Learner-Support Agents for Collaborative Interaction: A Study on Affect and Communication Channels

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Abstract: This study investigated if and how a conversational agent facilitates better explanations from students in a computer-based collaborative activity. Pairs of students enrolled in a psychology course performed a task where they attempted to explain to their partners the meanings of technical psychological terms. During the task, they interacted with an affect-based conversational agent, which was programmed to provide back-channel feedback and metacognitive suggestions through visual and/or audio output. The study compared students' performance after using this agent with their performance after using an agent without audio output or affective expressions. Our findings suggested that the use of multiple communication channels for feedback facilitates collaborative learners' understanding of concepts. This provides implications for designing pedagogical agents for effective collaboration.

Introduction

Past studies on collaborative problem solving in cognitive science have revealed how concepts are understood or learned through interaction. Researchers have shown that asking reflective questions for clarification to conversational partners is an effective interactional strategy to better understand a problem or concept (e.g., Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Miyake, 1986; Okada & Simon, 1997; Salomon, 2001). The use of strategic utterances such as asking for explanations or providing suggestions has been found to stimulate reflective thinking and metacognition involved in understanding concepts. Playing different roles during an explanation could also help problem solvers construct external representations and develop their understanding of concepts (Shirouzu, Miyake, & Masukawa, 2002). These studies suggest that one's ability to explain is key to understanding and learning concepts. However, effective explanation often fails if retrieving and associating relevant knowledge required for the explanation is difficult. These difficulties typically rise among novice problem solvers (Coleman, 1998; King, 1994). Additionally, people cannot learn effectively if they cannot communicate fluently with each other, such as when they have little conversation experience or have conflicting perspectives (Hayashi & Miwa, 2009).

One way to help collaborative problem solvers could be introducing a third-party facilitator who could provide suggestions or back-channels. An important breakthrough has been the use of computer-based technology, such as pedagogical conversational agents, for this purpose. Pedagogical agents can serve not only as multimedia extensions, but also as social entities that become learning companions (Moreno & Mayer, 2002). The present study investigated the use of pedagogical conversational agents that could facilitate effective explanations.

Pedagogical conversational agents as learning advisers

The effects of affective feedback

Recently, studies have shown that conversational agents that act as educational companions or tutors can facilitate learning (Baylor & Kim, 2005; Holmes, 2007). Many computer-based tutoring systems use conversational agents (Graesser & McNamara, 2010), but it is not fully understood what kinds of support from such agents could improve collaborative learners' performance. Collaborative activities are difficult, especially for new learners who are not used to expressing their thoughts or understanding others' viewpoints. It is assumed that learners would have high cognitive loads during explanation, and paying attention to both their partners and third parties (computer agent) could be too difficult. Holmes (2007) indicated that learning pairs ignored the presence of an agent and conducted the learning activities on their own. Therefore, investigating how to design and use pedagogical agents for effective enhancement of collaborative activities is very important. These agents should be designed using concepts based on human collaborative activities. One point that must be considered in studies of human performance is emotion. Emotions affect individuals' performance in both negative and positive ways and these effects are especially important for learning activities (Baylor & Kim, 2005). For example, Bower and Forgas (2001) revealed that positive mood can increase memory performance. Mayer (2001) also demonstrated that a positive state of mind can improve text comprehension. Moods may also affect people's verbal and non-verbal performance on activities. Kim, Baylor, and Shen (2007) examined how positive and negative comments from conversational agents can affect learning performance. They programmed a pictorial image of an agent to project a textual message to the participant; in the positive condition, a visual avatar produced a short comment such as "This task looks fun." In the negative condition, it produced a comment such as "I don't feel like doing this, but we have to anyway." The results showed that the conversational agents that provided comments in a positive mood increased participants' motivation to learn. In addition, it is important that students acquire confidence, even if it is only the "illusion of knowing." This phenomenon describes how students sometimes do not accurately acquire knowledge, but still become confident that they have learned something. This confidence is important for facilitating students' motivation towards learning.

