The Role of Peer Agent's Learning Competency in a Trialogue-based Reading Intelligent System

Haiying Li, Qinyu Cheng, Qiong Yu, and Arthur C. Graesser

University of Memphis, Memphis, United States
{li5; qcheng; qyu1; graesser@memphis.edu}

Abstract. This paper investigates how the peer agent's learning competency affects English learners' reading, engagement, system self-efficacy, and attitudes toward the peer agent in a trialogue-based intelligent tutoring system (ITS). Participants learned a summarizing reading strategy in the compare-contrast text structure in the ITS. Results detected the significant main effect of the peer agent's learning competency on learners' performance and on engagement.

Keywords: learning competency · summarizing· engagement · self-efficacy

1 Introduction

Learning companion agents or peer agents have been included in the intelligent tutoring systems (ITSs) to facilitate learning [1,2]. The peer agent may provide correct or incorrect information, encourage or motivate the human learner, and collaborate or compete with the learner [3]. Previous work has shown the adoption of the peer agent impacts students' learning outcomes and system-self efficacy in one-on-one (i.e., peer agent and student) learning systems with limited pre-defined dialogue options [1,2]. However, relatively little work has investigated the effects of the peer agent's learning competency in trialogue-based learning systems.

Vygotsky's [4] zone of proximal development (ZPD) confirms the benefits of cooperative learning with peers. When compared to independent learning, students in peer learning appear to adopt more effective learning strategies by learning proactively in their thinking, questioning, and knowledge sharing [5]. A peer's learning competency can be broadly classified into high, middle and low [1,2]. A high-competency peer may tutor other students by providing feedback, hints and correct information, or by providing a model of the learning process [1,3]. When student peers have similar expertise and competency level, each student takes turns to model their learning and provide their perception of the content [5]. However, when there is a mismatch of competency and expertise between the student and the peer agent, the low-competency peer can enhance the student's self-efficacy beliefs and increase the student's self-esteem, confidence, and sense of responsibility [2].

Kim et al.'s study focused on a novice instructional design course in a one-on-one system. Whether their findings will hold true for other populations, academic skills, or in one-on-two trialogue-based learning systems is still unclear. The present study attempts to replicate these findings with the English as Foreign Language (EFL)

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learners as the population, the summarizing strategy as the target academic skill, and a trialogue-based intelligent system as the learning setting. We designed two conversational computer agents in the ITS, a teacher agent and a peer agent, and investigated four research questions: (1) Does the high-competency peer agent improve the EFL learners' reading performance, and (2) enhance the EFL learners' positive attitude toward the peer agent? (3) Does the low-competency peer agent enhance the EFL learners' engagement and (4) the EFL learners' system self-efficacy?

2 Method

Participants consisted of 47 Chinese EFL learners (68% female; Age: *M*=37, *SD*=8.80), who have studied English for at least 8 years. Each participant was randomly assigned into one of the three conditions: low-competency, 20% of Jordan's answers were correct (*n*=18); middle-competency, 50% correct (*n*=15); and high-competency, 80% (*n*=14) based on gender. Actually, more participants would like to participate in the study, but later they rejected because of the requirement for their social security number for being paid. This resulted in an uneven distribution in the conditions. They first took the pre-survey (30 minutes), then interacted with the agents (20 minutes), and finally completed the post-survey (10 minutes). The pre-survey consisted of basic demographics questions, self-efficacy survey questions [6] (see Table 1), and the Gates MacGinitie reading test [7]. Participants were paid $15 for this one-hour experiment.

Participants learned a summarizing strategy in a compare-and-contrast text structure. The strategy involves the detection of the signal words that signify similarities and differences between two things/persons, and the identification and the justification of the good summary. The summarizing strategy lesson also prompts learners to provide a justification of good summaries. The mastery of these skills was evaluated by analyzing the quality of the learners' responses to the related reading comprehension questions. The reading comprehension questions were primarily multiple-choice questions with three options per question. Only one open-ended question was asked, which prompted participants to provide a justification for a good summary. All of answers were automatically evaluated by the system. To assess the open-ended response, the semantic match between a learner's verbal input and the expectations were evaluated by Regular-Expressions and latent semantic analysis. See Li, Shubeck and Graesser [4] for more details about the automatic scoring and rubrics.

The self-reported engagement after this reading was accepted as the engagement score, with 6-point scale from 1 (not at all engaged) to 6 (very engaged). The post-survey consisted of questions that gauged the students' system self-efficacy and attitudes toward the peer agent (see Table 1) with the same scale as prior self-efficacy.

