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The evaluation of concept map recomposition order and its effect on learning outcomes

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Abstract

Concept map serves as a visual tool in education, facilitating the organization and representation of knowledge. Concept map recomposition activity, which is a kind of concept map building activity, has been shown to promote meaningful learning and enhance reading comprehension. In this process, the teacher creates an expert map from a text material, decomposes it into individual concepts and links, and the learners then recompose these components. During the recomposition activity, learners connect concepts and links to form propositions, using information acquired from teacher's explanation and/or by reading the text material. However, since the information in the text is generally presented in a specific sequence, it is important to evaluate whether following this sequence during the recomposition affects their learning outcomes. Understanding this is beneficial for teachers in providing support in concept map recomposition activities. This research evaluated the similarity between the recomposition order and the text's information order, and how it relates to learning outcomes. The results revealed that various recomposition orders led to equal learning outcomes. However, the recomposition order was related to the aspects of the activity, which are time on task, time required to perform each action and map quality. This finding suggests that teachers should provide support that adapts to differing recomposition order, recognizing that learners may approach the recomposition activity in different ways.

Keywords: Concept map, Kit-Build, Sub-map, Recomposition order

Introduction

The concept map is a well-suggested approach to organizing knowledge graphically and is a beneficial tool for enhancing learning activities (Anastasiou et al., 2024; Novak & Symington, 1982). The concept mapping activities involve learners either observing or creating a map. While a concept mapping activities in which learners are tasked with observing the map could improve learning, building the map as a learning activity has been revealed to promote meaningful learning by incorporating mental process, encompassing various functions of the mind, such as thinking, reasoning, problem-solving, and high-order thinking (Hsu, 2019; Tseng, 2020).

The activity of building the concept map could be based on either of two strategies: scratch or recomposition (Pinandito et al., 2021; Prasetya et al., 2019). In scratch building, learners construct a map on a blank slate, where they are free to create its components, such as concepts and links, and then connect them to form a complete map. In recomposition, the teacher provides the components to recompose the map. Initially, the teacher creates an expert map that then decomposed into set of components consisting of disconnected concepts and links. The learner's task is to reconnect the components, including concepts and links, into a complete map (Alkhateeb et al., 2015; Hirashima et al., 2015). Recomposition has been proven to improve learning by enabling knowledge sharing between teachers and learners and promoting better high-order thinking (Nurmaya et al., 2023). Kit-Build (KB) is a framework that supports the recomposition activity through a computer-aided learning tool. KB provides valuable benefits, such as the feasibility of assessing map quality, enabling recomposition process evaluation, and facilitating collaborative recomposition (Hirashima, 2019; Sadita et al., 2020).

In the concept map recomposition, the expert map was created by extracting propositions consisting of concepts and links that derived from the knowledge and information of a text material. During the learning activity, teacher gives explanations about the text material and provides the text to read. Learners are then tasked to recompose the map using the information they acquired from teacher's explanation and by reading the text. Therefore, to recompose the map, learners have two resources, their own understandings from teacher's explanation, and the information from the text material. While the text material is fundamentally designed to present information in a specific order of sequence (Sahin, 2011), this order is not enforced during the recomposition activity. Learners may recompose the map in the various order relative to the text's information order.

In the KB concept map recomposition, all the components (concepts and links) required to build the map are readily available. Therefore, learners could start to recompose from any components and subsequently proceed to any of the next components. Learners can recompose based on the text's information order, performing a similar recomposition order of sequence with the text's information order. They can also recompose based on their own understandings from listening to the teacher's explanation and perform the recomposition in a different order of sequence from the text's information order.

This variation leads to different orders of learner's concept map recomposition relative to the text information order. However, how these differing recomposition orders affect learning outcomes has yet to be evaluated. The difference between learner's order with information order and how it affects learning outcomes has been observed in several prior research (Liegle & Janicki, 2006; Melara, 1996; Reed & Rosenbluth, 1995). These studies observed learner activities in the hypermedia that can be navigated in various order in relation to the information order. It was revealed that the differing behaviors in the interaction with the hypermedia in terms of various navigational orders resulted in equal learning outcomes, which suggested that the media could facilitate any approach in navigation. It highlights the importance in providing support that could accommodate these differing behaviors in the learning activities.

Therefore, understanding how the difference between recomposition order and text's information order affect learning outcomes is essential, as it might influence teachers' decision in providing support and giving specific directions to achieve the best possible outcomes in the concept map recomposition activity. The evaluation of recomposition order was performed by analyzing the recomposition process, focused on the sequence of propositions creation. Several studies mentioned that the process in concept map building has relation with learning outcomes, as high performer learners tend to make more effort in creating several closely related propositions continuously and placed them in a close proximity (Chiu & Lin, 2012; Wong, 1998). A process evaluation on concept map recomposition suggests that better process, indicated by connecting several closely related propositions in continuity, leads to a better learning outcome (Rismanto et al., 2024). Those closely related propositions are grouped into a segment called sub-map, each of it corresponds to a subset of knowledge derived from a text material (Gerstner & Bogner, 2009; Kinchin & Alias, 2005). This knowledge subset is represented by the text's organization, such as paragraphs or sub-topics. Therefore, a sub-map contains several propositions that are related to a specific paragraph or sub-topic. Assumed that the information in the text is written and arranged in sub-map units, this research evaluated the similarity of the sub-map recomposition order with the text's information order.

This research was conducted using KB system which enables the recomposition order analysis using log data collected when learners perform the recomposition. KB also enables automatic map quality assessment, in which the learner's concept map is automatically scored by the system, in the form of map score. This map assessment has been proven in having a high correlation with learning outcomes (Wunnasri et al., 2018). For the purpose of this study, learning outcomes and recomposition activity were evaluated through multiple metrics, including test scores, task completion times, action performed, and map scores. The learning outcomes include post-test scores as an evaluation of the immediate learning outcomes, delayed-test score as an evaluation of the memory retention, and map scores as an evaluation of the map quality. The evaluation of task completion time was conducted to see whether time spent in the recomposition activity has a relation of how learners recompose the map by following the information order from the text or not. Moreover, task completion time indicates the extent of effort in information organization, which is required in concept map building (Sweller, 1988). It was suggested that during a problem-solving activity, slower time on task indicates a higher effort in organizing information. Evaluating the task completion time could provide an information whether learners' effort in information organization could affect their learning outcomes. However, the task completion time itself can also be affected by the number of actions performed during the recomposition activity. Therefore, evaluation on the learning outcomes, time on task and their number of actions performed were conducted in this study. The correlations between these factors provide further insight into the influence of concept map recomposition order. Moreover, the research questions for this research are as follows: Does following the order of learning materials in recomposing the map affect learning outcomes (RQ1)? Is there any effect on the recomposition activity such as time on task and the number of actions performed to complete the recomposition (RQ2)?

