Measuring Knowledge Elaboration Based on a Computer-Assisted Knowledge Map Analytical Approach to Collaborative Learning

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ABSTRACT

The purpose of this study is to quantitatively measure the level of knowledge elaboration and explore the relationships between prior knowledge of a group, group performance, and knowledge elaboration in collaborative learning. Two experiments were conducted to investigate the level of knowledge elaboration. The collaborative learning objective in the first experiment concerned the understanding of curriculum objectives, and that of the second experiment was related to the theory and application of consumer behaviour in microeconomics. A total of 91 undergraduate students participated in the first experiment and 94 participated in the second experiment. Students were randomly divided into 30 groups of three or four in each experiment. Students’ interactions were analysed based on the computer-assisted knowledge map analytical approach to measuring the level of knowledge elaboration. Empirical evidence from 60 groups demonstrates that the network structure entropy, degree distribution index, depth, and weighted path length of the activation spanning tree of the target knowledge map can be used for the precise measurement of knowledge elaboration. The results also reveal that knowledge elaboration is positively related to both prior knowledge of a group and group performance.

Keywords

Knowledge elaboration, Collaborative learning, Knowledge map, Computer-assisted instructions

Introduction

It has been widely acknowledged that collaborative learning facilitates knowledge gains (Dillenbourg, 1999; Stahl, 2011). Moreover, elaboration is an important activity for promoting knowledge acquisition during collaborative learning activities (Denessen et al., 2008; Goliancs & Nussbaum, 2008; Stegmann et al., 2012). Knowledge elaboration has been defined as organising, restructuring, interconnecting, and integrating new information with prior knowledge (Reigeluth et al., 1980; Weinstein & Mayer, 1986; Kalyuga, 2009). It can facilitate the retention of the target information (Anderson, 1983) and stimulate the reorganisation of information. Educators have pointed out that elaboration processes are necessary for meaningful learning, which emphasises the integration of new knowledge into existing knowledge (Novak, 2002; Kalyuga, 2009). The importance of elaboration is also supported by the generative model of learning put forward by Wittrock (1989), who indicated that new information should be meaningfully related to prior knowledge to generate connections between the informing information and memory representations in order to retain new information.

Researchers have further indicated that knowledge elaboration is the key factor in collaborative learning (Denessen et al., 2008). Many studies have reported that knowledge elaboration has positive effects on students’ learning achievements (Van Boxtel et al., 2000; Stark et al., 2002; Hwang et al., 2007; Denessen et al., 2008; Stegmann et al., 2012). However, most previous studies measured knowledge elaboration by questionnaire (Draskovic et al., 2004), by coding think-aloud protocols (Stegmann et al., 2012), by coding discussion transcripts into different categories (Eysink & de Jong, 2012), or by assigning values of -1, 0, and 1 (Ding et al., 2011) to assess knowledge elaboration. Such coding is subjective and ignores the domain knowledge when segmenting and coding discourse data (Suthers et al., 2010; Zheng et al., 2012). Little research has been performed to determine how to measure knowledge elaboration accurately and objectively.

The present study attempts to overcome the methodological limitations in measuring knowledge elaboration. The purpose of this study is to go beyond the scope of previous studies by measuring the level of knowledge elaboration based on the knowledge map analytic approach, and by examining the relationships between the prior knowledge of
a group, group performance, and knowledge elaboration. The knowledge map approach is quite different from concept mapping in terms of knowledge representation. The nodes in a knowledge map can denote symbols, concepts, principles and formulas, processes and steps, cognitive strategies, and facts and instances (Yang, 2010), while those in a concept map mainly denote concepts, facts and instances (Novak & Cañas, 2006). More specially, concepts are defined as abstract objects (Laurence & Margolis, 1999), or perceived regularities or patterns in events or objects (Novak & Cañas, 2006). Based on the knowledge map approach, the following research questions are investigated in this study:

- What are the indicators of knowledge elaboration from the perspective of graph theory and knowledge semantic properties?
- Does students’ knowledge elaboration level positively affect their group performance?
- Is students’ knowledge elaboration level positively related to their prior knowledge?

**Literature review**

Knowledge elaboration plays a crucial role in collaborative learning. When group members interact with one another, they need to explain large quantities of information about the learning material to others and therefore process information more deeply. Slavin et al. (2003) believed that elaboration can be achieved by explaining information to others when interacting during collaborative learning. Researchers assume that interaction with others promotes the processing of information and the modification of cognitive structures (Baker, 2003; Wibeck et al., 2007; Mitnik et al., 2009; Suthers et al., 2010). Therefore, interactions in collaborative learning can stimulate knowledge elaboration and consequently promote individual knowledge gains.