3 Results and Discussion

Prior and post system self-efficacy and attitude toward the peer agent used in the Principal Components Analysis (PCA) to extract one component, respectively, named as prior self-efficacy, system self-efficacy, and attitude (see Table 1).

The prior self-efficacy component explained 62.93% of the total variance, and its regression score was performed on a One-way ANCOVA. Results showed there was no difference in participants' prior self-efficacy, $F(2,44)=.194$, $p>.05$, $M=1.53$, $SD=.504$. The regression score of prior self-efficacy was used as a covariate along with pretest reading score in the analyses. The system self-efficacy component explained 84.78% variance, and the attitude component, 71.24%. Both regression scores were used as dependent variables along with reading score and engagement score.

Table 1. PCA for Prior Self-efficacy, System Self-efficacy and Attitude toward Peer Agent

Items in Prior Self-efficacy	Loadings	Community
If I can't do a job the first time, I keep trying until I can.	.838	.703
Failure just makes me try harder.	.837	.701
When I have something unpleasant to do, I stick to it until I finish it.	.755	.570
When I make plans, I am certain I can make them work.	.737	.543
Eigenvalue	2.520	
Items in System Self-efficacy	Loadings	Community
The agents are helpful in learning reading strategies.	.964	0.929
This system could help me improve my reading comprehension.	.963	.927
The strategies could help me improve my reading.	.903	.815
A conversational discussion is a more valid assessment.	.849	.720
Eigenvalue	3.391	
Items in Attitude Toward Peer Agent	Loadings	Community
I enjoy reading with Jordan.	.870	0.756
I like Jordan very much.	.841	0.707
I like Jordan's reading to be better than me.	.821	0.674
Eigenvalue	2.137	

The ANCOVA on reading scores detected a significant main effect with the control of prior self-efficacy, $F(2,38)=3.47$, $p<.05$, $R^2=.241$. Results revealed marginal significant differences between low ($M=8.25$, $SD=1.406$) and high ($M=8.58$, $SD=1.436$), $F(1,38)=4.63$, $p=.076$, and low and middle ($M=8.30$, $SD=1.436$) conditions, $F(1, 38)=5.452$, $p=.075$. These findings suggest EFL learners who worked with both high- and middle-competency peer agents achieved higher reading performance than those with the low-competency agent in the trialogue-based ITS. These findings also suggest that the high-competency agent facilitates learning not only the novice knowledge on the instructional design [2], but also the reading strategies.

The ANCOVA revealed a marginal significant main effect on engagement with the control of prior reading score, $F(2,38)=2.540$, $p=.092$, $R^2=.182$. A marginal significant difference existed between low ($M=4.86$, $SD=1.150$) and high ($M=4.69$, $SD=1.351$) groups, $F(1,38)=4.96$, $p=.096$. These findings suggest learners who work with the low-competency agent tend to be more engaged in learning than those with the high-competency agent [2]. The majority of participants achieved extremely low pretest scores and consequently may have perceived their reading abilities as "low". This perception may have influenced reported self-efficacy beliefs before the intervention. When low-achievers work with the low-competency peer agent, they may find another person is worse than themselves. With this in mind, their confidence may

increase, which would improve their overall engagement with the system. However, when low-achievers work with a high-competency agent, they may not experience the increase in confidence, which may lead to their lower engagement reports.

Results did not show any significant effects of competency on system self-efficacy and attitude toward the peer agent. Our study failed to support the assertion that learners who work with the low-competency agent achieve higher self-efficacy [2]. However, a trend was found that learners who worked with the low-competency peer agent reported higher system self-efficacy (M=.09, SD=1.110), followed by the middle- (M=.03, SD=.681) and high competency groups (M=–.15, SD=1.179). Similarly, our findings failed to support the claim that learners who work with high-competency agents have a higher positive attitude towards the peer agent. [3]. However, another trend was found that learners who worked with the high-competency peer agent (M=.29, SD=1.053) reported they liked the system more than those in the middle (M=-.06, SD=.734) and low competency groups (M=–.17, SD=1.145). The insignificance effects may be caused either by the small sample size or by the influence of other individual differences, such as the experience of using educational techniques.

In conclusion, peer agents in educational intelligent systems do help to improve learning outcomes and enhance student engagement [1,2]. Specifically, the peer agent with the high or middle competency facilitates learners to achieve higher academic performance, whereas the low-competency agent enhances the learners' engagement. These findings are confirmed both by college students in learning the domain-specific academic skills [2], and by EFL learners in learning language reading skills. As both high- and low-competency agents benefit learners from different perspectives, the peer agent's competency in the educational ITS should be adaptively designed with the consideration of the trade-off of learning outcomes and engagement.

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