Chapter 2
A Knowledge Map Approach to Analyzing Knowledge Elaboration in Collaborative Learning

Abstract This study aims to analyze and quantify the level of knowledge elaboration as well as examine the relationships between knowledge elaboration and group performance. A sample of 527 college students voluntarily participated in this study. They were randomly divided into 161 groups of 3 or 4 to conduct collaborative learning. In total, 121 groups conducted face-to-face collaborative learning and 40 groups conducted online collaborative learning. The collaborative learning task covered six topics. The results indicated that the knowledge map method can be used to analyze knowledge elaboration processes. The weighted path length of the activation spanning tree was a strong predictor of knowledge elaboration. The level of knowledge elaboration was significantly related to group performance. The practical implications of the findings are subsequently discussed.

Keywords Knowledge elaboration · Collaborative learning · Information flows

2.1 Introduction

It has been widely acknowledged that knowledge elaboration is an important activity for promoting knowledge gains during collaborative learning (Denessen et al. 2008; Golanics and Nussbaum 2008; Stegmann et al. 2012). Knowledge elaboration is conceptualized as organizing, interconnecting, restructuring, and incorporating new information with existing knowledge (Reigeluth et al. 1980; Weinstein and Mayer 1986). Previous studies have revealed that knowledge elaboration can facilitate the retention of the new information (Anderson 1983; Wittrock 1989), enhance meaningful learning (Novak 2002), and stimulate the integration of information into prior knowledge (Kalyuga 2009). Researchers have further indicated that knowledge elaboration had a significant effect on students' learning performance (Denessen et al. 2008; Hwang et al. 2007).

Furthermore, previous studies adopted different methods to analyze knowledge elaboration, including questionnaires (Draskovic et al. 2004), coding schemes (Eysink and de Jong 2012), think-aloud protocols (Stegmann et al. 2012), and

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assigning different values (Ding et al. 2011). However, these methods ignore the domain knowledge and cannot measure the level of knowledge elaboration. In addition, as yet, agreement on how to measure the level of knowledge elaboration has not been reached. Little research has been performed to determine how to quantify knowledge elaboration accurately and objectively. The present study aims to analyze and measure the level of knowledge elaboration beyond existing methods and scopes. The following research questions were investigated in the study:

- How to analyze knowledge elaboration in collaborative learning?
- How to measure the level of knowledge elaboration in collaborative learning?
- Can learners' knowledge elaboration level predict group performance?

2.2 Literature Review

Knowledge elaboration can be achieved better through collaborative learning, because when group members interact with each other during collaborative learning they process information and explain information to others. Thus, they frequently have to integrate prior knowledge with new information. Researchers also believed that interacting with others could promote information processing and the adjustment of cognitive structures (Mitnik et al. 2009; Wibeck et al. 2007), which could stimulate elaboration of knowledge to a large extent.

However, there is no consensus concerning the method of measurement of the level of knowledge elaboration. Typically, there are two approaches to coding knowledge elaboration. The first one is to develop schemes based on the research purposes and questions. For example, Van Boxtel et al. (2000) analyzed the characteristics of elaboration of conceptual knowledge through collaborative learning. They developed a code scheme to analyze elaborative episodes by categorizing utterance or episodes into giving elaborated answers, elaborated conflict, reasoning, and cognitive example elaboration. They also found that elaboration of conceptual knowledge was related to the individual learning outcomes in concept-mapping conditions. Stark et al. (2002) coded the behavior of example elaboration into cognitive example elaboration, meta-cognitive example elaboration, and other types of elaboration. The cognitive example elaboration dimension included principle-based considerations, goal-explication or goal–operator combinations, noticing coherence, and elaboration of situation. The meta-cognitive example elaboration dimension included positive monitoring and negative monitoring. Other elaboration meant that task texts or single solution steps were read off repeatedly. They found that the elaboration training had a positive effect on the quality of example elaboration. In addition, Denessen et al. (2008) constructed five verbal interaction categories to code cognitive elaborations, including instrumental help seeking, help giving with labeled explanations, challenging help received with labeled explanations, acknowledging help with labeled explanations, and self-questioning with labeled explanations. They found that students with a high ability showed more cognitive elaborations than students with low ability. Eysink and de Jong (2012) coded elaborative activities into developing and testing hypotheses, relating and integrating, and giving (self-) explanations. Their results suggested that elaboration was indeed the key learning process.

