Khudhur et al. *Research and Practice in Technology Enhanced Learning* (2026) 21:21
https://doi.org/10.58459/rptel.2026.21021

Research and Practice in
Technology Enhanced Learning

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From learner-built to expert concept maps: An evaluation of the effects of closed concept map recomposition on learning

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Abstract

Kit-Build concept map framework offers a unique approach to enhancing learning through concept mapping. It involves decomposing an expert map into components, which are then used by learners to construct their own concept maps. Kit-Build concept map can accurately detect differences between the learner's map and the original expert map at a propositional level. In this study, we developed an activity that guides learners to complete the same map as the expert map by presenting the detected proposition-level differences and encouraging learners to correct them. We report on the learning effects of this activity by comparing it to a Kit-Build concept map activity conducted without the feedback or expert map completion task. Our findings reveal that engaging in Kit-Build concept mapping with expert map completion task significantly enhances reading comprehension compared to the Kit-Build concept mapping control group. Importantly, this improvement persists even after a two-week interval. Although the activity requires more time than Kit-Build concept mapping control group, the time-on-task does not predict learning improvement, underscoring the value of the proposed guidance. Further analysis demonstrates that this process not only helps learners acquire new knowledge but also consolidates their understanding of previously learned information.

Keywords: Concept map, Closed concept map, Kit-Build, Expert map, Feedback, Learning analytics

Introduction

Reading involves comprehending information. It is a process that consists of connecting the information in the text to prior knowledge. When education shifts from early reading skills, such as word recognition, to comprehension-related skills, a portion of learners may experience difficulties (Hirsch, 2003; Moss, 2005). Low-income families tend to have a higher incidence of this problem (Chall & Jacobs, 1983). One successful approach to improving reading comprehension is the use of concept mapping (Chang et al., 2002; Dias et al., 2010; Guastello et al., 2000; Riahi & Pourdana, 2017; Usman et al., 2017). In this study, the term *concept map* is defined as a graphical tool that represents knowledge, as described by Novak (Novak & Cañas, 2006). A concept map is comprised of concepts and links connecting those concepts. A proposition, which is composed of two concepts connected by a link, is the smallest unit of a concept map. Even simply studying concept maps built by experts has been shown to improve comprehension (Nesbit & Adesope, 2006). One explanation for how concept maps help comprehension is that they provide a template for organizing and structuring information (Cañas & Novak, 2010). Moreover, graphical structures such as concept maps are closer to the macrostructure of a text, making them easier to understand (Van Dijk et al., 1983). In addition, constructing the map enables learners to continuously process the concepts of the materials (Armbruster & Anderson, 1984).

Retention of information is also important in learning. Information from texts not only needs to be comprehended but they also have to be retained for future retrieval. Concept mapping has been shown to improve retention, possibly through similar mechanisms as those that aid in comprehension, such as aiding in knowledge organization and continuous processing (Armbruster & Anderson, 1984; Cañas & Novak, 2010; Van Dijk et al., 1983). For example, Kim and Olaciregui (2008) investigated the impact of different electronic portfolio visualization methods on retention. Their study found that fifth-grade learners who used a concept map structure to view their electronic portfolios outperformed those who used a traditional folder-based hierarchical structure after a three-day retention period. The tree structure in their study followed a conventional folder-subfolder organization, similar to directory structures in computer operating systems, allowing learners to navigate through nested categories. In contrast, the concept map structure presented learning content in an interconnected network of labeled nodes and relational links, encouraging a more flexible, associative organization of knowledge. Nesbit and Adesope (2006) conducted a meta-analysis of studies using concept maps, which indicated that concept maps were effective for both retention and transfer of knowledge. This finding applies to both studying through map construction and map visualization.

Computer-based tools for creating concept maps have also gained popularity (Hadjileontiadou et al., 2018; Liu et al., 2023; Mammen, 2016). These tools have been used successfully to improve learning in various domains (Hwang et al., 2013; Kim & Olaciregui, 2008; Willerman & Mac Harg, 1991), including reading comprehension (Alkhateeb et al., 2015; Morfidi et al., 2018; Omar, 2015). Prior research has highlighted several advantages of computer-based concept mapping, such as ease of correction and construction (Liu et al., 2010), the ability to add behavior-guiding constraints (Reader &

Hammond, 1994), and personalized creation process, as well as reducing frustration (Anderson-Inman & Zeitz, 1993). Among these tools, some provide pieces for learners to construct their concept maps (Hirashima et al., 2011; Wu et al., 2012). In these tools, the learner cannot directly input the text that will appear in the links and concepts. What learners do in building concept maps is usually moving connectors around and associating one piece with another.

One advantage of closed concept maps is that they can be automatically scored by comparing the learner-built maps to expert maps. This comparison can also be used to demonstrate precisely how the learner-built map differs from the expert map. Educators have utilized this approach to gain insight into the learners' knowledge, making it a form of learning analytics (Jeong, 2020; Sugihara et al., 2012). The differences between the learner map and the expert map could also be shown to the learner. This is in line with recent research that encourages showing learning analytics to the learners (Bodily & Verbert, 2017). Learners can use this information to modify their maps and move closer to the expert level, ultimately improving their understanding of the material. Encouraging learners to construct a concept map and then modify it to match the expert map by looking at the differences is, therefore, a promising activity for enhancing comprehension and retention.

However, it is important to note that there is a risk of learners changing their maps without actively processing the information, which can undermine the effectiveness of the activity. By explicitly showing the differences between the two maps, learners may simply mimic the expert map without fully comprehending the material. Thus, while the activity is promising, it is crucial to evaluate its effectiveness in improving learners' understanding of the subject matter.

Previous research has employed this activity to explore its effectiveness. One study evaluated differences in cognitive load between two closed concept map interfaces, both of which required learners to reconstruct the expert map based on feedback received after building their own map (Khudhur et al., 2024). One interface had a partially decomposed layout while the other had a fully decomposed layout. The results showed that the partially decomposed layout reduced cognitive load while maintaining similar learning gain. However, the study did not examine the effectiveness of the expert map recomposition in itself. Another study examined learning gains in more detail, distinguishing between reviewing information and acquiring new information (Furtado et al., 2019). The study found that organizing parts automatically can also reduce cognitive load but also reduce long-term learning gain. Nonetheless, it did not provide a detailed analysis or evaluation of the expert map recomposition or feedback received.

This work presents an implementation for the activity of constructing a closed concept map and then recomposing the expert map. It also presents the validation of this activity by comparing it to the construction of a closed concept map without recomposing the expert map. Learning gains are also separated into reviewed knowledge and newly attained knowledge, to offer further detail into how reconstructing the expert map affects learning gains. The main research questions of this study are: (1) whether learners' recomposition of the expert map affects immediate reading comprehension gains, (2) whether the retention of the reading comprehension gains is affected by the activity. (3) How learning gains differ between new information and reviewed information would be a secondary research question. Exploratory analyses are also added to give better insight into the results and provide additional avenues for future research. Overall, this study contributes to the growing body of knowledge on the use of concept mapping in education and sheds light on the potential benefits of expert map recomposition as a teaching strategy.

