Togetherness: Multiple Pedagogical Conversational Agents as Companions in Collaborative Learning

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Abstract. This study investigates the design of effective interaction using pedagogical conversational agents (PCAs) as companions in collaborative learning activities. Specifically, we focus on the use of embodied PCAs that evoke social awareness and engagement from human learners. In controlled experiments, paired collaborative learners were selectively accompanied by “peer-advisor” PCAs in a set of learning activities. Results show that learners who engaged with multiple PCAs gained a better understanding of target concepts than those using a single PCA. Furthermore, learners who engaged PCAs playing different collaborative roles (e.g., “mentor” and “expert”) outperformed those who engaged PCAs without distinct roles. The implications of these results are explored and directions for future study are discussed.

Keywords: Pedagogical Conversational Agents; Collaborative Learning; Explanation Activities; Social Facilitation.

1 Introduction

As a result of Vygotsky's sociocultural learning theories and Lave's Situated learning theories, it is now widely accepted that group-based learning is an effective strategy for facilitating learning [1, 2]. Recent studies in CSCL have implemented artificial intelligence technologies in tutoring systems and show the benefits of pedagogical conversational agents (PCAs) [3, 4, 5, 6, 7, 8, 9]. One of the challenges is to design and develop PCAs that can effectively facilitate a learner's cognitive state. To accomplish such a goal, it is necessary to use interaction models and theories from cognitive and learning sciences [10, 11]. Studies show how effectively collaborative learning facilitates the understanding of new concepts depends on how the explanations are provided [12]. Based on this theory, the present study focuses on a collaborative learning where students attempt to explain a classroom-taught concept.

1.1 Supporting Learner-Learner Collaborative Learning with PCAs

Recently, studies have shown that conversational agents acting as educational companions or tutors can facilitate learning [5, 13]. Many computer-based tutoring systems

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use conversational agents [4], but it is not fully understood what kinds of support from these agents improve learner-learner collaborative learning. There are several issues that need to be solved when designing PCAs for this purpose, for instance, (1) interface and media design [7], (2) responses and feedback [14, 15], and (3) agents roles [6], and the design of the interaction [9].

Working in groups in a classroom provides an opportunity for learners to re-construct their knowledge and organize their ideas by themselves [16]. During such activities, it is important for learners to adopt a conversational manner known as "constructive interaction" [17]. When pair of learners is working on a problem together, constructive interaction is where one learner works on the problem by externalizing explanations and the other simply observes and questions his/her partner to facilitate meta-cognitive perspectives [18]. Despite the idealistic interaction model, collaborative activities are somewhat difficult, especially for new learners who are not used to expressing their thoughts or understanding other viewpoints. Assuming that learners experience high cognitive loads during explanation activities, paying attention to both their partners and third parties (e.g., computer agents) could be too difficult. It is difficult to make learners continually pay attention to a PCA in a human-human based collaborative task [19]. Holmes (2007) indicated that learning pairs ignored the presence of an agent and conducted the learning activities on their own [9]. Hayashi (2012) showed that some students who did not achieve high learning scores on a pair explanation activity did not consider the PCA's suggestions that were needed to construct an effective explanation [20].

There are several methods to make learners pay attention to a PCA's suggestions. For example, Kumar and Rose (2000) designed methodologies such as requiring the students to ask the PCA to initiate the learning session or move it forward (ask when ready strategy) and/or having the PCA interrupt their conversation (attention grabbing strategy) [3]. However, in human-human collaborative learning, it is important not to forcibly interrupt or disturb the learners' natural interaction and compromise their self-reliant learning activities. It is important to design the interface such that it naturally attracts the learners' attentions in a way that is psychologically consistent with their internal processes. In the next section, we present our methods for bringing attention to the PCA's suggestions in a psychologically consistent way and thus maintaining the learners' natural conversation.