The second approach is to assign different values to represent elaboration during interactions. For example, van Ginkel and van Knippenberg (2008) assigned "1" when information was completely ignored by all four group members, assigned "2" when one of the members mentioned a crucial item of information but no one responded to it, assigned "3" when one of the members mentioned an item of information and at least one responded to it, assigned "4" when one crucial piece of information was mentioned and at least two or three members clearly reacted to them, assigned "5" when one crucial piece of information got fully discussed and at least two members responded to it, assigned "6" when at least two pieces of crucial information were fully discussed, and assigned "7" when all three crucial items of information were fully discussed. While Ding et al. (2011) assigned "−1" when the message was off task and distracted learners' attention, assigned "0" when the message was a task-related message but did not improve the problem solving, and assigned "1" when the message was related to the task and contributed to the final success of the problem solving.

In fact, the level of knowledge elaboration cannot be measured accurately by the previous approaches. There are many reasons for this. First, the current coding schemes only centered on speech acts of interactions. Thus, knowledge elaboration was ignored, which runs counter to the conception of knowledge elaboration. For example, the approach to coding discussion transcripts into developing hypotheses, relating and integrating, and giving explanations did not consider the processes of knowledge elaboration. Second, coding discussion transcripts into different speech acts is very subjective and can be ambiguous. The main reason for this is that the purpose of human behaviors is too implicit to judge accurately. Third, coding discussion transcripts into speech acts cannot record the process of knowledge elaboration.

To sum up, the previous approach can neither quantify the level of knowledge elaboration nor measure knowledge elaboration precisely. Therefore, the present study sought to adopt the graph theory approach to analyze and measure knowledge elaboration. Existing studies have reported that the graph theory is a promising and appropriate approach for analyzing knowledge structure (Ifenthaler 2010; Pirnay-Dummer et al. 2010). Moreover, Hwang et al. (2013) revealed that representing knowledge and relationships between knowledge via graphs is an effective way of evaluating learners' knowledge structure. Thus, this study adopted a knowledge map analytical approach to analyze and quantify the level of knowledge elaboration. The following section will illustrate the indicators, the analytical method, and the empirical study in depth.

2.3 Indicators of Knowledge Elaboration

In order to measure the level of knowledge elaboration, we assume that the following two graphical indices can serve as indicators of knowledge elaboration. The first indicator is the weighted path length of the activation spanning tree. The weighted path length of the activation spanning tree was adopted in Zheng et al. (2015). A spanning tree consists of all the vertices and some of the edges of a graph (Hassin and Tamir 1995). The activation spanning tree is created by activating knowledge in collaborative learning. The weighted path length of the activation spanning tree can be calculated by Eq. 2.1:

$$\mathrm{WPL} = \sum_{i=1}^{N} W_i L_i \tag{2.1}$$

where WPL denotes the weighted path length of the activation spanning tree; W_i denotes the weight of vertex i, which equals its activation quantity; L_i denotes the path length of vertex I; and N denotes the total number of vertices.

The second indicator is the degree distribution index, which indicates the relevance of knowledge and the connectivity of the knowledge map (Barabasi and Albert 1999). The degree distribution index can be calculated using Eq. 2.2:

$$D = e^{\frac{-2K \times \sum_{i=1}^{N} I_i \ln I_i}{N}} \tag{2.2}$$

where $D(G)$ denotes the degree distribution index and I_i indicates the importance of node i; $I_i = \frac{d_i}{\sum_{i=1}^{N} d_i}$ K denotes the total edges of the knowledge map; and N denotes the total number of vertices.

In addition, the group performance was measured by the average difference between the pre-test and post-test of group members.