Hayashi (2012) examined how the expressions of positive and negative pedagogical conversational agents could facilitate explanations between collaborative pairs. Participants were required to explain a concept taught in a university psychology course to others through a computer chat system. During the task, they interacted with a conversational agent, which was programmed to provide back-channel feedback and metacognitive suggestions to encourage and facilitate conversational interaction. Their results suggested that positive affective feedback from these conversational agents facilitates explanation and better learning. Thus, conversational agents can play a role in pedagogical tutoring and may help trigger deeper understanding of a concept that students are trying to explain. The above studies have suggested that explanation performance will also be enhanced if suggestions are given in a positive mood either verbally or through visual feedback. Unfortunately, further analysis of the dialogue process shows that learners sometimes do not listen to agents' comments or suggestions. This indicates a need to further investigate how to provide such affective feedback more effectively. However, there are several difficulties in providing feedback during interactions among learners, such as (1) timing of feedback, (2) quantity/quality of information, and (3) communication channels. Appropriate communication channels are especially important for new learners, as it helps them avoid cognitive overload from the information provided by both agents and learners. In the next section, discuss are made on such communication channels.

Communication channels during pedagogy in online tasks

While the issue discussed above concerns the nature of the information in collaborative tasks, it is more concerned with identifying the communication channels that could improve learners' comprehension of unfamiliar concepts when affective feedback is presented

A related issue is how information is processed (and how it is processed in the most efficient manner), which has been a long-considered topic in psychology. For example, Baddeley and Hitch (1974), in their "working memory" model, argued that there are two subcomponents of information processing that handle different types of information (visual and verbal). Thus, human cognition comprises different components or modules for different kinds of information, allowing us to predict that people perform better when information is presented more efficiently and economically. That is, when people perform two kinds of activities at the same time, they may do better if information is presented through different communication channels rather than a single channel. Moreover, previous research has suggested that information in working memory may overload processing when the same modality is used for various types of information, thus making it harder for learners to understand (Chandler & Sweller, 1991; Mousavi, Low, & Sweller, 1995; Sweller, Chandler, Tierney, & Cooper, 1990). Mayer (2001), who extended this view to multimedia learning, reported that students who viewed an animation depicting the formation of lightning while listening to a narration explaining this process generated more useful solutions on a subsequent problem solving transfer test than did students who viewed the animation with the narration as subtitles. In the case of collaborative problem solving tasks, learners may perform better if agent feedback is provided through voice messages (i.e., auditorily) than by text message, since they are already engaged in reading a description through a computer monitor (i.e., visually).

Another important point to consider in relation to communication channels is the problem of attention during tasks, which is related to the efficiency problem discussed above. This is generally referred to as the "split attention effect," which is often observed in poorly designed instructional materials where, for example, the same modality (e.g., visual) is used for different types of information within the same display. In such cases, learners' attention may be split between different materials, making it difficult to use the materials effectively. When individuals are engaged in a challenging task, they may be preoccupied with information that is more directly related to the task and pay less attention to information, which although useful, is only indirectly related to the task.

For collaborative learning via online communication, possible ways to communicate with one another include using text chats (visual) and/or voice messages (auditory). Unlike recent web-based tutoring and e-learning systems, the most widely used technology is text-based communication (e.g., Hayashi, 2012; Holmes, 2007). In this case, attention may be paid primarily to the exchange of textual information on the computer display, since explanation is performed via online visual communication, with students describing concepts by typing. It is likely that learners, especially novice learners, are able to pay sufficient attention to affective feedback from a computer agent, even if this feedback is given in the same modality (visually). However, collaborative learners may be able to pay more attention if they are given the feedback in a different modality (auditorily).

