to properly interpret the results. That is, the independent variables were the AG signs, the dependent variables were the users' final impressions after the interaction (I_{after}), and the covariate was the users' impressions of the agents before the experiment (I_{before}). At first, we had assumed that the users' expected/perceived functions and their impressions about agents before/after the interactions would be independent of each other, but this assumption turned out to be incorrect. In the former study, we focused on how the AG signs affect the users' **impressions** about the agents. However, as mentioned in Sect. 1, we also need to focus on how the AG signs affect the users' **behavior** toward agents.

In the current study, we carefully and clearly assigned the independent variable (AG signs) and the dependent variable (users' behaviors toward agents) in order to exclude the effects of any covariates. This reassignment of independent and dependent variables helps us clarify how the AG signs affect the users' behavior toward the agents.

4 Experiment

We conducted an experiment to investigate how positive or negative AG signs affected the users' behavior towards an agent. This experiment consisted of two phases: in the first, we measured the AG signs as an independent variable (exploration phase), and in the second, we measured the users' behavior as a dependent variable (exploitation phase).

4.1 Experimental environment

We chose a "treasure hunting" video game (Fig. 3) as the experimental environment for observing the interaction between a user and an agent in both phases. In this game, a character on a computer monitor operated by a user walks on a straight road with three tiny hills appearing along the way. A gold coin is inside one of the three hills, while the other two hills have nothing. In the exploration phase, we ended the game after the character met 40 sets of hills. The approximate duration of each game was about three minutes. In the exploitation phase, we ended the game after 20 sets of hills. The goal of this game is to find as many gold coins as possible. A robotic agent (MS; MindStorms, LEGO Corporation, Fig. 4) placed next to the user tells the user where it expects the coin to be each time. MS did this by beeping the numbers: e.g., one beep meant the first hill (left), two beeps meant the second hill (middle), and three beeps meant the third hill (right). The users were free to accept or reject the agents' suggestions. They were informed that one gold coin was equivalent to 10 yen (about 10 US cents) and that, after the experiment, they could purchase some stationery (e.g., file holders or USB flash memories) of equivalent value with their acquired coins. The beep sounds of the robotic agent were remotely operated by an experimenter in the next room performing in the Wizard of Oz (WOZ) manner via an FM transmitter and radio tuner loaded on the MS. The treasure hunting video game was projected on a 46-inch LCD screen in front of the participants (Figs. 5 and 6).