Given these differing possibilities in how learners approach the recomposition activity, it becomes important to explore whether these differences—particularly in the sequence of recomposition—impact learning outcomes. Furthermore, factors such as time on task and the number of recomposition actions may reflect underlying cognitive effort, strategy use, or navigation difficulty. Therefore, this study aims to examine how the recomposition order, time on task, and number of actions interact and whether they influence the quality of the concept map and learning outcomes. These investigations will offer insight into the mechanisms underlying learner interaction with the recomposition task and inform design of more effective learning support.

Background

Concept map building

A concept map supports graphical learning beneficially through knowledge organization. A concept map consists of two components: concepts and links. A concept represents ideas, terms, or objects related to a specific knowledge. A link connects concepts within a concept map, representing relationships, associations, or dependencies between concepts (Novak, 1990). With their visual representation of knowledge, concept maps play a significant role in education, research, and practice by offering insights into how individuals perceive and organize information (Canas et al., 2015; de Ries et al., 2022). Incorporating concept maps in a learning activity could be done either passively, where learners are tasked to observe the concept map the teacher provided, or actively, where learners are tasked to build the map. From a cognitive point of view, actively building concept maps promotes better learning in deepening comprehension, aids memory retention, and promotes critical thinking. In summary, whether created on paper or using a computerized platform, concept map building empowers learners to organize and connect information effectively (O'Donnell et al., 2002; Schroeder et al., 2018).

Building a concept map could be done either from scratch or recomposition. Scratch-building concept maps offer flexibility and deep exploration, and it has been proven to effectively facilitate learners to organize and visualize their knowledge. Moreover, concept map recomposition promotes additional benefits for meaningful learning, by enabling knowledge sharing between teacher and learner. By providing components, learners are guided to use the knowledge boundary and requirement referenced from the teacher's knowledge. One characteristic of recomposition is that it restricts the concept map building. However, as Cañas et al. (2023) revealed, introducing a certain degree of limitations could improve meaningful learning in a concept mapping activity. Introducing a restriction, such as providing a list of concepts, could promote better meaningful learning compared to having no restriction. Moreover, recomposition can help learners achieve meaningful learning and maintain the quality of the concept map (Cañas et al., 2023; Pinandito et al., 2021).

In a concept map recomposition, teachers create an expert map which extracts the content from a specific text material. Thus, the expert map contains knowledge and information from the text. The expert map is then decomposed into a set of components, consisting of concepts and links in a disconnected form. These components are then provided to learners to be recomposed back into a map, called learner map. Before performing the recomposition activity, learners were given explanations from the teacher about the text material and tasked to read the entire text material. The text material was the same text used by the teacher to create the expert map. Afterwards, learners conduct the recomposition using the provided components. While recomposing, they can check the text as a reference to find the information they needed to connect the concepts and links. Because all of the components are readily available for learners to use, they can start the recomposition from any part of the components. They create a proposition by connecting two concepts with a link, based on the information they obtained from teacher's explanations and from reading the text, and they can create subsequent propositions in any order of sequences. This allows them to perform the recomposition in a various order, without strictly following the order of information in the text.

A computerized framework of concept map recomposition has been introduced in the KB framework system (Hirashima et al., 2011). KB enables teachers and learners to work on concept map recomposition seamlessly and allows automatic assessment of the learner-built concept map (Funaoi et al., 2011). In KB, the system automatically assesses the learners' map after completed their recomposition, by superimposing the map with the teacher map and calculating the map score as an assessment of map quality. The map score has been proven to assess learners' map quality with a high correlation to a manual assessment performed by a human rater (Wunnasri et al., 2018). Figure 1 explains the general lifecycle of the KB framework.

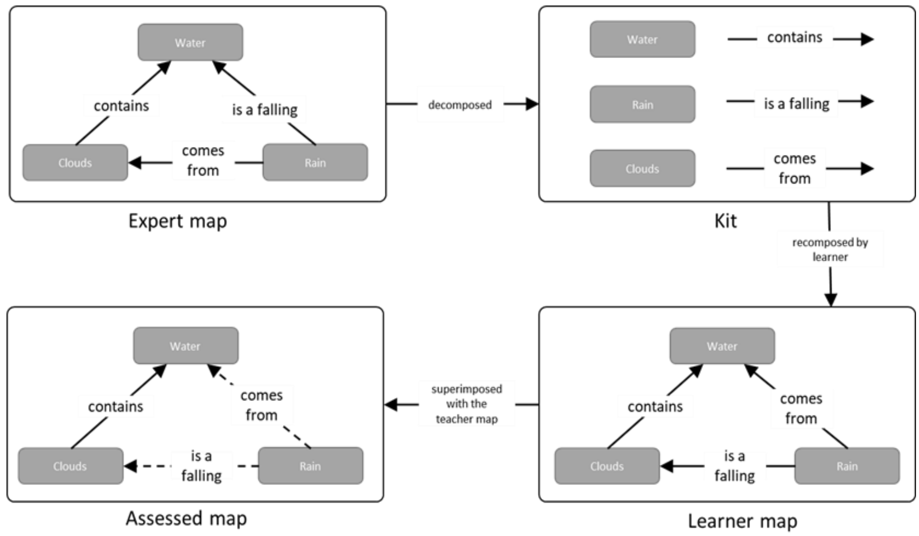

Fig. 1 Kit-Build (KB) concept map recomposition framework

KB provides the assessment information to the teacher so they can observe any knowledge disparities by watching for any incorrect links made by learners (Yamasaki et al., 2010). This way, teachers can provide feedback on knowledge disparities or concept misunderstandings to improve meaningful learning and overall outcomes. Several research studies incorporated KB in supporting concept map recomposition (Furtado et al., 2019; Khudur et al., 2024; Pailai et al., 2018). Research by Wunnasri et al. (2018) implemented a reciprocal concept map recomposition in KB, demonstrating its effectiveness in promoting effective discussions and shared understanding between pairs of learners. Rismanto et al. (2023) evaluated the learner's process in concept map recomposition in KB. The characteristics of KB, in which the components are provided, allow automatic process evaluation by analyzing log data and the learner's sequence in connecting the concepts and links into propositions in a concept map.

Concept map recomposition order

Concept map recomposition allows learners to build the map using the provided components. In KB, these components are known as "kit" which contains concepts and links that are required to recompose the map. Learners connect two concepts using a link to form a proposition, which reflects information presented in the text. There is no restriction to the order of propositions to be recomposed, and learners can work on their activity by recomposing the propositions in the various order in relation to the information's order from the text material.