Traditional concept mapping, closed concept mapping and the cognitive implications

While this study does not employ Traditional Concept Mapping, it is important to discuss it as the foundational method to help readers understand Closed Concept Mapping and to clarify why Closed Concept Mapping is explored as an alternative approach in this research.

Concept maps are a type of graphic organizer. When used for reading comprehension, graphic organizers have an array of advantages for organizing and finding information (Lee, 2007). Graphic organizers can act as scaffolds when compared to understanding information directly from texts (Dollins, 2011). As mentioned in the introduction, concept maps, are useful for improving both comprehension and retention and this is often due to their nature of being a graphic organizer. While there are many ways to use concept maps in education, one method is to give an empty canvas to the learner and request building a concept map based on a given subject. The learners are then free to create any link or concept they want. Let us call that activity Traditional Concept Map Creation (TMC). In contrast, instead of giving an open canvas and full freedom, we can limit the options of the learner by only allowing them to use predetermined terms for the links and concepts. Let us call that activity closed concept map assembling (CMA). To simplify this discussion, TMC and CMA will be discussed in the context of building maps without looking at the source material, which is the case of this study.

In TMC, the learner has to think about terms for nodes and links in a free-recall fashion. Learners cannot rely on any terms to help guide them through this process, unlike in CMA. Furthermore, deciding when the map is "done" also becomes the duty of the learner. As such, map size will be different depending on what criteria learners use to build the map. In contrast, with closed concept maps, learners tend to use every term in the map, freeing the learner from having to decide when the map is done.

From the above paragraph, one might think that CMA works as a scaffolding for TMC, being an easier activity. However, the activities are different in nature. In TMC, to build a proposition, the learner has to remember relevant information, translate a portion of it into a proposition and then translate that proposition into two concepts and a link. In CMA, to build a proposition, the learner has to find two related nodes, access their memory to find a relationship between them and find, among the provided links, the one which best describes that relationship. TMC involves free recalling of information and describing that information in terms of freely created concepts and links. CMA involves cued recalls, a constant search of pieces, and trying to fit one's knowledge into the concepts and links that another person made. Results from a study that compared TMC to CMA showed no significant differences in immediate comprehension, but CMA had significantly higher scores than TMC after a two-week retention period (Alkhateeb et al., 2015). In this study, learners built the map while looking at the text, so the differences in recall mechanisms were not present. The explanation given for this difference in retention was that CMA challenges learners to understand the entire text in order to be able to use every concept and link provided, which does not help in TMC since the learner creates the concepts and links themselves. Furthermore, it was said that CMA requires high memory access and deeper processing of the meaning in the text. This could be interpreted as CMA having a higher cognitive load than TMC depending on the number of nodes and links. However, it is important to note that this increased cognitive load in CMA may primarily be germane cognitive load, which is beneficial for learning as it relates to the processing and construction of schemas (Paas et al., 2003). As such, while CMA with a large number of pieces may not be an easier version of TMC in terms of cognitive demand, the nature of this demand (germane load) could contribute to better learning outcomes and retention.

To make this difference clearer for the reader, one good metaphor would be "writing a text" and "organizing the paragraphs of a text". It is hard to say that organizing the paragraphs that someone else wrote is an "easier version" of writing your own text since they require different skills. Both activities have their own purpose in learning environments. Similar to how CMA and TMC each have their own purpose in learning.

Both TMC and CMA have been implemented in computer-based tools, which not only facilitate concept map construction but also support advanced functionalities such as automated assessment. By leveraging computational techniques, these tools can analyze learner-generated maps with minimal human intervention. One approach to performing such assessment is through semantic web technologies (Park & Calvo, 2008), which enable a flexible rubric setting. Another study utilized word proximity data to score concept maps, providing an alternative method to score concept maps (Taricani & Clariana, 2006).

Another possibility to perform automatic diagnosis is to compare learner-constructed maps in a CMA context with expert-constructed maps. Several concept mapping tools that offer automatic diagnosis through expert map comparison include CmapAnalysis (Cañas et al., 2013), Kit-Build (Hirashima et al., 2011, 2015), KAS (Tao, 2015), ICMLS (Wu et al., 2012) and jMAP (Jeong & Seok-Shin, 2023). This type of automatic diagnosis is possible because the maps are closed concept maps, meaning they are built using the same set of pieces, allowing for direct comparison between learner and expert maps. This approach has been found to correlate with standard science tests (Yoshida et al., 2013) and demonstrated to be reliable compared to traditional map scoring approaches (Wunnasri et al., 2017, 2018b). Teachers can use this diagnosis information to adjust their lessons and provide targeted feedback to learners, which has been shown to improve retention rates, especially when using concept maps as feedback (Sugihara et al., 2012). Additionally, this type of automatic diagnosis enables automated feedback, which has been effective for enhancing reading comprehension (Wu et al., 2012).

Finally, a recent study by Furtado et al. (2018) presented an activity design in which learners create their own concept map, compare it with an expert map, and then modify their map to match the expert map. However, the study compared two different concept map interfaces, with both conditions utilizing the same activity design. While both conditions exhibited positive learning gains, it is unclear whether the observed learning gains were due to the map construction process alone or the additional step of modifying the map to match the expert map. To address this gap in the literature, the present study includes a control group that only builds a concept map without modifying it to match the expert map, allowing for a clearer assessment of the effect of modifying the map to match the expert map on learning outcomes.

Kit-Build concept map recomposition

In this study, we investigate our research questions via the Kit-Build Concept Map Recomposition methodology. In this section, we introduce the Kit-Build Concept Map Recomposition and underscore its significance by drawing upon relevant studies.

Hirashima et al. (2015) introduced recomposition concept mapping known as Kit-Build that adopts the CMA approach. As with a closed concept map, in Kit-Build, learners rearrange a set of concept map components created from the expert concept map. The expert concept map in Kit-Build refers to the ideal map according to the understanding of a professional (teacher in an educational setting) in the subject of matter. The expert map serves as the baseline for learners to have a shared understanding of a particular subject. The basic steps of a Kit-Build activity are as follows: 1) The expert creates a concept map for a material. 2) The expert concept map is then decomposed into its basic parts by removing the connections, thus creating a *kit* of concepts and links. 3) The kit is then given to the learners to recompose it back to the expert map.

The effectiveness of recomposition concept maps has been demonstrated in several studies targeting university students, to cite a few (Hirashima, 2019; Khudhur et al., 2023; Nurmaya et al., 2023; Pinandito, Hayashi et al., 2021; Rismanto et al., 2024; Sadita, Furtado et al., 2020; Sadita, Hirashima et al., 2020; Wunnasri et al., 2018a). These studies have consistently reported significant achievements, providing empirical support for the theoretical underpinnings of the recomposition concept map.