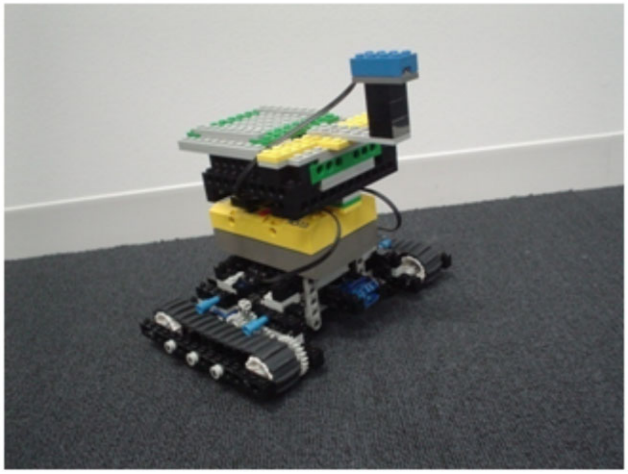

Fig. 4 MindStorms robot

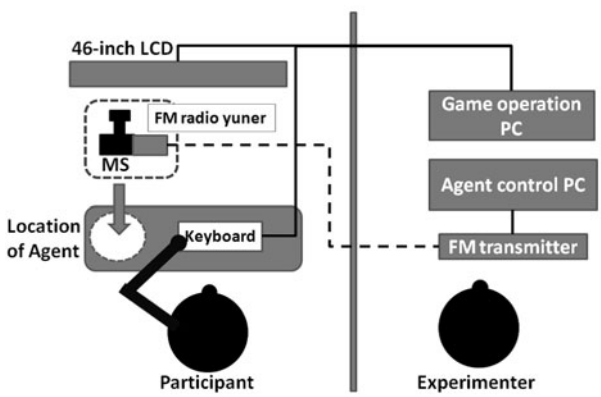

Fig. 5 Experimental set-up

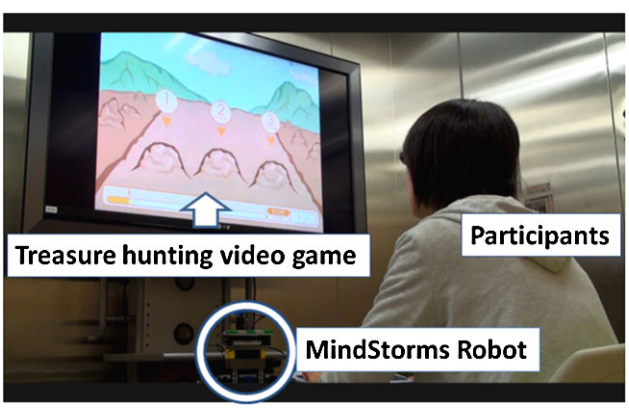

Fig. 6 Experimental scene

In this experiment, the robotic agent also emitted a "four-beep" sound that did not relate to any of the hills appearing on the display. In the preliminary experiment, in which the MS only expressed the three different beep sounds (one, two, and three beeps) that correlated to the hills appearing on the display, we observed that most participants unthinkingly accepted the robot's suggestions, even though they thought and believed the robot's ability was not perfect. Actually, a posterior analysis of this preliminary experiment revealed that the reason for such behavior by the participants was based on the fact that there were no clues for them to find the coin in this game. We then concluded that this phenomenon could be explained by Koehler's argument [19], which states that "the confidence level of another's hypothesis tends to be higher than one of their own hypotheses, especially in a situation where users could not find any counter-evidence." In addition, Kiyokawa, Ueda, and Okada [20] argued that the confidence level in a user's own hypothesis increases when they are given counter-evidence against the other-generated hypothesis. We therefore introduced the "four-beep" sound as counter-evidence indicating that the robots' generated hypotheses were not always correct. The presence of counter-evidence works to create an environment in which users must think carefully about the robots' suggestions.

In the exploration phase, the participants were allowed to know whether the robots' and their own selections were correct or not in each trial because the game showed the actual position of the gold coin after the participants made a selection. In contrast, in the exploitation phase they were not allowed to know whether the given or their own selections were correct or not: the selected hill just showed a question mark on a closed treasure box (Fig. 3). We did this because we needed the participants to estimate the robots' functions only in the exploration phase in order to determine the AG signs; in the exploitation phase, we only needed to observe whether the participants accepted or rejected the robots' suggestions.

4.2 Participants

Thirty Japanese university students (22 men and 8 women; 19–25 years old) participated in the experiment. The mean age of these participants was 21.66 years old (SD = 1.56).

4.3 Experimental Group

These participants were randomly divided into the following two groups in terms of the experimenter's instructions about the agent's ability.

- Lower Expectation Group (15 participants): Before the exploration phase, the experimenter gave these participant an instruction "the rate at which this robot succeeds in detecting the position of a coin is 10%," thus this instruction was for setting the participants' expectations (F_{before}) at 10%.
- Higher Expectation Group (15 participants): Before the exploration phase, the experimenter told these participants that "the rate at which this robot succeeds in detecting the position of a coin is 90%," thus setting the participants' expectations (F_{before}) at 90%.

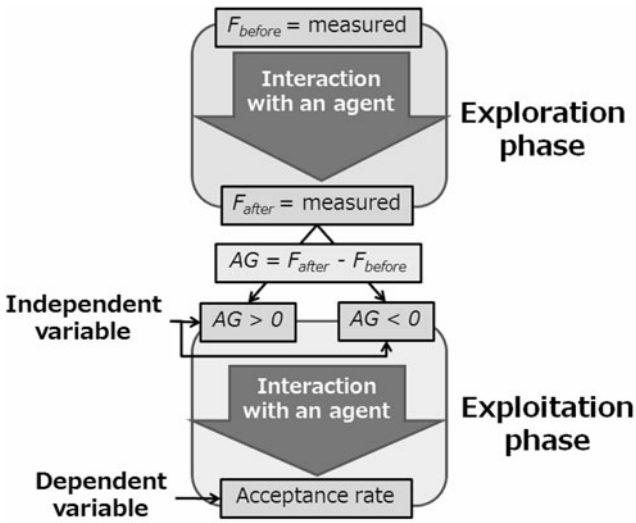

Fig. 7 Relationship between independent and dependent variables in this study

The actual rate at which the robotic agent succeeded in detecting the position of a coin in the exploration phase was set at 33% regardless of the experimental groups. We selected a rate of "33%" which is the same rate as pure chance. We assumed this rate would become the F_{after} values for all participants in both groups, thus automatically determining the values of AG (AG values). That is, the ideal AG values in the Lower Expectation Group should be around +23 (i.e., $F_{after} - F_{before} = 33\% - 10\%$), while the values in the Higher Expectation Group should be around −57 (i.e., $F_{after} - F_{before} = 33\% - 90\%$).