Research Goal and hypothesis

The goal of this study was to experimentally investigate if and how conversational agents facilitate students' understanding and learning of concepts. It was hypothesized that the use of affective feedback could facilitate collaborative learners' understanding of concepts. In addition, explanation performance would be enhanced if positive feedback from computer agents were given through multiple communication channels (i.e., visual or auditory modalities). This paper analyzes the performance of student pairs who performed an explanation activity on two types of technical terms.

Method

Experimental task and procedure

The experiment was conducted in a room where the computers were all connected by a local area network. Participants were given two technical terms presented on the screen. They were "schema" and "long-term memory," and had been previously introduced in the psychology class. Along with the key terms, a brief explanation of the concept was provided. Participants were asked to describe these concepts in their own words. After this pretest, participants logged into computers and used the chat program installed from a USB flash drive (see the next section for details). Pairs of participants then communicated through this program, with one participant explaining to another the meaning of each word presented on their computer screen. After one concept had been explained, the partners switched roles and the other partner explained the remaining concept. This was then repeated, so that both students had a chance to explain both terms. All participants received the same suggestions from the agent on how explanations should be given and how questions should be asked about the concepts. They then took a posttest, which consisted of the same material as the pretest. Participants' descriptions of the concepts in the posttest were compared with those of the pretest to determine if the participants had gained a deeper understanding of the concepts after the collaborative activity.

Experimental system

In the experiments, a computer-mediated chat system was set up through computer terminals connected via a local area network and the participants' interactions during the activity were monitored. The system used in the experiments was programmed in Java (Hayashi, 2012 a).

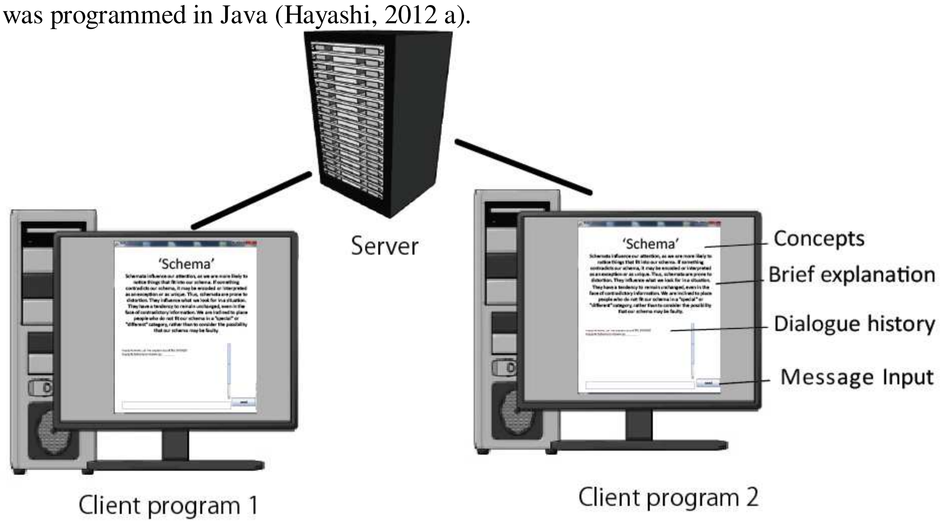

Figure 1. Interface of the task.

The system consisted of three program modules, including: (1) server, (2) client, and (3) agent, all of which were simultaneously activated. The server controlled all communication traffic during the task, and the client programs were installed in the students' computers to activate the graphical user interface (GUI) for communication (Figure 1). Multithreads were used so that the server program could send all messages to the clients' chat systems and the agent simultaneously.

