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Analysing students' concept mapping style and its association with task performance in computer-based inquiry learning

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Abstract

Background: In scientific inquiry learning, students often have difficulties conducting hypothetical reasoning with multiple intertwined variables. Concept maps have a potential to facilitate complex thinking and reasoning. However, there is little investigation into the content of student-constructed concept maps and its association with inquiry task performance.

Objectives: This study explored students' concept mapping style and its association with task performance in computer-based inquiry learning.

Methods: An exploratory study was conducted with 80 Grade 11 students, who collaboratively constructed concept maps in a free style to support inquiry learning with a virtual ecosystem. Student-constructed concept maps was analysed by firstly identifying different types of propositions formed in the maps and then determining the style of each concept map based on the dominant type of propositions in the map. Finally, the association between the concept map style and inquiry task performance was explored.

Results and Conclusions: Two major concept map styles were identified: (1) knowledge-oriented concept maps (KCMs) mainly representing problem-related subject knowledge as a set of concepts and their relationships, and (2) problem-oriented concept maps (PCMs) mainly representing problem situation as a sequence of changes and their causal relationships. Compared with those constructing KCMs, the students constructing PCMs formed higher-quality propositions in their maps and performed better in hypothesising, reasoning, and drawing conclusions in the inquiry task.

Implications: Besides KCMs, students in inquiry learning can be encouraged to construct PCMs to foster effective thinking and reasoning; that is, constructing a concept map to represent the problem situation as a sequence of changes and the causal relationships between the changes.

KEYWORDS
computer simulation, concept map analysis, higher-order thinking, reasoning, science inquiry learning

1 | INTRODUCTION

Inquiry-based learning has been widely promoted in educational practice especially in science education (Furtak et al., 2012; Hmelo-Silver et al., 2007). In science inquiry learning, students are exposed to authentic problems or natural phenomena in real-world contexts; they are expected to acquire knowledge through observations, explanations, and experiments with real-world problems (Bybee, 2002; de Jong et al., 2013; National Research Council, 2012; Pedaste et al., 2015).

With the support of information and communication technology, inquiry learning has been extended from classrooms and physical laboratories to technology-supported environments such as computer simulations (Brinson, 2015; de Jong et al., 2013), online laboratories (Brinson, 2015; de Jong et al., 2013), mobile technology-supported informal learning settings (Chu et al., 2010; Hwang et al., 2022). Such technology-based environments can support inquiry learning with a variety of affordances. First, they can mimic real-world situations and allow learners to interact with simulated problems to obtain hands-on experiences without exposure to dangerous environments or using expensive materials (Wörner et al., 2022). Second, they can integrate multiple representations (such as animation, simulation model, picture, and text) to make complex or invisible phenomena observable for investigation (de Jong et al., 2013; Olympiou et al., 2013). Third, technology-based learning facilities (e.g., prompts, scaffolding, feedback) can be incorporated to support inquiry learning (Hovardas et al., 2022; Trundle & Bell, 2010). In short, technology-supported learning environments have made inquiry learning more accessible to students and have shown promising effects on improving inquiry skills.

Inquiry learning includes an iterative cycle of activities and higher-order thinking processes. Students often work in small groups to perform inquiry activities such as making observations, gathering data and information, and doing experiments. More importantly, students need to engage in higher-order thinking processes such as conceptualizing the problem, integrating subject knowledge, and analysing and reasoning about data (Bell et al., 2010; Kyza, 2009; Lazonder & Harmsen, 2016). Such thinking processes are often implicit or not immediately observable, which may pose severe cognitive challenges to learners (Hmelo-Silver & Azevedo, 2006; Reiser, 2004; Saidin et al., 2024).

To address the challenge, researchers highlight the importance of using external representations to make complex thinking visible or accessible to learners (Cox, 1999; Jonassen, 2003; Wu & Wang, 2012). Among various forms of external representation, concept maps have shown promising effects on improving inquiry-based learning, for example by representing the subject knowledge required to solve a problem (Dmoshinskaia et al., 2021) or by visualizing the situation (e.g., events, dynamics) of the problem to be investigated (Eggert et al., 2017).