Understanding the effects of recomposition order on learning outcomes in KB could provide teachers with insights into which activities lead to better learning outcomes, allowing them to provide appropriate support. When a learner connects a proposition, they access or navigate the text material related to that proposition. The evaluation of differing recomposition orders aligns with previous studies on how navigational order in learning media affects learning outcomes, such as in hypermedia. Reed et al. (2000) explained this differing behavior as a linearity styles, they observed characteristics between two styles of linearity based on the amount of "jumps" that the learner's made when navigating a "hypercard". The definition of jump was when learners performed a navigational direction differing with the order of the information structure provided in the hypercard. Linear style navigation tends to make less jump, resulting in more similar order of navigation with the structure of the hypercard, in contrast, non-linear style navigation tends to made more jump, resulting in a more divergent order of navigation with the hypercard's information structure.

Cagiltay et al. (2006) and Liegle and Janicki (2006) confirmed that the learning style affects the learner's activity in terms of navigational order in a computer-based learning environment, which used "jumps" similar with Reed et al. (2000), as an indication of non-similar order of movement in terms of the information structure. Melara (1996) suggested that both behaviors could perform equally effective using computer-based system that designed to support each behavior. Moreover, in a modern learning strategy, a learning medium that supports and accommodates both behaviors are highly preferred (Schwab et al., 2017). It allows learners to perform their activity without being limited by the media and the necessity to achieve optimal outcomes (Liegle & Janicki, 2006).

With concept map recomposition, learners need to comprehend and be able to elaborate on the knowledge related to each component by using the text material as a reference. Therefore, they recompose each proposition based on the information depicted in the text material. Following the text material structure and information order is one approach in recomposing each proposition. However, since this is not enforced, learners could also diverge from this approach and recompose propositions in differing order. This is because they also have the knowledge required to recompose the map by listening to the teacher's explanation. In relation to the recomposition order, Reigeluth introduced the elaboration theory (Reigeluth, 1999), which stated that each knowledge domain from a learning resource can be learned in a different sequence. A set of knowledge domains could be learned so that an appropriate understanding of a specific domain is needed to learn the next domain. Nevertheless, the learning outcomes affected by the order of elaboration sequence is still in question (Cock & Meier, 2012). In the case of concept map recomposition, this resulted in the variety of recomposition order. When a learner recomposes components that belong to a specific sub-map, they elaborate the knowledge depicted in that sub-map, and then they might use that knowledge to recompose the next sub-map.

Furthermore, in terms of recomposing each proposition to build a map, there is a tendency for learners to recompose it using the text material organization (paragraph or sub-topics) as a "unit of meaning" and not sentence-by-sentence (Andoko et al., 2019). In the concept map, this unit of meaning is depicted as a "segment" or "sub-map". Each sub-map corresponds to each unit of meaning in the text material. Learners have the tendency to recompose several propositions that belongs to one sub-map in continuity, and by doing so, have a better learning outcome compared to those who do not have the continuity (Rismanto et al., 2023). In terms of continuity, the order of connected propositions inside the sub-map was not considered, as long as the learners connect propositions in the sub-map continuously, they have the continuity. In relation to the recomposition order, the order of recomposed sub-maps may vary between each learner. Previous research also stated that the paragraph or unit of meaning that the learners use as a reference to recompose the map may vary between each learner. Still, how it affects the learning outcomes has not yet been known. The learner's behavior in comprehending each component in the concept map will lead to various recomposition order of sub-map in relation to the information order in the text material.

The recomposition order is a part of the evaluation of concept map recomposition process. The importance of concept map building process has been mentioned in several studies. Wong (1998) conducted a probing on the process of concept map creation by interviewing learners to recall and explain the steps involving in constructing a concept map. It was found that high performing learners made more effort in creating and grouping closely related propositions. Correspondingly, Chiu and Lin (2012) analyzed the sequence of created proposition, and it was suggested that among high performing learners, there were a pattern to create propositions that are closely related to each other continuously. In terms of concept map recomposition, Rismanto et al. (2024) suggested that learners who have a better process, indicated by how well a learner can comprehend a domain knowledge by continuously connect several propositions that are closely related, have a better knowledge understanding which resulted in a better learning outcome.

Moreover, recomposing the concept map requires learners to organize the information they receive from the text. The information organization introduces a certain extent of cognitive load and affects the time required to complete a task in a problem-solving activity (Sweller, 1988). As a result, how well the learners can organize the information could impact the time required to complete the recomposition. Additionally, Chi et al. (1981) suggested that high performing learners can recall and organize information quickly due to deeper conceptual understanding, whereas lower performer learners take longer. Novak and Cañas (2008) suggested that in terms of concept mapping, there are limitations on learner's working memory in observing and memorizing propositions. Faster recomposition could suggest less effort in recalling knowledge to create propositions.

Faster recomposition, however, could also be affected by the actual actions performed while doing the recomposition activity. Therefore, evaluation on how recomposition order and learning outcomes relate to time on task and action performed is required.

The evaluation of recomposition order

Learners recompose the map based on the knowledge they acquire by listening to teacher's explanation and reading the text material. Recomposing the map means connecting with the provided concepts and links to create propositions into a complete map. The text material is used as a guidance when deciding which propositions they need to create. Because a proposition consists of components extracted from the text material, learners use the text material as a reference to create a proposition.

Accordingly, the order in which the proposition should be created is entirely up to the learners. This leads to various connected proposition orders between each learner. However, evaluating the order of each connected proposition will lead to many combinations, depending on the number of concepts and links being recomposed.

Our previous research on the concept map recomposition process underlined the importance of evaluating the recomposition order based on the idea of a sub-map (Rismanto et al., 2023). This is because a sub-map contains a set of propositions that reflect knowledge from the text material. Therefore, evaluating it based on the sub-map level is essential instead of the propositional level.

The sub-map and the base order

In this research, we defined a base order as the reference order of sub-maps. The base order was determined by the teacher when creating the expert map and defining the sub-maps. Each sub-map contains propositions belonging to a specific knowledge domain from the text material (Schneider et al., 2021). In relation to the text material, a sub-map reflects a unit of organization from the text material, which could be in the form of sub-topic or paragraph. Figure 2 illustrates how the sub-map was defined.

The teacher defined the base order following the text material's unit of organization. For example, if a text is organized in paragraphs, the paragraphs are used as a unit of organization. The concept map extracted from this text is then divided into several sub-maps; each sub-map contains knowledge from each paragraph. Therefore, the base order would naturally reflect the order of the paragraph from the text material. This approach was in line with the task sequencing and learning principle, where the knowledge domain is sub-divided into several components. These components can be learned separately but can also be learned in combination to enable learners with different levels of prior knowledge to learn efficiently (Cock & Meier, 2012).

