A Robot That Encourages Self-Disclosure to Reduce Anger Mood

Takuto Akiyoshi, Junya Nakanishi, Hiroshi Ishiguro, Hidenobu Sumioka, and Masahiro Shiomi

***Abstract*—One essential role of social robots is supporting human mental health by interaction with people. In this study, we focused on making people's moods more positive through conversations about their problems as our first step to achieving a robot that cares about mental health. We employed the column method, typical stress coping technique in Japan, and designed conversational contents for a robot. We implemented conversational functions based on the column method for a social robot as well as a self-schema estimation function using conversational data, and proposed conversational strategies to support awareness of their self-schemas and automatic thoughts, which are related to mental health support. We experimentally evaluated our system's effectiveness and found that participants who used it with our proposed conversational strategies made more self-disclosures and experienced less anger than those who did not use our proposed conversational strategies. Unfortunately, the strategies did not significantly increase the performance of the self-schema estimation function.**

***Index Terms*—Human-robot interaction, stress coping.**

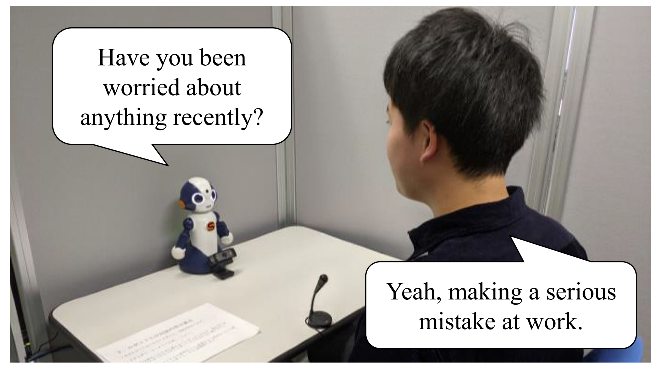

Fig. 1. Dialogue example to encourage self-disclosure.

I. Introduction

SOCIAL robots are becoming conversational partners for human beings. At the beginning of human-robot interaction research fields, conversational functions were mainly used for information-providing tasks in such real environments as a museum [1], a shopping mall [2], an airport [3], an elementary school [4], etc. Recent advances in autonomous conversational techniques, including natural speech synthesis and speech recognition, enable social robots to deal with more complex conversational tasks, such as counseling support [5] and interviewers for clinical screening [6]. Undoubtedly, social robots will play a greater support role in people's mental health in the near future.

Based on these contexts, we focused on improving people's mood states by conversations about their problems/worries as a first step to achieve a robot that cares about mental health. We developed a conversational robot system that encourages self-disclosures to support the awareness of negative self-schemas (a person's core self-conception [7]) and automatic thoughts [8] because they influence unproductive mental states from cognitive distortion. In fact, such common mental therapy techniques as Cognitive-behavioral Therapy (CBT) also focus on self-schemas and automatic thoughts [9], [10]. Using CBT reduces several negative mood states, including anger, depression, and anxiety [11]–[14].

To encourage self-disclosures during conversations, we designed conversational content for a robot by focusing on the column method, which is typical stress coping technique in Japan [15]–[17] (details in the next section) (Fig. 1). We implemented conversational functions to concentrate on the concerns of interacting partners to reduce their negative feelings. The robot finally estimates and describes a self-schema type using conversational histories to support their own awareness of their self-schemas and automatic thoughts. We experimentally evaluated our developed system's effectiveness by measuring the number of self-disclosures, the perceived correctness of the estimated self-schemas, and their mood states.

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II. Related Work

A. CBT and Column Method

In this study, we design a robot's conversational strategies with the column method [15]–[17], which is often used for self-stress coping in the CBT context [11]–[14]. This method helps users address their problems by achieving self-schemas and automatic thoughts to avoid negative thinking patterns. The column method typically lists concerns from seven viewpoints: situations, feelings, automatic thoughts, evidence, facts, helpful thoughts, and current feelings after completing the list.