The present study formulated the following two hypotheses:

H1: The weighted path length of the activation spanning tree can predict the level of knowledge elaboration.
H2: The degree distribution index can predict the level of knowledge elaboration.

2.4 Method

2.4.1 Participants

The present study recruited 527 college students by advertising at one university in Beijing. They majored in education science, psychology, economics, and computer science. Of the sample, 86 % of them were female. All of the participants were randomly divided into 161 groups of 3 or 4 people. All of them had experience of collaborative learning from previous courses. They could only participate in the experiment once.

2.4.2 Collaborative Learning Tasks

The collaborative learning tasks included six topics. These six topics cover different subject matter, including strategies for problem solving in general, self-regulated learning case studies, the conception and application of curriculum objectives, the theory of graphs, the application of consumer behavior theory, and the theory and application of knowledge transfer. Four of these were conducted in face-to-face collaborative learning settings with the other two being conducted in online collaborative learning settings. Among the 161 groups, 32 groups completed the task about strategies of problem solving in general via the online collaborative learning tool, 8 groups completed the task about self-regulated learning case study via the online collaborative learning tool, and 31 groups completed the task about the theory and application of knowledge transfer via face-to-face collaborative learning. The remaining 90 groups completed the remaining three tasks via face-to-face collaborative learning. For these three tasks, 30 groups completed one task face-to-face. A real-life context was provided to participants for each collaborative learning task. Here is an example of the self-regulated learning case study.

> Mike is a primary school student and he is not very interested in learning. However, he can finish the assignment on time. Sometimes he watches TV when he does his homework. His parents can find some errors when they check his assignments. He seldom read books in his spare time. Sometimes he does his homework until 11 p.m. or 12 p.m. before the new semester begins. He also does not know how to improve his learning strategies.

Please analyze this case and illustrate what is wrong with Mike's approach. Please also recommend appropriate self-regulated learning strategies for Mike. In addition, how do you help students to improve their self-regulated learning abilities if you are a teacher? Please discuss these questions with your group members online and formulate your ideas. The final product will be a written document expressing your opinions.

2.4.3 Experimental Procedure

This study adopted a pre-test/post-test research design. The experimental procedure was as follows.

First, the collaborative learning tasks and test items were designed based on collaborative learning objectives. In this study, six collaborative learning tasks were designed. Furthermore, the sample was a knowledge map. This was no different to the previous studies that viewed participants as the sample. In this study, each group generated one knowledge map. Therefore, different kinds of knowledge were selected to generate different knowledge maps. Concepts, principles, facts or examples, formats, and processes and steps were included in this study. Each collaborative learning task focused on one or two kinds of knowledge.

Second, participants were recruited using posters advertising the study on campus. Before collaborative learning, all participants received the same instructions about the purpose and procedures of the experiment. Then they took the pre-test lasting about 20 min. After that, they were randomly divided into different groups.

Third, participants collaborated face-to-face or online for approximately 2 h in different time slots. If they collaborated online, the each member was placed in different labs and was unable to discuss face-to-face. When students conducted face-to-face collaborative learning, researchers videotaped the whole collaborative learning process to be used as a data source. If they collaborated online, logs were automatically recorded by an instant message tool and used as data sources. For each collaborative learning task, there were about 30 groups participating in collaborative learning. The final product of each collaborative learning task was a written text. After they finished collaborative learning, the post-test was immediately administered to ensure no interference. The test items of pre-test and post-test were same so as to measure group performance.

2.4.4 Data Analysis

This study adopted the knowledge map analytical method to analyze the level of knowledge elaboration. There are three steps when analyzing and calculating the level of knowledge elaboration.

First, an initial knowledge map is drawn, based on collaborative learning tasks via the analytical tool. The initial knowledge map can be drawn based on domain knowledge related to a collaborative learning task. The initial knowledge map represents the mutual relationships of the domain knowledge. Figure 2.1 demonstrates a portion of an initial knowledge map, where SM represents symbols, CN represents concepts, PF represents principles, FM represents formats, PS represents processes and steps, CS represents cognitive strategies, and FC represents facts and cases (Zheng et al. 2015).