Hirashima (2019) introduces the Kit-Build concept map as a reconstruction type of concept map, emphasizing its utility in educational settings for both assessment and learning. This approach allows for direct comparison between the reconstructed and original maps, facilitating the detection of differences in understanding. The paper highlights the practical applications of KB maps in classrooms and collaborative learning environments, demonstrating their effectiveness in promoting mutual understanding and automatic assessment.

In a recent investigation by Nurmaya et al. (2023), the significance of Kit-Build concept maps in fostering higher-order thinking was explored. Undergraduate students were assigned to two conditions: TMC and Kit-Build recomposition. The study found that Kit-Build was more effective in enhancing higher-order thinking skills than TMC. The authors contend that Kit-Build concept mapping enables students to allocate more cognitive resources to organizing and integrating knowledge, rather than becoming halted in defining concepts. By relieving students from lower-order tasks like concept definitions, they can more deeply engage in higher-order cognitive activities, such as analyzing relationships and synthesizing concepts, ultimately enhancing their higher-order thinking abilities.

Khudhur et al. (2023) proposes a new application for recomposition concept map called Conceptual Representation of the Source-Code (CRS). CRS integrates theoretical and practical knowledge of Object-Oriented Programming (OOP) through a concept map created by educators. This map combines OOP concepts with their behaviors in source-code. Students then recompose the disassembled concept map, enhancing their understanding of OOP relationships rather than focusing solely on source-code syntax. The study demonstrated that this method significantly improved comprehension and performance in OOP concepts among students compared to traditional teaching methods.

Another study proposed reciprocal Kit-Build concept mapping. The study was implemented in a real classroom setting, allowing the reconstruction of a partner's concept map. The proposed method revealed improved pair discussions about map differences before collaborating to construct a new map. This approach was deemed valuable for eliciting ideas, understanding partners, and integrating diverse perspectives (Sadita, Furtado et al., 2020; Sadita, Hirashima et al., 2020). Furthermore, Pinandito (Pinandito, Hayashi et al., 2021; Pinandito, Wulandari et al., 2021) showcased that Kit-Build surpasses TMC in collaborative environments, particularly in fostering meaningful discussions among students and enhancing overall learning outcomes. The Kit-Build approach encourages students to engage in discussions about the content of the concept maps, shifting the focus from procedural matters. The study also found that Kit-Build stimulates students to explore and contemplate ideas beyond those suggested by the prescribed components, thereby fostering curiosity and creating a "spread of effect" that motivates them to consider additional ideas.

Rismanto et al. (2024) evaluated the Kit-Build (KB) concept mapping process by introducing Sub-Map Scoring (SMS) as a new assessment method. Unlike Full Map Scoring (FMS), which only assesses the final product, SMS analyzes the continuity of the recomposition process for each sub-map, reflecting learners' understanding. The study highlights the importance of process analysis in learner assessment within the KB framework.

One potential limitation of prior research is the lack of clarity on whether the observed learning gains are specifically attributable to the expert map recomposition process itself, or simply due to the general benefits of engaging in concept map construction. Previous studies did not include control groups engaging solely in closed concept mapping without a specific expert map as the goal, making it difficult to isolate the effects of recomposition. In this study we address this by incorporating a control group that engages in Kit-Build concept mapping without the expert map completion task, allowing us to determine whether the observed benefits arise from expert map guidance or from closed concept map building in general. Additionally, while previous studies have demonstrated positive learning outcomes, they have not explicitly examined the role of direct feedback and error correction in enhancing learning through recomposition concept maps. Although the Kit-Build framework inherently allows for expert map comparison, many studies may not have analyzed how structured feedback influences the learning process within this framework. Moreover, prior research has largely focused on overall knowledge gains without distinguishing between the acquisition of new knowledge and the consolidation of existing understanding. This distinction is critical for understanding the specific cognitive benefits of recomposition. In this study, we aim to provide deeper insights into how this process supports both knowledge acquisition and retention, offering a more comprehensive understanding of its learning effects.

By addressing these gaps, our study contributes to a more nuanced understanding of Kit-Build concept mapping and informs the development of more targeted and effective instructional strategies based on this approach.

Activity design

This section provides an overview of the Kit-Build interface and the process of constructing closed concept maps. Specifically, the workflow of creating a map and converting it into an expert map is outlined. Additionally, the mechanisms for processing new knowledge and reviewing existing knowledge are discussed, along with feedback mechanisms used in closed concept maps.

Kit-Build as a tool

Figure 1 shows a screenshot of the interface of Kit-Build, a software tool used for creating closed concept maps. The concepts and links are arranged in separate columns side by side. The concepts in white color, represents the concepts in an article, while the links in blue color, represent the relationships that connect the concepts.

To create a proposition, which is a node-link-node connection, learners must drag-and-drop the connector gizmos of each link to connect nodes. The connector gizmos are two circles that exist in each link. When the gizmo comes into contact with a node by drag-and-drop, the circle disappears, and the node and link are connected. To disconnect nodes, learners must first click on the link, which will make the gizmos reappear. These gizmos can then be moved away from the nodes, making the nodes and link disconnected once again.

Learners can also drag-and-drop the links and nodes to manage the layout of the map. Once the learner feels satisfied with their map, they can click on the 'DONE' button located on the top-right corner of the interface to evaluate their recomposed concept map.