When applying concept maps to support inquiry learning, students are often required to construct maps in a free style, without the provision of predetermined map elements (such as relevant concepts and linking words). Different styles of concept maps may reflect different ways of thinking, which may affect inquiry task performance. When analysing student-constructed maps, some studies have focused on the map structure such as the number of nodes, number of links, and number of hierarchy levels in a concept map (Conradty & Bogner, 2012; Öllinger et al., 2015). Some other studies analysed the map content reflected in the propositions or statements formed in student-constructed concept maps (Chen et al., 2021; Metcalf et al., 2018; Schroeder et al., 2018).

Research shows that students' achievements in subject knowledge are highly correlated with the content, rather than the structure of student-constructed concept maps (Chen et al., 2021; Talbert et al., 2020). However, there is inadequate research analysing the content of student-constructed concept maps and its association with student learning outcomes. This paper presents an exploratory study that analysed the content of student-constructed concept maps in the context of computer-based inquiry learning. Based on the map content analysis, we identified students' mapping styles that may reflect different ways of thinking and explored the association between concept mapping style and inquiry task performance.

1.1 | Higher-order thinking in inquiry learning

Scientific inquiry learning exposes students to authentic problems or natural phenomena in real-world contexts. An inquiry task often begins with constructing a problem space or conceptualizing a problem (Delahunty et al., 2020; Jonassen, 1997). To do so, students need to collect problem information to analyse the problem situation and identify relevant subject knowledge to establish an understanding or conceptualization of the inquiry problem (Eberbach & Crowley, 2009; Wang et al., 2022).

Conceptualizing a problem serves as the foundation to determine how to approach and investigate the problem and highly affects the quality of problem solving (Delahunty et al., 2020; Eseryel et al., 2013; Jonassen, 2003). As stated in the US National Science Education Standards (2000): "*They [students] should be able to describe a problem in detail before attempting a solution, determine what relevant information should enter the analysis of a problem, and decide which procedures can be used to generate descriptions and analyses of the problem*" (p. 117).

Based on the conceptualization of the problem, students need to analyse the problem and construct scientific explanations of the given problem or phenomenon, mainly by (1) formulating hypotheses as tentative explanations, (2) reasoning with problem data and subject knowledge to test the hypotheses, and (3) making conclusions (McNeill & Krajcik, 2008; Slof et al., 2010); Hypotheses are generated as tentative and testable explanations of a phenomenon (Gijlers & de Jong, 2013; Kyza, 2009). Hypotheses can be tested mainly by reasoning or experimenting to demonstrate logical connections between the evidence and hypotheses (Berland & Reiser, 2009; Hsu et al., 2015). Evidence can be in a number of forms such as problem data and subject knowledge. Consistent with this framework, students' inquiry task performance is often evaluated in terms of formulated hypotheses, reasoning, and the conclusions (Bell et al., 2010; Chen et al., 2018).

1.2 | Concept maps for external representation of higher-order thinking

To make complex thinking accessible to learners, external representations have been used to support the communication of complex ideas or thoughts (Cox, 1999; Jonassen, 2003). External representations refer to a wide variety of representations in the linguistic (e.g., natural language, logic) and graphical (e.g., diagrams, tables, lists) modalities (Cox, 1999). Graphical or diagrammatic representations of knowledge or information using maps, diagrams, or pictures have received wide attention (de Vries, 2006; Rau et al., 2021). Constructing such representations can focus learners' attention and engage them in self-explanations or communication of their thinking and understanding about complex ideas (Moritz et al., 2020; Van Amelsvoort et al., 2007). In inquiry learning, student-generated external representations (such as concept maps or diagrams) can help learners conceptualize the problem, formulate hypotheses, make inferences or reasoning, and articulate explanations (Cox, 1999; Jonassen, 2005; Löhner et al., 2003; Öllinger et al., 2015). They are increasingly used as an important strategy for inquiry learning (Dmoshinskaia et al., 2021; Hwang et al., 2020; Tang et al., 2019).

Among various forms of external representation, concept maps have been widely used in educational practice. A concept map is a graph consisting of nodes connected by labelled lines; it represents a set of concepts and the relationships (e.g., compositions, inclusions, and categorizations) between the concepts (Novak et al., 1983; Schroeder et al., 2018). Concept maps are often used to communicate complex ideas or organize knowledge about a given subject to support conceptual learning and knowledge integration (Hwang et al., 2022; Schroeder et al., 2018; Schwendimann & Linn, 2016). In a concept map, two linked concepts along with the linking words or phrases form a meaningful statement or proposition (e.g., "*a force on an object* leads to *a change in its motion*"), which is the fundamental unit of analysis of concept map content (Eggert et al., 2017; Safayeni et al., 2005).