1.2 Using Multiple Agents to Enhance a Tutor's Social Presence and Role

The present study uses the notion of "social facilitation" effects, taken from social psychology and dynamics research [21]. Studies in this field have shown that when one feels that he/she is engaging in an intellectual task with several members, it motivates him/her to work harder to satisfy other group members [22]. It is also well known that a person often feels social pressure from others when he/she is persuaded or informed of something by several group members during intellectual tasks. It is assumed that if a learner is collaborating with other learners and advised by several tutors, he/she may feel more pressure to include their comments into the learning activities. This study proposes a new methodology for creating a virtual group-based learning platform that enhances the co-presence of the tutoring agents and uses multi-agent techniques to facilitate such social presence.

The first question to answer is whether agents can generate social pressure to make learners pay attention to them. A few studies in human-computer interaction have investigated the impact of social pressure from embodied agents. For example, Lee and Nass [23] examined the impact of visual representations of multiple agents on performance in a social dilemma task. Beck, Wintermantel, and Borg [24] investigated how social relationships with multiple agents affect persuasion. These studies imply that under some conditions, the use of multiple-agents can motivate and facilitate a change in human opinions. Therefore, the use of multiple PCAs may have the potential to exaggerate their presence and facilitate social pressures such as the need to work harder by causing the learners to consider the PCA's comments and suggestions. Based on the discussion above, the following hypothesis is presented:

H1: Multiple PCAs are more effective than a single PCA at facilitating their presence and motivating learners to engage in explanation activities and thus facilitate learning performance.

The next question that arises is what kind of roles the multiple agents should take during those interactions. It may be sufficient to increase the number of PCAs, however, it may also be necessary to design the character types and roles for each agent to provide more social presence. Many studies in collaborative problem solving and learning have pointed out the importance of member diversity and the beneficial effects of members taking different roles during those activities [18]. The diversity of tutors with different roles in group-based learning activities may also play an important role. If learners engage with multiple tutors that have different roles, it helps them to distinguish between the different tutoring content. If learners perceive agents as individual actors, this implies to them that there are different ways and viewpoints to consider when solving a problem. We may also find synergetic effects with regards to social pressure, as multiple members with diverse perspectives may create more impact and direct attention back to the learners than tutors with the same perspectives would. Past studies have shown that human learners can correctly understand the different roles that an agent may take. For example, Baylor and Kim [5] found that learners apply the same social rules and expectations to human-agent interactions as they do to human-human interactions. They pointed out that if agents are designed to have particular roles, learners could understand those roles as intended. Their results showed that when using agents with motivational characteristics and roles (motivator and mentor), the agents were more human-like and self-sufficiency was improved. They also found that using expertise characteristics (expert and mentor) facilitated learning outcomes along with positive feelings towards the agents such as credibility and had the best impact on learning and motivation.

Although this study showed that people can distinguish between an agent's roles and this led to different types of impressions during learning, they did not investigate different of combinations of the multi-party situation nor directly compare the effects of divisive PCA roles. This study focuses on the use of multiple PCAs with different roles versus no roles and investigates whether learners can perceive the variety of members in the group. It also looks at the effects of divisive PCA members.

H2: By splitting the roles of multiple agents, learners can more sensitively distinguish between the types of facilitations provided by the agents and thus can perform better interactions.

1.3 Aim of the Study

This study investigates the most effective way for PCAs to attract adequate attention in learner-leaner explanation activities and thus help them gain a deeper understanding of the problem. Based on the notions of learning science those stress the importance of learner-centered activities, the study focuses on a situation where a pair of learners' main activity is to collaboratively explain a key conceptual term to each other. During such activities, we investigated the use of a PCA that facilitates activities from a third-person point of view; for instance, providing (1) encouragement and (2) meta-cognitive suggestions. In this study, we investigate in particular the use of multiple PCAs that produce a social presence that could avoid the misuse of the agents and leads to more awareness of and attention to its suggestions and instructions. In addition, based on the studies of human-human collaborative problem solving, we investigate whether dividing the types of PCA facilitation can create a diversity of the group members and facilitate more aggressive behaviors to assist the explanation activities.

