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How shared concept mapping facilitates explanation activities in collaborative learning: An experimental investigation into learning performance in the context of different perspectives

Shigen SHIMOJO* **& Yugo HAYASHI**
College of Comprehensive Psychology, Ritsumeikan University, Japan
*cp0013kr@ed.ritsumei.ac.jp

Abstract: Studies in collaborative learning have shown that explanation activities drawing on diverse perspectives facilitate deeper understanding and metacognition. However, it is difficult to develop an explicit understanding of others' perspectives and knowledge through communication in a computer-mediated environment. The present study investigated the use of a visually shared concept map interface, expected to facilitate dyadic awareness of different perspectives and thus improve learning performance during explanation activities. In this study, each dyad built a concept map about a key technical term in psychology, and generated explanations of the term and generated explanations of the term on mutually accessible concept maps. We predicted that learners would be able to (1) gain deeper knowledge through the shared explanations; and (2) explain the key term from different perspectives or knowledge sets. Twenty-six university students participated in this experiment, and we assessed their performance through free recall tests before and after they used the concept mapping tool. Our findings showed that learners were able to (1) gain learning performance and (2) explain a concept based on different perspectives. We discuss the implications of our findings and suggest directions for further research on the development of learning support systems.

Keywords: Explanation Activities, Computer-Supported Collaborative Learning (CSCL), Perspective Taking, Concept Map

1. Introduction

Explanations generated and shared among learners in collaborative learning are important strategies to facilitate metacognition and sophisticated interactions (Chi, Leeuw, Chiu, & Lavancher, 1994; Miyake, 1986; Shirouzu, Miyake & Masukawa, 2002; Hayashi, 2019). When developing efficient computer-supported collaborative learning (CSCL) environments employing explanation activities, it is important to understand the type of interactions useful in the facilitation of such activities.

Drawing on Vygotsky's sociocultural learning theories (Vygotsky, 1980; Lave & Wenger, 1991), numerous studies in the cognitive sciences have focused on learner-to-learner collaborative learning (Roschelle,1992; Schwartz, 1995; Okada & Simon, 1997; Hayashi, 2018a). Throughout these studies, the importance of posing questions and developing explanations to share with peers in the facilitation of metacognition and deeper understanding has been emphasized (Miyake, 1986; Shirouzu et al., 2002). Past research in cognitive psychology has shown that self-explanation facilitates metacognitive processing, further supporting the implication that peer-to-peer explanation benefits the learning process.

What are the mechanisms that facilitate effective peer-to-peer explanation activities? Shirouzu, et al. (2002), through their investigation of a simple origami task, point out that the generation of peer-to-peer explanations provides individuals with an opportunity to externalize their particular perspectives and sharing it with their collaborators. The listener will interpret this externalized thought based on their own perspective, which could lead to a request for further explanation of the first individual's perspective. In this iterative process, reflective feedback between peers provides an opportunity to reconsider the context that was initially posed to the collaborator. Furthermore, the listener may interpret the content in a different way, providing the speaker with an opportunity to re-consider the content from a different perspective. This indicates that interactions based on different perspectives facilitate metacognition and improved content learning through the exchange of different perspectives.

Studies in cognitive science have explored the process of successful collaboration between participants holding different perspectives (Hayashi, Miwa & Morita, 2007; Hayashi, 2008b) and found that collaborative problem-solving based on different perspectives in a setting with constrained communication channels, including computer-mediated interactions, are more likely to fail (Hayashi & Miwa, 2011). On the other hand, richer environments where learners have access to multiple communication channels, are more likely to succeed in such type of activities. This leads us to consider the types of technology that can be used in CSCL environments to facilitate a successful exchange of knowledge and perspectives among peers.