CBT and the column method are often used by integrating information systems, such as WEB-based approaches [16], [18] and with a chatbot [19]. These systems encourage users to input information and thoughts about problems using typical CBT procedures or column sheets. These studies showed their effectiveness, although they focused less on the application aspect of social robots. Even though CBT and the column method are effective, implementing them for such robots remains unknown. Past study reported the effectiveness of embodied agents like a robot encourages more self-disclosure than non-embodied agents like a smart speaker [20], but the work less focused on CBT and the column method. Compared to related works, one unique point of our study is that our method implemented a robot based on additional conversational techniques and evaluated them.

B. Mental Health Support By Agents/Robots

Although the column method is not generally used in the human-robot interaction research field, many research works exist in the context of mental health support. Conversational agents and robots are typical approaches for this purpose [21]–[23]. For example, researchers developed a virtual agent that behaves like a counselor [24], [25]. Others investigated the effectiveness of robot-enhanced therapy for autistic children [26] or senior citizens [27]. Another study focused on the effectiveness of the embodiment of agents to encourage self-disclosure [20], i.e., because robots have advantages over non-embodied conversational agents. Even though these studies described the benefits of mental therapy effects with conversational robots, they insufficiently focused on specific stress coping techniques, i.e., the implementation and the effectiveness of the column method.

Another approach for mental health support is focusing on such non-verbal interactions as haptic interaction with robots. One famous mental therapy robot is Paro [28], which has a seal-like appearance and whose design resembles a social assistive pet robot for senior citizens. A small creature-like robot, Keepon, was developed for both human-robot interaction and robot-therapy purposes by non-verbal interaction [29]. Another research work compared the therapeutic effects of a therapy dog and a robot dog and concluded that a robot device might support children [30]. However, these studies focused less on conversational interaction and dialogue management systems.

In summary, past studies provided rich knowledge and showed the effectiveness of using agents and robots for mental health support. On the other hand, using the column method for designing conversation strategies remains relatively unexplored. Our study enables social robots to use an additional stress coping technique that expands their potential to support mental health.

III. Scenario Design

This section describes the details of our robot's dialogue scenario design based on the column method and adds three additional conversational strategies to encourage more self-disclosures.

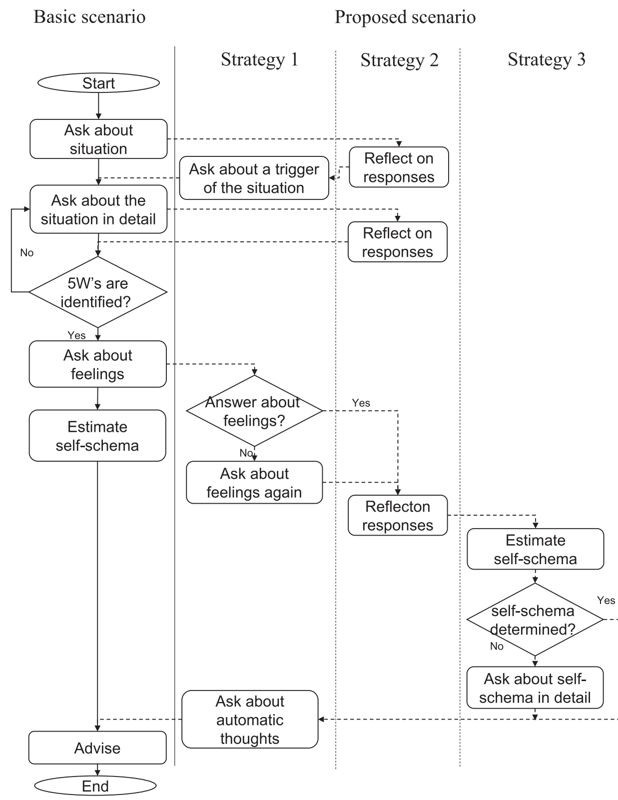

Fig. 2. Scenario flows of basic/proposed scenario in our study.

