Chapter 3
Analyzing Knowledge Convergence in CSCL: An Empirical Study

Abstract The assessment of collaborative learning is a central issue and its challenges are well known in this field. This study aims to analyze knowledge convergence through an innovative analytical method. A total of 192 participants were randomly divided into 48 groups of 4 people. They conducted online collaborative learning for 2 h. The process and outcome of knowledge convergence were analyzed by the knowledge map method in this study. The results indicated that the activation quantity of the common knowledge map is an effective indicator for knowledge convergence. Knowledge convergence can also significantly predict group performance in a CSCL context. The implications of the results and future studies are discussed in detail.

Keywords Knowledge convergence · Knowledge map · CSCL

3.1 Introduction

Collaborative learning is a coordinated and synchronous activity that aims to construct and maintain a shared conception of a problem (Roschelle and Teasley 1995). In order to obtain a shared understanding of subject matter, group members should have the same range of actions, the same level of knowledge, and a similar status concerning their community (Dillenbourg 1999). However, collaborators cannot achieve shared understanding without a certain degree of convergence. Researchers have indicated that convergence is more significant in explaining why collaborative learning leads to productive outcomes (Fischer and Mandl 2005; Roschelle 1996).

Convergence, especially knowledge convergence has attracted much attention in recent years (Kapur et al. 2011; Spemann and Fischer 2011). Convergence is an emergent behavior originating from the transactional interaction in collaborative learning (Kapur et al. 2011). Knowledge convergence is also viewed as evidence that collaborative learning has occurred (Roschelle 1996). Different researchers hold different opinions on knowledge convergence. However, it is widely

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acknowledged that knowledge convergence emphasizes increasing similarity with respect to knowledge among group members (Ickes and Gonzalez 1996; Jeong and Chi 2007; Weinberger et al. 2007).

Furthermore, it has been found that learners who converge in knowledge benefit more than learners who do not (Fischer and Mandl 2005). Collaborative learning has been considered as a mutual influence process through interactions among group members (Strijbos and Fischer 2007). However, how to assess the degree of mutual influence has not achieved a consensus. Researchers have also indicated that it is a big challenge to understand how to achieve convergence in collaborative learning (Fischer and Mandl 2005; Kapur et al. 2011). This study sought to understand and analyze the degree of mutual influence through the lens of knowledge convergence. The research questions addressed are as follows:

1. How to analyze knowledge convergence in collaborative learning?
2. How to measure the level of knowledge convergence in collaborative learning?
3. Can the level of knowledge convergence predict group performance?

3.2 Literature Review

3.2.1 Related Work

Knowledge convergence has been defined and operationalized in different ways. Roschelle (1996) believed that convergence refers to a mutual influence among collaborators. For example, part of a group has an impact on others, which in turn has an impact on their own learning activities. Ickes and Gonzalez (1996) considered knowledge convergence as the more uniform of cognitive responses among group members. Jeong and Chi (2007) defined knowledge convergence as an increase in common knowledge. Weinberger et al. (2007) operationalized knowledge convergence as knowledge equivalence and shared knowledge. Knowledge equivalence means that group members become more similar with regard to their knowledge. Shared knowledge refers to the concepts that all group members possess. Kapur et al. (2011) viewed knowledge convergence as an emergent behavior mediated by tools and artifacts from the perspective of complex systems. Therefore, convergent is a group-level phenomenon that cannot be attributed to an individual behavior.

Understanding the nature and mechanism of knowledge convergence is still a big challenge (Fischer and Mandl 2005). A sufficient level of convergence is only required to conduct a conversation on the same objects (Brennan and Clark 1996). However, a deep level of convergence means that collaborators form shared intentions and understandings of objects (Clark and Lucy 1975). So far, there has been considerable research examining how convergence occurs (Clark and Brennan 1991; Fischer and Mandl 2005; Kapur et al. 2011; Roschelle and Teasley 1995). As

Kapur et al. (2011) reported, convergence is an emergent behavior, which means that the simplicity of the individual-level can lead to the complexity of the collective-level (Bar-Yam 2003). Collaborative learning mainly occurs at the group level, thus, convergence can serve as a vehicle for unpacking how shared understanding is achieved.