In inquiry learning, concept maps have been used to help learners to externalize the subject knowledge and highlight causal relationships between relevant concepts or variables (Dmoshinskaia et al., 2021). The constructed maps may help learners consider what variables need to be considered to formulate hypotheses or develop scientific explanations (Chen et al., 2018; Metcalf et al., 2018; Öllinger et al., 2015; Park et al., 2021). For example, Gijlers and de Jong (2013) asked students to construct concept maps to represent the key concepts about kinematics (such as velocity, acceleration, and position) and the relationships between them to support the formulation of hypotheses in a simulation-based environment. They found that such students performed better in experimentation, data interpretation, and drawing conclusions than those not constructing concept maps. In the study of Kim and Hannafin (2011), students drew concept maps to present their understanding of the predator–prey causal relationships. It was found that concept mapping activities helped students understand the subject knowledge and explain the dynamics of the ecosystem.

In addition to externalizing subject knowledge, concept maps have also been used to represent problem situations in inquiry learning. For example, students used concept maps to represent problem events or changes and their causal relationships to support inquiry learning (e.g., Metcalf et al., 2018). Such concept map allows students to view the complex and dynamic problem space in its entirety and think about all possible solutions (Eseryel et al., 2013). In the study of Chen et al. (2021), students built a concept map to represent subject knowledge and a reasoning map to represent reasoning process to support inquiry learning. This study assessed the quality of student-constructed maps by scoring proposition in the maps and revealed that the quality of concept maps predicted the quality of reasoning maps, and the latter predicted inquiry task performance. However, this study didn't analyse students' concept mapping styles, which may reflect their different ways of thinking (Eshuis et al., 2022).

1.3 | The present study

Research shows that inquiry learning involves complex and implicit thinking processes. External representations such as concept maps have a potential to make complex thinking visible and accessible to learners. While applying concept maps in inquiry learning, most studies have focused on representing the subject knowledge relevant to the inquiry problem, with a few others representing the problem situation such as dynamics and ongoing changes in a concept map. Both styles of concept mapping are consistent with the literature on learning in inquiry or problem solving contexts, which highlights the importance of identifying problem situation and subject knowledge for conceptualizing the problem for investigation (Delahunty et al., 2020; Eseryel et al., 2013; Jonassen, 2003). While students are often asked to construct concept maps in a free or flexible style to facilitate inquiry learning, different styles of concept maps may reflect different ways of thinking about problem conceptualization, which may directly affect their inquiry into the problem. However, research on students' concept mapping styles and how the styles might associate with their inquiry task performance is underdeveloped (Bleckmann & Friege, 2023).

This paper presents an exploratory study with secondary school students who constructed concept maps to facilitate inquiry learning with a computer-based virtual ecosystem. The participants received relevant instruction on concept mapping and were encouraged to be open-minded and flexible in constructing a concept map. The great flexibility in concept mapping may lead to great variability in the ways chosen by students to represent their ideas in a concept map (Metcalf et al., 2018). In this study, we firstly identified different types of propositions formed in student-constructed concept maps. Next, we identified different styles of concept maps based on the dominant type of proposition formed in each map. Finally, we explored how concept mapping style might associate with map quality and inquiry task performance.

The research questions (RQs) of the study are as follows.

- RQ1: How do students represent their thoughts in a concept map in flexible ways to facilitate inquiry learning with a computer-based virtual ecosystem?
- RQ2: How might students' concept mapping styles associate with their inquiry task performance?

2 | METHOD

2.1 | Participants

The study was conducted in a secondary school. The participants were 80 students from a 11th grade class (39 males and 41 females). The students' average age was 16.6 (SD = 0.5). They were randomly divided into small groups of three members, that is, they formed 27 small groups in total.

This research was approved by the Human Research Ethics Committee of the researchers' university. The participants signed a consent form before the commencement of the study. The proposed inquiry learning with a virtual ecosystem was aligned with the curriculum standards for the participants in the 11th grade. The students had no experience of conducting such inquiry learning tasks or constructing concept maps before participating in the study, as their typical classroom instructions was organized in traditional lecture mode.