2 Method

2.1 Experimental Setting

To investigate our hypotheses, the present study set up an activity in which a pair of participants (called learners) participated. The learners consisted of one 118 students taking a psychology course who participated as a part of their coursework and were randomly assigned to three conditions that varied according to the PCAs' types of suggestions, number, and roles (see the section below for details). Learners were required to form explanations for a key term that was introduced in one of their course lectures, "figure ground reversal," and participated in groups of the same gender.

During the task, they used a desktop computer and a text-based chat application developed for this study (see Figure 1). All messages were sent and processed through the server. On the server side, all their text messages were analyzed by the PCA (details of this system are described in the next section). On the screen, there was a text area to input messages and a history of the conversation. In addition, a fundamental description of the key term was presented on their screen for basic guidance. Learners were instructed to explain the key term to each other by inputting text-based messages. As they proceeded with the task, a companion agent appeared on their screen and gave them suggestions as how to form a sufficient explanation (e.g., use examples or try to take turns), applauded them (e.g., for using important keywords), and/or gave back-channel feedback. They were also told that the agents would only participate as mentors to guide them and that their main activity was to discuss the key term and reach a mutual understanding of the key concept with their partner.

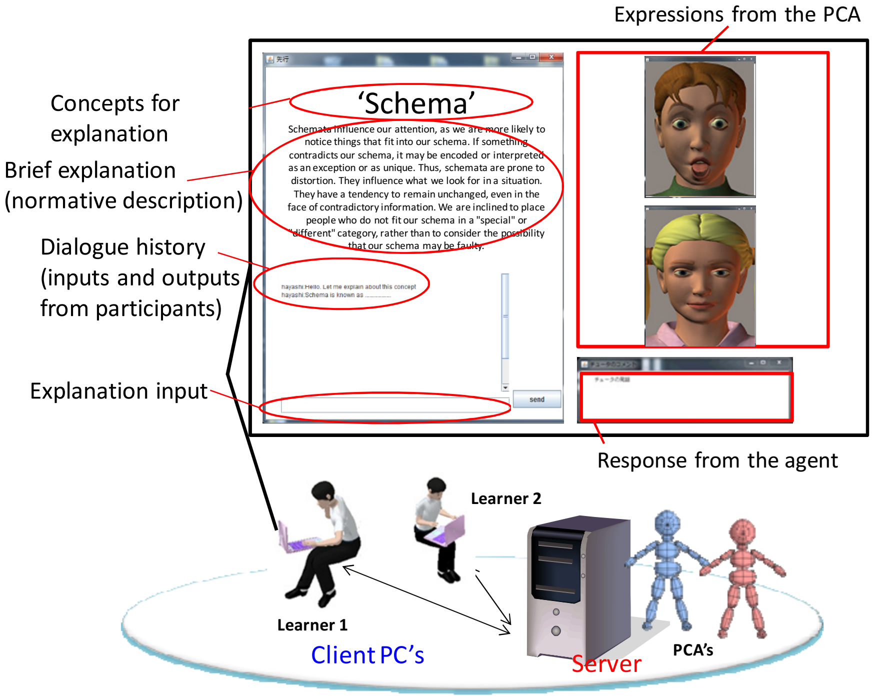

Fig. 1. The chat application (top) and experimental situation (bottom)

To analyze the learners' performance, they were required to take a pre- and post-test. In these tests, learners were asked to describe the meaning of the same technical words. As in Hayashi [19], the results were then compared to find out how the different conditions facilitated learners' learning of the concepts. In the comparison, descriptions were scored in the following way: 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. Two graders (with a correlation of 0.74) graded the answers and discussed their results before making any final decisions. The pre- and post-test scores were used to assess the degree of learning performance.

2.2 Structure of the PCA

The application was programmed in Java and designed as a server-client based network application using multi-cast processing methods. The system consisted of three sub-systems: (1) a chat interface, (2) server, and (3) agents. For the agent, three components comprised the system: (a) the input analyzer, (b) generator, and (c) output handler.

Input Analyzer. Important messages related to the explanation activities are stored in the keyword database. These keywords (phrases) were extracted from dialogues in Hayashi (2012) and each of their values was weighted by importance [19]. The system detects keywords from an inputted sentence and lists the patterns of those keywords. Next, the detected keywords were sent in an array to the generator along with information about the order of turn-taking. If no keywords were detected, a null result was returned.