Previous studies have adopted different approaches to measure the level of knowledge convergence. One approach is to adopt qualitative analytical methods to analyze convergence in collaborative learning. For example, the interaction analysis method, discourse analysis method, and conversation analysis method have all been adopted to examine the knowledge convergence processes (Barron 2003; Stahl 2005). These methods provide insightful accounts of knowledge convergence in collaborative learning. Another approach is to employ quantitative analytical methods to measure knowledge convergence. For example, Fischer and Mandl (2005) employed Euclidean distances of resource usage frequencies to measure knowledge convergence. Jeong and Chi (2007) argued that knowledge convergence refers to the increase in common knowledge. In their study they measured the level of knowledge convergence by subtracting the amount of common knowledge at the pre-test from the amount of common knowledge at the post-test. Weinberger et al. (2007) measured knowledge convergence through knowledge equivalence and shared knowledge prior to, during, and after collaborative learning. Knowledge equivalence is equal to the coefficient of variation of individual test scores. Shared knowledge can be calculated using the score of pair-wise comparisons of knowledge tests divided by the mean value of the group. Kapur et al. (2008) adopted content analysis to code discussion transcripts, and then they assigned different values to each interaction unit. A value 1 was assigned when the group discussion moved toward the goal of the activity. A value 0 was assigned when the group discussion maintained status quo. A value 1 was assigned when the group discussion moved away from the goal of the activity. The level of knowledge convergence can be calculated using the Eq. 3.1:

$$C = \frac{n_1 - n_{-1}}{n_1 + n_{-1}} \tag{3.1}$$

Additionally, Clariana et al. (2011) adopted the degree centrality of a graph to measure knowledge convergence. The degree centrality of a graph can be computed by Eq. 3.2:

$$C(G) = \frac{\sum_{i=1}^{v} [C(v^*) - C(v_i)]}{\max \sum_{i=1}^{v} [C(v^*) - C(v_i)]} \tag{3.2}$$

where $C(v_i)$ represents the degree centrality of the node v_i and $C(v^*)$ represents the highest degree of centrality.

To sum up, previous measures either depended on qualitative analysis of the interaction process, or on pre-test and post-test. However, convergence is a group-level phenomenon, which cannot be measured by individual behaviors. How to quantify the level of knowledge convergence objectively in collaborative learning still requires resolution.

3.2.2 The Present Study

This study aims to develop a more precise measurement of knowledge convergence in CSCL. In this study, knowledge convergence is defined as how much common knowledge was activated during and after collaborative learning. An innovative knowledge map analytical method was adopted to analyze the process and outcome of knowledge convergence. The following section illustrates this method and shows how to measure the level of knowledge convergence in detail.

3.3 Method

3.3.1 Participants

In total, 192 college students voluntarily participated in this study. They majored in educational technology, psychology, and educational science. Of these students, 85 % of them were female. The average age of the participants was 21 years old. All of the participants were randomly divided into 48 groups of 4 people. They had received experience of collaborative learning during previous courses. However, they never interacted with each other prior to this study. All of the students participated this study only once.

3.3.2 Collaborative Learning Tasks

The collaborative learning task was related to general problem-solving strategies. Participants needed to collaboratively illustrate strategies for solving ill-structured problems and identify differences between experts and novices. Of these groups, 48 completed the same collaborative learning task online. The final product was a written document about group members' solutions.

3.3.3 Procedure

The procedure comprised three phases, namely pre-test, collaborative learning, and post-test. In the first phase, the pre-test was administered to all participants. This pre-test took about 20 min to complete. Subsequently, 48 groups conducted collaborative learning online via Microsoft Service Network (MSN) in different labs in different time slots. It took about 2 h for each group to conduct collaborative learning. During collaborative learning, participants received no intervention except when they had procedural or technological problems. No specific training was performed for participants since they had prior experience of using MSN. In the last phase, the post-test was immediately administered to all participants after collaborative learning. The post-test took 20 min to complete. The items of pre-test and post-test were the same, i.e., open-ended questions about domain knowledge.