What is still unclear is the nature of knowledge elaboration in collaborative learning. Insights into measuring knowledge elaboration are an important step towards unravelling the nature of knowledge elaboration. However, there is no consensus regarding how to measure the level of knowledge elaboration in collaborative learning. De Leng et al. (2009) investigated elaboration by analysing the frequency and duration of activities related to inquiry, interpretation, and reflection recorded in log files and administering a questionnaire to assess students’ perceptions of the working process. Ding et al. (2011) endowed each message with an elaboration value: -1, 0, or 1. Many researchers have developed coding schemes to analyse discourse data to measure knowledge elaboration. In Table 1, different instruments for measuring knowledge elaboration via a coding scheme are presented.

<table>
<thead>
<tr>
<th>Instrument</th>
<th>Analytical focus</th>
<th>Coding scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>Van Boxtel et al. (2000)</td>
<td>Elaborative episodes</td>
<td>- giving elaborated answers</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- elaborated conflict</td>
</tr>
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<td></td>
<td></td>
<td>- reasoning</td>
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<tr>
<td></td>
<td></td>
<td>- cognitive example elaboration</td>
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<tr>
<td>Stark (2002)</td>
<td>Example elaboration</td>
<td>- meta-cognitive example elaboration</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- other elaboration</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- instrumental help seeking</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- help given with labeled explanations</td>
</tr>
<tr>
<td>Denessen et al. (2008)</td>
<td>Cognitive elaboration</td>
<td>- challenging help received with labeled explanations</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- acknowledging help with labeled explanations</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- self-questioning with labeled explanations</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- 1: information was completely ignored by all four group members</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- 2: one of the members mentioned a crucial item of information, but no one reacted to it</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- 3: one of the members mentioned an item of information and at least one of the members reacted to it</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- 4: one crucial piece of information was mentioned by at least one member and at least two of the other three members reacted to it</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- 5: one crucial piece of information was fully discussed by at least three members and integrated with other</td>
</tr>
</tbody>
</table>

van Ginkel & van Knippenberg (2008)  Information elaboration
information
- 6: at least two crucial pieces of information were fully discussed by at least three group members and integrated with other information
- 7: all three crucial pieces of information were clearly and fully discussed by at least three of the four members
- Providing explanations
- Asking questions
- Acceptance with further elaboration
- -1: the message was off task and distracted the students’ attention

Prinsen et al. (2009) Elaborated contribution

Ding et al. (2011) Knowledge elaboration values
- 0: the message was a task-related message but did not improve the solving process
- 1: the message was pertinent to the task and contributed to the final success of the problem solving
- Developing and testing hypotheses

- Relating and integrating
- Providing (self-) explanations
- The depth of cognitive elaboration can be computed by the duration of cognitive elaboration (multiply the number of segments by the length of the segments) according to think-aloud protocols

Stegmann et al. (2012) Depth of cognitive elaboration and argumentation-related cognitive elaboration
- The transcripts of argumentation-related cognitive elaboration was coded into claim, grounds, and qualification according to think-aloud protocols

There are some limitations to using these coding schemes to measure knowledge elaboration. Firstly, the coding schemes only focus on speech acts in discourse transcripts, such as providing explanations, asking questions, or acceptance with further elaboration. In fact, judging which messages belong to which types of speech act is both ambiguous and subjective (Strijbos, 2006). In addition, coding is very difficult because the purposes of humans’ speech acts are implicit; thus, the identification of speech acts is also subjective and lacks a reference point (Zheng et al., 2012). Secondly, these coding schemes ignore domain knowledge construction, which runs counter to the definition of knowledge elaboration. Thirdly, assigning each speech act to an isolated meaning does not record the indexicality of the meaning (Suthers et al. 2010). Therefore, it is necessary to develop a new method to precisely quantify knowledge elaboration.

Since the internal knowledge structures during the knowledge elaboration process cannot be directly observed, we seek to externalize them based on a graph theory approach. Previous studies have reported that graph theory is a promising educational diagnostic approach (Ifenthaler, 2010; Pirnay-Dummer et al., 2010). Furthermore, representing knowledge and relationships between knowledge in graphs has been recognized as being an effective way of evaluating students’ knowledge structure as well as helping them organize knowledge (Hwang, Yang, & Wang, 2013). Knowledge elaboration has been conceptualised as processes that connect new knowledge with existing knowledge structures (Weinstein & Mayer 1986). In this study, some measures from graph theory are employed to diagnose the level of knowledge elaboration.

Methodology

Development of knowledge elaboration indicators and the computer-assisted analytic tool

Indicators of measuring knowledge elaboration levels

In order to measure the level of knowledge elaboration, we designed a set of graphical indices to represent the structural and semantic properties of target knowledge maps, which are composed of the target knowledge selected and identified by designers according to the collaborative learning objectives. We hypothesize that the following attributes of knowledge maps can serve as indicators of knowledge elaboration.
Network structure entropy

Network structure entropy can represent the heterogeneity of the target knowledge map (Wu et al., 2007; Xiao et al., 2008; Hwang et al., 2010). Lower heterogeneity indicates that different nodes have an almost equal importance, while higher heterogeneity means that there are significant differences in the importance of nodes (Tan & Wu, 2004). Meanwhile, the higher heterogeneity of a knowledge map also indicates the more differences of elaborating knowledge. Network structure entropy can be calculated using formula (1) (Tan & Wu 2004):

$$E(G) = - \sum_{i=1}^{N} I_i \ln I_i$$  \hspace{1cm} (1)

where $E(G)$ denotes network structure entropy and $I_i$ denotes the importance of vertex $i$, with $I_i = \frac{d_i}{\sum_{i=1}^{N} d_i}$.