A. Basic Scenario

Fig. 2 shows the basic scenario's flow based on the column method (transitions with straight lines, the left side of the figure), which encourages people to use column sheets to describe their concerns by themselves. In this study, however, we employed a conversation style, where the robot asked users about their concerns instead of having them fill out sheets. For example, "Have you been worried about anything recently?" The robot also asks about the details of any worries until it can identify each factor: when, where, with whom, and what. Then it asks the users to explain why such situations happened and about feelings and automatic thoughts. For example, "What were you feeling during that situation?" and "What thoughts were going through your mind?"

The results of the column sheets support the realization of self-schema and automatic thoughts by the users themselves. The robot estimates their self-schemas based on conversational histories and provides suggestions related to them to support this process. We followed the Depressogenic Schemata Scale (DSS) [31], which is used in Japan to investigate self-schemas through questionnaires. This scale has 24 items that evaluate individual differences in depressogenic schemata. DSS has three different trait groups: Intention of High Achievement (IHA, eight items), Dependence of Evaluation on Others (DEO, eight items), and Fear of Failure (FF, eight items). The robot chooses one trait from these three based on the amount of obtained keywords related to each trait's items by conversations as an estimation result (Section IV.D).

Finally, the robot offers suggestions related to the estimated self-schema. For example, if the estimated self-schema is IHA, the robot might respond, "I've been thinking about your self-schema based on what you've shared with me. Although this may not necessarily apply to you, it might be useful. One of your self-schemas is having high ideals and being hard on yourself. Why don't we focus on one thing at a time instead of doing so many things simultaneously? What do you think?"

B. Proposed Scenario

Fig. 2 also shows our basic scenario flow with additional conversational strategies (transitions with dotted lines, the right side of the figure): more detailed questions about the users' concerns and reflecting on their responses.

1) Asking About the Details of User Concerns and Automatic Thoughts: The robot interrogatively digs into situations, feelings, and automatic thoughts to gather detailed information about them. When the robot asks about a situation, it also asks about potential triggers: "Do you have any idea what might've caused or provoked your reaction, such as a failure or a perceived stress?" Although the robot is asking about feelings, sometimes users provide thoughts instead of feelings. In such situations, the robot focuses on feelings: "I think you're describing a topic rather than sharing your feelings about your mood. In general, a mood can be expressed in one word, like sad or happy. How do you feel about the thoughts you mentioned earlier?" In addition, depending on the answers to its questions, the robot asks about automatic thoughts by limiting the situation: "How did you feel when you failed?"

2) Reflecting Responses: The robot provides feedback about the user's responses to the questions about situations and feelings. After hearing a response, the robot repeats a keyword or a similar word for verification: "Well, if I understand, you made a mistake. Is that correct?"

3) Asking About the Details of User Self-Schemas: Even though additional conversational strategies are used, sometimes users' information is inadequate to estimate self-schemas. In such situations, the robot asks which self-schema type is most applicable before asking about automatic thoughts. For example, when the robot could not estimate a self-schema after two candidates (e.g., IHA or DEO), the robot asked: "Are your negative feelings based on an idea that was different from your expectation?" Then it uses the answers to estimate the self-schema.

IV. System Overview

Fig. 3 shows our system, which consists of the following components: a robot, a voice recognition function, a scenario management function, and a self-schema estimation function.

A. Robot

We used Sota, a tabletop-sized humanoid communication robot, as an embodied conversational agent. It has eight degrees of freedom: three in its neck, one in each shoulder, one in each elbow, and another in its base. The output unit has a speaker and three LEDs: one on each eye and another on its mouth. It speaks through a voice synthesis function that produces child-like, machinelike, and gender-neutral sounds. We used child-like voice to 1) avoid a cross-gender effect between speaker and listener genders [32] and 2) to avoid mismatch feelings between robot's appearance and voice.

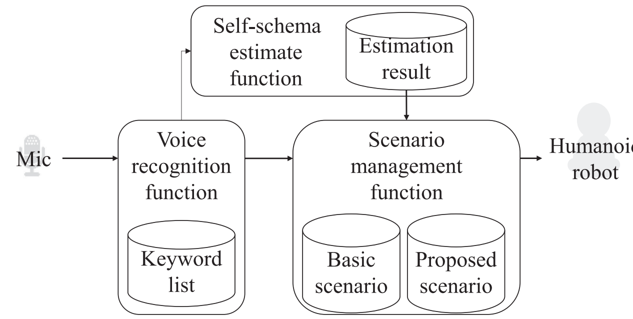

Fig. 3. System overview of developed system.