Previous CSCL studies investigating the use of social awareness tools have explored the ways in which the use of such technology foster learning performance and support learner interaction (Dillenbourg & Fischer, 2007; Bodemer, 2011). For example, studies using shared concept-mapping that allows participants to observe different knowledge sets have demonstrated participants' ability to collaboratively obtain new knowledge (Engelmann & Hesse, 2010; Sangin, Molinari, Nüssli & Dillenbourg, 2011). In the study conducted by Molinari, Sangin, Dillenbourg and Nüssli (2009), dyads were able to access visualizations (individual concept maps) of their own and their partners' prior knowledge through both own and peer-generated maps. They found that the degree to which participants co-manipulate the same objects in the collaborative map was higher when they discussed identical information. This indicates that information provided by their partners helped learners gain deeper levels of understanding. However, the limitations of this study possess two problems. Firstly, the researchers did not analyze learning performance based on a pre-post design, which limits inferences about learners' process of knowledge acquisition. Secondly, the study did not focus on the mechanism through which different perspectives and knowledge were acquired in peer-to-peer interactions. It is therefore necessary to investigate the types of knowledge and perspectives that emerge through the whole process.

Against this backdrop, we conducted an experiment where individuals paired into collaborative learning dyads each built a concept map about a key technical term in psychology and generated explanations to each other while being able to see each other's concept maps. It was predicted that learners would be able to (1) gain deeper knowledge through the explanations (H1), and (2) explain the term from different perspectives or using different knowledge sets (H2).

2. Method

2.1 Research design and participants

For this experiment, 26 university students (male = 11, female = 15) were recruited and separated into 13 pairs. The average age was 20.7 (SD = 1.37) and the experiment utilized a factorial within-subjects design.

2.2 Experimental set-up

In the experiment, two PCs were prepared for use by participants. Two monitors were connected to the PCs; two video-recording devices (Sony, HDR-CX680) were set up; and Cmap software (https://cmap.ihmc.us/) for the development and synchronization of concept maps was installed on the PCs. This set-up allowed for the simultaneous production and sharing of concept maps, thereby enabling efficient sharing of knowledge and externalized experiences among participants.

In the experimental task, participants were not able to see each other, although they were able to do so in the face-to-face setting.

2.3 Procedure

The experiment consisted of two phases. Participants first read the material provided on the key psychological term (attribution theory) individually, and then developed their explanations of the term through concept-mapping, using the Cmap software. Before the collaboration, they were instructed to make the concept map about it explaining to each other by themselves. Prior to the explanation activity, participants developed concept maps individually to familiarize themselves with the system, after which they received instruction on concept maps (e.g. the use of concept maps in demonstrating relationships between concepts) and the use of Cmap software.

Next, participants had 15 minutes to study the learning material on attribution theory, followed by the middle-test to evaluate the extent of learners' gained knowledge on attribution theory. It was expected that learners would acquire more information following the middle-test, thus increasing the amount of generated content.

Participants were instructed to "freely write about attribution theory" as a test to assess participants' knowledge. As will be explained in the next section, this was conducted before they read the material(pre-test), after they finished reading(middle-test) and after the task(post-test). It was expected that effective interaction between learners during this task would enhance their post-test performance, compared to the pre- and middle-test conditions.

2.4 Dependent variables

Learning performance and lexical network analysis were set as dependent variables and expected to change between tests. As explained previously, the dependent variables were collected through three phases. The pre-test was conducted prior to starting the task and middle-test after they read the description to determine the change in the first variable. The post-test after collaborative learning using concept maps was conducted to determine changes in the experimental task.

Learning performance was assessed through coding, conducted by two coders. The first coder conducted all coding and the second conducted coding on 20% of the data, selected at random. Krippendorff's alpha coefficient was 0.96 and coding conducted by the first coder was used for analysis (Schneider & Pea, 2014). Coding was standardized as follows:

- naïve correct or not based on demonstrated knowledge: 1 point;
- participants provided an abstract answer based on demonstrated knowledge, without explanation: 2 points;
- participants' answers reflected demonstrated knowledge, but the answer or knowledge were incorrect: 3 points; and
- participants answered correctly based on demonstrated knowledge: 4 points.