3.3.4 Measures

In this study, knowledge convergence was measured by the activation quantity of the common knowledge map, which is equal to the sum of the activation quantity of each vertex in the common knowledge map. This algorithm was developed in a previous study (Zheng 2015). The level of knowledge convergence can be calculated using Eq. 3.3:

$$C(G_1 \cap G_2 \cap G_3 \cap G_4) = \sum_{i=1}^{N} A_i = \sum_{i=1}^{N} \sum \frac{F * \log(d+2) * r}{\log(n * (D - d + 2))} \tag{3.3}$$

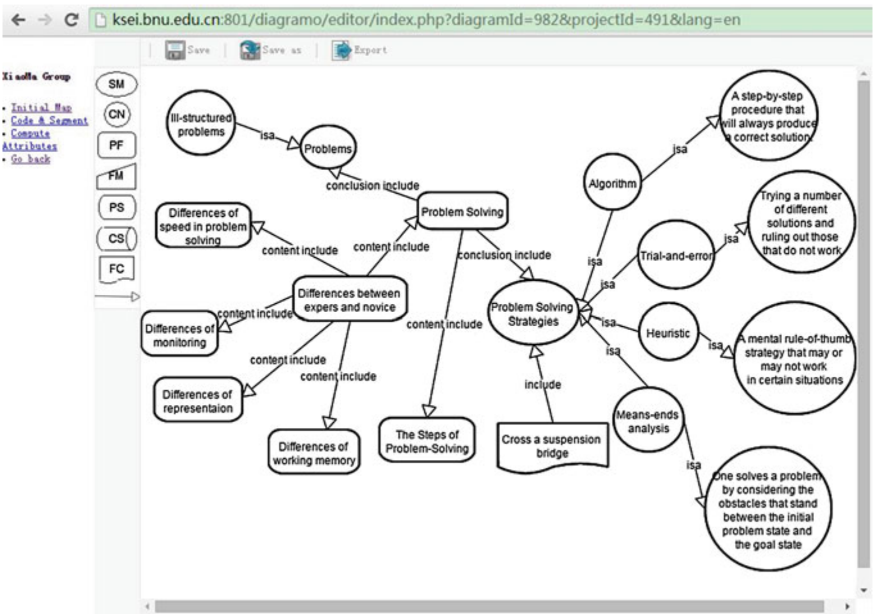

Fig. 3.1 A portion of the initial knowledge map

where $C(G_1 \cap G_2 \cap G_3 \cap G_4)$ denotes the level of knowledge convergence; $(G_1 \cap G_2 \cap G_3 \cap G_4)$ denotes the common knowledge map; G_1, G_2, G_3, and G_4 denote the knowledge map generated by each group member; A_i denotes the activation quantity of the common knowledge map, which is equal to $\sum \frac{F*\log(d+2)*r}{\log(n*(D-d+2))}$; and N represents the total number of vertices.

3.3.5 Data Analysis

This study adopted an innovative knowledge map analytical method and tools to analyze and compute the level of knowledge convergence. This new method is

Table 3.1 Fragments of discussion transcripts

Time	IPL_i	Discussion transcripts
6″	IPL_1	Hello, everyone. Let's get started
15″	IPL_2	This task is about the problem-solving strategies
20″	IPL_1	Yes, it is. It is related to the problem-solving strategies of crossing a suspension bridge
1′02″	IPL_3	Do you know any strategies of problem solving?
1′32″	IPL_1	Yes. For example, algorithm, heuristic, trial-and-error, and means-ends analysis method are strategies of problem solving
1′40″	IPL_2	Sure. I agree with you. Then what is the algorithm?
1′51″	IPL_1	An algorithm is a step-by-step procedure that will always produce a correct solution
2′10″	IPL_3	Oh. I see. I believe the algorithm is a very effective problem-solving strategy
2′15″	IPL_4	How about the heuristic?
2′20″	IPL_2	A heuristic is a mental rule-of-thumb strategy that may or may not work in certain situations
2′48″	IPL_1	You are right. I adopted the heuristic to solve the problem before. In addition, I have also used the means-ends analysis and trial-and-error before
3′19″	IPL_3	Oh. Yes. The trial-and-error refers to trying a number of different solutions and ruling out those that do not work. Then would you like to illustrate the means-ends analysis in detail?
3′53″	IPL_1	The means-ends analysis means that one solves a problem by considering the obstacles that stand between the initial problem state and the goal state
4′17″	IPL_2	But we should know that problems include ill-structured problems
4′25″	IPL_3	Sure. You know there are many differences between experts and novices in problem solving
5′01″	IPL_4	Really? Can you explain these differences?
5′16″	IPL_3	For example, experts and novices differ in representations of problems, speed of problem solving, working memory capacity, and how to monitor problem-solving processes
6′01″	IPL_4	Oh. Great. Let's talk about the steps of problem solving