B. Voice Recognition Function

This function recognizes a user's voice to detect specific keywords based on a pre-defined keyword list to manage dialogue scenarios. We conducted a web survey and a preliminary experiment to create a keyword list beforehand. In the web survey, 382 subjects answered questions in the column method. The core words in each answer were registered in a list as keywords for our study. In the preliminary experiment, 30 subjects engaged with a prototype of this dialogue system and selected keywords that needed to be recognized for smooth dialogues. For example, we registered to back-channel feedback and words that indicated that users had completed their answers as well as words that repeated the users' answers by the system. We prepared about 1520 keywords.

We used an additional microphone for the speech recognition software (Cloud Speech-to-Text, Google LLC) to send the keywords in the speech text to both the scenario management and self-schema estimation functions.

C. Scenario Management Function

This function sends behavior commands to a robot to reference a dialogue scenario that is dependent on the received keywords and estimation results. We followed the structure of finite state machines [33] to manage the scenarios. The behavior commands contain vocal and physical movement instructions for the robot. We wrote two kinds of dialogue scenarios: basic and proposed (Fig. 2).

D. Self-Schema Estimation Function

This function estimates the user's self-schema based on DSS [31] by choosing one trait based on the amount of obtained keywords related to each trait from conversations. We selected specific keywords for IHA/DEO/FF from the 1520 keywords gathered from web surveys and our preliminary experiment. For instance, one IHA item is "I should not be satisfied with average evaluations," for which we chose the key phrase "I have to work harder" (or similar keywords). One DEO item is "I feel unhappy if I am isolated from others," for which we chose keywords "isolation," "loneliness," etc. One FF item is "If I make a mistake at work, then I feel like a loser," and we chose "failure," "self-hatred," or related keywords. In total, we made 192/230/151 keywords for IHA/DEO/FF.

Our system uses the selected keyword lists to estimate the traits of users. For example, it extracted ten keywords from a conversation with a user, and if the numbers of keywords are 6 for IHA, 3 for DEO, 1 for FF, the user is labeled as belonging in the IHA trait group because that category got the most matches. If two types have the same number of matches, the system randomly chooses between them.

V. Experiment

A. Hypothesis and Predictions

Facing stressors is essential for reducing negative mood states because stressor types determine appropriate stress coping strategies [34], [35]. In fact, such coping techniques focus on these points. For example, CBT concentrates on building a self-schema and automatic thoughts [9], [10] because these factors are related to how users face their problems. Several studies showed CBT's effectiveness for reducing people's negative mood states [11]–[14]. We focused on the column method, and designed conversational contents for a robot that encourages self-disclosures about problems and estimates self-schema types using conversational histories. If our developed system succeeds, participants will make more self-disclosures, and the robot will more accurately estimate their self-schema category. Such conversations will also make people's mood states more positive. Based on these concerns, we made the following predictions:

Prediction 1: People who use a robot with our proposed scenario will engage in more self-disclosures than people who use a robot with the basic scenario.

Prediction 2: The robot with our proposed scenario will estimate people's self-schema types more accurately than the robot with the basic scenario.

Prediction 3: The robot with our proposed scenario will make people's mood states more positive than the robot with the basic scenario.

B. Conditions

This experiment had a between-participant design. We separated the participants into two groups based on gender ratios.

- Alternative condition: The participants interacted with the robot with our system and the basic scenario described on the left side of Fig. 2.
- Proposed condition: The participants interacted with the robot with our system and all three strategies of our proposed scenario, described in the entire Fig. 2.

C. Environment

Fig. 4 shows our experimental environment. The participant sat inside walled participations in front of a robot, a camera, and a microphone.