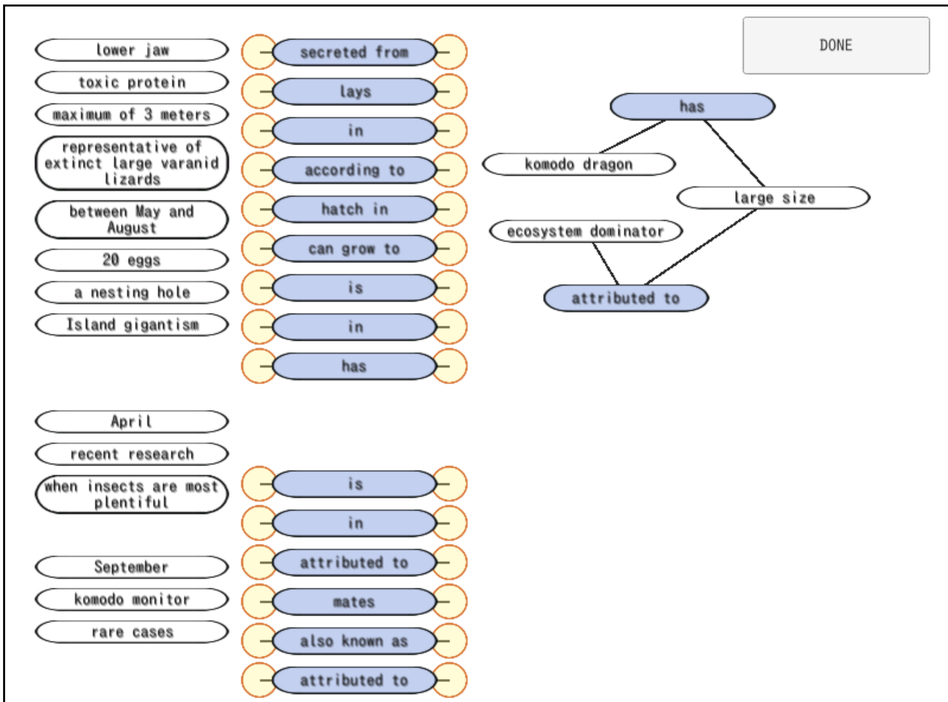

Fig. 1 The Kit-Build interface used in the experiment

Changing into the expert map

The overall process of how a learner constructs and changes their concept map to match the expert map is illustrated in Figure 2. Initially, the learner uses the Kit-Build tool to create his/her own map about a given topic. When the learner is satisfied with the constructed map, he/she presses the 'DONE' button. At this point, the built map is compared to the expert map by the system. The activity completes when the two maps are identical. Otherwise, the learner is presented with a visualization of the differences between his/her map and the experts' map. The visualization consists of two components: the parts of the expert map that are missing from the learners' map, and the parts of the learners' map that are not present in the expert map. The difference visualization screen is shown in Figure 3.

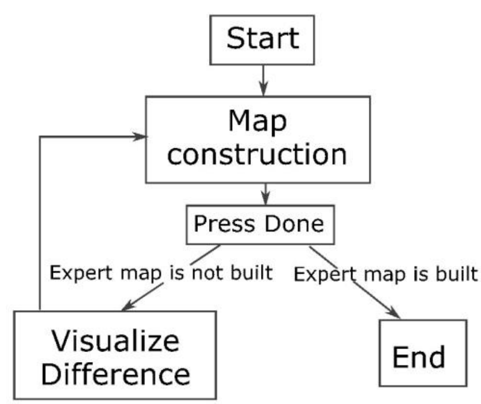

Fig. 2 Flow diagram for building the map and changing it into the expert map

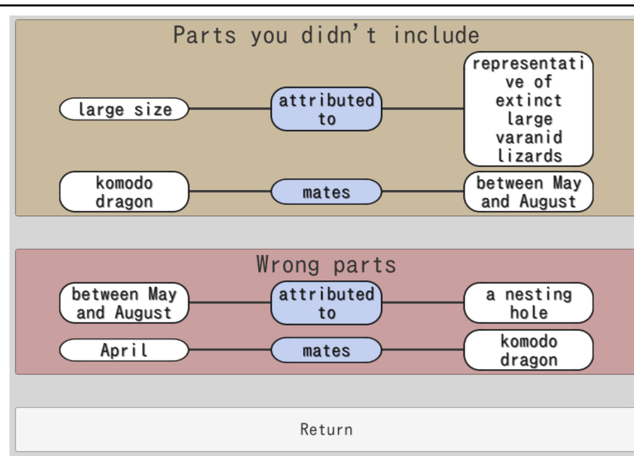

Fig. 3 Map difference visualization screen

After visualizing the differences, the learner may press the 'Return' button to return to map recomposition state. As depicted in Figure 2, the learner iterates through a loop between recomposing the map and visualizing the differences until he/she successfully recomposes the expert map, at which point the learner may exit the loop.

To recompose the expert map, learners must decompose the parts of their map that are not present in the expert map, and also include the missing parts from the expert map. The feedback system provides learners with an indication of their progress toward the expert map by displaying fewer items in the difference visualization as they approach the perfect match.

Reviewing in closed concept maps during construction and recomposition

The act of reviewing involves the recall of previously learned information. For example, suppose a learner responds in the pre-test that **Komodo dragons are referred to as "Komodo monitors"**. Then, when constructing the map, the learner builds a proposition that states **"Komodo dragon – known as – Komodo monitor"**, indicating that they have reviewed the information about Komodo dragons while constructing the map. However, this is a simplification of the actual process that occurs, as building propositions can be quite challenging due to the vast number of pieces that need to be organized. For instance, research has shown that the use of closed concept map interfaces, which automate the layout of concept map, can hinder retention of reviewed information (Furtado et al., 2019). This is believed to be because having to manage the layout may increase the number of recalls required during map construction (Furtado et al., 2018, 2019).

The process of building the map allows learners to express their knowledge using available pieces, facilitating the review process. However, after building their map, learners actively recompose the expert map, thereby shifting the focus from reviewing to identifying and correcting misunderstandings. Thus, it might seem like the learner stops reviewing information that is already correct and instead starts correcting and acquiring information. Nonetheless, it is still possible for the learner to construct propositions that represent valid information but are not present in the expert map. During the expert map recomposition phase, the learner must disassemble those valid propositions to recompose the expert map, indicating that reviewing may also occur during this phase.

In the context of this study, this means that both groups should have comparable performance in terms of reviewing, although it is possible that the experiment group might have a slight edge over the control group.

New knowledge in closed concept creation

In this study, new knowledge acquisition is assessed based on the correct response to a question that the learner could not answer correctly before building the concept map. For instance, if the learner thinks that “apples are blue” before constructing the map, but later corrects it to “apples are red” after map construction, then the learner has effectively gained new information during the map construction. This is a metaphor for the underlying mechanisms that occur, and is measured via a pre-test and post-test conducted during the study.

In closed concept maps, the primary method of acquiring new knowledge is via automated feedback, the design of which determines the nature of the information that is acquired. One approach involves informing the learner of the correctness or incorrectness of their propositions, as well as identifying any missing propositions in their constructed map compared to the expert map. This approach is utilized by the experiment group in this study. Previous studies have used other forms of feedback, such as requesting the learner to justify their incorrect propositions using specific phrases from the base text (Pailai et al., 2018).

Additionally, new knowledge can be acquired through inferential reasoning based on the nodes and links available to the learner. For example, an expert map might include a proposition of the form “apple”, “colored”, “red”. If the only color available in the map is the “red”, then the learner may infer that apples are red in color, even if he/she did not possess this knowledge prior to constructing the map. Again, this is a simplification of the actual process that occurs, as other grammatical and semantic factors may influence it. The extent to which inferential reasoning occurs during map construction can be observed by examining the control group, as they do not engage in the process of recomposing the expert map with the aid of feedback.

Method

This study used a between-subjects design with two conditions: the experiment group and the control group. There was no overlap between the two groups. The experiment consisted of a main phase and an optional delayed phase. Quantitative analyses were conducted on test results. In the main phase, participants were required to:

- Read tool instructions.
- Build the training map using Kit-Build.
- Change their maps into the expert training map (Experiment group only)
- Read a narrative.
- Take the comprehension pre-test.
- Build the text map using Kit-Build.
- Change their maps into the expert map (Experiment group only).
- Take the comprehension post-test.