The pedagogical agent used in this study was a simple rule-based production system composed of the following three different modules: (1) semantic analyzer, (2) generator, and (3) motion handler. First, the textual input of all of the participants' conversational exchanges was sent to the semantic analyzer in the agent. The agent monitored all the chat dialogues and messages were analyzed according to a list of keywords via the "bag of words" method (e.g., "I think that a **schema** is some kind of **knowledge** that is used based on one's own

experience" (detected keywords are shown in bold italics). The list of keywords was stored in a database (the "Dictionary Database") in the semantic analyzer. Thirty different keywords were registered in the database. These keywords were selected according to a past study (Hayashi, 2012 a). Next, the extracted keywords were sent to the "working memory" in the generator and processed by a rule base, where various types of rule-based statements such as "if X then Y" were stored to generate prompt messages (if there are several matching statements for the input keywords, a simple conflict resolution strategy is utilized). When the matching process was completed, prompt messages were selected and sent back to the working memory in the generator. The messages consisted of information about the goals and the achievements of the task, and some initial suggestions on how to give good explanations to others. This point was designed according to the method used in Holmes (2007). The basic response rule was that if too many keywords were detected in the system, then prompts were generated asking students to use different words. For example, if the learner simply copied and pasted the words used by the system, it would provide messages such as "You should use more original words in your explanations." When the system detected some keywords such as technical words, it generated messages such as "Good! You are explaining the concept with some unique words. Keep on going!" When the system detected combinations of technical keywords and questions, it provided messages addressing those combinations. For example, "It seems you have difficulty answering this. But you use good keywords!" Each output message was presented in text on the computer display.

The messages generated by the rule base were also sent to the motion handler module to activate an embodied conversation agent, a computer-generated virtual character that produced human-like behaviors such as blinking and head-shaking. The types of affective expressions used were based on an affective model developed in a preliminary study (Hayashi, 2012 b). These expressions were created using the 3D-image/animation-design tool Poser 8 (www.e-frontier.com).

Participants and conditions

In this study, 58 participants (23 men and 35 women; mean age = 19.78) participated in pairs. Participants were all undergraduate students taking a psychology course, who participated as a part of coursework. They were randomly assigned to three conditions, which varied according to how the suggestion prompts were presented and how the conversational agents were used (see the section below for details). In all conditions, the participants were given positive suggestions, which were synchronized with the facial expressions of the embodied agent. The messages were given through chat dialogue and the virtual character moved its hands and lips while the participants chatted on the computer. Furthermore, in one condition, a male voice was generated using the Microsoft speech platform while the agents produced facial expressions.

Three conditions were used to test our hypothesis (see Figure 2). In the "no suggestion" condition (Group SSA, n = 18), participants were given no suggestions without any affective expressions. In the text suggestion condition (Group SSA+T, n = 20), participants were given suggestions via textual prompts with affective feedback according to the affective model. In the text and voice suggestion condition (Group SSA+TV, n = 20), participants were given no suggestions via textual prompts but rather via audio output. In the SSA+TV condition, participants wore headphones to listen to the responses from the agent.

In the pretest and posttest, participants were asked to describe the meaning of the same technical words. As in Hayashi (2012 a), the results of the pretest and posttest were then compared to find out how the different conditions facilitated participants' learning of the concepts. In the comparison, descriptions were scored in the following ways: one point was awarded for a wrong description or no description, two points for a nearly correct description, three points for a fairly correct description, four points for an excellent description, and five points for an excellent description with concrete examples. It was judged that the greater the difference in scores between the two tests, the greater the effect of the explanation activity. Two coders then coded the results, and their correlations were 0.67. The coders discussed their results before making any final decisions. The pretest and posttest scores were used to assess the degree of learning performance.