comprised of three steps. First, it is required to draw the initial knowledge map based on the collaborative learning objectives and tasks. The initial knowledge map consists of nodes and edges, which represent knowledge and their mutual relationships, respectively. Figure 3.1 demonstrates the portions of the initial knowledge map.

Second, it is necessary to code information flows generated during collaboration, based on the rules of segmentation. These information flows can be automatically recorded by MSN. Each information flow can be coded into the following format:

<Time><IPL_i><Cognitive Level><Information type><Representation format><Knowledge sub-map>.

Table 3.1 shows fragments of information flows from one group, which can be coded and segmented into information sequences, as is shown in Fig. 3.2.

Third, calculate the activation quantity of the common knowledge map via the analytical tool. Thus, the activation quantity of each knowledge map can be calculated automatically using this tool. Figure 3.3 shows the final knowledge map with the activation quantity. This knowledge map is generated after collaboration. We can use the analytical tool to export the knowledge map generated by each group member. Then the common knowledge map can be formed correspondingly. Thus, the level of knowledge convergence can be computed using the Eq. 3.3.

The knowledge maps generated by each group member are shown in Figs. 3.4, 3.5, 3.6, and 3.7. The common knowledge map is shown in Fig. 3.8.

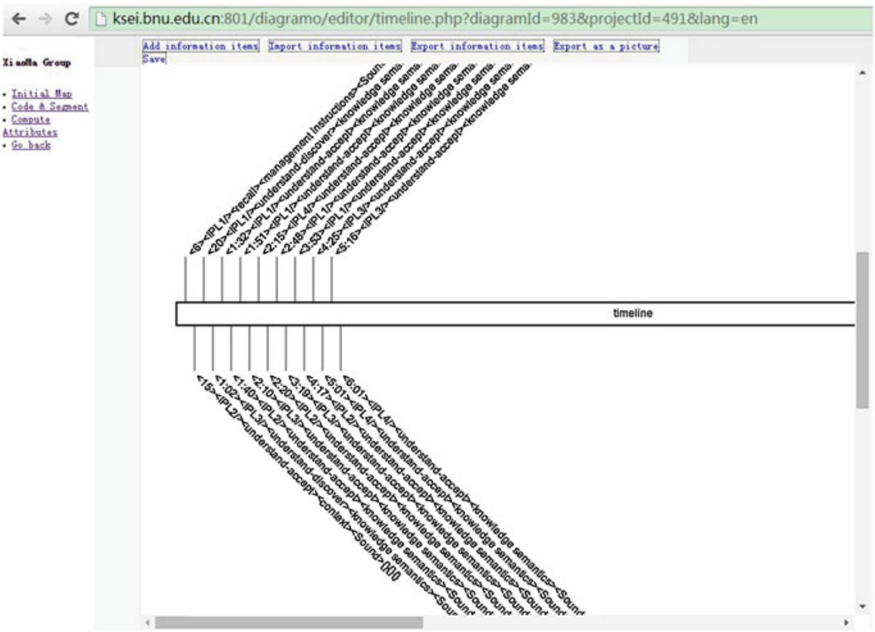

Fig. 3.2 Fragments of coding and segmenting

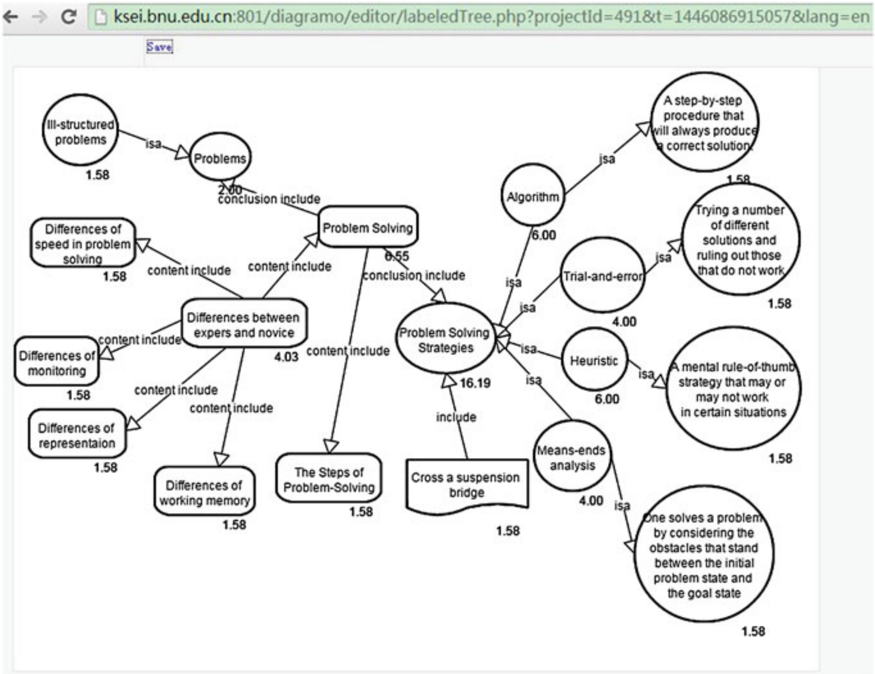

Fig. 3.3 Final knowledge map with the activation quantity

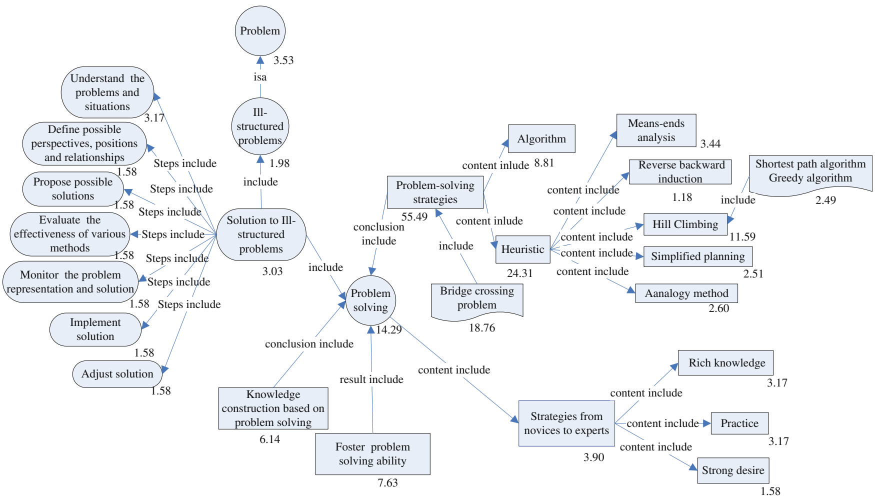

Fig. 3.4 The knowledge map generated by IPL_1

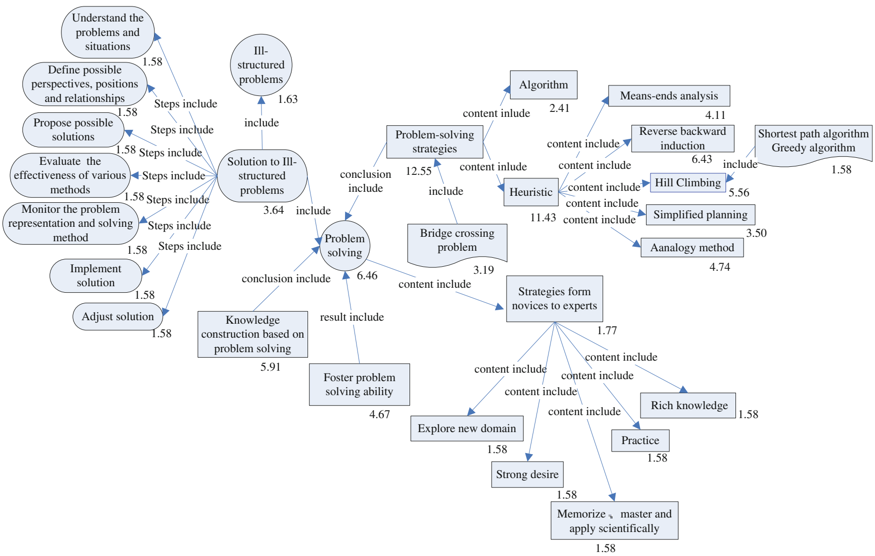

Fig. 3.5 The knowledge map generated by IPL_2

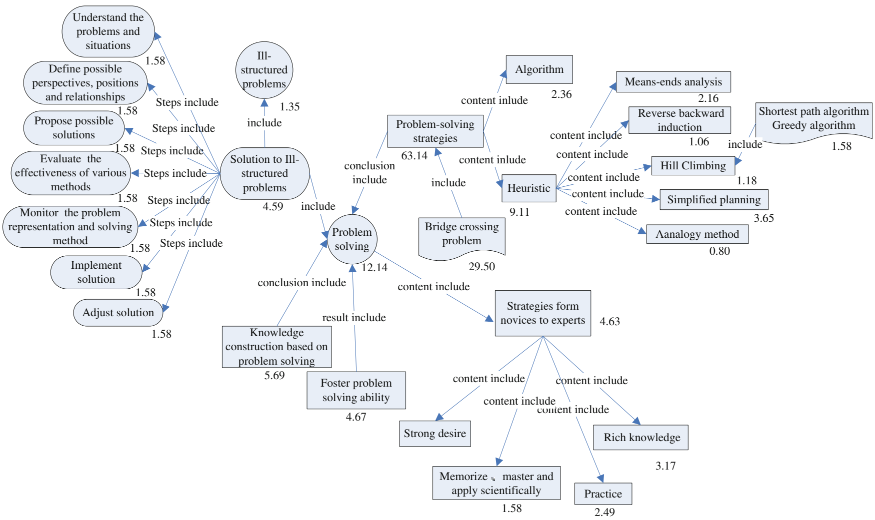

Fig. 3.6 The knowledge map generated by IPL_3

3.3.6 Inter-rater Reliability

Two trained raters independently coded and segmented all of information flows from the 48 groups. They also assessed the items of the pre-test and post-test. The