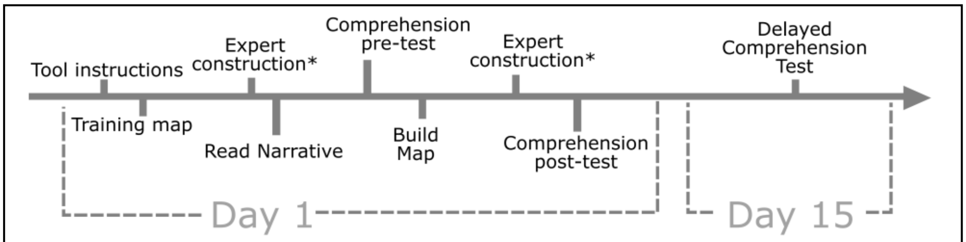

Fig. 4 Timeline for the Experiment. Only the experiment group performed the "Expert Construction" activities

Only participants in the experiment group underwent the expert map conversion process. Participants who completed the main phase were invited to participate in the delayed phase, which involved the same comprehension post-test as the main phase, but with a two-week delay. A timeline for this experiment is provided in Figure 4.

Participants

Participants were recruited through Amazon Mechanical Turk (AMT), a platform that facilitates remote crowdwork. AMT has been extensively utilized in prior research across diverse disciplines, with its data quality well established in the literature (Paolacci et al., 2010). The experiment group comprised 24 participants, while the control group consisted of 30 participants. Inclusion criteria mandated U.S. residency and a track record of completing over 5000 tasks on AMT, coupled with an approval rate exceeding 97%. These prerequisites were implemented to ensure data quality and mitigate the participation of automated processes in the experiment. Further, participants were required to utilize a computer since the software used in the experiment was not optimized for mobile devices.

Materials

The base text employed in this study described various characteristics of the Komodo dragon. This text is a modified, condensed version of a text from Wikipedia (https://git.io/JyeDr). The comprehension pre-test and post-tests shared identical questions, comprising a set of ten multiple-choice questions designed to assess the base text comprehension. A native English speaker proficient in English as a second language education, and associated with a university, reviewed and verified the content of the test.

The assigned concept map to participants was based on the text and the reading comprehension exercises. The expert map used in this experiment had seventeen concepts and seventeen links. Since each link corresponds to a proposition, it contained seventeen propositions. The expert map was built based on the text.

Procedure

The experiment was administered via an online platform. Participants completed informed consent and then proceeded to read instructions on how to use Kit-Build. Afterward, they would construct the training map to become familiar with using Kit-Build interface. The training map consisted of three concepts and three links. The content of this training map had no relation to the rest of the experiment. Only participants from the experiment group were shown how different their maps were from the expert map. Afterward, only the experiment group was requested to change their map into the expert map.

After building the training map, participants from both groups read the narrative and answered the pre-test. Then, they used Kit-Build to construct a map related to the base text. Only the experiment group was later asked to modify their map to match the expert map, as they had done with the training map. Participants then answered the post-test, ending the main phase of the experiment. All activities in the main phase had a 5-minute limit, except for building the map, which had a 20-minute limit.

Two weeks later, participants were contacted by email to take part in the optional delayed phase. The delayed phase consisted of the same comprehension test taken in the pre-test and post-test. Participants did nothing else other than answering the comprehension test questions.

For the analysis of the data, the time is measured in seconds while the testscores are calculated as the ratio of the correct answer over the total number of questions. Based on the pre-test and post-test scores, the normalized change score is calculated. While for delayed normalized change, pre-test and delay-test scores were used. Normalized change metric measures the proportion of improvement or declines in academic achievement relevant to the maximum of what can be improved or lost, thus avoiding the pre-test score bias (Marx & Cummings, 2007; Perdana & Azhari, 2017; Setiawan, 2020). For taking into account new knowledge and reviewed knowledge, formulas are applied to the pre-test/post-test scores as explained in the subsection below.

Metrics for new knowledge and reviewed knowledge

Four metrics are defined to examine both newly acquired knowledge and reviewed knowledge. These metrics find their foundation in the dynamics of answer transitions across three distinct phases: the pre-concept map construction phase (pre-test), the post-construction phase (post-test), and a subsequent two-week delayed phase (delayed post-test). Table 1 shows how each question can be classified. Each classification is related to one of the research questions.

Table 1 Question classification table

	Answer Correctness		
Classification	**Pre-test**	**Post-test**	**Delayed Post-test**
Review	Correct	Correct	NA
New	Incorrect	Correct	NA
ReviewOnDelay	Correct	Correct	Correct
NewOnDelay	Incorrect	Correct	Correct

Table 2 Calculated learner metrics and their formula

Metric	Formula
Normalized Review	$\frac{Review}{Pre}$
Normalized New	$\frac{New}{1 - Pre}$
Normalized Review Retention	$\frac{ReviewOnDelay}{Review}$
Normalized New Retention	$\frac{NewOnDelay}{New}$

Note: Pre refers to pre-test scores. Review, New, ReviewOnDelay, and NewOnDelay refer to the number of questions belonging to each classification for that particular learner.

"Review" pertains to reviewed knowledge while "New" is associated with new knowledge. These categories correspond to the immediate measurements undertaken during the pre-test and post-test, conducted immediately before and after the concept map construction process.

The two "OnDelay" metrics (NewOnDelay and ReviewOnDelay) are associated with the delayed post-test, which occurred after a two-week retention period following the completion of the concept map.

The questions are classified and then counted for each metric. This gives raw metrics for each learner. Based on the raw metrics, normalized metrics are then calculated. The normalized metrics and their corresponding mathematical formulations are provided in Table 2.

Results

39 people attempted the experiment as the control group. Of these, 9 people were excluded for failing to obey the instructions or for having difficulties completing the experiment. Of the 30 learners remaining in the control group, only 21 completed the delayed test. As for the experiment group, the data for the 24 Kit-Build learners were used. Of these, 16 completed the delayed test. In total, 54 learners completed the main phase and 37 learners completed the delayed phase. Mean and standard deviation for pre-test, post-test, and

normalized change scores are shown in Table 3, while similar metrics for people who completed the delayed post-test can be seen in Table 4. Figure 5 visualizes how the test scores vary through time. A difference between the two groups can be seen both in the post-test and in the delayed post-test. The Shapiro-Wilk test for normality could not show the normality of residuals in the test scores data. Therefore, data analysis is made using non-parametric two-tailed methods at a significance level of $\alpha = 0.05$.