Second, code and segment information flows generated by group members. The coding format of information is as follows:

<Time> <IPLi><cognitive level><information type><representation format><knowledge sub-map>.

In this coding, time refers to the start time of the information flows and IPL_i denotes the information processing of different learners. The cognitive levels include discriminating or distinguishing, remembering, comprehending, and putting into practice. Information types include learning goals, learning environment,

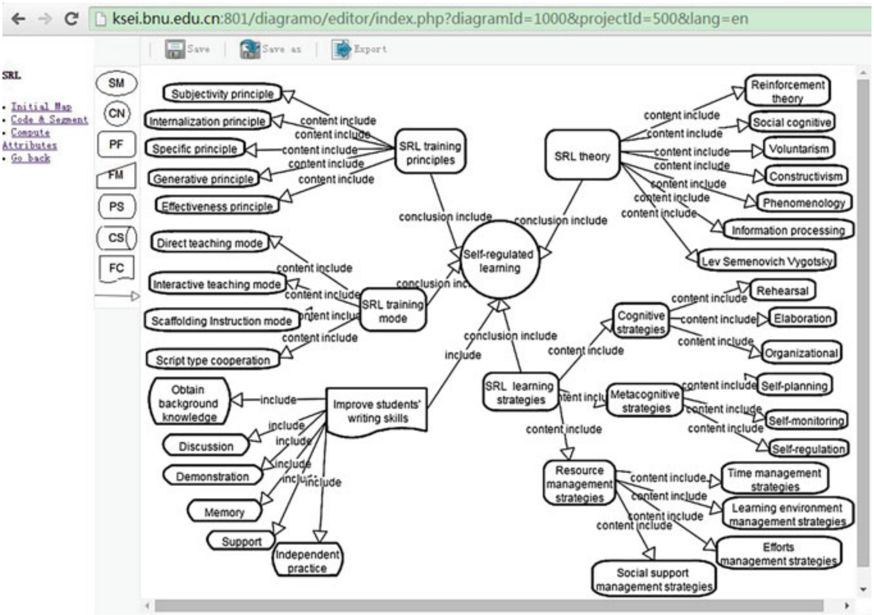

Fig. 2.1 A portion of the initial knowledge map

knowledge, questions, examples, management guidelines, and other information. The values of the representation formats include text, sound, graphs, photos, tables, videos, animations, objects, and body language. The knowledge sub-map, mapped by the output information flows, denotes pieces of knowledge and mutual relationships. Table 2.1 demonstrates the fragments of discussion transcripts from one group. In addition, Fig. 2.2 shows the fragments of coding and segmenting.

Table 2.1 Fragments of discussion transcripts

Time	IPL_i	Discussion transcripts
22″	IPL_2	Hello, do you remember whether we finished the similar task?
1′27″	IPL_1	No. This is the first time. There are lots of self-regulated learning theories
1′37″	IPL_3	The cases that I have learned are quite different from this one
1′56″	IPL_2	Oh. Really!
2′01″	IPL_1	Let's focus on this case
2′17″	IPL_2	I think there are many kinds of self-regulated learning strategies
3′08″	IPL_1	Yes, exactly. For example, resource management strategies, metacognitive strategies, and cognitive strategies
3′34″	IPL_2	Who can help to search for information?
4′06″	IPL_4	I can. I found meta-cognitive strategies include self-planning, self-monitoring, and self-regulation