Additionally, $d_i$ and $N$ denote the degree of vertex $i$ and the total number of vertices, respectively. The degree of a vertex is the number of edges incident with the vertex.

Degree distribution index

The degree distribution index indicates the relevance of knowledge and the connectivity of the target knowledge map (Barabasi & Albert, 1999; Ifenthaler, 2010). Higher relevance and stronger connectivity represent that the group of students have effectively elaborated their knowledge during the collaborative learning process. The degree distribution index can be calculated using formula (2):

$$D(G) = e\left(-\frac{2K \sum_{i=1}^{N} I_i \ln I_i}{N}\right)$$  \hspace{1cm} (2)

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

Depth of knowledge map

The depth of the knowledge map can indicate the level of elaborating on target knowledge (Lund et al., 2007; Salminen, Marttunen & Laurinen, 2010). The depth can be calculated using formula (3):

$$\text{Depth}(G) = \sum_{i=1}^{N} \left(\text{depth}(K_i)\right) = \sum_{i=1}^{N} e^{\max(L(P_{i1}), L(P_{i2}), L(P_{i3}), \ldots, L(P_{im}))}$$  \hspace{1cm} (3)

where Depth $(G)$ denotes the depth of the knowledge map. $K_i$ denotes knowledge sub-maps. $P_{ij}$ denotes the simple paths of the knowledge sub-map, and $L(P_{ij})$ denotes the path length of the simple paths. A path in a graph is a sequence of edges which connect a sequence of vertices. A path with no repeated vertices is defined as a simple path. The path length is the number of edges in the path. $N$ denotes the number of knowledge sub-maps.

Breadth of knowledge map

The breadth of the knowledge map indicates the scope of knowledge elaboration (Lund et al., 2007; Salminen, Marttunen & Laurinen, 2010). It represents the breadth of the understanding of the subject matter. We adopt the diameter of the knowledge map to compute its breadth, as shown in formula (4):

$$\text{Diam}(G) = \max \max d(u, v) = \max \{d(u, v) \mid \forall u, v \in V(G)\}$$  \hspace{1cm} (4)

where $d(u, v)$ is the distance between vertices $u$ and $v$ in graph $G$. $V(G)$ denotes the set of vertices.
where Diam (G) denotes the breadth of the knowledge map and \( d(u, v) \) denotes the distance from vertex \( u \) to \( v \). The diameter of a graph is the maximum of \( d(u, v) \) over all vertices \( u \) and \( v \).

**Weighted path length of the activation spanning tree**

A spanning tree is composed of all the vertices and some (or perhaps all) of the edges of a graph (Hassin & Tamir, 1995). The activation spanning tree is generated through activating knowledge by the group of students. As is shown in Figure 1, arcs with arrows and nodes consist of the activating knowledge map, while the straight lines and nodes consist of the spanning tree of this knowledge map. The weighted path length of the activation spanning tree represents the semantic richness of a knowledge map, namely the amount of semantic information contained in the knowledge map. Higher semantic richness represents more amount of semantic information when the group of students elaborate knowledge. It can be calculated using formula (5):

\[
WPL = \sum_{i=1}^{N} W_i L_i
\]

(5)

Where \( WPL \) denotes the weighted path length of the activation spanning tree and \( W_i \) denotes the weight of vertex \( i \), which equals its activation quantity. The activation quantity of vertex \( i \) equals \( \frac{F \times \log(d + 2)^n r}{\log(n^2(D - d + 2))} \), where \( d \) denotes the number of the activated edges, \( D \) denotes the total number of edges that is incident with the vertex \( i \). \( F \) and \( r \) are adjustable parameters. The quantity of activation can measure the semantic properties of knowledge (Zheng et al., 2012). \( L_i \) denotes the path length of vertex \( i \). \( N \) denotes the total number of vertices.

![Figure 1. The spanning tree when activating knowledge](image)

**Hypotheses**

We assume that the abovementioned indicators can measure the level of knowledge elaboration. Thus, the following five hypotheses are proposed:

- **H1**: The heterogeneity of the target knowledge map is positively related to group performance and prior knowledge of a group.
- **H2**: The connectivity of the target knowledge map is positively related to group performance and prior knowledge of a group.
- **H3**: The depth of the target knowledge map is positively related to group performance and prior knowledge of a group.
- **H4**: The breadth of the target knowledge map is positively related to group performance and prior knowledge of a group.
- **H5**: The semantic richness of the target knowledge map is positively related to group performance and prior knowledge of a group.
**Computer-assisted knowledge map analytic tool**

This study adopted the computer-assisted knowledge map tool to analyse and measure knowledge elaboration. This analytical tool developed by the authors is a web-based system built with html5 and PHP to draw knowledge maps and calculate the level of knowledge elaboration. The system architecture of this tool is shown in Figure 2.