4.4 Analysis

We investigated the effect of the AG signs on the participants' behavior towards the robotic agent. The independent variable was the AG signs and the dependent variable was the participants' behavior (Fig. 7). In order to acquire the AG signs, we measured the F_{before} values of participants who were asked just prior to the exploration phase "At what rate **will** this robot succeed in detecting the position of a coin?" and measured the F_{after} values of participants who were asked just after the exploration phase "At what rate **did** this robot succeed in detecting the position of a coin?" Thus, the values and AG signs can be calculated by the acquired F_{before} and F_{after} values (i.e., $AG = F_{after} - F_{before}$). Here, we assumed that the participants in the Lower Expectation Group would show positive AG signs while those in the Higher Expectation Group would show negative ones.

In order to acquire the participants' behaviors as dependent variables, we calculated the acceptance rate indicating how many of the agents' suggestions the participants accepted in the exploitation phase. As mentioned previously in Sect. 1, we predicted that "in the case of $AG < 0$, users will eventually stop interacting with an agent, and in the case of $AG > 0$, they will continue." However, in this experiment it is unrealistic to assume a situation in which participants suddenly stop interacting with an agent. We therefore assumed that the attitude of such participants would directly reflect their behavior toward the agent in terms of whether or not they would accept the agent's suggestions. In other words, if the participants wanted to stop interacting with an agent they would reject the robot's suggestions, and if they wanted to continue the interaction they would accept the robot's suggestions. Among 20 trials in the exploitation phase, the "four-beeps" sound was utilized twice so that the maximum number of the acceptance rate would be 18.

The purpose of this experiment was to compare the acceptance rates of the two experimental groups. If we could observe participants in the Lower Expectation Group having a significantly higher acceptance rate than those in the Higher Expectation Group, we would be able to conclude that the AG signs significantly affected the participants' behavior toward the agents in the way we had expected. In such a case, we could argue that the AG properties mentioned in Sect. 1 were clearly verified.

4.5 Manipulation Check

As manipulation checks, we firstly checked to determine whether the values of F_{before} were appropriately set or not in both groups just before starting the experiment (exploration phase). The average value of F_{before} in the Lower Expectation Group was 16.2 (SD = 8.38) and that in the Higher Expectation Group was 75.1 (SD = 22.0). This result shows that the F_{before} values in both groups were not rigidly set as 10% and 90%. However, the results of a t-test (between-subjects design, independent variable: Lower/Higher Expectation Group, dependent variable: F_{before} values) showed a significant difference between these two experimental groups ($t(28) = 9.361$, $p < .01$, effect size $r = .87$). Therefore, it can be said that the F_{before} values were appropriately set by means of the experimenter's verbal instruction.

We then checked if the acquired independent variables (i.e., AG signs) were appropriately set in the exploration phase; specifically, whether the participants in the Lower Expectation Group showed positive AG signs and whether the ones in the Higher Expectation Group showed negative ones. For the 15 participants in the Lower Expectation Group, the average AG value was +6.0 (SD = 8.79) a nd for the 15 participants in the Higher Expectation Group, the average AG value was −43.9 (SD = 25.2). Although these values were not the same as the ideal AG values (i.e., +23 in the Lower Expectation Group and −57 in the Higher Expectation Group), the participants in the Lower Expectation Group actually showed positive AG signs while the