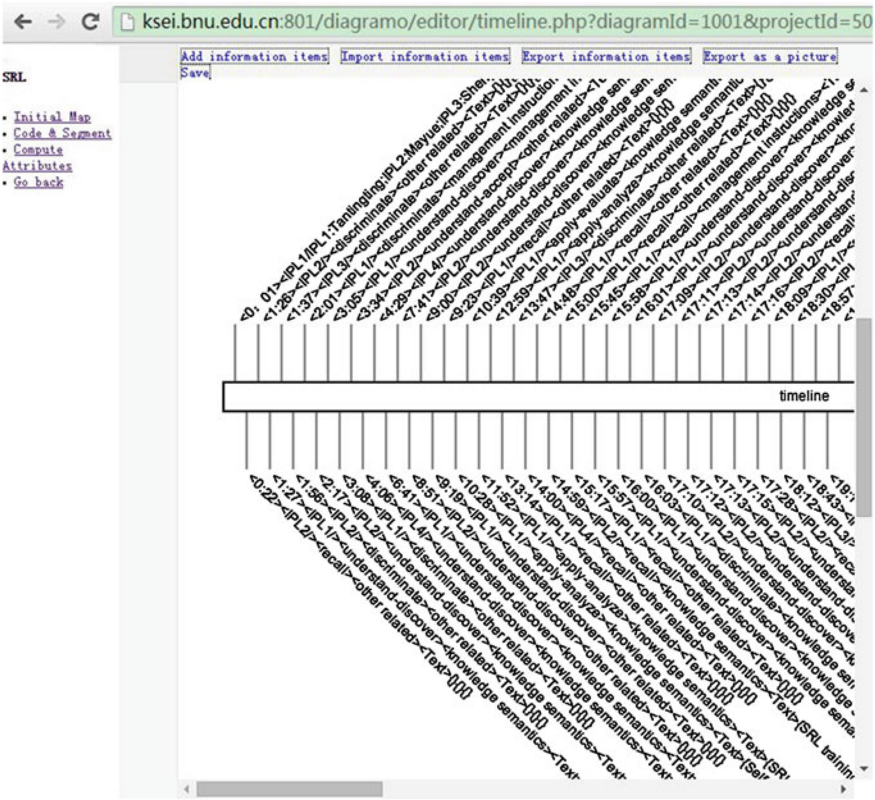

Fig. 2.2 Fragments of coding and segmenting

Third, the final knowledge map of each group was automatically generated. The level of knowledge elaboration was also automatically calculated by the analytical tool. Figure 2.3 shows the final knowledge map with weighted path lengths. The numbers next to the knowledge in Fig. 2.3 represent the weighted path lengths which can be calculated with Eq. 2.1 using the analytical tool.

2.4.5 Inter-rater Reliability

Two raters independently coded and segmented the information flows from the 161 groups via the abovementioned analytical tool. They also independently evaluated the 527 pre-test and post-test items. A percentage agreement index was adopted to compute the inter-rater reliability in this study. The reliability coefficient for coding information flows ranged from 0.87 to 0.92. All inter-rater reliability coefficients for