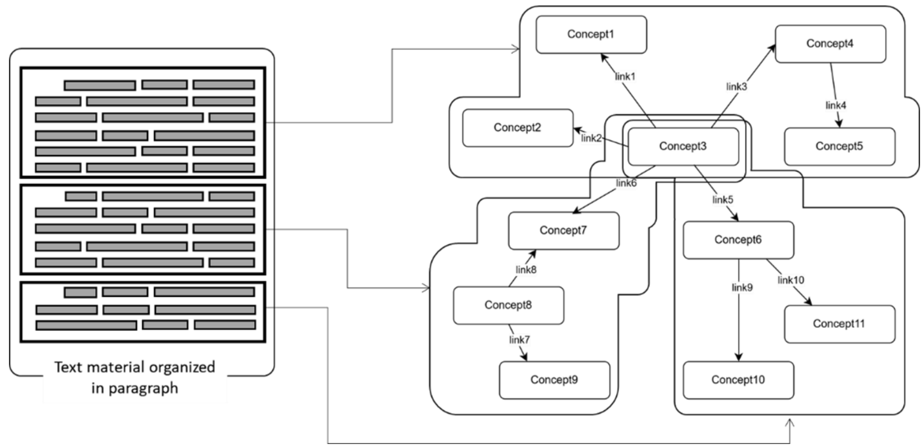

Fig. 2 Sub-map in a concept map

The learner order

Moreover, recomposition order was evaluated by comparing learner order when recomposing the map with the base order. A learner order was the order of sub-maps where the learner connects one or more propositions, as shown in the bottom left part of Figure 3. When a learner connected one or more propositions that belonged in a sub-map, this was counted as step one. When a learner moved to connect the next propositions belonging to another sub-map, this is counted as step two because the learner moved from one sub-map to another, regardless of the number of propositions they connected in the subsequent sub-map.

A recomposition order was considered similar if the base and learner orders were identical. In other words, the learner worked in a sub-map and moved to the next sub-maps identically to the base order.

Comparing learner order with the base order

To evaluate the recomposition order, we used a form of scale that used Levensthein distance (LD) (Levenshtein, 1965) to analyze the similarity between the learner order of sub-maps and base order. A zero LD would mean that the learners performed recomposition in a similar learner order to the base order. The greater the LD, the more the learner's recomposition order deviated from the base order. The bigger the LD value, suggests that the recomposition order was more towards non-similar.

The sub-map order is illustrated in Figure 3. Assuming the base order is sub-map 1 (SM1), SM2, SM3, SM4, SM5, from now on referred to as 1, 2, 3, 4, 5. Proposition 1 (P1) and P2 belong to SM1, therefore written as SM1(P1, P2). Consecutively, SM2(P3, P4), SM3(P5, P6), SM4(P7, P8) and SM5(P9, P10).

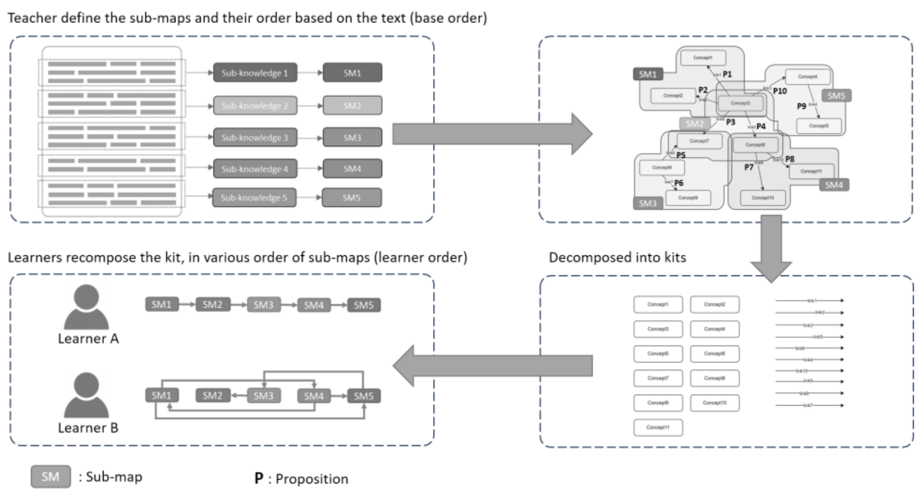

Fig. 3 The sub-map order and learner order

In this example, there were two learners, learner A and B. Learner A recompose P1, P2, P4, P3, P5, P6, P8, P7, P9, P10. Based on this recomposition order, learner order of A would be 1, 2, 3, 4, 5. This is because P1 and P2 belong to sub-map 1, hence SM1(P1, P2), P4 and P3 belong to sub-map 2, hence SM2(P3, P4) and so on. Learner B recompose P1, P8, P2, P7, P10, P9, P5, P6, P3, P4. P1 belongs to SM1, P8 belongs to SM4, P2 belongs to SM1, this is an example of the learner recompose proposition from one sub-map to another and back again (SM1 - SM4 - SM1). P7, P10 belongs to SM5, and so on. Based on this recomposition order, learner order of B would be 1, 4, 1, 5, 3, 2. The LD of Learner A and B would be described as:

Learner A:
base order: 1, 2, 3, 4, 5
learner order: 1, 2, 3, 4, 5
LD(base order, learner order) = 0

Learner B:
base order: 1, 2, 3, 4, 5
learner order: 1, 4, 1, 5, 3, 2
LD(base order, learner order) = 5

In this example, learner A tended to perform concept map recomposition in a more similar order with the text structure and information's order compared with learner B.

LD, or edit distance, is a string metric that measures the difference between two sequences. It quantifies the number of single-character edits (insertions, deletions, or substitutions) required to transform one sequence into another (Levenshtein, 1965). Prior research revealed the feasibility of LD in evaluating sequence similarity (Koishybay et al., 2021; Ruddle et al., 2022). In Hauge et al. (2021), LD was applied to assess a sequence of a complex cognitive motor in a humanoid robot and compare it with a reference sequence in performing an action. The LD was a reliable performance marker and can be used to assess sequence similarity. LD has also been proven adequate in assessing the similarity between different sequences. Beernaerts et al. (2019) emphasized that LD is an adequate distance metric method for comparing sequences with different lengths, because it allows operations of insertions and deletions. For example, in the string comparation operation, insertions allow to add character to the shorter string. Deletion allows to remove character from the longer string, reducing its length to match the shorter string. These operations give LD the flexibility to align and compare sequences of different lengths to measure the minimal set of operations needed to convert one sequence into another.