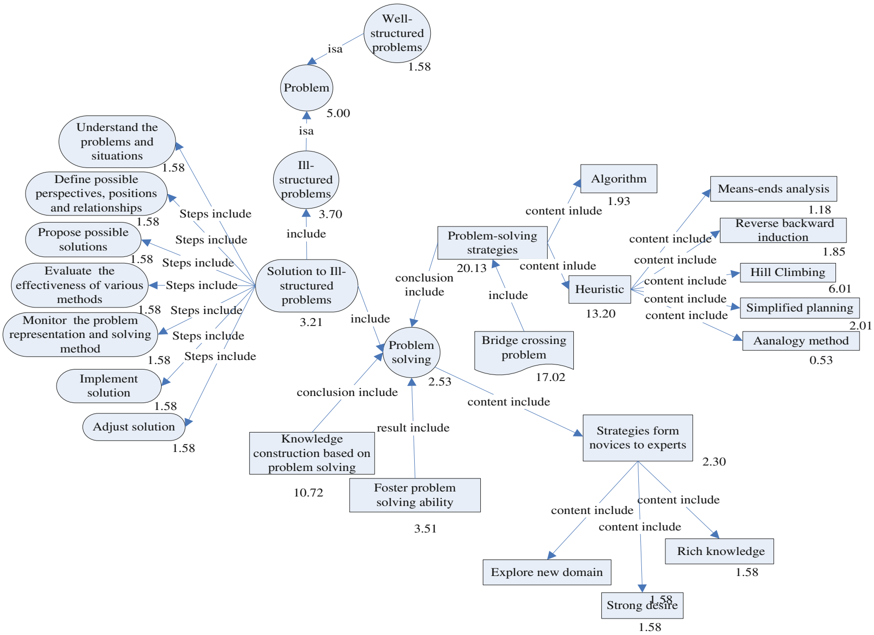

Fig. 3.7 The knowledge map generated by IPL_4

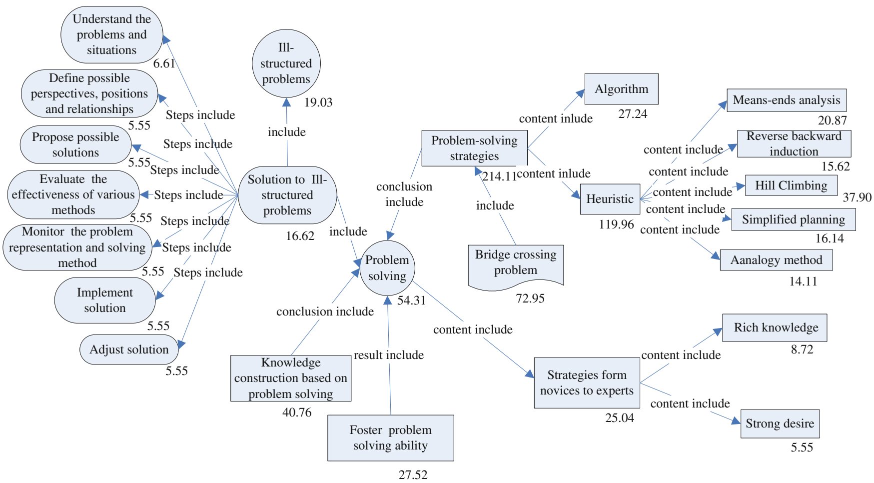

Fig. 3.8 The common knowledge map

percentage agreement achieved 0.83 for coding information flows and 0.85 for assessing the pre-test and post-test, respectively. All of the discrepancies were solved by face-to-face discussion.

3.4 Results and Discussion

In order to examine whether level of knowledge convergence can predict group performance, correlation analysis and regression analysis were conducted using SPSS 20.0 software. Table 3.2 shows the descriptive statistics for group performance and the level of knowledge convergence. The results indicated that the level of knowledge convergence was positively related to group performance ($r = 0.338$, $p = 0.019$). Moreover, linear regression analysis was conducted in order to examine the predictive validity of the level of knowledge convergence. The normal Q–Q plot was used to test normality of data. This test confirmed that the group performance variable had normal data. The findings revealed that level of knowledge convergence can predict group performance (adjusted $R^2 = 0.10$, $\beta = 0.338$, $t = 2.432$, $p = 0.019$). The level of knowledge convergence was found to explain 10 % of the total variance. The means that the level of knowledge convergence was a significant predictor. Therefore, the activation quantity of the common knowledge map can be adopted to measure the level of knowledge convergence.