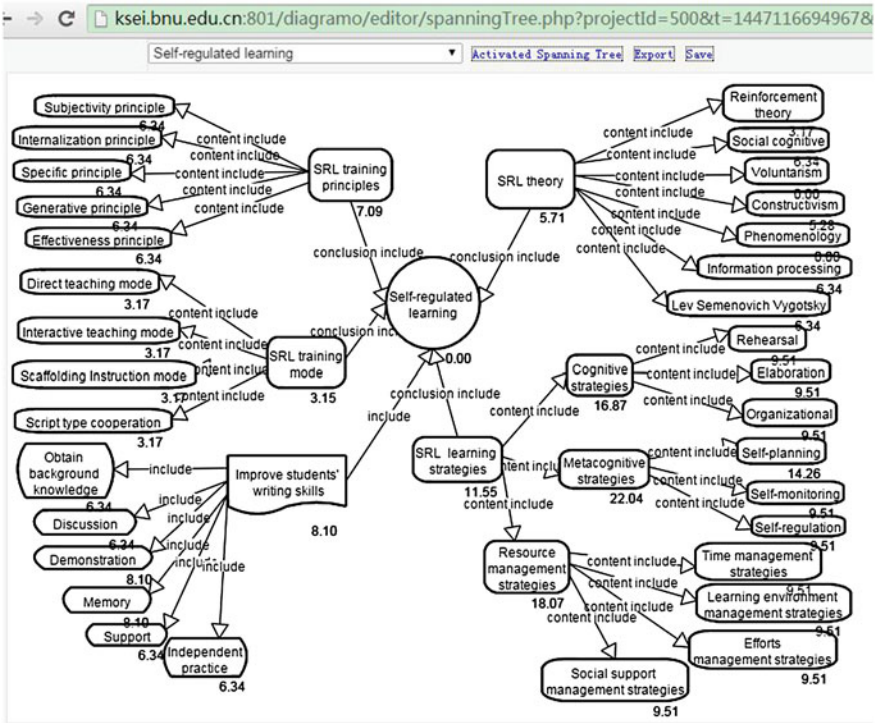

Fig. 2.3 Final knowledge map with weighted path lengths

assessing test items were above 0.9. The two raters discussed and resolved all discrepancies. These results indicated an excellent reliability for coding and assessing test items.

2.5 Results

In order to examine the two hypotheses in face-to-face collaborative learning and online collaborative learning, correlation analysis and regression analysis were conducted.

Table 2.2 shows the descriptive statistics for group performance, the degree distribution index, and the weighted path length of the activation spanning tree. In the face-to-face collaborative learning settings, the results indicated that the weighted path length of the activation spanning tree was significantly related to group performance ($r = 0.306$, $p = 0.001$). Furthermore, in order to examine the predictive validity of the weighted path length of the activation spanning tree on group performance, a linear regression analysis was conducted. The normal Q–Q

Table 2.2 Descriptive statistics in face-to-face collaborative learning settings

Items	Mean	Standard deviation
Group performance	24.45	14.61
The degree distribution index	6.303	0.844
The weighted path length of the activation spanning tree	844.63	447.69

plot was used to test normality of data. This test confirmed that the group performance variable had normal data. This is consistent with the hypothesis, in that the weighted path length of the activation spanning tree can predict group performance (adjusted R^2 = 0.086, β = 0.306, t = 3.503, p = 0.001). The weighted path length of the activation spanning tree can explain 8.6 % of the total variance. This indicated that the weighted path length of the activation spanning tree was the significant predictor. Therefore, H1 was supported in face-to-face collaborative learning settings. Moreover, the finding also revealed that the degree distribution index was positively related to group performance (r = 0.435, p = 0.000). In agreement with the hypothesis, the degree distribution index can also predict group performance (R^2 = 0.182, β = 0.435, t = 5.269, p = 0.000). The degree distribution index can explain 18.2 % of the total variance. These results indicated that the degree distribution index was another predictor in face-to-face collaborative learning. Thus, H2 was supported in face-to-face collaborative learning settings.

Table 2.3 shows the descriptive statistics for group performance n, the degree distribution index, and the weighted path length of the activation spanning tree in online collaborative learning settings. The findings indicated that the weighted path length of the activation spanning tree was significantly related to group performance (r = 0.356, p = 0.024). The results of linear regression analysis revealed that the weighted path length of the activation spanning tree can predict group performance (adjusted R^2 = 0.104, β = 0.356, t = 2.351, p = 0.024). The weighted path length of the activation spanning tree can explain 10.4 % of the total variance. Therefore, H1 was supported in online collaborative learning settings. However, the results also indicated that the degree distribution index was not related to group performance (r = 0.123, p = 0.448). Thus, the degree distribution index was not a significant predictor. Therefore, H2 was not supported in online collaborative learning settings.

Table 2.3 Descriptive statistics in online collaborative learning settings

Items	Mean	Standard deviation
Group performance	16.66	8.99
The degree distribution index	1734.35	795.53
The weighted path length of the activation spanning tree	1255.22	515.01