In concept map recomposition, the base sequence’s length is expected to be shorter than the assessed sequence. Therefore, LD is an adequate way to compare the two since the learner order sequence length could differ from the base order sequence length in this research. For example, the base order is 1, 2, 3, 4, 5 in which the length is 5. A learner recomposed with learner order of 3, 2, 1, 3, 4, 5, 2 in which the length is 7. As can be seen that this learner revisit sub-map 3 and 2 which makes the length longer than the base order. LD does not necessitate that those two sequences be of identical length. Therefore, in this case, LD can be used to calculate the similarity between those sequences with different length. To calculate the LD, the following formula is used (Levenshtein, 1965). To calculate the distance between two strings a, b is given by ⟦lev⟧_(a,b) (|a|,|b|) where:

$$lev_{a,b}(i,j) = \begin{cases} \max(i,j) & if \min(i,j) = 0, \\ min \begin{cases} lev_{a,b}(i-1,j)+1 \\ lev_{a,b}(i,j-1)+1 \\ lev_{a,b}(i-1,j-1)+1_{(a_i \neq b_j)} \end{cases} & otherwise, \end{cases}$$

The following matrix (i, j) is populated and performs the calculation on each cell according to the formula, as shown in Figure 4. The first row is the base order, and the first column is the learner order. The second row and column are added by default indicating the length of string in the row and column respectively. Comparison of each string in the third column and row is then performed. If the string in the column is the same with the row, then the cell value will be the same with the cell positioned diagonally before the current cell. If the string in the column is different with the row, then take minimum value from three conditions: The “cell value positioned in the row before” + 1; The “cell value positioned in the column before” + 1; The “cell value positioned diagonally before” + 1.

		1	2	3	4	5
	0	1	2	3	4	5
3	1	1	2	2	3	4
2	2	2	1	2	3	4
1	3	2	2	2	3	4
3	4	3	3	2	3	4
4	5	4	4	3	2	3
5	6	5	5	4	3	2
2	7	6	5	5	4	3

Fig. 4 Matrix (i,j) populated to calculate the LD

The calculated LD result of this example is at the bottom right cell from the matrix (i,j), which is 3.

Methods

Experiment details

The subject of this research consisted of 27 second-year undergraduate students majoring in the Computer Science Program. Subjects were not familiar with concept mapping in general and recomposition specifically. The experiment was conducted using the KB concept map recomposition system. Subjects had never used the KB system or did not know of it.

Therefore, at the first stage of the experiment, subjects were given a tutorial about general concept maps and how to perform concept map recomposition in the KB system. The author of this paper conducted the tutorial for a total of 15 minutes of KB demonstration and 20 minutes for KB recomposition activity. In the second stage, subjects were given a pre-test of 20 multiple-choice questions and 30 minutes to finish the test. In the third stage, the teacher provided teaching and explanation about the learning topic for 30 minutes. Teacher provided explanation following the text material, in a way following common teaching practices in the course, and therefore, following the information sequence from the text material. In the fourth stage, subjects performed concept map recomposition using the KB system for 30 minutes. There were no intervention or specific direction from the teacher on how the recomposition should be performed. The learners were given a set of concepts and links that are arranged and placed randomly. Learners were free to choose where to start and end the recomposition, which concepts and links they want to connect to make the subsequent propositions. In the fifth stage, subjects were given a post-test with the same questions as the pre-test, with 30 minutes to finish the test. The final stage of the experiment was conducted one week later, with subjects being given a delayed-test consisting of the same questions used in the pre- and post-test.

The experiment topic followed the class course, object-oriented programming (OOP), and the topic was encapsulation. Considering the course timeline, subjects have not yet received a lecture about encapsulation. Therefore, this minimizes the bias of preexisting knowledge of the subject. The expert map used in the KB was extracted from the OOP learning module authored by a teaching team responsible for teaching and designing the material for the OOP course. The author of this paper created the expert map and discussed it, and the teaching team approved it. The map consisted of 15 propositions with 14 concepts and 15 links.

In addition to the regular usage of the KB concept map recomposition, the expert map's author was required to define the sub-maps and the base order in this experiment. The author and the teaching team also discussed this step. Furthermore, the map was prepared in a style based on the linearity of the text material, in which the corresponding sub-map linearity follows the text material.

Analysis

A Pearson correlation test and non-parametric significance test were conducted to analyze the effect of concept map recomposition order on learning outcomes. The tests were performed on the LD, pre-test, post-test, and delayed-test scores and learning gain. The LD was used as a similarity scale, measuring the similarities between each learner's sub-map order and base orders.

The test scores and learning gain were analyzed to find a relation between recomposition order and learning outcomes. The learning gain was based on the normalized gain formula that calculates the pre-test and post-test scores to evaluate the learner's understanding (Hake, 1998). Compared to regular gain calculation in which gain = post-test score – pre-test score, the normalized gain measurement has significant advantages (Bao, 2006; Coletta & Steinert, 2020; Marx & Cummings, 2007). It compares increases in scores for many learner populations by considering pre-test scores and thereby focusing on the potential for improvement, making learners with different pre-test scores more comparable.

To analyze the effect on the recomposition activity, a similar test of correlation and non-parametric significance tests were also carried out on the variables of LD, time on task, actions performed, and time per action. The time on task was calculated from the start of the recomposition until the end. Actions performed were taken from the log data consisting of several components: the learner connected a concept with a link, disconnected a concept from a link, and moved either the concept or link. Time per action was the average time required to perform each action. Furthermore, to evaluate the effect on recomposition order on concept map assessment, correlation tests between LD and KB's map scores were evaluated. The map score was ranging from 0 to 100. 0 means no correct proposition were made, and 100 means that all the propositions are correct according to the expert map.

Results and analysis

The summary of all the test scores and variables are shown in Table 1: learning gain, map scores, times, actions performed, and times required per action.

A correlation test between map score and test scores (post, delayed) and learning gain was conducted to show how the map score correlates with learning outcomes. Results shown in Table 5 indicated that the map score has a correlation with post-test (R-value = 0.511), delayed-test (R-value = 0.405) and learning gain (R-value = 0.500). It shows that map score can properly reflects the learning outcomes.

To evaluate the effect of recomposition order on learning outcomes, we evaluated the LD value as shown in Table 1.

The smaller value of the LD means there was a high similarity between the sub-map and base orders. Because the maximum LD value depends on the sequence length, the LD value was normalized using min-max normalization. This normalization was performed for easier analysis and to ensure uniformity when comparing varying lengths of sequences by defining a standard measure of similarity (Beernaerts et al., 2019; Hauge et al., 2021; Li & Liu, 2007). The normalization adjusts the scale of the data into a scale between 0 and 1 without changing its overall distribution (James et al., 2023).

The data was divided into three parts (tertile) to define the three groups based on the value of normalized LD. The low LD group consisted of subjects with the lowest LD value between 0% and 33.3% of normalized LD value; the medium LD group was in the second tertile, between 33.3% and 66.6% of normalized LD value; and the high LD group was in the third tertile, between 66.6% and 100% of normalized LD value. The normalization result and the group division of low, medium, and high LD can be seen in Table 3. The low LD group was the most similar learner order with the base order, the high LD group

Table 1 Data summary

Variables	Min	Max	Mean	Median	Std. Deviation
Pre-test score	15	55	33.33	35	12.17
Post-test score	40	95	76.48	80	14.52
Delayed-test score	25	100	70.19	70	18.28
Learning gain	0.25	0.94	0.65	0.73	0.19
Map score	13.3	100	70.62	73.3	26
Time (minutes)	6.48	16.42	13.19	14	2.56
Actions performed	26	112	44.59	38	17.38
Time per actions (seconds)	8.8	35.47	19.35	18.38	6.38
LD value	2	6	3.85	4	1.3

was the most different learner order with the base order, and the medium LD group was in between the high and low LD.