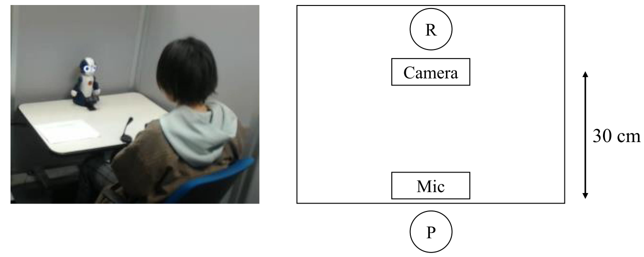

Fig. 4. Experiment room and overview.

D. Participants

Thirty-one people joined our experiment: 18 women and 13 men whose average ages were 41.097, and their S.D. was 9.783. All were native Japanese speakers who were referred to us based on their registration with an employment agency.

E. Measurements

In this study, we measured the number of self-disclosures during the experiments to evaluate our system's effectiveness. A coder transcribed all the recorded video/audio data conversations, segmented all the conversation data into 860 scripts, and categorized all the scripts as either self-disclosure or non-self-disclosure. For example, if the scripts broached hobbies or personal experiences, the coder placed them in the self-disclosure category. If the scripts only included mundane topics like the weather, they categorized them as non-self-disclosure. Then another coder coded 10% of these data. We calculated the coding's validity based on previous work [36]. The kappa coefficient was 0.845, indicating substantial agreement between the two coders.

We evaluated the accuracy of the self-schema type estimation function by having the participants rate the degree of accuracy of the robot's estimated self-schema types on a 1-to-7 value (1: strongly disagree, 7: strongly agree).

To evaluate whether our system improved the participants' mood states, they also completed questionnaires of the Japanese version of the Profile of Mood States (POMS2-A) [37] before and after their conversations with the robot. This questionnaire evaluates seven different moods: anger - hostility (AH, 11 items), confusion - bewilderment (CB, 10 items), depression - dejection (DD, 13 items), fatigue - inertia (FI, six items), tension - anxiety (TA, ten items), vigor - activity (VA, nine items), friendliness (F, six items), and total mood disturbance (TMD). TMD is calculated by subtracting the VA scores from the total AH, CB, DD, FI, and TA scores. Each item is rated on 0-to-4 values from "not-at-all" to "extremely."

F. Procedure

Before the experiment, the participants were given a brief description of its purpose and procedure. Our institution's ethics committee approved this research for studies involving human participants (No. 20-501-3). Written, informed consent was obtained from each one.

First, the experimenter explained the important points of the dialogues, how to start a dialogue, how to answer the robot's

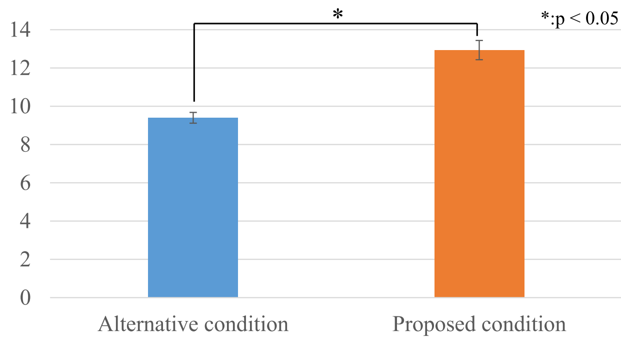

Fig. 5. Number of self-disclosures.

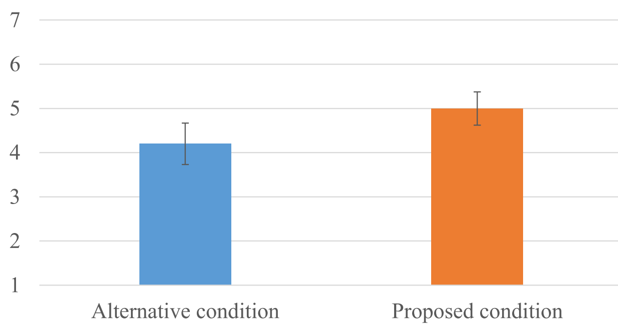

Fig. 6. Degree of correctness about estimated self-schema types.

questions, and reminded them to speak clearly and loudly when the robot was in the experimental room. Next the participants answered questionnaires to evaluate their mood states before the dialogues. After completing the questionnaires, they had conversations with the robot that typically lasted from seven to ten minutes. After a dialogue ended, the participants again answered questionnaires to evaluate their post-dialogue mood states and the accuracy of the self-schema type estimated by the system.