In addition to these, one point was added for each of the following: using a concrete example; providing a unique explanation; demonstrating a new discovery through the explanation; and using own words instead of verbatim replication of the text.

The final dependent variable, lexical network analysis, focused on the lexical networks extracted from the responses to the middle- and post-tests. All the textual data from the middle- and post-tests were analyzed using morphological analysis, following the method proposed by Hayashi & Inoue (2015). We developed a lexical network for each phase and compared the results.

3. Result

3.1 First hypothesis: Analysis of the test evaluation scores

To test H1, we analyzed the changes in learners' scores on tests evaluating learning performance.

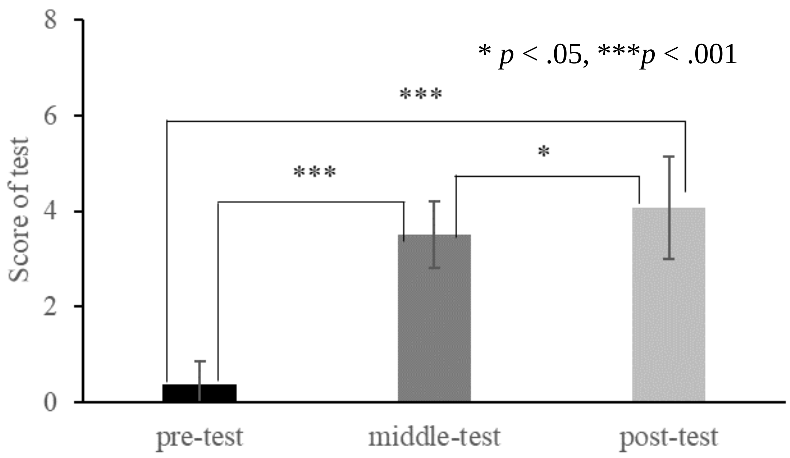

Figure 1. Comparison between mean test scores. The error bar indicates SD and asterisks indicate statistical significance.

Figure 1 depicts the mean test scores derived from coding, showing significant differences among the three test phases ($F\ (2, 25) = 173.78$, $p < .001$, partial $\eta^2 = 0.87$). Multiple comparisons using the Ryan's method revealed that pre-test scores were significantly lower than other tests ($p = .00$, $p = .00$), consistent with results obtained through comparison of the average numbers. Furthermore, the average post-test score was higher than that of the middle test ($p = .02$). This result supports our hypothesis, indicating that learners gain better understanding through explanation activities using the concept map.

3.2 Second hypothesis: Analysis of lexical networks of the test descriptions

Learners' performance on the middle and post-test was analyzed to explore the impact of different types of knowledge and perspectives on their performance, in consideration of H2. Pearson's correlation analysis was conducted to compare noun production between middle- and post-test individually, with the average established at -0.39 (SD = 0.22). All participants had a negative correlation between the two phases of the lexical network analysis, indicating that learners utilized different types of words between the middle- and post-tests. Figure 2 shows an example of one participant's lexical network, indicating its negative correlations.