In order to measure the knowledge elaboration level in collaborative learning, the following three steps need to be conducted with the aid of the knowledge map analytic tool:

First, drawing an initial knowledge map according to the collaborative learning tasks. Each collaborative learning task has a definite learning objective, and the initial map represents the designers’ understanding of the domain knowledge with this objective. The initial knowledge map consists of nodes and edges, where the nodes represent knowledge and the edges represent the mutual relationships of that knowledge. The knowledge map can be drawn based on the knowledge modelling norm (Yang, 2010). Figure 3 shows a portion of an initial knowledge map, where SM denotes symbols, CN denotes concepts, PF denotes principles and formulas, FM denotes formats, PS denotes processes and steps, CS denotes cognitive strategies, and FC denotes facts and cases.

![Figure 2. The system architecture of the analytic tool](image-url)

Second, coding and segmenting information flows generated in collaborative learning processes. The coding format of information is defined as: `<time><IPL_i><cognitive level><information type><representation format><knowledge sub-map>`. Time refers to the start time of each information flow. The subscript “i” in IPL_i is used to distinguish different learners. That is to say, IPL_1 indicates the first learner’s information processing; IPL_2 indicates the second learner’s information processing, and so on. The cognitive levels of IPL_i include discriminating, recalling, understanding, and applying. Information types include description of the objectives, context, knowledge semantics, answers and questions, facts and examples, management instructions, related information, and unrelated information. The values of the representation formats include text (T), sound (S), graph (G), photo (P), table (Tb), video (V), animation (A), object (O), and body language (B). The knowledge sub-map mapped by the information flows represents pieces of knowledge and their interrelationships. The initial knowledge map may be revised according to the information flows generated by each group. Table 2 shows the interactional fragments of a group. Two researchers coded these information flows into information items with the aid of the knowledge map analytic tools, as shown in Figure 2. For example, when the information flow in the second row of the Table 2 was coded, the first step was to identify time, IPL_i, cognitive level, information type, representation format, and knowledge sub-map.
based on the aforementioned coding format. In terms of this information flow, time was 4:59, IPLi was IPL2, cognitive level was "understanding," information type was "knowledge semantics," representation format was "sound," and knowledge sub-map contained two nodes (i.e., curriculum objectives and expected results) and their relationship (i.e., equals) in the initial knowledge map, as shown in Figure 3. The second step was to input the information one by one into the right part of Figure 4 via the knowledge map analytic tool. The coding result was the second information item in the middle part of Figure 4. The final knowledge map was generated after all of the information flows were coded.

![Diagram](image.png)

*Figure 3. A portion of an initial knowledge map*

<table>
<thead>
<tr>
<th>Time</th>
<th>IPLi</th>
<th>Information flows</th>
</tr>
</thead>
<tbody>
<tr>
<td>4:12</td>
<td>IPL1</td>
<td>“The task was to understand the concept of curriculum objectives. Let’s begin!”</td>
</tr>
<tr>
<td>4:59</td>
<td>IPL2</td>
<td>“I believe that curriculum objectives equal the expected results.”</td>
</tr>
<tr>
<td>5:08</td>
<td>IPL2</td>
<td>“For example, the curriculum objective of a course.”</td>
</tr>
<tr>
<td>5:18</td>
<td>IPL3</td>
<td>“Yes, except the curriculum objective of a course, there was the curriculum objectives of a class.”</td>
</tr>
<tr>
<td>5:28</td>
<td>IPL3</td>
<td>“So curriculum objectives equal the standards and requirements of instruction.”</td>
</tr>
<tr>
<td>5:40</td>
<td>IPL3</td>
<td>“In addition, I think curriculum objectives also equal the required knowledge and competences.”</td>
</tr>
<tr>
<td>6:10</td>
<td>IPL1</td>
<td>“Would you like to tell me the relationships between curriculum objectives and instructional objectives?”</td>
</tr>
</tbody>
</table>

Table 2. Fragments of information flows

Third, generating the final knowledge map and computing the level of knowledge elaboration of this knowledge map. We hypothesized that some attributes of the knowledge map can represent the level of knowledge elaboration. When clicking the button of “compute attributes” in Figure 4, the network structure entropy, degree distribution index, depth, breadth, and weighted path length of the activation spanning tree of the target knowledge map can be automatically calculated via the analytical tool. This study therefore aims to validate whether they can measure the level of knowledge elaboration. The numbers next to the knowledge in Figure 5 are the weighted path lengths which
were calculated with formula (5). For example, if we selected the vertex of “curriculum objectives” as the root vertex, then the path length of vertex “instructional objectives” was 2 and the activation quantity of this vertex was 3.584. Therefore, the weighted path length of vertex “instructional objectives” was 7.17. The analytical tool can calculate the weighted path lengths of all vertices.