VI. Results

A. Verification of Prediction 1

Fig. 5 shows the results of the number of self-disclosures in each condition. We conducted a t-test and found a significant difference among the conditions ($t(29) = 5.834$, $p = 0.001$, $r = 0.73$). Thus, the robot in the proposed condition produced more self-disclosures than the robot in the alternative condition; prediction 1 was supported.

B. Verification of Prediction 2

Fig. 6 shows the results of the degree of accuracy of the estimated self-schema types in each condition. Due to a lack of answers from some participants who neglected to completely answer the questionnaires, the valid number is 29. We conducted a t-test for the results and did not find a significant difference among the conditions ($t(29) = 1.34$, $p = 0.192$, $r = 0.24$). Thus, the robot with our system and the proposed scenario did not more accurately estimate the participants' self-schema types than the robot with our system and the basic scenario; prediction 2 was not supported.

C. Verification of Prediction 3

Figs. 7 and 8 show the questionnaire results about the respective differences of each POMS2-A mood in each condition and TMD. Due to a lack of answers from some participants, the valid number is 26. We conducted a t-test for each scale and found a significant difference in AH among the conditions ($t(15.010) = 2.429$, $p = 0.028$, $r = 0.53$). We also found a significant trend in FI among the conditions ($t(26) = 1.973$, $p = 0.059$, $r = 0.36$).

We did not find significant differences in other moods: CB ($t(26) = 0.277$, $p = 0.784$, $r = 0.05$), DD ($t(26) = 0.711$, $p = 0.483$, $r = 0.14$), TA ($t(26) = 0.413$, $p = 0.683$, $r = 0.08$), VA ($t(26) = 0.156$, $p = 0.877$, $r = 0.03$), F ($t(26) = 0.275$, $p = 0.785$, $r = 0.05$), TMD($t(26) = 0.878$, $p = 0.388$, $r = 0.17$).

Thus, the robot with our system and the proposed scenario partially improved people's mood states more in the context of AH than the robot with our system and the basic scenario, although other moods did not change; prediction 3 was partially supported.

D. Summary of Statistical Analysis

Based on these analyses, the robot with our system and the proposed scenario significantly increased the number of self-disclosures and significantly reduced the angry moods of the participants more than the robot with our system and the basic scenario. On the other hand, we found no significant differences between the performances of the self-schema estimation and moods among the conditions.

E. Participant' Behaviors and Self-Disclosures

We report the observed behaviors and self-disclosures of the participants. In both conditions, they typically explained their concerns based on the robot's questions. The following are the more common topics of the self-disclosure contents: families, school, and work, some of which are influenced by various COVID-19 situations.

For example, one woman was concerned that she might have to repeat a year of college due to poor grades, a situation that was exacerbated by the pandemic. Since she explained this concern without any potential triggers the robot first verified her concern and feeling by following conversational strategy 2 (Section III.B.2). Then it asked for more details of her concern using conversational strategy 1 (Section III.B.1). Then, she explained that she felt great stress because she could not attend classes in-person due to a lockdown. The robot probed into the details of her self-schema by following conversational strategy 3 (Section III.B.3), and she described her anxiety about her future. Finally, after categorizing her self-schema as IHA, i.e., high achievement, the robot gave her some advice (Section III.A). After the experiment, she said that "I was able to put my thoughts into words and organize them through conversations with the robot."