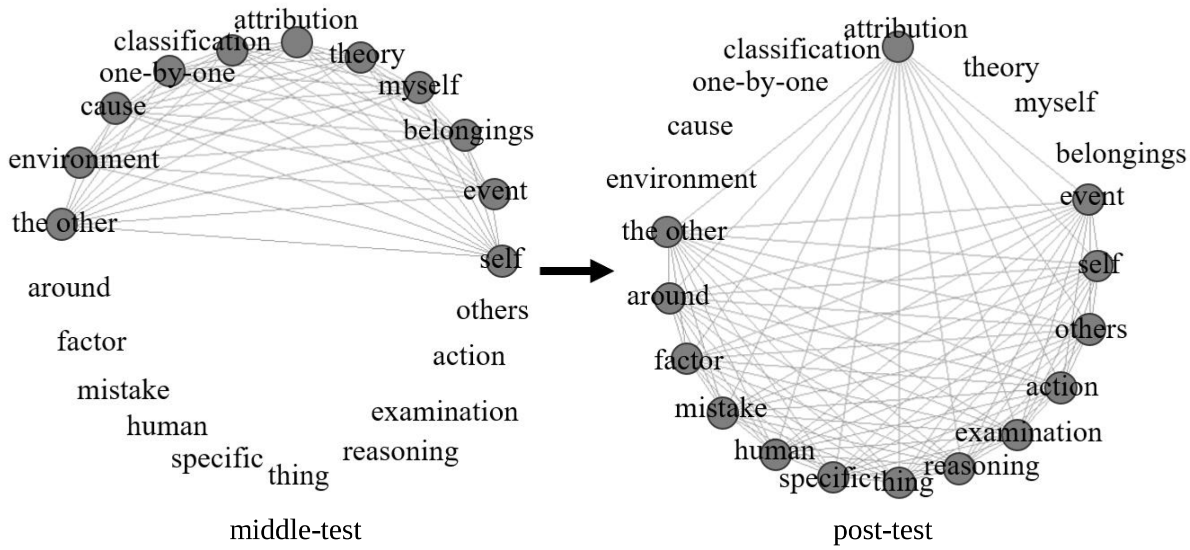

Figure 2. An example of one learner's lexical network. The correlation between lexical networks for this participant was -0.67.

Taking into consideration our finding that learners used different types of perspective and knowledge sets at post-test, this finding supports our second hypothesis.

4. Discussion and conclusions

The goal of this study was to conduct an experiment on collaborative learning dyads, where each dyad built a concept map on a key technical term in psychology, and generated explanations of the term to each other where they were able to see each other's concept maps. It was predicted that learners would able to (1) gain deeper knowledge through the explanations (H1), and (2) explain the key term from different perspectives or knowledge sets (H2). Results of the comparisons between the pre-, middle- and post-tests in terms of the amount of descriptions generated and the evaluation scores, suggest that the learners drew on more sophisticated learning strategies to gain knowledge. Moreover, results obtained when we tested H1 suggest that learning performance increased between the middle- and post-test phases, supported our first hypothesis. This indicated that learners actually gained more knowledge through interaction using the concept map. It is important to note that previous studies (Engelmann & Hesse, 2010; Sangin et al., 2011) did not conduct similar comparisons between test phases. Our study therefore expands the empirical evidence base through more sophisticated data collection.

The results obtained in testing H2 demonstrated the variety of perspectives and knowledge sets utilized between the middle- and post-test phases, supporting our second hypothesis. Through this analysis we were able to capture the degree to which learners used different types of knowledge during their explanation activities, using the concept map. Considering the analysis conducted in a previous study (Hayashi & Inoue, 2015), there was a drastic change in the use of different types of perspective and knowledge sets between the two phases. This could be attributed to the use of the concept map. However, as the goal of this study was not the clarification of this phenomenon, further investigation is needed to assess the effect of the concept map in this regard.

One future study will investigate the development of collaborative learning systems that enable the facilitation of increased awareness of other learners' knowledge, and we are considering the use of conversational agent to monitor learners' activities while also providing direct suggestions on the use of different perspectives and knowledge sets during their interactions. In our laboratory, we have conducted a number of studies on the use of these conversational agents (Hayashi, 2019; Hayashi, 2018a; Hayashi, 2018c; Hayashi & Inoue, 2015). However, to date there have been very few attempts to use these technologies to improve awareness of different perspectives and knowledge sets of collaborative partners, based on concept maps. The analysis from the current study provides an initial framework for the use of concept maps in generating different perspectives, suggesting that the use of conversational agent may yield even better results.

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