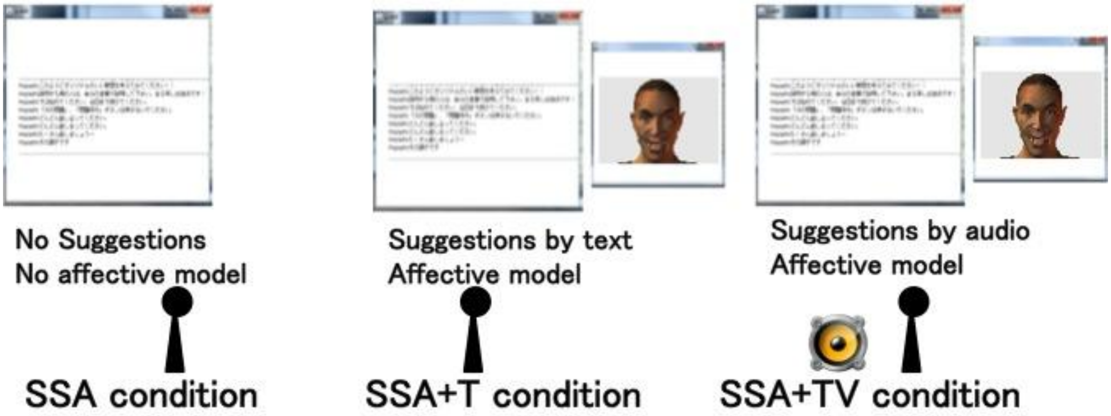

Figure 2. Experimental Conditions.

Results

Figure 3 shows the results of the pretest and posttest for the term "schema." The vertical axis represents the average scores of the tests for the three groups at the two different test times. A statistical analysis was performed using a 2 (evaluation test: pretest vs. posttest) × 3 (conversational agent condition: SSA vs. SSA+T vs. SSA+TV) mixed-factor analysis of variance (ANOVA).

There was a significant interaction between the two factors ($F(2, 55) = 12.457$, $p < .01$). First, an analysis of the simple main effects was done on each level of the conversational agent factor. In the SSA, SSA+T, and SSA+TV conditions, average scores on the posttest were higher than on the pretest ($F(1, 55) = 99.604$, $p < .01$; $F(1, 55) = 53.616$, $p < .01$; $F(1, 55) = 8.899$, $p < .01$, respectively). These results showed that the explanation activity had an effect on learning.

Next, simple main effects were analyzed according to evaluation test time. In the pretest, there were no differences between conditions ($F(2, 110) = 0.48$, $p = .95$), indicating no differences between participants before conducting the experiment. On the other hand, differences between conditions were found in the posttest ($F(2, 110) = 23.599$, $p < .01$). Post-hoc analysis on the posttest was conducted through Ryan's method. Results indicated that the average score of the SSA+TV condition was higher than that of the SSA+T and SSA conditions ($p < .01$ for both), and the average score of SSA+T was higher than that of the SSA ($p < .01$). The difference in scores between the SSA+TV and SSA+T conditions in the posttest indicated that using different communication channels to explain a concept to a partner and receiving learning prompts from a PCA are useful to facilitate participants' understanding of the concepts, compared with using the same communication channels.

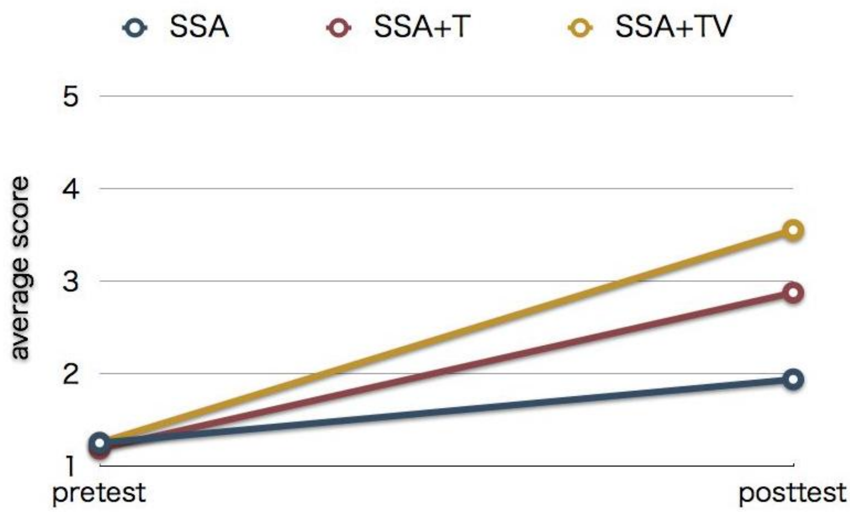

Figure 3. Results of 'schema'.