Figure 4. Fragments of coding and segmenting

Figure 5. Final knowledge map with weighted path lengths

Compared with previous coding schemes which focused on speech acts and overlooking knowledge construction (Suthers et al. 2010; Stahl, 2011; Zheng et al., 2012), the proposed analytical approach can represent the relationships
between new knowledge and prior knowledge on the knowledge map. The level of knowledge elaboration can also be automatically calculated via our analytical tool. Moreover, this new approach can provide insight into the semantic richness of knowledge elaboration. Therefore, it is an effective method to measure the level of knowledge elaboration.

**Experiment design**

The present study included two experiments that aimed to explore the knowledge elaboration level of different knowledge types at the group level. The type of knowledge in the first experiment was concepts, while the knowledge type of the second experiment was principles. The collaborative learning objective of the first experiment focused on understanding concepts of curriculum objectives, while the learning objective of the second experiment focused on solving problems by applying the theory of consumer behaviour in microeconomics. The experiment procedures were identical in each experiment. However, the collaborative learning tasks, participants, and measuring tools differed. The following section illustrates the collaborative learning tasks, participants, measuring tools, and procedures in detail.

**Collaborative learning tasks**

The collaborative learning tasks of the first experiment are related to the curriculum objectives, and are described as follows:

- How do you understand the concept of curriculum objectives?
- Please describe the strengths and weaknesses of three representations of curriculum objectives.
- How do you determine curriculum objectives? Please describe the procedure in detail.

The collaborative tasks of the second experiment are related to the theory of consumer behaviour in microeconomics. The details of the tasks are as follows:

- What is your opinion of consumer equilibrium? How can you determine the demand curve?
- Case study: When Xiao Yang works 9 hours a day, he is paid 40 RMB per hour. When his hourly wage rises to 60 RMB, he decides to work only 7 hours a day and to spend more time with his family and at leisure. Please describe Xiao Yang’s response to a wage increase using the theory of consumer behaviour.
- The utility function and budget constraint of one consumer can be represented as $U = \frac{1}{X^3}Y + 3X + 4Y = 100$, respectively. Another consumer’s utility function and budget constraint equations are $U = X^{\kappa}Y^4 + 1.5\ln X + \ln Y$ and $3X + 4Y = 100$, respectively. Please solve the following problems:
  1. What are the optimal commodity purchase quantities for the two consumers? Please compute them using two methods.
  2. Does “two indifference curves cannot intersect” contradict the conclusion?
  3. If the equation of the inverse demand function of a consumer is $p = a - b \cdot q$ ($a, b > 0$). When the government imposes a consumption tax, the price paid by this consumer will increase from $p$ to $p (1 + t)$, where $t$ denotes the tax rate. Please prove the following proposition using two methods: The loss of consumer surplus is always more than the revenue of the government from taxation.

**Participants**

The first experiment recruited 91 undergraduates majoring in curriculum theory, while the second experiment recruited 94 undergraduates majoring in economics. In each experiment, the participants were randomly divided into thirty groups of three or four. Thus, a total of 60 groups participated in the two experiments.

**Measuring tools**

In this study, a pre-test and a post-test were conducted to measure the learning performance of individual groups in terms of “curriculum objectives” and “the theory of consumer behaviour in microeconomics”. The test items were
developed by one of the researchers and the two experts in the field of curriculum theory and microeconomics. The purpose of the pre-test was to evaluate the students’ prior knowledge at the group level; that is, the prior knowledge of a group was equal to the average of the group members’ pre-test scores. On the other hand, the post-test aimed to evaluate group performance in the collaborative learning. The test items of the pre-test were the same as those of the post-test.

The group performance was measured based on the group members’ pre-test and post-test scores and was calculated according to formula (6), which represents knowledge gains during collaborative learning based on the measure proposed by Zheng et al. (2012).

\[
X = \frac{P \times (\sum_{i=1}^{N} X_{\text{posttest}} - \sum_{i=1}^{N} X_{\text{pretest}})}{N \times \sqrt{CV}}
\]  

(6)

where \(X_{\text{posttest}}\) and \(X_{\text{pretest}}\) denote the pre-test and post-test total scores of a group, respectively. \(P\) denotes the difficulty coefficient and \(P = 1 \cdot L / W\). \(L\) denotes the mean of loss score of post-test and \(W\) denotes the perfect score. \(CV\) denotes the variation coefficient and \(CV = \frac{S}{\bar{X}} \times 100\%\). \(S\) denotes the standard deviation of difference between the post-test and pre-test in each test item. \(\bar{X}\) denotes the mean of difference between the post-test and pre-test. \(N\) denotes the size of the group. For example, if the \(X_{\text{posttest}}\) and \(X_{\text{pretest}}\) in a group of three were 160 and 60.5, respectively. \(W\) equalled 100 and \(L\) equalled 47, then \(P\) equalled 0.53. \(S\) equalled 4.7 (The differences between the post-test and pre-test in each test item was 19.5, 12.6, 10, 21, and 13) and \(\bar{X}\) equalled 33.17, then \(CV\) equalled 0.14. Therefore \(X\), namely group performance equalled 47.51.