2.2 | Computer-based environment for inquiry learning

The inquiry learning with a fish die-off problem was performed in a virtual ecosystem implemented in a computer-based learning system. As shown in Figure 1, the learning system consisted of two modules: *problem context* and *learning support*. The *problem context* module presented a pond ecosystem with a fish die-off phenomenon in three sub-modules: *information collection*, *data observation*, and *field guide*. The sub-module *information collection* provided rich background information on the phenomenon (e.g., pond environment, weather, events) in eight webpages. The sub-module *data observation* provided data graphs for 16 variables (e.g., green algae, bacteria, oxygen dissolved in water) related to the pond ecosystem, showing how the values of these variables changed over approximately two months. The sub-module *field guide* presented relevant subject knowledge about the pond ecosystem (e.g., general characteristics of green algae, feeding habit of largemouth bass) in 20 webpages.

The module *learning support* provided the instructions and guidelines necessary for students to perform their inquiry activities. These instructions and guidelines were documented as separate files entitled

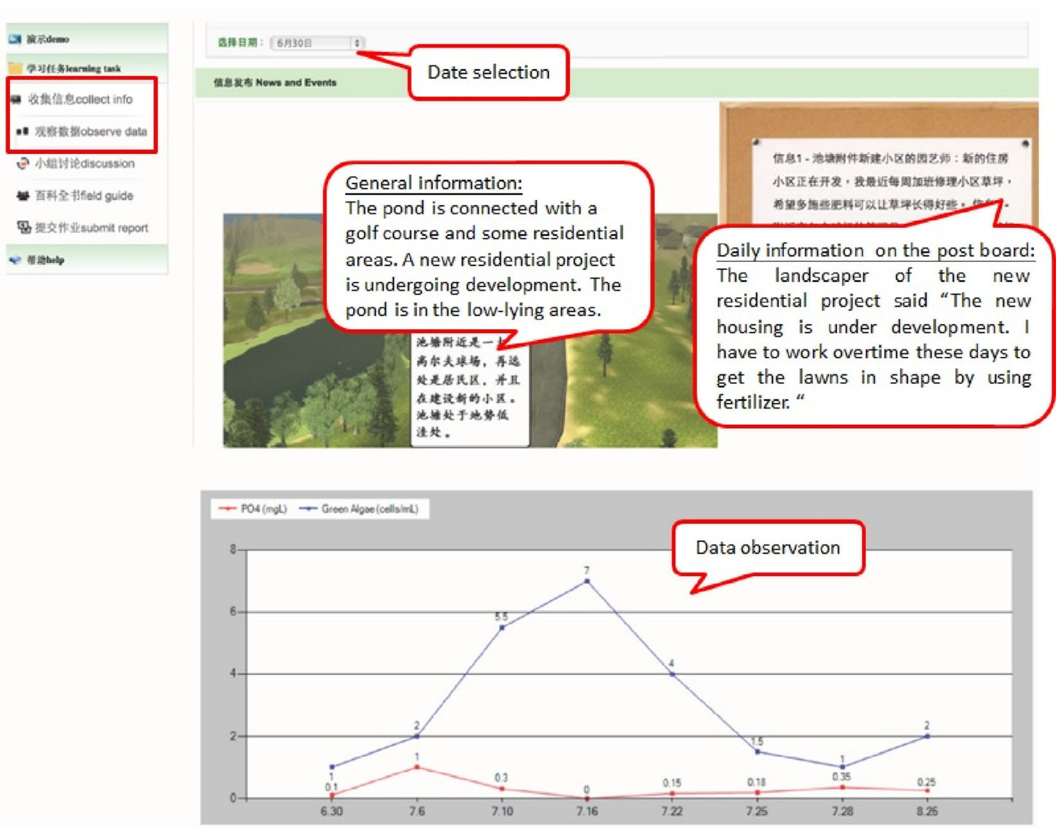

FIGURE 1 Computer-based system for inquiry learning.

as follows. (1) "Subject knowledge" about ecosystems and ecological processes in general (e.g., photosynthesis, decomposition). (2) "How to use the system". (3) "How to perform the inquiry", which introduced the skills and steps required for scientific inquiry (such as hypothesising and evidence-based reasoning). (4) "How to have a group discussion". (5) "How to draw a concept map", which provided guidelines for creating concept maps.

The *learning support* module also included an example of inquiry report, which served as a template for students' reference when writing their inquiry task report. The example report was structured to include three parts: generated hypotheses, reasoning or testing the hypotheses, and conclusion. When presenting their reasoning, students were asked to explicitly name their sources of evidence, such as "The field guide says that wolves eat deer".