Figure 4 presents the results of the pretest and posttest for the term "long-term memory." The vertical axis represents the average scores of the pretest and posttest for the three conditions. The same type of statistical analysis was performed as above.

There was a significant interaction between the two factors ($F(2, 55) = 10.143$, $p < .01$). First, simple main effects were analyzed according to conversational agent. In the SSA+T and SSA+TV conditions, the average scores on the posttest were higher than on the pretest ($F(1, 55) = 62.662$, $p < .01$; $F(1, 55) = 23.673$, $p < .01$, respectively). In the SSA condition, the average scores did not differ ($F(1, 55) = 0.127$, $p < .01$). The increases shown in the SSA+T and SSA+TV conditions show that the explanation activities produced a learning effect related to affect.

Next, simple main effects were analyzed according to evaluation test. In the pretest, no differences were found between conditions ($F(2, 110) = 0.022$, $p = .97$), indicating no differences between participants before conducting the experiment. There were differences between conditions in the posttest ($F(2, 110) = 16.535$, $p < .01$). Post-hoc analysis on the posttest was conducted using Ryan's method. The results indicated that the average score of the SSA+TV condition was higher than that of the SSA+T and SSA conditions ($p < .01$ for both), and the average score of SSA+T was higher than that of the SSA ($p < .01$). This result was consistent with the results of the analysis of "schema."

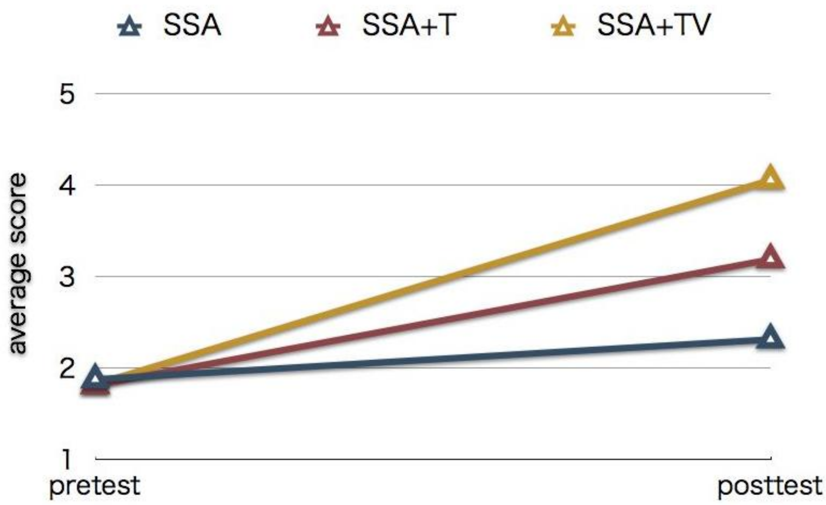

Figure 4. Results of 'long-term memory'.

Discussion

Affective factors and communication channels

The results of this study have several implications on the advantages of using pedagogical agents and providing feedback through different communication channels. First, the SSA+TV and SSA+T conditions had greater influences on students' performance than the SSA condition. This indicates that the use of an affective model has a strong effect on the performance of learning activities. This result is consistent with the results of a previous study by Hayashi (2012 a). In that study, agents with positive expressions had greater influences on performance compared with agents with no expression. However, because Hayashi (2012 a) did not conduct a direct comparison between positive affective agents and text-only prompts, the present study shows results that are more reliable on the advantages of using affective conversational agents during learning activities. Furthermore, the present study used more sophisticated affective models in the conversational agents. Although pedagogical agents have great potential, they should be modeled with parameters that are more detailed and based on human cognition.