Generator. The array list of keywords (phrases) transferred from the input analyzer is processed in the generator. The generator contains a rule-based system in the IF THEN format typically used in artificial intelligence. The system was originally developed in Java and uses forward chaining methods to constrain the keyword list patterns [15, 19]. When the rule-based matching is complete, one sentence is randomly chosen from the database to be the output sentence. The agent was designed to respond based on the related keywords. For example, if the system detects a constant rate of some keywords (phrases) related to 'explanations' (e.g., "for example", "this means", etc), then the system would generate (1) encouragement suggestions like "Yes!! Keep on like that and keep up with explaining. Try to use some original ideas too. Good job!!.". If a constant rate of keywords (phrases) related to ‘trouble’ (e.g., "don't know", "help", etc) were detected, then the system would generate (2) metacognitive suggestions from the database such as "I know this is a tough one. Why not explain it using examples from a daily situation."

Output Handler. Based on Hayashi (2012), the learners were given positive suggestions that were synchronized with facial expressions of the embodied agent [19]. Output text messages generated by the generator were next sent to the output handler. In this module, the system counted the number of words of the output messages and calculated the length of time needed to move the agent. Then the agent sent the text message along with the required motion time to each chat client system. The messages were given through chat dialogue while the virtual character moved its hands and lips. The agent graphics were designed by Poser8 (www.e-fronteir.com) and presented in frame-by-frame playback. A male or female agent was randomly used. Furthermore, a corresponding a male or female voice was generated using the Microsoft speech platform while the agents produced facial expressions.

2.3 Experimental Conditions

As explained in the previous section, the PCA used in this experiment produced prompts such as encouragement and meta suggestions. In various sessions, these two types of prompts were either both presented by one agent or presented separately by two PCAs. In the single condition (n = 38), learners engaged in the task using one PCA as a mentor. In the double condition (n = 42), learners engaged in the task using two PCAs. The PCAs in this condition did not have any distinct roles and both generated (1) encouragement and (2) meta suggestion prompts. To adjust for the amount of information quantity given the single condition, only one PCA generated a message per turn. In the split double condition (n = 38), learners used two PCAs as in the double condition, however, each agent had a distinct role. One PCA only generated prompts based on (1) encouragement and the other PCA generated messages based on (2) meta suggestions. The PCA expressing encouragement was labeled as the "mentor" and learners were told that this PCA would give them comments based on their conversation. The PCA that gave meta suggestions was labeled as the "expert" and learners were told that this PCA would sometimes give directions and comments of a more sophisticated nature.

3 Results

In this section, we present results from three different dependent variables: (1) length of descriptions, (2) pre- and post-test scores, and (3) number of turn-takings. The first variable, description length, was measured by the length of the rows of the post-test (written on a sheet where one row consists of 20 words). The second variable, pre- and post-test scores consist of the graded results of those descriptions. The analysis of variables (1) and (2) indicate the performance of the task. The third variable, number of turn-taking, is the number of transaction between the learners and focuses on the process during the explanation task.

3.1 Length of Descriptions

A statistical analysis was performed using a 2 (evaluation test: pre-test vs. post-test) × 3 (PCA condition: single condition vs. double condition vs. split double condition) mixed-factor analysis of variance (ANOVA). There was no significant interaction between the two factors ($F(2, 115) = 0.18$, $p = .83$) and there were no main effects between conditions ($F(2, 115) = 0.22$, $p = .97$). However, there were differences between the pre- and post- test, where learners tended to write longer answers on the post-test ($F(2, 115) = 101.38$, $p < .01$). However, these performance results only show the increase in quantitative outputs of the learners. In the next analysis we see how these results change qualitatively (i.e., analysis done by grading).