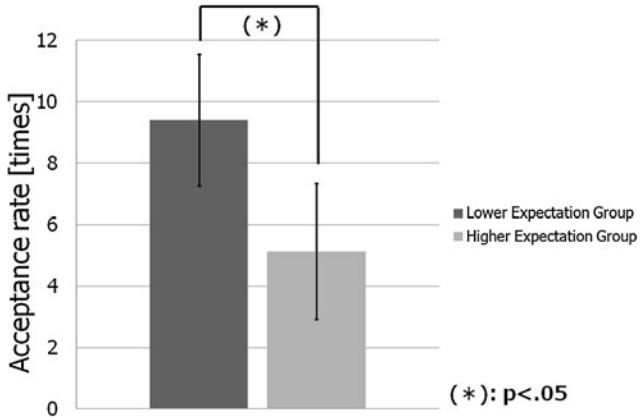

Fig. 8 Acceptance rate in each experimental group

ones in the Higher Expectation Group showed the negative AG signs. Moreover, the result of a t-test (between-subjects design, independent variable: Lower/Higher Expectation Group, dependent variable: AG values) showed significant differences between the two AG values ($t(28) = 7.009$, $p < .01$, effect size $r = .80$). This confirmed that the independent variables were appropriately set in the experiment.

4.6 Results

We then calculated the acceptance rate as a dependent variable. For the 15 participants in the Lower Expectation Group, the average acceptance rate of the robot's 18 suggestions was 9.40 (SD = 4.33), and for the 15 participants in the Higher Expectation Group it was 5.13 (SD = 4.47) (see Fig. 8). The acceptance rates for both experimental groups were then analyzed using a t-test (between-subjects design, independent variable: Lower/Higher Expectation Group, dependent variable: acceptance rate). The results of the t-test showed a significant difference between the two experimental groups ($t(28) = 2.564$, $p < .05$, effect size $r = .44$); that is, the participants in the Lower Expectation Group showed a significantly higher acceptance rate compared to those in the Higher Expectation Group. We therefore concluded that the AG signs significantly affected the participants' behavior towards the agents. We also confirmed that the AG properties mentioned in Sect. 1 could be clearly verified.

5 Discussion

5.1 Design Policy Utilizing Adaptation Gap Concept

From the results of this experiment, we eventually succeeded in showing evidence that AG signs affect the participants' behavior toward an agent, which suggests that understanding the AG signs will become indispensable for designing interactions between users and agents. Actually, these experimental results are in clear agreement with the AG properties mentioned in Sect. 1, which suggests that they can play a role in the development of novel interaction design policies. For example, our finding that "agents that evoke higher expectations than their actual functions should not be used for interaction with users" should prove to be a key contribution. These results seem to suggest a specific design policy, such as "The F_{before} values should be set as low as possible to easily make the AG signs positive." However, such lower F_{before} values would likely result in some users being deeply disappointed with the agent before the interaction, leading to a failure to start the interaction at all. Therefore, clarifying the appropriate F_{before} range is also a significant issue in terms of utilizing the AG concept for an actual interaction design policy, along with the issue of how to create F_{before} values for users. However, in this study, we did not manipulate the appearance or design of robotic agents *per se*. So considering the relationship between the F_{before} and the elements of the agents' appearance or design is definitely our next target.

Here, the design policy derived from AG and Matsumoto's minimal design policy [10] are quite similar because both mentioned that the F_{before} value was important for designing the agents. However, the clear difference between these two concepts was that AG was proposed based on the concrete hypothesis focusing on the relationship between F_{before} and F_{after} and this was experimentally verified, while the minimum design policy was not.

5.2 How to Determine the F_{before} Values

In this experiment, the experimenter gave verbal instructions to the participants, such as "The rate at which this robot succeeds in detecting the position of a coin is 10%/90%" in order to create specific F_{before} values for each of the experimental groups. Some may argue that the F_{before} values should be naturally and spontaneously determined by the participants themselves without any outside interference. However, the reason the experimenter gave verbal instructions to participants about the F_{before} values was based on the results of our former study [18]. In that study, we prepared two different types of robotic agent (one was the same MS we used in the current study and the other was an AIBO robot (Sony Corporation, ERS-7, Fig. 9)) and then had the participants acquire the F_{before} values by asking "At what rate will this robot succeed in detecting the position of a coin?" in the same treasure hunting video game environment. We expected that the participants would assign lower F_{before} values to the MS and higher ones to the AIBO. However, the results showed that the average F_{before} value for MS was 57.0% (SD = 19.97) and that for AIBO was also 57.0% (SD = 16.91), meaning there was no significant