2.6 Discussion

To sum up, only the weighted path length of the activation spanning tree can be used to measure the level of knowledge elaboration both in face-to-face collaborative learning settings and online collaborative learning settings. The degree distribution index was not a significant predictor. The main reason for this is that the weighted path length of the activation spanning tree can measure the semantic richness of a knowledge map, namely the amount of semantic information contained in the knowledge map, while the degree distribution index only represents the topological characteristics of the knowledge map. Therefore, the weighted path length of the activation spanning tree can be adopted in future studies to measure the level of knowledge elaboration. Furthermore, the weighted path length of the activation spanning tree can be applicable for different types of knowledge, including concepts, principles, facts or examples, processes, as well as formats. In addition, consistent with previous studies (Noroozi et al. 2012; Stegmann et al. 2012), this study revealed that knowledge elaboration was positively associated with group performance. Furthermore, knowledge elaboration was found to significantly predict group performance in collaborative learning settings. Therefore, the weighted path length of the activation spanning tree can be adopted to measure the level of knowledge elaboration and predict group performance in future studies.

This study adopted the knowledge map analytical approach in order to analyze the process and level of knowledge elaboration. This innovative approach is based on graph theory, which focuses on the topology characteristics and semantic relationships of knowledge maps. The empirical results indicated that the semantic richness of the knowledge map was more important than the topology characteristics. The weighted path length of the activation spanning tree can better represent the richer semantic information than the degree distribution index. The knowledge map is considered as the sample in this new approach, because knowledge is relatively stable but learners are ever-changing. Therefore, this approach can be replicated in different contexts, representing a more scientific approach than previous studies.

This study has some implications for practitioners and educators. First, knowledge elaboration is helpful for meaningful and productive learning by integrating prior knowledge and new information (Kalyuga 2009). Therefore, the collaborative learning task should be designed to promote the link between prior knowledge and new information. Second, it is strongly recommended that prior knowledge related to the collaborative learning task should be reviewed before collaborative learning. Thus, learners find it easy to associate existing knowledge with new information. Third, examples, analogies, asking questions, and self-explanation can be adopted during collaborative learning in order to elaborate knowledge in depth. Fourth, summarizing what has been learned via drawing concept maps is very useful and effective for knowledge elaboration. Fifth, some useful tools such as the Cmap tool, Mindmanager, and iMindmap can be employed to organize ideas and concepts. Learners can also use these tools to collaboratively draw concept maps.

However, this study was constrained by several limitations. First, the weighted path length of the activation spanning tree only can explain 8.6 % of the total variance in face-to-face collaborative learning and 10.4 % in online collaborative learning, respectively. The prediction power is not very high. Therefore, the other indicators of knowledge elaboration need to be explored in future studies. Second, this study only examined how to measure the level of knowledge elaboration. How to promote knowledge elaboration needs to be investigated in future studies.

2.7 Conclusion

All in all, this study examined how to analyze and measure knowledge elaboration both in face-to-face collaborative learning and online collaborative learning. The findings indicated that knowledge elaboration processes and outcomes can be analyzed based on the knowledge map method. This innovative method views knowledge maps as the sample, which makes the study more scientific and replicable. The results also revealed that the weighted path length of the activation spanning tree can be adopted to calculate the level of knowledge elaboration both in face-to-face collaborative learning and online collaborative learning. Moreover, knowledge elaboration was significantly related to group performance. In the future, the level of knowledge elaboration can be employed to predict group performance without pre-test and post-test. In short, the main contribution of the present study lies in the indicator of knowledge elaboration and the knowledge map analytical method.

References

Anderson, J. R. (1983). A spreading activation theory of memory. *Journal of Verbal Learning and Verbal Behavior, 22*(3), 261–295.

Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks. *Science, 286* (5439), 509–512.

Denessen, E., Veenman, S., Dobbelsteen, J., & Van Schilt, J. (2008). Dyad composition effects on cognitive elaboration and student achievement. *The Journal of Experimental Education, 76*(4), 363–386.

Ding, N., Bosker, R. J., & Harskamp, E. G. (2011). Exploring gender and gender pairing in the knowledge elaboration processes of students using computer-supported collaborative learning. *Computers & Education, 56*(2), 325–336.

Draskovic, I., Holdrinet, R., Bulte, J., Bolhuis, S., & Van Leeuwe, J. (2004). Modeling small group learning. *Instructional Science, 32*(6), 447–473.