Procedure

The experiment employed a pre-test/post-test research design. The experimental procedures were as follows:

Firstly, the researchers designed the collaborative task and pre-test and post-test items according to target domain knowledge. The target domain knowledge was selected according to collaborative learning objectives. For the first experiment, the target domain knowledge included the concepts, together with categories of curriculum objectives, and methods for determining the curriculum objectives. That is, the target domain knowledge in the first experiment mainly consisted of concepts, while the second experiment was conducted to replicate the results of the first experiment and extended in two ways. First, the results were generalized to collaborative learning tasks that represented different knowledge types. Second, the data from more samples were collected to determine the robustness of knowledge elaboration indicators. Therefore, the target knowledge in the second experiment was extended to include cardinal utility theory, ordinal utility theory, consumer demand theory, consumer equilibrium theory, and consumers' surplus theory. That is, the target domain knowledge in the second experiment mainly consisted of principles.

Secondly, participants were recruited by posters on the campus. A total of 185 undergraduates voluntarily participated in these experiments. Before collaborative learning, all participants received the same instructions about the purpose and procedures of the experiment.

Thirdly, participants collaborated face-to-face for approximately two hours to complete the tasks in different labs. For each group, group members elected one member to be a group leader. Then the group leader allocated different roles to members based on each member’s abilities or willingness, including information searchers, recorders, analysers, and so on. They could ask for help from the Internet via computers or mobile phones. The final product of each collaborative learning task was a written text. The tasks were the same for the thirty groups in each experiment, as were the pre-test and post-test items. To ensure no interference during the collaborative learning process, we videotaped the entire collaborative learning process for all sixty groups for analysis; moreover, the post-test was performed immediately after the learning activity.
Data collection and analysis

During the collaborative learning processes, we carried out video recording to document each group’s information flows and elaboration processes. In addition, two coders independently segmented information flows generated in collaborative learning processes according to the segmentation rules via our analytical tool. The information flow is segmented if the contributor of information changes. When the cognitive level changes from “discriminating, recalling, and understanding” to “applying”, the information flow is segmented. If the information types changes from one type to another, the information flow is also segmented. If the knowledge sub-map changes, it is also necessary to segment the information. However, the change of representation formats does not influence the segmentations because one information flow could have many kinds of representation formats such as sounds, texts or graphs. The attributes of the target knowledge map, such as the network structure entropy, degree distribution index, depth, breadth, and weighted path length of the activation spanning tree were computed by our analytical tool.

Inter-rater reliability and retest reliability

To guarantee the objectivity of the information flow coding and test item assessment, two trained raters blind to the experimental conditions coded the information flows of the sixty groups and assessed the test papers of the 185 participants. The percent agreement index was used to compute the inter-rater reliability. The reliability coefficient for coding information flows ranged from 0.900 to 0.974. All inter-rater reliability coefficients for assessing test items were above 0.9. The two raters discussed and resolved all discrepancies. These values of inter-rater reliability were regarded as an indication of excellent agreement. The retest reliability of the two coders for 10% of the data reached 0.93.

Results

In order to test the five hypotheses, descriptive statistical analysis, correlation analysis and regression analysis were conducted for group performance, prior knowledge of a group, and five indicators of knowledge elaboration. Table 3 shows the mean and standard deviation of group performance, prior knowledge, and various indicators. Table 4 shows the regression analysis results for predicting group performance by knowledge elaboration indicators. Both Table 3 and Table 4 show the results of the first experiment.

Table 3. Descriptive statistics for group performance, prior knowledge and predictors of knowledge elaboration

<table>
<thead>
<tr>
<th>Items</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group performance</td>
<td>19.232</td>
<td>9.748</td>
</tr>
<tr>
<td>Prior knowledge</td>
<td>26.183</td>
<td>8.778</td>
</tr>
<tr>
<td>Network structure entropy</td>
<td>3.723</td>
<td>.245</td>
</tr>
<tr>
<td>Degree distribution index</td>
<td>6.249</td>
<td>.709</td>
</tr>
<tr>
<td>Depth</td>
<td>75.869</td>
<td>34.345</td>
</tr>
<tr>
<td>Breadth</td>
<td>7.270</td>
<td>1.112</td>
</tr>
<tr>
<td>Weighted path length of activation spanning tree</td>
<td>619.66</td>
<td>328.76</td>
</tr>
</tbody>
</table>

Table 4. Regression analysis for knowledge elaboration indicators predicting group performance