Fig. 9 AIBO robot (Sony Corporation, ERS-7)

difference of F_{before} values between the two robots. This meant that it was quite difficult to create specific F_{before} values among participants with various background details, i.e., gender, educational level, technophobia [21], and so on; that is, F_{before} can be determined by the participants' various kinds of preferences. Actually this notion accords with our former study "we assumed that this phenomenon was due to the fact that the agents' appearances do not have a strong enough effect to make the participants evoke uniform F_{before} and I_{before}"; that is, F_{before} could not be determined by the agents' appearance in previous study. We assumed that the differences of the participants' backgrounds were what caused the wide range of standard deviation of the F_{before} values (i.e., SD = 19.97 for MS and SD = 16.91 for AIBO). Therefore, we gave verbal instructions about the F_{before} values in order to force our desired F_{before} value setting in this experiment.

While the F_{after} values would be automatically determined by the actually implemented function of the agents, so determining how to set the appropriate F_{before} values without using verbal instruction becomes a critical issue. We are currently planning to conduct a questionnaire based survey, in collaboration with product designers and social psychologists, to clarify the relationship between specific appearances or behaviors and the functions they evoke in terms of the type of given task and users' preferences. We believe such collaborations would provide an elegant solution to controlling the F_{before} values and contribute to a much more sophisticated AG concept. As mentioned previously, Matsumoto et al. [10] and Kiesler [13] have proposed design "road maps" to design agents that must interact with users, so it would be worthwhile to consider how these studies could be used to create specific F_{before} values among users.

5.3 Effects of Values of Adaptation Gap (AG Values)

Some might point out that the comparison of the negative AG as -57% ($= 33\% - 90\% = F_{after} - F_{before}$) of the positive AG as $+23\%$ ($= 33\% - 10\%$) is unfair because the absolute values are different. In this study, we did not focus on the AG values but rather on the AG signs. Therefore, the purpose of this study was to investigate whether the hypothesis of AG can be verified as a primary step by introducing extreme conditions.

Actually, we currently do not have any specific methodologies that can precisely comprehend or measure the users' expected or perceived functions in terms of percentage. Although the functions of the agents cannot always be quantified in a percentage manner, we utilized the percentage for describing their expected and perceived functions in order to comprehend the relative differences among them, and we believe that our approach utilizing a percentage was worthwhile to show the concept of adaptation gap objectively. Specifically, we investigated the relationship between the AG values and the participants' acceptance rate by calculating the correlation coefficient between them. As a result, we were able to observe the medium, positive correlation ($r = .529$, $p < .01$), so it can be said that the AG values affected the users' behaviors to some degree.

However, from our viewpoint as experimenters, the participants judged the abilities of the agent (both F_{before} and F_{after}) compared to the chance level for detecting the position of a coin as "33%"; when they felt that the ability of the agent was good, they rated it as better than 33%, whereas when they felt that the ability was not very good, they rated it as worse than 33%. Such a decision would also be affected by differences in the participants' backgrounds, as mentioned in Sect. 4.1. Therefore, finding or developing a methodology that can precisely comprehend or measure the functions a user expects and perceives in terms of percentage is also a critical issue when it comes to comprehending the effects of AG values. If we succeeded in finding or developing such a methodology, we could tackle the reminding issue of the adaptation gap, for example, by analyzing the case of $AG = 0$ in which the user is informed of the actual function of the agent prior to their interaction.[1]

6 Conclusions

We assumed that the difference between the users' expectations regarding the functions of an agent and the function that they actually perceived would significantly affect

[1] Actually, we did not focus on this condition $AG = 0$ because it was quite difficult to realize it in this experimental setting even though the participants were told the actual function of the agent prior to the interaction.

their behavior toward the agent. That is, when the users' expectations exceed their perceptions, they would be disappointed by the agent and do not believe the agents' outputs. In contrast, when their perceptions exceed their expectations, they would get interested in the agent and do believe the agents' outputs. We then defined this differences as the adaptation gap and experimentally investigated how the adaptation gap signs affected the users' behavior toward the agents in order to determine if the above assumptions were correct. The independent variable was the adaptation gap signs and the dependent variable was the acceptance rate indicating how many of the agents' suggestions the participants accepted. Specifically, we assumed that the higher acceptance rate meant that the participants wanted to continue interacting with the agent, while the lower acceptance rate meant that they would stop interaction. The results showed that the participants with positive adaptation gap signs had a significantly higher acceptance rate than those with negative ones. This led us to conclude that the adaptation gap signs significantly affected the participants' behavior toward agents in the way that we expected, and that comprehending these signs will become indispensable for designing interaction between users and agents. The results of this experiment also highlighted the need to clarify the unsolved issue of "how to create specific F_{before} values among users." Needless to say, this issue is our immediate challenge.