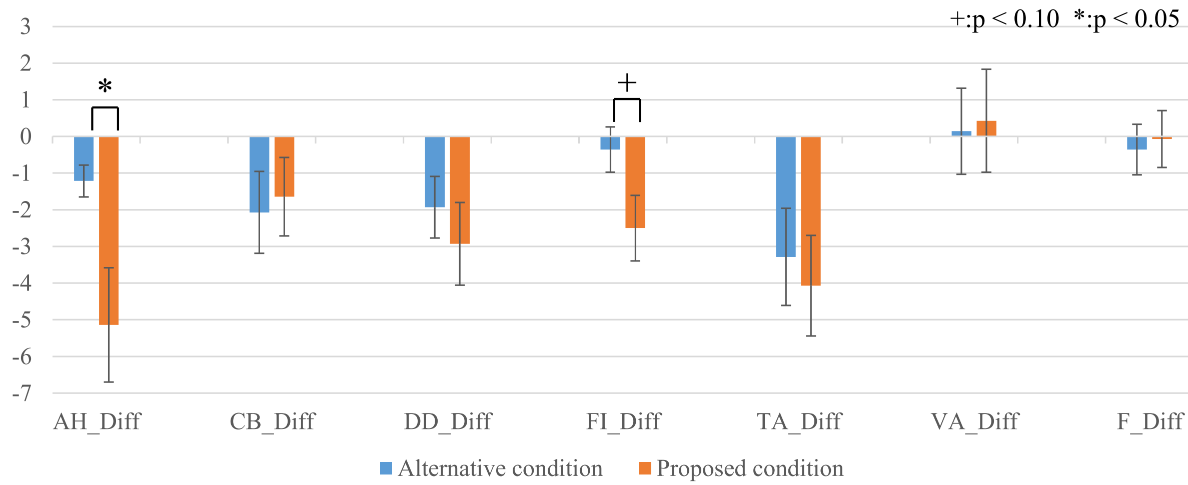

Fig. 7. Differences of each POMS2-A mood (without total mood disturbance, see Fig. 8). Minus values indicate negative mood states are mitigated.

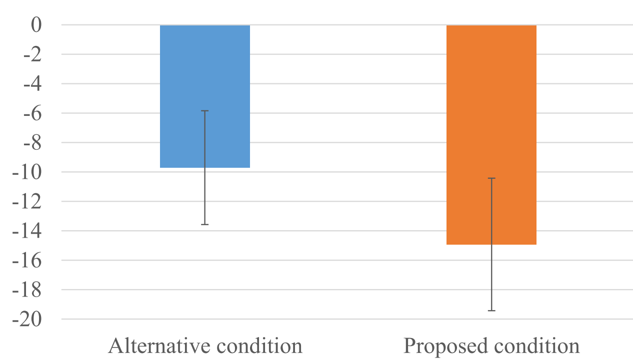

Fig. 8. Differences in total mood disturbance (calculated by subtracting VA scores from total AH, CB, DD, FI, and TA scores, shown in Fig. 7). Minus values indicate negative mood states are mitigated.

TABLE I
AVERAGE DURATIONS OF TOTAL ROBOT/PARTICIPANTS SPEECH, THINKING, AND OTHER BEHAVIOR

	Total	Robot	Participants	Thinking time	Others
Alternative	7:27	3:31	1:30	0:34	1:52
Proposed	10:35	5:21	1:34	0:55	2:45

Related to participant behaviors, we measured the time features that are related to the conversations between the robot and the participants (Table I). Note that the "other" category contains all the periods of silence from both the robot and the participants (e.g., pauses between speech, waiting for speech recognition results, etc.). In other word, the robot in the proposed condition talked a lot more than the alternative condition. Related to the number of speech contents, the "other" time is also different among conditions due to more pauses between contents.

However, the total and self-disclosure times of the participants are not so different among conditions, although the number of self-disclosures is significantly different. On the other hand, the participants in the proposed condition took more thinking time (durations from the robot's questions to the participants' answers) than the alternative conditions; note that the robot in both conditions did not cajole the participants to respond. Based on these differences, we assumed that our conversational strategy encouraged relatively short self-disclosures, and the robot in the proposed condition supported participants to think more about themselves.

F. System Evaluation

In this study, we used Google STT and keyword-matching based on its results for dialog management and measure the speech recognition performances and the interaction failures.