Eysink, T. H., & de Jong, T. (2012). Does instructional approach matter? How elaboration plays a crucial role in multimedia learning. *Journal of the Learning Sciences, 21*(4), 583–625.

Golanics, J. D., & Nussbaum, E. M. (2008). Enhancing online collaborative argumentation through question elaboration and goal instructions. *Journal of Computer Assisted learning, 24* (3), 167–180.

Hassin, R., & Tamir, A. (1995). On the minimum diameter spanning tree problem. *Information processing letters, 53*(2), 109–111.

Hwang, W.-Y., Chen, N.-S., Dung, J.-J., & Yang, Y.-L. (2007). Multiple representation skills and creativity effects on mathematical problem solving using a multimedia whiteboard system. *Educational Technology & Society, 10*(2), 191–212.

Hwang, G. J., Yang, L. H., & Wang, S. Y. (2013). A concept map-embedded educational computer game for improving students' learning performance in natural science courses. *Computers & Education, 69*, 121–130.

Ifenthaler, D. (2010). Scope of graphical indices in educational diagnostics. In D. Ifenthaler, P. Pirnay-Dummer, & N. M. Seel (Eds.), *Computer-based diagnostics and systematic analysis of knowledge* (pp. 213–234). US: Springer.

Kalyuga, S. (2009). Knowledge elaboration: A cognitive load perspective. *Learning and Instruction, 19*(5), 402–410.

Mitnik, R., Nussbaum, M., & Recabarren, M. (2009). Developing cognition with collaborative robotic activities. *Educational Technology & Society, 12*(4), 317–330.

Noroozi, O., Busstra, M. C., Mulder, M., Biemans, H. J., Tobi, H., Geelen, A., et al. (2012). Online discussion compensates for suboptimal timing of supportive information presentation in a digitally supported learning environment. *Educational Technology Research and Development, 60*(2), 193–221.

Novak, J. D. (2002). Meaningful learning: The essential factor for conceptual change in limited or inappropriate propositional hierarchies leading to empowerment of learners. *Science Education, 86*(4), 548–571.

Pirnay-Dummer, P., Ifenthaler, D., & Spector, J. M. (2010). Highly integrated model assessment technology and tools. *Educational Technology Research and Development, 58*(1), 3–18.

Reigeluth, C. M., Merrill, M. D., Wilson, B. G., & Spiller, R. T. (1980). The elaboration theory of instruction: A model for sequencing and synthesizing instruction. *Instructional Science, 9*(3), 195–219.

Stark, R., Mandl, H., Gruber, H., & Renkl, A. (2002). Conditions and effects of example elaboration. *Learning and Instruction, 12*(1), 39–60.

Stegmann, K., Wecker, C., Weinberger, A., & Fischer, F. (2012). Collaborative argumentation and cognitive elaboration in a computer-supported collaborative learning environment. *Instructional Science, 40*(2), 297–323.

Van Boxtel, C., Van der Linden, J., & Kanselaar, G. (2000). Collaborative learning tasks and the elaboration of conceptual knowledge. *Learning and instruction, 10*(4), 311–330.

van Ginkel, W. P., & van Knippenberg, D. (2008). Group information elaboration and group decision making: The role of shared task representations. *Organizational Behavior and Human Decision Processes, 105*(1), 82–97.

Weinstein, C. E., & Mayer, R. E. (1986). The teaching of learning strategies. In C. M. Wittrock (Ed.), *Handbook of research in teaching* (pp. 315–327). New York, NY: Macmillan Publishing Company.

Wibeck, V., Dahlgren, M. A., & Öberg, G. (2007). Learning in focus groups an analytical dimension for enhancing focus group research. *Qualitative Research, 7*(2), 249–267.

Wittrock, M. C. (1989). Generative processes of comprehension. *Educational Psychologist, 24*(4), 345–376.

Zheng, L., Huang, R., Hwang, G.-J., & Yang, K. (2015). Measuring knowledge elaboration based on a computer-assisted knowledge map analytical approach to collaborative learning. *Educational Technology & Society, 18*(1), 321–336.