3.2 Pre- and Post-Tests

The gain scores were calculated by subtracting the pre test scores from the posttest scores. An analysis was performed using a one-way between-factor analysis of variance (ANOVA). There was a significant interaction ($F(2, 115) = 3.254$, $p < .05$). Next, analysis from multiple comparisons indicates that the average of test scores of the split double condition and double condition was higher than that of the single condition ($p < .05$ for both). There were no differences between the split double condition and double condition ($p = .55$). These results show that the use of multiple PCAs is more effective than using only a single PCA, supports hypothesis H1.

3.3 Turn-Taking

Statistical analysis was performed using a one-way between-factor analysis of variance (ANOVA). There was a significant interaction ($F(2, 56) = 6.571$, $p < .01$). Next, analysis from multiple comparisons indicates that the average number of turns of the split double condition was higher than that of the double condition and the single condition ($p < .01$ for both). Results also show that the number of turns of the split double condition was higher than that of the single condition ($p < .01$). This result indicates that using multiple PCAs with different roles may facilitate the turn-taking process. This may be due to the effects of the divisiveness of the roles of PCAs, which brings better impact on its presence. The results show that using multiple PCAs significantly influences turn taking when suggestions are made from various roles/viewpoints. This result supports hypothesis H2.

4 Discussion

The analysis shows that the use of multiple agents outperforms learning performance when using single agents in a learner-leaner centered collaboration task. This shows that the methodology of using multiple agents can produce a stronger PCA social presence and thus reduce the learners' tendency to ignore them. Avoiding such a lack of attention to or misuse of the PCA has been a big problem when designing these systems [3, 14, 15]. It is also difficult not to interrupt the learners' natural interactions and scaffolding should be made in an implicit way. Using multiple agents can afford such implicit psychological impact and thus provide more social presence compared to the ordinary use of a single agent. Since the number of prompts from the PCA was controlled to be the same in all conditions, the only effects on the learner's experience were the presence of the PCAs. However, there are some issues that need to be studied in the future, such as the amount of time learners spent actually paying attention to the PCAs. We are now conducting more experiments and collecting eye movement data to find how frequently learners look at the PCAs under various conditions.

The results in the analysis also show that when using multiple PCAs, it is better to split their roles rather than mix the roles together. Splitting the roles of the PCA brings more variety to the group members and thus provides more PCA social presence. In addition, it may help the learners distinguish the types of content provided by the PCA. In this study, one agent (the mentor) was assigned to generate prompts based on keywords to provide learners with reflective thoughts about the keywords they were using. On the other hand, one agent (the expert) generated meta-suggestions and gave directions about how to think or make explanations. Such kinds of suggestions are useful when the learner is thinking what to put in a message or how to form explanations. Results from the conversational analysis show that learners using PCAs with different roles took more turns than PCAs with no distinct roles. This indicates that learners may have found it easier to capture the information provided from the PCA (expert) that gave directions on what to speak. On the other hand, where the learners interacted with PCAs with mixed roles, they may have been unable or found it difficult to capture the messages that included directions and meta-suggestions. This point could also be investigated by further detailed analysis about when the learners looked at or responded to each PCA.

5 Conclusion

The present study investigated the most effective interaction design to evoke the presence of an embodied PCA on a multi-agent platform while creating social awareness and engagement with the learners. A controlled experiment was conducted to investigate the effects of using such PCAs and their roles during pedagogical activities. In the experiment, pairs of students collaboratively formed explanations about a key concept taught in the classroom and PCAs joined their activities as peer-advisors. Results of the experiment show that learners who engaged with the multiple PCA gained a higher understanding of the concept than learners using a single PCA. In addition, learners using PCAs with distinct of roles such as the meta-cognitive advisor (expert) and the emotional supporter (mentor) enhanced better interactions. The results lead to implications such as the possibility of using the multi-agent platform to facilitate social awareness and help learners gain a better understanding of target concepts. Furthermore, using different PCA roles (e.g., “mentor” and “expert”) outperformed those who engaged PCAs having same roles in terms of amount of turn-taking activities thus facilitating explanation activities. The present study contributes to the knowledge about the design of PCAs that are effective at facilitating human-human explanation activities in learning. Future work includes the implementation of these findings to tutoring systems for use in classrooms and other learning situations.

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