The average misrecognition numbers were 3.1 and 3.3 in the proposed and alternative conditions. These numbers included simple typos which did not influence the schema estimation functions. Moreover, since our scenarios are designed to re-ask about situations (both basic and proposed) and feelings (proposed only) when the system could not detect related words from the speech recognition results, these designs worked as error-recovery functions when such misrecognition happened. Therefore, the system misrecognized the speech recognition results, which are related to the failure of the self-schema estimation functions, just once in the proposed condition and never in the alternative condition. Based on these results, we believe that the number of failures of the speech recognition functions is basically acceptable for the total performance of both conditions.

We also measured the number of cases where the robot randomly chose a self-scheme type in the interactions because such cases happen if multiple types have the same number of matches. We found one case in the proposed condition and nine in the alternative condition. The difference probably indirectly influenced the perceived impressions of the participants. Such a difference is caused by the robot's conversation design as well as the speech recognition results.

VII. DISCUSSION

A. Implications

One main contribution of this letter is the anger reduction of participants through conversations with our autonomous system. Our conversation strategy supports the awareness of self-schemas and automatic thoughts by considering the self-disclosure of participants. Existing conversational systems for mental therapy purposes are designed to encourage self-disclosures, but they are less focused on strategies for interactive social robots, and our system can be used to expand their potential.

In this study, we conducted a short-term conversational experiment. For having more effective stress coping support, we need to consider a long-term interaction. For example, a past study reported the effectiveness of robot-mediated therapeutic intervention for people with visual and intellectual disabilities that was done for more than one month [38]. Designing conversational contents and memorization functions considering the changes of users' concerns and their self-schemas would be needed in long-term interaction. Moreover, building relationships between robots and users is also essential.

A possible technical improvement is to consider basic prosody features and emotional expressions, which are useful to encourage self-disclosure [20]. In this study, we did not implement these functions to the robot because we focused on a conversational strategy, but it can be integrated and would be effective for stress coping. For this purpose, it is important to design rules between appropriate expressions and conversational contents.

From another perspective, using different entities such as chatbots [19] and virtual agents [23], [24] with our conversation strategies would provide interesting knowledge. Even though previous studies showed the advantages of embodied agents (i.e., robot) compared to non-embodied agents (e.g., smart speaker or virtual agent) [20], [39]–[41] in conversational contexts, those non-embodied agents have advantages such as ease of use and costs. Moreover, a recent study reported non-significant differences considering physical representation effects in a conversational setup [42].

Note that an anger reduction effect was previously reported in a CBT meta-analysis [11]; our study provides additional evidence supporting this positive CBT effect. Although our robot failed to significantly reduce negative moods, such as depression and anxiety [13], [14], our result contributes to the design of conversational strategies for social robots in order to improve support interaction for people's mental health.

B. Limitations

Since we only used a specific robot in this study, testing different types of robots is critical to generalize our results. We also measured the perceived feeling of participants on a single day. Future work must investigate the effectiveness of long-term interactions in continuous experiments.

In addition, we only evaluated our system with child-like voices (Section III.A). If we were to use different types of robots and agents (e.g., various appearances and embodiments), the appropriate voice types will be different as well as their prosody features. Nor did we did not evaluate the effectiveness of our conversational strategy in text-based communication styles. Although this study has several limitations, our developed system and its anger reduction results merit attention by researchers working on conversational robot systems.

VIII. Conclusion

This study focused on conversational interactions to make people's mood states more positive using the column method, which is typical stress coping technique in Japan. We implemented conversational functions to encourage more self-disclosures to support the awareness of individual self-schemas and automatic thoughts for our robot system. We also implemented a function that estimates the self-schemas of an interacting partner and additional conversational strategies.

We experimentally evaluated our developed system with human participants. Our results showed that our system with additional conversational strategies significantly increased the number of participants' self-disclosures and reduced their anger through conversations. Although the strategies did not increase the accuracy of the self-schema estimation function, our experiment results about reducing anger moods do provide insight into conversational strategy designs for robotics researchers.

One possible future work is involving touch behaviors in conversational interactions between robots and people. Enabling touch interaction is an advantage possessed by physical agents over non-physical agents. Investigating human-robot touch interaction effects for improving human mood states might be interesting.

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