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Adjusted R²</th>
<th>Beta</th>
<th>t</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network structure entropy</td>
<td>.326</td>
<td>.591</td>
<td>3.879</td>
<td>.001</td>
</tr>
<tr>
<td>Degree distribution index</td>
<td>.259</td>
<td>.533</td>
<td>3.337</td>
<td>.002</td>
</tr>
<tr>
<td>Depth</td>
<td>.132</td>
<td>.402</td>
<td>2.325</td>
<td>.028</td>
</tr>
<tr>
<td>Weighted path length of activation spanning tree</td>
<td>.345</td>
<td>.606</td>
<td>4.036</td>
<td>.000</td>
</tr>
</tbody>
</table>

H1 assumed that the network structure entropy of the target knowledge map was positively related to group performance and prior knowledge. The result indicated that network structure entropy was significantly positively correlated with group performance ($r = .591, p = .001$), and could explain 32.6% of the total variance. This finding indicated that the network structure entropy of the target knowledge map could predict group performance.
significantly well. The main reason for this good performance is the ability of network structure entropy to measure the heterogeneity of the knowledge map. Meanwhile, the network structure entropy of the target knowledge map was positively related to prior knowledge ($r = .714, p = .000$).

H2 assumed that the degree distribution index of the target knowledge map was positively related to group performance and prior knowledge. The result showed that the degree distribution index was significantly positively correlated with group performance ($r = .533, p = .002$). The degree distribution index could explain 25.9% of the total variance, indicating that the degree distribution index of the target knowledge map could predict group performance significantly well. This good performance is attributed to the ability of the degree distribution index to indicate the degree of association among target knowledge and the connectivity of knowledge map. In addition, the degree distribution index of the target knowledge map was also positively related to prior knowledge ($r = .751, p = .000$).

H3 assumed that the depth of the target knowledge map was positively related to group performance and prior knowledge. The result indicated that the depth of the target knowledge map was significantly positively correlated with group performance ($r = .402, p = .028$). The depth of the target knowledge map could explain 13.2% of the total variance, indicating that it could predict group performance significantly well, which is attributed to its ability to represent the elaboration level of knowledge construction. Moreover, the depth of the target knowledge map was positively related to prior knowledge ($r = .449, p = .013$).

H4 assumed that the breadth of the target knowledge map was positively related to group performance and prior knowledge. However, the result indicated that it was not significantly correlated with group performance ($r = .281, p = .133$), which is attributed to its inability to represent a deeper understanding of the subject matter. Furthermore, the breadth of the target knowledge map was not related to prior knowledge ($r = .242, p = .198$).

H5 assumed that the weighted path length of the activation spanning tree of the target knowledge map was positively related to group performance and prior knowledge. The result indicated that the weighted path length of the activation spanning tree of the target knowledge map was significantly positively correlated with group performance ($r = .606, p = .000$), and it could explain 34.5% of the total variance. This finding indicated that it can significantly predict group performance, which is attributed to the ability of the weighted path length of the activation spanning tree to measure the semantic richness and deep structure of the knowledge map. It was also positively related to prior knowledge ($r = .676, p = .000$).

Both Table 5 and Table 6 are the results of the second experiment, which also revealed that the network structure entropy ($r = .483, p = .007$), degree distribution index ($r = .482, p = .007$), depth ($r = .399, p = .029$), and weighted path length of the activation spanning tree ($r = .448, p = .013$) of the target knowledge map were positively related to prior knowledge. In addition, we examined the relationships between these indicators and group performance. Table 5 shows the results for different indicators predicting group performance. The results indicated that H1, H2, H3, and H5 were supported by the data. However, H4 was not supported, indicating that the breadth of the target knowledge map ($M = 11.130, SD = 1.040$) was not significantly positively correlated with group performance ($r = .173, p = .360$) or with prior knowledge ($r = .351, p = .057$). This finding also indicated that the network structure entropy, degree distribution index, depth, and weighted path length of the activation spanning tree of the target knowledge map can significantly predict group performance. It was thus obvious that the conclusions of the second experiment were the same as those of the first experiment. Therefore, we believe that these four indicators are stable and have strong predictive power.

**Table 5.** Descriptive statistics for group performance, prior knowledge, and predictors of knowledge elaboration

<table>
<thead>
<tr>
<th>Items</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group performance</td>
<td>16.128</td>
<td>10.885</td>
</tr>
<tr>
<td>Prior knowledge</td>
<td>23.688</td>
<td>7.873</td>
</tr>
<tr>
<td>Network structure entropy</td>
<td>4.003</td>
<td>.176</td>
</tr>
<tr>
<td>Degree distribution index</td>
<td>6.109</td>
<td>.622</td>
</tr>
<tr>
<td>Depth</td>
<td>10.885</td>
<td>46.403</td>
</tr>
<tr>
<td>Breath</td>
<td>11.130</td>
<td>1.040</td>
</tr>
<tr>
<td>Weighted path length of activation spanning tree</td>
<td>1204.554</td>
<td>527.308</td>
</tr>
</tbody>
</table>
Discussion and conclusions

In this study, the topological properties of knowledge maps were adopted and analyzed using graph theoretical approaches (Hwang, Wu, & Ke, 2011). The network structure entropy, degree distribution index, and depth represented the topological characteristics of targeting knowledge maps. When the weighted path length of the activation spanning tree reflected the semantic richness, it has stronger predictive power than other indicators. Furthermore, knowledge maps display knowledge elaboration processes by representing sequences, branches, and pathways that are involved in collaborative learning.