To address our first research question, whether learners transitioning their maps into the expert map affects immediate reading comprehension gains, we performed a Mann-Whitney test with normalized change as the dependent variable and condition as the

Table 3 Mean and standard deviation of measured statistics for both groups, including all participants

Group	N	Pre-test	Post-test	Time-on-task	Normalized Change
Experiment	24	0.58 (0.22)	0.82 (0.11)	944.50 (259.82)	0.53 (0.30)
Control	30	0.64 (0.24)	0.67 (0.24)	610.73 (289.21)	0.12 (0.32)

Table 4 Mean and standard deviation of measured statistics for both groups, only for the participants who completed the delayed test

Group	N	Pre-test	Post-test	Delayed Test	Time-on-task	Normalized Change	Delayed Norm Change
Experiment	16	0.59 (0.22)	0.82 (0.10)	0.70 (0.17)	920.69 (258.40)	0.46 (0.34)	0.25 (0.37)
Control	21	0.66 (0.20)	0.68 (0.19)	0.58 (0.22)	640.33 (257.67)	0.08 (0.29)	-0.11 (0.30)

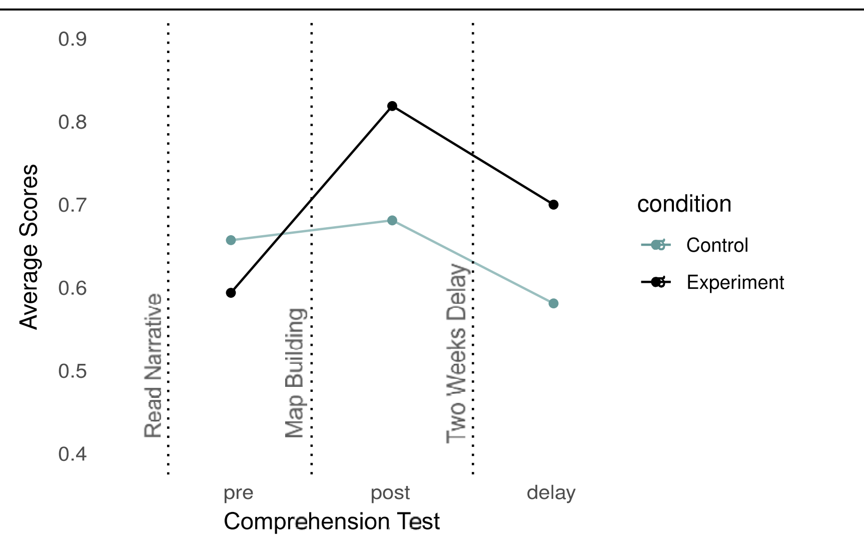

Fig. 5 Pre-test, post-test and delayed-test score averages for participants who completed the delayed test

predictor. The median scores for the experiment condition and control condition were 0.54 and 0 respectively. The test revealed that the normalized change score for the experiment condition was significantly higher than the normalized change score for the control condition ($U = 15.60$, $n1 = 24$, $n2 = 30$, $P < .001$).

Table 3 shows the descriptive statistics of the concerning metrics. The findings suggest that the practice of transitioning learner-built concept maps into the expert map has facilitated an average immediate gain of approximately 53% among the learners. Moreover, the outcomes indicate that furnishing learners with components of a concept map, without a predefined expert map as a target, might not lead to a significant enhancement in learning gains.

To address our second research question, whether learners transitioning their concept maps into the expert map affects the retention of reading comprehension gains, we performed a Mann-Whitney test with delayed normalized change as the dependent variable and condition as the predictor. The median scores for the experiment condition and control condition were 0.26 and -0.18 respectively. The analysis yielded a statistically significant divergence in delayed normalized change between the experiment condition and the control condition ($U = 7.93$, $n1 = 16$, $n2 = 21$, $P < .01$).

Table 4 shows the mean and standard deviation of the concerned metrics for learners who completed the delayed test. Learners from the experiment group answered around 7 questions in the delayed test. This is still an improvement over the pre-test, despite the two-week delay. In comparison, learners from the control group answered around 6 questions in the delayed test. There is a drop from the pre-test scores which amounts to almost one question forgotten. Comparing the delayed post-test scores in both groups to their post-test scores, both groups tend to forget similarly. So both groups appear to have similar behaviors in retention. What is worth noting, however, is that the experiment group still outperforms their pre-test results, meaning that not only do they improve after building the expert map, but they are also able to retain some of this improvement as seen from the delayed normalized change score. Experiment group learners kept 25% of improvement over their pre-test score while control group learners lost 11% of their improvement over their pre-test score.

Additionally, we have investigated the final concept map quality between the two activities. By design, all participants in the experiment group achieved a perfect score on the concept map by the end of the activity. This outcome was ensured through feedback and guidance, enabling participants to adjust their maps until all links aligned with the expert map. This perfect score, while demonstrating the effectiveness of the feedback mechanism, precludes using final map quality as a differentiating factor within this group. In contrast, the control group, who did not receive corrective feedback, showed varying

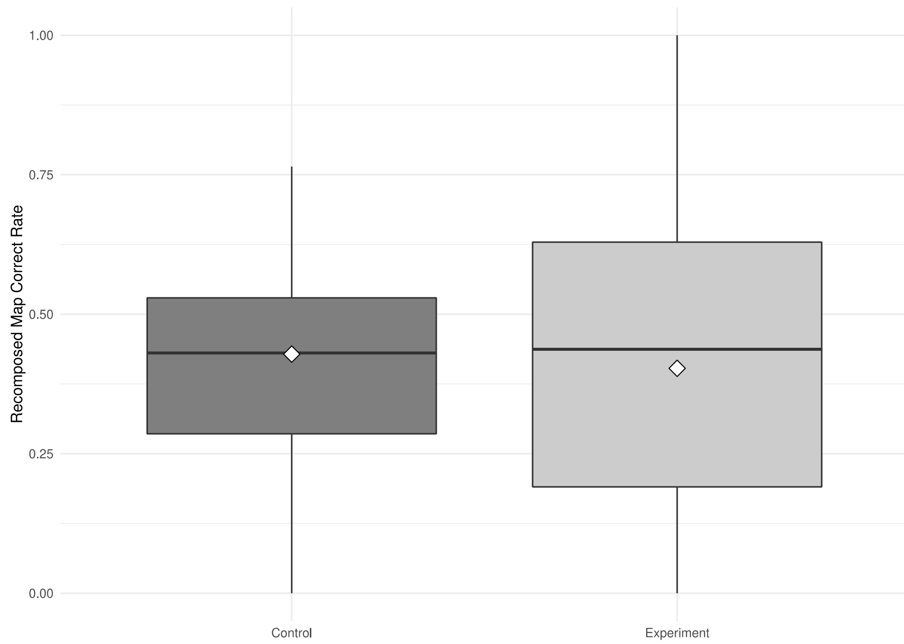

Fig. 6 Map quality between the two groups

levels of map quality in their final submissions. The mean percentage of correct links in the control group's final maps was 0.43 (SD = 0.19).

Both main research questions have been addressed with the analysis above. Next, the two secondary research questions are answered. Those exploratory analyses are done to get more details on the learning mechanisms.

Analysis on new knowledge and reviewed knowledge

The mean and standard deviation of the four normalized metrics for new and reviewed knowledge is provided in Table 5. Furthermore, for easier visualization of the differences between the two groups, a box plot is presented in Figure 7. The most pronounced difference is observed in the normalized 'New' metric, reflecting the extent of new knowledge acquired by learners during the activity. This aligns with the theoretical assumption that the feedback mechanism aids in the acquisition of new knowledge.