The experimental results also showed that participants performed better in the SSA+TV condition (receiving verbal comments from the agent) compared with the other two conditions. According to the split attention method and the multimedia design model, using different communication channels for the learner's conversations and the suggestions from the agent is a good pedagogical method. Our results supported the notion that using different communication channels enables learners to pay more attention to agents' suggestions, and encourages them to consider the terms according to its comments. Post-hoc analyses showed that agents' comments facilitated students' use of related conceptual terms, and allowed them to understand the target keyword from a different perspective (see Table 1 for an example). Furthermore, learners—especially those not trained to give effective explanations—confronted their difficulties in giving explanations by asking appropriate questions. Therefore, they were concentrated on their partner's text messages, which occupied their visual attention. Table 2 shows some examples of participants' dialogue, where one student failed to pay attention to the pedagogical conversational agent.

In previous pedagogical agent studies, some attempts have been made to understand how an environment rich with multiple communication channels could facilitate the learning process. Unfortunately, some of these investigations showed that pedagogical agents had no significant learning effects. Moreno and Mayer (2002) conducted an experiment using a pedagogical agent named "Herman the bug," and presented information to learners via a desktop computer or head-mounted display. The head-mounted display condition was used to examine whether virtual reality could lead to better learning results, as it may encourage learners to engage in more active cognitive processing. However, the results yielded no difference between the virtual reality conditions (using a head-mounted display while walking or sitting) and the desktop computer condition in performance on retention or transfer tasks (Moreno & Mayer, 2002). These results are likely because virtual reality distracts the learner from the learning task. Therefore, additional features such as more technically complex learning environments do not necessarily facilitate learning. Another explanation is that the way the information was presented resulted in cognitive overflow. The present results indicated that if information is provided in a cognitively economical way, such as using multiple communication channels and splitting attention, computer-based learning with agents can be a powerful learning tool.

Table 1: Example dialogue of participants interacting frequently in SSA+TV condition.

Speaker	Dialogue
Participant A	"In the case of short term memory, the amount of the information affects memory, right?"
Conversational Agent	"Good! You're using important keywords such as 'short-term memory'!"
Participant B	"Oh. So, long-term memory is the opposite and we can remember more."
Participant A	"I'm not sure, but I think so…"
Conversational Agent	"Nice, keep on it guys! Our goal in this activity is to reach a better understanding of this term by explaining it to each other."
Participant B	"Then how about length of time…by using long-term memory, can we remember information for longer?"

Table 2: Example dialogue of participants not paying attention to the agent in SSA+T condition.

Speaker	Dialogue
Participant B	"Okay, so please continue explaining the term 'schema'."
Participant A	"They influence what we look for in a situation."
Conversational Agent	"Good job! However, a couple of times you used the same words that were written in the example. Try to use your own words!"
Participant A	"We are inclined to place people who do not fit our schema in a special or different category…."
Participant B	"I think it's better to not copy the sentences from the examples."
Participant A	"Oh, I missed the instructions."
Participant B	"The computer agent said that."
Participant A	"I wasn't paying attention to it at all. Oops…"

Conclusion and future work

The present study investigated the effectiveness of a conversational agent in a collaborative activity, where paired students explained to each other the meaning of several psychological terms to improve their understanding. The agents were used to encourage and facilitate students' interactions through both verbal and visual output. The experimental results suggested that affective conversational agents using multiple communication channels can help trigger a deeper understanding of a concept when attempting to explain that concept. This gives us a new perspective on how to design pedagogical agents for collaborative activities such as giving explanations to others.

The present study used conversational agents that exhibited only positive affective expressions; future studies could use expressions that are more specific or according to personal preferences. Those personal preferences may be based on social constructions such as gender and culture. In future studies, these preferences for affective expression should be investigated and implemented into the system to produce more effective learning. For example, Kim, Baylor, and Shen (2007) found that learners had positive impressions of male agents with positive expressions than of female agents. This indicates that social stereotypes in the real world are applied to the agent-learner relationship.

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