To evaluate the effect in recomposition, only the high LD and low LD groups were compared. It is sufficient to compare these two groups because these groups represent the biggest difference between similar and non-similar of recomposition order.

The overall outcomes from the learning activity were evaluated and the result was shown in Table 2 and Figure 5. According to the results, both groups demonstrated adequate learning outcomes, with increased post-test score compared with pre-test score. Mann–Whitney non parametric U-test shown significance between the pre-test and post-test with p-value < 0.05 in both groups. This shows the relatively high difference between pre-test and post-test scores in both groups and the equality in the learning gain in both groups. It shows that both groups achieved meaningful learning in performing the learning activities including the concept map recomposition activity using the KB system.

To address the first research question, a significant test using the Mann–Whitney U-test between low LD and high LD groups was performed. The test scores and learning gain distribution of low and high LD groups can be seen in Figure 5. The result of the test is shown in Table 4.

Table 2 Pre and post-test difference in low and high LD Group

	Mean		p-value	Sig
	Pre-test	Post-test		
Low LD Group	36.82	78.64	< 0.05	*
High LD Group	35.00	77.50	< 0.05	*

Significant code: ****p-value* < 0.001, ***p-value* < 0.01, **p-value* < 0.05

Table 3 Group division

Group	T range	N	Normalized LD range	LD range
Low LD	0% - 33.3%	11	≤ 0.33	≤ 3
Medium LD	33.3% - 66.6%	8	> 0.33 and < 0.66	> 3 and < 5
High LD	66.6% - 100%	8	≥ 0.66	≥ 5

Table 4 Significant differences analysis between low and high LD group using Mann–Whitney U-test

Variables	Mean		W	p-value
	Low LD	High LD		
Pre-test score	36.82	35	51	0.586
Post-test score	78.64	77.5	47.5	0.801
Delayed-test score	73.18	73.18	39	0.709
Learning gain	0.68	0.65	48	0.772

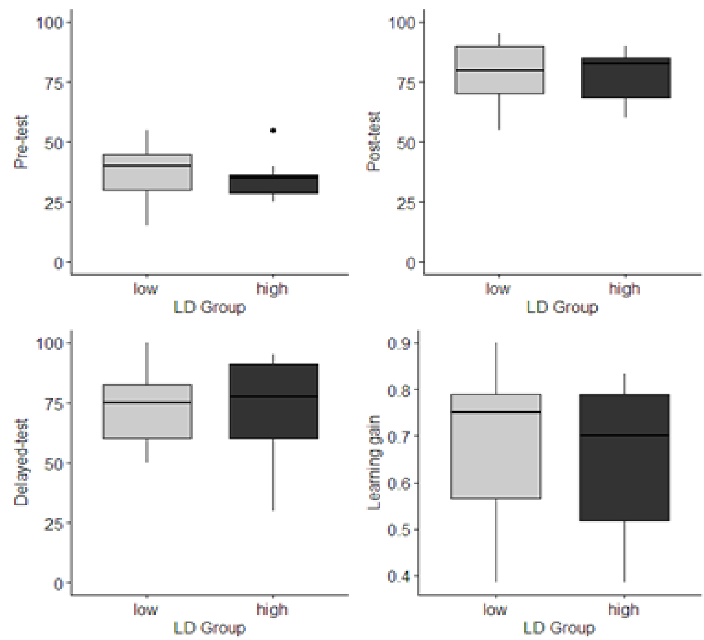

Fig. 5 Distribution of test scores and learning gain on low and high LD groups

Table 5 High correlation between map score and post-test, delayed-test and learning gain

Variables	t	p-value	R-value
Map score - Post-test score	2.974	0.006	0.511
Map score - Delayed-test score	2.224	0.035	0.406
Map score - Learning gain	2.887	0.008	0.500

Table 6 Low correlation between LD and pre-test, post-test, delayed-test and learning gain

Variables	t	p-value	R-value
LD - Pre-test score	-0.432	0.670	-0.086
LD - Post-test score	-0.385	0.703	-0.077
LD - Delayed-test score	-0.307	0.761	-0.061
LD - Learning gain	-0.506	0.617	-0.101

Regarding the difference in learning outcomes between the two groups of different recomposition order, there were no significant differences in the test scores (pre, post, and delayed) and the learning gain between the high and low LD groups as shown in Table 4. The p-value for all the tests was more than 0.05 ($p > 0.05$). To confirm these results, an additional correlation analysis on all subjects was performed.

The correlation test was conducted between LD and test scores (post, delayed) and learning gain, and the results showed in Table 6. There was no correlation between LD and pre-test scores, with an R-value of -0.086. It means that learners' prior knowledge did not affect how they recompose in terms of linearity. In regard to learning outcomes, the correlation test between LD, post-test (R-value = -0.077) and delayed-test scores (R-value = -0.061), and learning gain (R-value = -0.101) revealed little to no correlation.

These significant differences test and correlation test results mean that the recomposition order did not affect the learning outcomes. Learners with similar recomposition order in the low LD group had equal test scores to those in the high LD group.

These results answered the first research question (RQ1) about the recomposition order and its effect on learning outcomes. Results revealed that various different recomposition order lead in a significant improvement from the pre-test to post-test, with equal in learning outcomes between the different recomposition order.

To address the second research question, a correlation test of the LD with the map score, time on task, actions performed, and time per action on all groups (low, medium, and high LD) was conducted. Results are shown in Table 7.

The result revealed that the recomposition order caused several effects. There was a negative correlation between LD and time on task, with an R-value of -0.467. The lower the LD, the higher the time. This means learners who recomposed with more similar order with the base order tended to spend more time than those who recomposed with more different order. However, in terms of the actions performed, there was no correlation with LD, which had a small R-value of 0.144. This means the actions needed to perform the recomposition were similar in any recomposition order.

In regard to the average time needed to perform each action, LD is correlated with an R-value of -0.481, which means the higher the LD, the quicker each action was performed. This aligns with total time on task, which also correlates with LD. The map score, however, correlated with the LD, meaning learners who recomposed with more differing order with the text's information order tended to have a better map quality.

To better understand the effect on the recomposition activity, we conducted a significant difference analysis test of time on task, action performed and time to perform each action on the low and high LD groups using the Mann–Whitney U-test. The mean value and result of significance tests are shown in Table 8, and the distribution in Figure 6.