Table 5 Mean and standard deviation of New/Review metrics for participants who completed the delayed test

Group	N	Normalized Review	Normalized New	Normalized Review Retention	Normalized New Retention
Experiment	16	0.91 (0.11)	0.59 (0.35)	0.89 (0.16)	0.60 (0.34)
Control	21	0.85 (0.19)	0.33 (0.28)	0.66 (0.29)	0.53 (0.45)

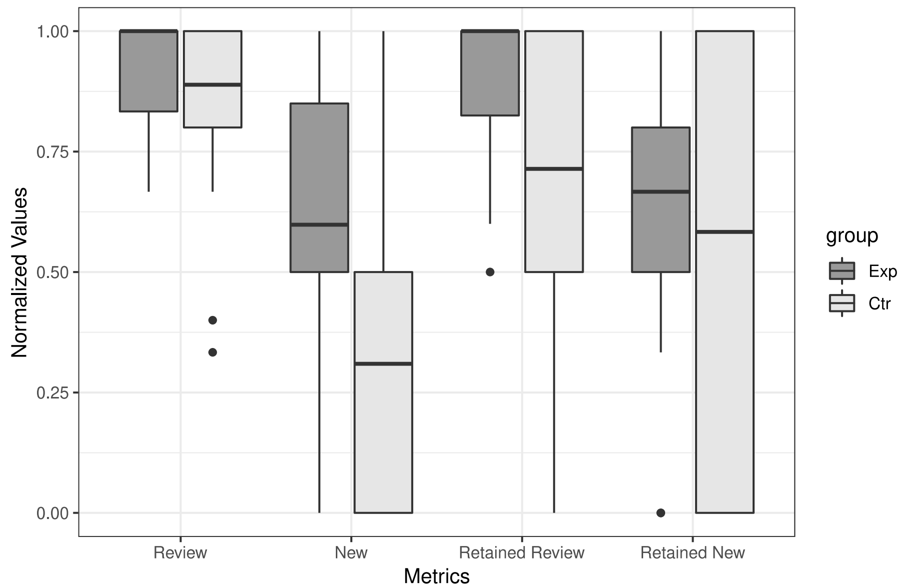

Fig. 7 Normalized metrics of reviewed knowledge, new knowledge, retained reviewed knowledge and retained new knowledge, for both control and experiment groups

However, a notable observation is the normalized 'Retained Review'. The difference between the means is considerable: learners who received feedback exhibited an average retention rate of 89% for reviewed information, while those without feedback retained only 66% of the reviewed information. This suggests that the cognitive process of deconstructing one's own map and subsequently reconstructing the expert map may have a memory-enhancing impact on the reviewed information. The subsequent section entails statistical analyses conducted on these two variables.

To address whether learners changing their maps into the expert map affects how they acquire new knowledge, we performed a Mann-Whitney test with normalized 'New' as the dependent variable and condition as the predictor. The test revealed that normalized 'New' for the experiment condition (Mdn = 0.60) was significantly higher than normalized 'New' for the control condition (Mdn = 0.31), ($U = 5.10$, $n1 = 16$, $n2 = 21$, $P < .02$).

To examine the impact of learners' transition of their concept maps into the expert map on their retention of reviewed knowledge, we conducted a Mann-Whitney test using normalized 'Retained Review' as the dependent variable and the condition as the predictor. The test revealed a statistically significant difference, with normalized 'Retained Review' for the experiment condition (Mdn = 1.00) notably surpassing that for the control condition (Mdn = 0.71), ($U = 5.30$, $n1 = 16$, $n2 = 21$, $P < .02$).

One interesting element of the results is that normalized 'Retained New' knowledge remains unaffected by the feedback intervention. This implies that despite learners absorbing more information, their forgetting rate remains akin to that of learners who did not receive feedback. This observation suggests that the acquisition of this new information does not translate into a substantially deeper memory retention. It is important to emphasize that while this finding implies similarity in the ratio of forgetting between the control and experiment groups, it does not imply equivalence in their performance after the two-week interval. The experiment group still maintains a performance advantage over the control group, even though their forgetting patterns align more closely. This finding is in line with prior research outcomes where the management of layout did not significantly impact normalized 'Retained New' knowledge (Furtado et al., 2019).

Another observation is the normalized 'Review' metric for the control group. On average, learners from the control group retain approximately 85% of their pre-map building knowledge. However, their average test scores demonstrate an increase, as evident in Figure 5. This gap is attributed to the acquisition of normalized 'New' knowledge during the process of map construction. Given that the control group does not receive explicit feedback, it is plausible that this newfound knowledge originates from the learners' inference while examining the components of the map.

Exploratory analysis on time-on-task

An important aspect that requires attention is the distinction in time-on-task between the two conditions. Table 6 outlines the mean and standard deviation of the time (measured in seconds) learners dedicated to the task of concept map recomposition for the entire learners and separately, for learners who completed the delayed test only. Notably, participants in the experiment group allocated more time to the map recomposition phase. It is necessary to examine whether the observed learning gains in the experiment condition could be attributed solely to increased time spent on the task, or whether the "Expert Construction" activity itself – characterized by its unique cognitive demands – plays a significant role.

Given that the applicability of the Mann-Whitney test is limited in a factorial design, a logistic regression model is adopted for this purpose. Two distinct models were formulated: one for normalized change (model 1) and another for delayed normalized change (model 2), with the former and latter serving as dependent variables, respectively. Both models encompass the condition as an independent variable and incorporate time-on-task as a covariate. This model allows us to isolate the effect of the "Expert Construction" activity while accounting for differences in the time participants spent on the task.

Table 6 Mean and standard deviation of time spent on the concept map construction task for all learners plus for learners who completed the delayed test only

Group	N	Time on Task	N (Delayed)	Time on Task (Delayed)
Experiment	24	944.50 (259.82)	16	920.69 (258.40)
Control	30	610.73 (289.21)	21	640.33 (257.67)

Table 7 Statistics for the two logistic regression models

Model	Predictor	Coefficients	S.E.	Wald Z	P(>|Z|)
1	Time-on-task	-0.00	0.00	-1.20	0.23
1	Condition	-2.71	0.67	-4.01	<0.001
2	Time-on-task	-0.00	0.00	-0.27	0.79
2	Condition	-1.95	0.72	-2.71	0.01

Note: Time-on-task, included as a covariate, is not statistically significant in both models. Condition is a statistically significant predictor in both models.

The results of the logistic regression analysis provide crucial insights into the effectiveness of the expert construction activity beyond mere additional review time. Table 7 summarizes these findings. Particularly, the condition variable (experiment vs. control) emerges as a significant predictor of both immediate ($p < 0.001$) and delayed ($p = 0.01$) learning gains, even when accounting for time-on-task. This strongly suggests that the observed improvements in learning outcomes are not simply a result of spending more time on the task, but rather stem from the specific cognitive processes involved in the expert construction activity.

Importantly, time-on-task itself does not show statistical significance as a predictor of learner improvement in either the immediate ($p = 0.23$) or delayed ($p = 0.79$) learning measures. This further reinforces the notion that the benefits of the expert construction activity extend beyond what would be expected from additional review time alone. The cognitive engagement required in aligning one's concept map with an expert model appears to foster deeper understanding and better retention, independent of the time invested in the task.