This study adopted the innovative knowledge map method to analyze the process and level of knowledge convergence. The indicator of knowledge convergence was also developed and validated by the empirical study. The results indicated that level of knowledge convergence can be measured by the activation quantity of the common knowledge map. In addition, the level of knowledge convergence can significantly predict group performance. This result was in agreemen with Kapur et al. (2008) who found that the level of knowledge convergence was positively related to group performance. This finding was also confirmed in Cannon-Bowers and Salas' (2001) report that knowledge convergence was a strong indicator for group performance. Fischer and Mandl (2005) also found that learners who converged more in knowledge benefited more that those who did not. Our findings also yielded a similar result.

Convergence is the united arrival at a shared understanding of a problem or solution during collaboration (Hübscher-Younger and Narayanan 2003). Convergence is regarded as a positive phenomenon and proof that collaborative learning occurs (Fischer and Mandl 2005; Hübscher-Younger and Narayanan 2003; Roschelle 1996). Convergence on correct understanding and explanations is one of the goals of collaborative learning (Hübscher-Younger and Narayanan 2003). Furthermore, knowledge convergence is one important aspect of convergence, which focuses on knowledge building among group members. I also take the position that knowledge convergence can be achieved as a consequence of social

Table 3.2 Descriptive statistics of group performance and the level of knowledge convergence

Items	Mean	Standard deviation
Group performance	13.41	6.67
The level of knowledge convergence	122.77	115.02

interactions during collaboration. Moreover, mutual influence and reciprocity during collaborative learning can also lead to knowledge convergence.