Table 7 Correlation tests between LD and time on task, action performed time per action and map score

Variables	t	p-value	R-value
LD - Time on task	-2.643	0.014	-0.467
LD - Actions performed	0.725	0.475	0.144
LD - Time per action	-2.742	0.011	-0.481
LD - Map score	2.567	0.017	0.457

Table 8 Significant differences analysis between low and high LD group using Mann–Whitney U-test

Variables	Mean		W	p-value	Sig
	Low LD	High LD			
Time on task	14.49	11.49	16.000	0.023	*
Actions	41.36	47.50	56.500	0.321	
Time per action	22.19	14.83	7.000	0.003	*
Map score	63.03	90.84	77.000	0.007	*

Significant code: ****p-value* < 0.001, ***p-value* < 0.01, **p-value* < 0.05

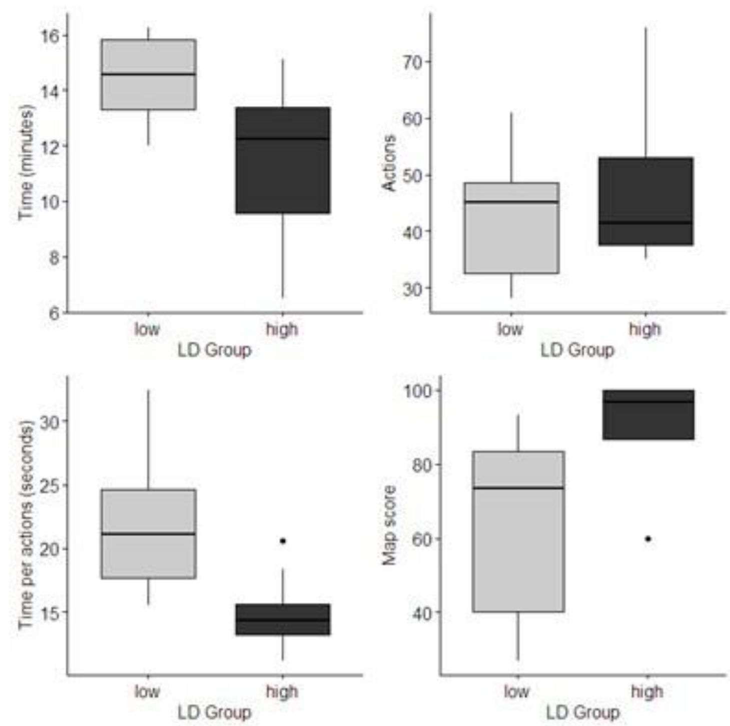

Fig. 6 Distribution of time, actions, time per actions and map score on low and high LD groups

In terms of time on task, there was a significant difference between the low and high LD groups, with a p-value of 0.023 and lower time on task in the high LD group. There was a similar result with time per action, with a p-value of 0.003. In terms of actions performed, there was no significant difference. The map scores significantly differed, with the low LD group being significantly lower than the high LD group, with a p-value of 0.007.

Figure 6 illustrates the data distribution for each group. Although the low LD group has the longest time on task, the distribution was denser in this group. In terms of actions performed, the distribution was similar in each group. The distribution in the high LD group was denser on the average time required per action. The difference in the map score shows that the distribution of the map score was denser in the high LD group.

Table 9 Correlation test between map score on post-test and learning gain of each LD group

	R-value		
Variables	Low LD	Medium LD	High LD
Map score – Post-test	0.48	0.75	0.17
Map score – Learning gain	0.47	0.79	0.24

This correlation and difference analysis result shows that learners' recomposition order affected how they interacted with the system, thus answering the second research question (RQ2). Overall, learners with the most different recomposition order had faster time on task and time required to perform each action compared to learners with more similar recomposition order.

To see how the map score correlates with learning outcomes in each group, we conducted a correlation test between the map score, post-test, and learning gain across all groups (low, medium, and high LD). This test revealed which group had the highest correlation between map score, post-test, and learning gain. High correlation in a group means that the learner's map score in this group can best reflect their learning outcomes, which reflected in their post-test score and learning gain. The result is shown in Table 9.

As shown in Table 9, the map score has the highest correlation with the learning gain and post-test on the medium LD group, with p-values of 0.75 and 0.79, respectively. It indicated that the map score could better represent learning outcomes in the medium LD group. The weakest correlation occurred in the high LD group, with R-values of 0.17 and 0.24.

Discussion

This study evaluated the similarity between recomposition order and text's information order in the KB system. We evaluated and defined their recomposition order based on the sub-map recomposition order (learner order) and compared the similarity with the text material's information order (base order) using LD and defined each group of order similarity. Results showed that different recomposition order did not affect learning outcomes. Therefore, we confirmed that these findings were in line with Melara (1996), which showed that those differing order of recomposition could be well accommodated in the KB concept map recomposition. For teachers, this suggests that there is a necessity for teacher to acknowledge that learners might approach the recomposition activity in various ways. This means allowing learners to work on the sub-map in a different sequence or order and not enforce a specific recomposition order. Teachers should ensure that the focus remains on how well learners grasp and integrate the information, rather than on a rigid order of recomposition.

In this study, it is found that memory retention, reflected by the delayed-test score, was not affected by the recomposition order. Similar result was showed in the correlation between recomposition order and learning gain. The learning gain also was not affected by the recomposition order. The learning gain evaluates learner's improvement in understanding, based on the formula that calculates the pre-test and post-test scores (Hake, 1998). The finding suggests that learner's increase in understanding also was not affected by the recomposition order. These results imply that surface-level variations in recomposition sequence may not substantially hinder learners' ability to internalize core conceptual relationships. It is possible that learners compensate for differing recomposition paths by using flexible reasoning strategies or by revisiting earlier segments of the map to reinforce their understanding. Nevertheless, a more thorough analysis of learning gain is necessary to fully understand the specific effects of recomposition order on knowledge acquisition. Further qualitative investigations, such as protocol analysis or learner interviews, would be beneficial to clarify the cognitive processes underlying the observed learning gain.

This finding also shows the flexibility of concept map recomposition that allows it to be applied in various educational learning conditions. Our finding suggests that teachers can use KB in many learning scenarios. Teachers can incorporate concept map recomposition in a traditional linear learning scenario, in which the learning was generally carried out in a specific direction and orderly manner. Another scenario is in learning activity which is designed non-linearly from the ground up, for example, problem-based learning (PBL). In PBL, learners are tasked with solving ill-structured problems, where the problem space and the information needed to solve them are spread across several domains of knowledge (Ge et al., 2016; Saqr & López-Pernas, 2023). In this scenario, learners need to perform back and forth checking between different domain of knowledge to solve the problem. Therefore, it is a prominent factor in choosing a learning tool that can support various learning activities that resulted in an optimal learning outcome (Schwab et al., 2017).