These results collectively demonstrate that although both activities serve as review exercises, the cognitive dynamics inherent in the expert construction activity appear to be superior for learners engaged in concept mapping. The guided process of map transition seems to enhance learning outcomes more effectively than unguided map construction, highlighting the unique benefits of this approach beyond mere additional review time.

Limitations and future directions

One of the key strengths of closed concept maps is that they allow for automated scoring and structured feedback by comparing learner-built maps to expert maps. However, a potential concern is that explicitly highlighting the differences between the learner and expert maps may lead to surface-level corrections rather than deep cognitive processing. In other words, learners might adjust their maps based on the provided feedback without fully understanding the conceptual relationships. While this risk exists, we argue that guided feedback serves as an instructional scaffold rather than merely "giving away the answer." The process requires learners to actively engage with the expert structure, refine their understanding, and differentiate between correct and incorrect propositions, thereby supporting conceptual learning.

To further assess the impact of feedback, we distinguished between reviewed knowledge (concepts learners initially misunderstood but corrected with feedback) and newly attained knowledge (concepts learned for the first time). This differentiation allows us to examine whether the observed gains stem from meaningful learning rather than simple correction.

An alternative approach, would be to compare closed maps with expert feedback to open concept maps followed by an expert review and revision phase. While such a comparison could provide additional insights into different learning strategies, our study specifically aimed to evaluate the role of guided recomposition within a structured concept mapping environment. Future research should explore how different levels of feedback and learner autonomy in concept mapping influence learning outcomes, particularly in open-ended settings where learners construct maps from scratch before receiving expert guidance.

Our findings contribute to the growing body of research on structured learning interventions in concept mapping. By demonstrating that guided expert map recomposition enhances both knowledge consolidation and acquisition, we provide empirical evidence for the benefits of this instructional approach and lay the foundation for further investigations into optimal feedback strategies in concept mapping environments.

Future directions – A promising direction for future research is investigating methods to prompt learners to reprocess recently acquired information as a means to prolong retention. One possible strategy is to task learners with constructing a new concept map from scratch, containing only the information in which they previously made errors. This could help reinforce learning by requiring students to engage with previously misunderstood concepts in a new context.

Additionally, providing learners with access to textual materials during concept map creation could introduce interesting dynamics. Future studies could explore whether such access enhances comprehension and reduces the need for transforming learner maps into expert versions. Understanding how external resources influence concept map construction can shed light on optimal instructional design strategies.

In this study, we have focused on the (Incorrect, Correct) and (Correct, Correct) transitions as they align with our primary objectives of evaluating learning gains and knowledge retention, respectively. Metrics such as (Correct, Incorrect) and (Incorrect, Incorrect) reflect forgetting or persistent misconceptions are also important areas to investigate in learning with concept maps.

Another possible direction is to provide an alternative interface for comparing student and expert maps that simply displays the wrong links in red colored links and the missing links in very light gray colored links (just like the way the jMAP software compares maps).

Then measure the extent to which this new interface reduces cognitive load and improves learning and retention.

Furthermore, automated comparison techniques for closed concept maps could be enhanced by leveraging AI-based methods such as natural language processing (NLP) and graph neural networks (GNNs). Future research could investigate how these technologies enable automated feedback in open concept maps, expanding the applicability of expert map comparisons. Understanding the role of AI in this context could offer insights into the relative strengths of closed and open concept mapping approaches across different learning scenarios.

Finally, investigating the number of mistakes detected during concept map construction and the number of remaining mistakes after feedback could be insightful. Future studies could analyze the number of iterations or error correction rates required to reach the expert map, emphasizing the learning process rather than just the final state. This would help educators better understand the impact of iterative feedback on student learning.

Conclusion

The effectiveness of both closed concept map construction and expert map visualization as learning methods has been established through this study. It suggests that introducing learners to the differences between their maps and expert maps, and subsequently guiding them to align their maps with the expert versions, can serve as a highly efficient learning approach. This activity, facilitated by closed concept maps and made feasible by technology, represents a novel and unexplored method in the realm of learning techniques to the best of our knowledge. While previous research has not delved into the efficacy of this approach, this study successfully proposes and implements the described activity, wherein learners construct a closed concept map and then transform it into an expert map. The results reveal that this practice not only enhances immediate comprehension compared to closed concept map construction, but also sustains these benefits over a two-week period. This indicates that the activity not only facilitates a better understanding of the subject matter but has the potential to achieve a level of cognitive processing that leads to enduring memory retention, thus relieving concerns about mindless transition of learner maps to expert maps.

A potential drawback is the increase in time-on-task due to the activity. However, the study's findings negate the notion that improved comprehension and retention are simply outcomes of spending more time on the task. The results indicate that learners who invest more time in the activity do not necessarily outperform those who spend less time. Consequently, extending the map-building phase might not yield the same outcomes as guiding learners to transition their maps to expert maps.

Distinguishing this study from others that build upon closed concept map construction is the incorporation of a control group solely engaged in constructing closed concept maps. This strategic inclusion clarifies whether the observed effects emerge from the transition approach or from closed concept map building. Another notable advantage of the approach adopted in this study is its minimal requirement for additional resources beyond the expert map itself. This relieves educators from the burden of developing feedback-related content.

Interestingly, the feedback mechanism did not influence the learners' capacity to retain new information acquired through feedback. This aligns with past research indicating that manipulating the layout of a concept map primarily aids the retention of reviewed information, rather than information gained from feedback. This study provides empirical evidence that expert map recomposition can be a valuable pedagogical approach, offering structured guidance for learners and contributing to improved knowledge retention.

Providing the first detailed examination of expert-based, proposition-level feedback in Kit-Build concept maps. Offering practical insights for educators on the potential benefits of structured feedback in concept mapping activities. Demonstrating the effectiveness of this approach for both immediate learning and long-term retention.

Abbreviations

TMC: Traditional Concept Map Creation; CMA: Closed Concept Map Assembling; CRS: Conceptual Representation of the Source-Code; OOP: Object-Oriented Programming; KB: Kit-Build; SMS: Sub-Map Scoring; FMS: Full Map Scoring; AMT: Amazon Mechanical Turk; NLP: Natural Language Processing; GNNs: Graph Neural Networks.

Acknowledgements

This work was partially supported by JSPS KAKENHI Grant Number 19H04227.

Authors' contributions

NK discussed the results and wrote the manuscript. PGFF managed the experiment and performed the data analysis. YH and TH contributed to discussing the overall content of the manuscript. All authors read and approved the final manuscript.

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Funding
This work was partially supported by JSPS KAKENHI Grant Number 19H04227.

Availability of data and materials
Sharing the entire study data and resources other than those specified in the paper is available upon request to the corresponding author and after getting permission from all authors.

Declarations

Competing interests
The authors declare that they have no competing interests

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Received: 14 May 2024 Accepted: 5 March 2025
Published online: 1 January 2026 (Online First: 5 August 2025)

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