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References

1. Imai M, Ono T, Ishiguro H Robovie: communication technologies for a social robot. Int J Artif Life Robot 73–77 (2003)
2. Watanabe T, Okubo M, Nakashige M, Danbara R (2004) InterActor: speech-driven embodied interactive actor. Int J Hum-Comput Interact 17:43–60
3. Prendinger H, Ishizuka M (2004) Life-like characters. Springer, Berlin
4. Cassell J, Stocky T, Bickmore T, Gao Y, Nakano Y, Ryokai K, Tversky D, Vaucelle C, Vilhjalmsson H (2002) MACK: Media lab autonomous conversational kiosk. In: Proceedings of Imagina02
5. Komatsu T, Yamada S (2007) How do robotics agents' appearances affect people's interpretations of the agents' attitudes. In: Extended Abstract of ACM-CHI2007, pp 2519–2525
6. Komatsu T, Yamada S (2011) How does the agents' appearance affect users' interpretation of the agents' attitudes—experimental investigation on expressing the same artificial sounds from agents with different appearances. Int J Hum-Comput Interact 27(33):260–279
7. Lee N, Shin H, Sundar SS (2011) Utilitarian vs hedonic robots: role of parasocial tendency and anthropomorphism in shaping user attitude. In: Proceedings of the 6th annual ACM/IEEE international conference on human-robot interaction, pp 183–184
8. Scholtz J, Bahrami S (2003) Human-robot interaction: development of an evaluation methodology for the bystander role of interaction. In: Proceedings of 2003 IEEE international conference on systems, Man and Cybernetics, vol 4, pp 3212–3217
9. Goetz J, Kiesler S, Powers A (2003) Matching robot appearance and behavior to tasks to improve human-robot cooperation. In: Proceedings of the 12 the IEEE international workshops on robot and human interactive communication, RO-MAN2003, pp 55–60
10. Matsumoto N, Fujii H, Goan M, Okada M (2005) Minimal design strategy for embodied communication agents. In: Proceedings of the 14th international symposium on robot and human interactive communication, RO-MAN2005, pp 335–340
11. Okada M, Sakamoto S, Muu N Suzuki (2000) Artificial creatures as an embodied interface. In: Proceedings of 27th international conference on computer graphics and interactive techniques, SIGGRAPH, p 91
12. Suzuki N, Takeuchi Y, Ishii K, Okada M (2000) Talking: eye: autonomous creatures for augmented chatting. Robot Auton Syst 31:171–184
13. Kiesler S (2005) Fostering common ground in human-robot interaction. In: Proceedings of the 14th international symposium on robot and human interactive communication, RO-MAN2005, pp 729–734
14. Clark HH (1992) Arenas of language use. University of Chicago Press, Chicago
15. Kanda T, Miyashita T, Osada T, Haikawa Y, Ishiguro H (2008) Analysis of humanoid appearances in human-robot interaction. IEEE Trans Robot 24(3):725–735
16. Yamada S, Komatsu T (2006) Designing simple and effective expressions of robot' primitive minds to a human. In: Proceedings of 2006 IEEE/RSJ international conference on intelligent robots and systems, IROS-2006, pp 2614–2619
17. Komatsu T, Yamada S (2008) Effect of agent appearance on people's interpretation of agent's attitudes. In: Extended abstract of ACM-CHI-2008, pp 2929–2934
18. Komatsu T, Yamada S (2011) Adaptation gap hypothesis: how differences between users' expected and perceived agent functions affect their subjective impressions. J Syst Cybern Inform 9(1):67–74
19. Koehler DJ (1990) Hypothesis generation and confidence in judgment. J Exp Psychol Learn Mem Cogn 20:461–469
20. Kiyokawa S, Ueda K, Okada T (2003) The effect of metacognitive suggestions on viewpoint change in collaborative problem solving. In: Proceedings of the 4th international conference on cognitive science and the annual meetings of the 7th Australian cognitive science society joint conference, CD-ROM
21. Michelle WM, Larry RD (1995) A study of technological sophistication and technophobia in university students from 23 countries. Comput Hum Behav 11(1):95–133

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