It is found that knowledge elaboration indicators can be applied to two different knowledge types. The results of the two experiments confirm that the network structure entropy, degree distribution index, depth, and weighted path length of the activation spanning tree of the target knowledge map are the general indices for measuring the level of knowledge elaboration. However, the breadth of the target knowledge map is not an indicator of knowledge elaboration. Therefore, network structure entropy, degree distribution index, depth, and weighted path length of the activation spanning tree will be effective indicators to measure the knowledge elaboration level.

In line with what has been reported by several previous studies (Stark et al., 2002; Noroozi et al., 2012; Stegmann et al., 2012), this study indicated that the knowledge elaboration values were significantly related to group performance. Therefore, we can predict the group performance of collaborative learning through the lens of knowledge elaboration. Elaborating knowledge entails integrating and refining new information by organising and connecting with prior knowledge. The present study also showed that knowledge elaboration was positively related to prior knowledge. This finding was also congruent with Wetzel et al. (2011) and Van Blankenstein et al. (2013), who found that elaboration was helpful for students with prior knowledge. It was also consistent with Gurlitt & Renkl (2010), who found that elaboration is a key process for prior knowledge activation. In fact, prior knowledge sets the stage for new learning and promotes the processing of new information related to the prior knowledge. The results of this study are also consistent with the definition of knowledge elaboration, which emphasises linking and integrating new knowledge with prior knowledge. In sum, the level of knowledge elaboration was found to be significantly related to group performance and prior knowledge of a group. Thus, researchers or teachers can know about group performance and prior knowledge by measuring knowledge elaboration without a pre-test or post-test.

Methodologically, the knowledge map analytic approach is based on topology characteristics and semantic relationships of knowledge maps, which can provide insights into the processes of knowledge elaboration. We believe that it is knowledge that can be replicated in different conditions, because knowledge is relatively stable but learners are ever-changing. Therefore, the samples in this study are not the participants but the target knowledge map. We attempted to analyse the relationships between the characteristics of the target knowledge map and the elaboration level. This new approach focuses on analysing different attributes of the same knowledge map. This study also contributes to the advancement of the collaborative learning field using the knowledge map-based analysis method.

This study has some implications for educators and practitioners in collaborative learning. Because knowledge elaboration is helpful for meaningful learning and knowledge gains, teachers should provide some external instructional guidance to facilitate knowledge elaboration. Van Boxtel (2004) postulated that elaboration occurred
when students used examples, analogies, and experiences to create new relationships. We believe that the design of collaborative learning tasks should promote relating prior knowledge to new information. Additionally, before collaborative learning, some relevant prior knowledge should be provided to students. During collaborative learning, teachers or facilitators can ask questions to retrieve relevant prior knowledge to promote knowledge elaboration. Teachers should also encourage group members to give more examples for concept learning. After collaborative learning, summarising what was discussed can also stimulate elaboration because students can integrate new knowledge into prior knowledge. Future research is encouraged to explore which kind of knowledge elaboration strategy will be more effective in different collaborative learning scenarios.

Of course, the present study also has some limitations. One limitation is that the learning activity was conducted in a face-to-face collaborative learning context. It would be interesting to investigate whether the result can be generalised to synchronous or asynchronous collaborative learning scenarios. Another limitation is that this study only examined the knowledge elaboration level of two kinds of knowledge type. It is worth exploring the elaboration level of other knowledge types in future studies. Finally, this study mainly focused on four indicators for measuring the level of knowledge elaboration. It is possible that other attributes of knowledge map can be considered to more accurately measure the level of knowledge elaboration in the future.

In conclusion, this study indicates that the network structure entropy, degree distribution index, depth, and weighted path length of the activation spanning tree of the target knowledge map are indicators of knowledge elaboration. It should be noted that the breadth of the target knowledge map is not an indicator since it cannot measure the knowledge elaboration level. Moreover, knowledge elaboration is positively related to both group acquisition of knowledge and prior knowledge of a group. The main contribution of this study resides in the indicators of measuring knowledge elaboration. In addition, an innovative analytic method is developed for analysing knowledge elaboration in collaborative learning. Analysis of the knowledge map can deepen our understanding of the nature of knowledge elaboration processes in collaborative learning. Measuring knowledge elaboration can also provide an insight into prior knowledge and group performance.

Acknowledgements

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References