In terms of the map score as an assessment of map quality, results show that in the medium LD group, the map score has the highest correlations between the map scores and the test scores (see Table 8). Referring to the time on task, the high LD group tend to perform faster compared to the low LD group (see Table 7). Given that in the activity, teacher provides explanation about the text material, and learners read and use the text as a reference to recompose, there are potentially two behaviors in recomposition: learners who recompose using mainly their own understanding from the teacher's explanation; and learners who recompose mainly by checking the information from the text. The faster time on the high LD group indicates that this group use their own understanding more as a resource to recompose and making fewer check on the text. Therefore, this group performed faster and considerably different order of recomposition with the text's information order. In contrast, the low LD group needs more time to complete the task, it indicates that this group uses the text material more as a resource to recompose and making more check on the text. Therefore, this group performed slower and has more similar order of recomposition with the text's information order. The medium LD group is potentially a mix of behaviors between these two groups, they have more balance in using the text and their own understanding as a resource to recompose. Therefore, it might suggest that this is the most common behavior in recomposition and resulting in the high correlation between map score and test scores. However, we cannot generalize it yet since currently there was no strong evidence on the exact behavior between the low LD, high LD and medium LD group. More investigations are required to observe the behavior between each group in order to confirm this finding.

Furthermore, the recomposition order itself could be affected by the learners; they prefer to base their decision to recompose on the structure and information order of the text, or based on how they use their own understanding from listening to the teacher's explanation. This differing behavior could be affected by the learner's learning style. Research explored how the learning style in terms of linearity affects how learners interact with the learning media (Cagiltay et al., 2006; Liegle & Janicki, 2006). These findings are relevant in the context of concept mapping activity that the learning style could also affect how learners interact with the concept map. Despite these differing behaviors, this study demonstrated that both yielded equivalent learning outcomes. Future research in concept map recomposition support should be addressing what form of supports that can be provided to accommodate these different behaviors in order to improve the effectiveness of the concept map recomposition activity. This support should focus on how to promote better process in recomposition which encourages learner to focus on recomposing one segment of the map before moving to another segment, but without limiting the sequence order to a specific order.

This study, however, was limited to a specific subject of OOP, where the purpose was to learn the theoretical concepts of OOP and how each idea relates to the others. Investigating broader varieties of topics could reveal the effect of recomposition order in the concept map recomposition. Other limitation is that a sub-map configuration needs to be set by the teacher after creating the expert map. This configuration consists of a set of sub-maps with each of it contains specific nodes and links, and also the base order of the sub-map. This limitation introduces an additional step in the regular concept mapping activity specifically in preparing the expert map. Another limitation is the detailed action performed analysis. This study's scope is limited to capturing the actions when learners connect, disconnect and move a concept or a link. However, many other kinds of action could happen in the KB system, such as when a learner changes the zoom view or the direction of link connections. A deeper investigation into more varied actions performed might reveal another aspect of the learner's interaction with the system. Those various actions and behaviors could also impact the learning activity and process.

This study limits the relation between recomposition order with the time spent in the activity and whether it was affected by the actions performed. However, deeper investigation whether the increased time reflects deeper cognitive engagement or results from technical factors like system response times needs to be evaluated in the future works. The KB system itself uses client-side web-based technology, therefore, the only significant loading time involved is when the participants load the system and the map at the first time. Based on this, we assumed that the system response time would not be noticeably different on each participant. However, possible technical issues can still exist and therefore, thorough investigation regarding system response time are required to evaluate whether it contributes to the total time on task.

While process evaluation through system logs allows us to observe the recomposition order, it does not fully capture learners' intentions or strategies. Post-task interviews or questionnaires could provide valuable insight into why learners chose particular recomposition sequences, how they managed their time, and whether certain decisions reflected deliberate strategy or confusion. Such qualitative data would help determine whether longer task durations indicate deeper engagement or inefficiencies in navigation.

The KB provides a platform for teachers to prepare expert maps and for learners to engage in concept map recomposition. While the effectiveness of KB in improving learning outcomes has been demonstrated by previous studies, the learning outcomes between each learner can still vary based on how they utilize the system. In the KB system, learners are free to recompose the map by connecting readily available concepts and links. They are free to connect which concepts and links to make proposition. There is no specific direction or guidance on selecting concepts and links to construct a particular proposition. The system provides uniformed features to each learner such as moving concepts, dragging the links to connect two components and modify the connections. The concepts and links were arranged in a random placement at the start of the activity, and it is up to learners to use those components to recompose the map. Despite these uniform supports, individual differences in learners' prior knowledge, attention, and motivation likely influence how effectively they utilize the system. This variability could account for the range of learning outcomes observed. Future research should explore how individual learner characteristics interact with system features to affect concept map quality and learning gain.

Conclusion and future works

This study evaluated the concept map recomposition order similarity with the text's information order and its effect on learning outcomes and interaction with the KB system. The definition of recomposition order was evaluated using the learner's activity data log acquired from the KB system and grouped based on the similarity between base order and learner order.

Learning outcomes reflected by post-test and delayed-test scores and learning gain were found to be equally adequate regardless of the recomposition order. Regarding interaction with the KB system, there was relation between recomposition order and time, which are time on task and time per action. The finding revealed that learners who recompose with more similar order with the information order spent more time than those who prefer to recompose in more different order, while the number of actions performed remained similar across all recomposition order. Our findings about map scores showed that the map score can best represent the learning outcomes in the medium similarity order group.

Future work could improve this study by incorporating more participants and varied learning topics. More detailed variables on the learner's action performed on the KB system, such as when learners adjusting the zoom and changing link directions, could reveal more insight into the effect of the concept map recomposition activities. Those actions could affect the recomposition and learning process. Evaluating the system response time can be performed to investigate whether there is any technical issue that affect the total time on task. Conducting interview or questionnaire towards learners after the activity could potentially reveal factors such as deeper cognitive engagement, the intentions and motivations during the recomposition. Thorough analysis on learning gain could reveal the recomposition order's specific impact on knowledge acquisition. Follow up work could be conducted involving various role and intervention of the teacher to evaluate how it influences the process of concept map recomposition. Designing a framework to provide support that accommodates both linearity and in the concept map recomposition activity is highly encouraged.

Abbreviations

KB: Kit-Build; LD: Levenshtein Distance; OOP: Object-Oriented Programming; P: Proposition; PBL: Problem-Based Learning; SM: Sub-Map.

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Authors' contributions

RR managed the experiments, developed the tool, analyzed the data, and wrote the manuscript. YH discussed and reviewed the analysis results. TH reviewed the experiment design, analysis results, and the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials

Availability of data and materials upon reasonable requests.

Declarations

Competing interests
The authors declare that they have no competing interests.

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