However, it is so difficult to reach convergence in knowledge at the beginning of collaborative learning. Usually, group members have divergent ideas at first because they have different backgrounds and different levels of prior knowledge. Subsequently, they maybe become convergent because of social interaction. Sometimes they become more divergent after a long and heated discussion. This means that divergence comes in advance of convergence. However, this kind of divergence is perhaps helpful because sometimes convergence can be achieved only after divergence. Previous research also reported that divergence had a positive influence on convergence (Hoadley and Enyedy 1999; Jorczak 2011; Stahl 2002). This is because convergence can be achieved only if the conflicts or misconceptions appearing in the process of divergence are jointly solved. Generally speaking, moving from divergence to convergence is very common in collaborative learning.

In order to reach knowledge convergence, external support is necessary in collaborative learning since knowledge convergence cannot occur automatically. These support mechanisms include external representation tools, shared environments, and teacher facilitation. Earlier studies indicated that collaboration scripts were effective tools for support and promotion of knowledge convergence (Fischer and Mandl 2005). In addition, previous studies also indicated that group knowledge awareness tools can promote knowledge convergence (Dehler et al. 2009). Therefore, specific tools to support shared input are necessary. It is essential to be aware of group members' status in order to reach knowledge convergence. Of course, teachers can guide group members to be more convergent through different kinds of intervention. For example, teachers can remind group members when they are off-topic or deviating from the target.

This study adopted the innovative knowledge map approach to analyze the processes and outcomes of knowledge convergence. The level of knowledge convergence can be calculated by the activation quantity of the common knowledge map after collaboration. Thus, the outcome of knowledge convergence can also be visualized and represented through this knowledge map analytical method. This method provides insights into how group members become convergent in knowledge after collaboration. The common knowledge map can be generated using the analytical tool at any time. Thus, how knowledge convergence evolves over time can be clearly demonstrated through this method.

This study has several implications for teachers and practitioners. First, convergence should be encouraged because it is evidence of collaborative learning. Knowledge convergence indicates that knowledge building by group members has achieved a higher level. Second, some external representation tools should be provided for collaborators so they can achieve knowledge convergence in the shared collaborative learning environment. Third, divergence is permitted since divergence to some extent can lead to convergence. Knowledge convergence is a spiral and evolutionary process. Fourth, teachers should intervene at the appropriate time when they find collaborators are struggling to become convergent in knowledge. Finally, negotiation of conflicts, multiple cycles of explanations and clarifications, and a warm collaborative learning atmosphere help students reach a higher level of convergence.

This study was constrained by several limitations. First, the predictability of the indicator is not very high and still needs to be improved in future studies. Currently, the activation quantity of the common knowledge map only explained 11 % of the total variance. Second, all of the participants completed only one collaborative learning task. Future studies will examine the predictability of the indicator through multiple kinds of tasks. Remember that the sample of this study is the knowledge map. Usually, different tasks contain different kinds of knowledge. Therefore, other kinds of collaborative learning tasks need to be designed in future studies. Third, sample size needs to be enlarged in future studies. It would also be very interesting to explore whether the findings of this study are applicable to other contexts.

3.5 Conclusion

This study adopted an innovative knowledge map approach to analyzing the level of knowledge convergence in a CSCL context. The results indicated that the activation quantity of the common knowledge map can be adopted to measure the level of knowledge convergence. In addition, knowledge convergence can significantly predict group performance in a CSCL context. Furthermore, the knowledge map approach is also an effective method for quantifying the level of knowledge convergence. Thus, group performance can be assessed through the lens of knowledge convergence. Knowledge convergence serves as a vehicle which is able to shed light on the nature of collaborative learning. Knowledge convergence can also provide insights into how group members influence each other. The main contribution of this study is to propose a new analytical method and an effective indicator for measuring the level of knowledge convergence in CSCL settings.

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