2.3 | Inquiry learning task

The students worked in small groups to perform the inquiry task, that is, explaining the fish die-off phenomenon in the virtual ecosystem. This task was based on the EcoMUVE curriculum (Metcalf et al., 2011). In this task, students were expected to explore a virtual pond and the surrounding watershed, observe simulated organisms over a number of virtual days, and collect relevant data to investigate a fish die-off phenomenon, that is, why many large fish have died suddenly in the pond.

Students were asked to perform the task by interacting with the computer-based learning environment to collect relevant information, observe data changes over time, make hypothetical reasoning based on compiled evidence, and draw conclusions. In particular, they could access the *information collection* sub-module to collect the problem information (e.g., "It rained heavily on July 6"). Further, they were asked to use the *data observation* sub-module to observe how the values of variables (e.g., algae growth, the amount of dissolved oxygen) changed over time. Moreover, students could access the *field guide* sub-module to search for relevant knowledge about the pond ecosystem. Meanwhile, they were asked to construct a concept map to represent their thinking during the task. When constructing the map, they were encouraged to be open-minded and flexible by representing anything they felt helpful for thinking and reasoning, without being given any predetermined concepts or linking words.

At the end of the task, each group was asked to submit the concept map in addition to a task report presenting the hypotheses they had formulated, the reasoning or testing of the hypotheses, and the conclusions made based on justified hypotheses. Throughout the task, they could access the *learning support* module in the system to find detailed guidelines for using the online system and performing the inquiry task.

2.4 | Procedure

The study lasted for two weeks and consisted of five 45-min sessions. In the first session, the participants signed consent forms and completed a questionnaire that collected their demographic information. The next four sessions were conducted in a computer laboratory equipped with desktop computers and network access.

In the second session, one of the researchers provided the students with 20 min of training in performing inquiry learning using the given system. An example of a forest ecosystem (including deer, wolf, trees, bushes, and rats) was used for illustration. This example presents a natural phenomenon of the sudden decrease of deer population in the forest ecosystem. Based on this example, the researcher demonstrated the construction of a concept map (see Figure 2) representing relevant subject knowledge and highlighting causal relationships between relevant concepts or variables. The concept mapping skills required for this study can be mastered by novice learners in about half an hour as reported in many previous studies.

Based on the example, students were also instructed on how to perform the inquiry task by collecting information, observing data, searching relevant knowledge, and developing explanations for the deer decrease problem with the support of concept mapping. In particular, the researcher displayed how to formulate hypotheses, test hypotheses, and make conclusions. For example, the researcher showed how to formulate hypotheses and perform reasoning by viewing the concepts presented in the map and relating them to the problem data.

After the 20-min training, the students performed the learning task in small groups in the rest of the session 2 and sessions 3–5. During the task, they generally collected information and observed data graphs individually (about 20 min). After having an overview of the problem, some group members expressed their conceptualization by drawing a concept map; then, other members began to participate in the discussion about the problem conceptualization. They frequently accessed the system to collect information for hypothesising and reasoning. At the end of the fifth session, students were asked to complete a survey to collect their perceptions of the learning experience.

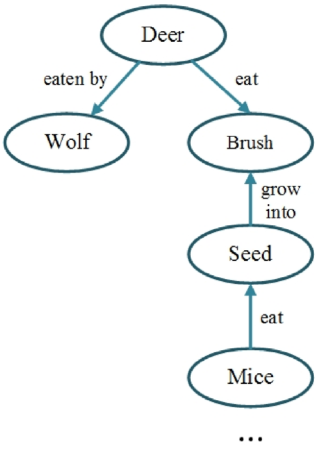

FIGURE 2 A concept map for a forest ecosystem.

2.5 | Measures and instruments

Student-constructed concept maps were analysed by (1) identifying different types of propositions formed in the maps and scoring the propositions, (2) categorizing the maps based on the dominant type of propositions formed in each map, and (3) assessing the map quality by summing up the scores for all proposition in each map. Moreover, group task reports were used to assess student inquiry task performance, and a survey was used to collect individual students' perceptions of their learning experience.

2.5.1 | Student-constructed concept maps

The concept map constructed by students were assessed to analyse students' thinking reflected in the maps. The analysis of the concept map started with the analysis of its propositions. Based on existing studies (e.g., Cañas et al., 2012; Chen et al., 2021; Eggert et al., 2017; Suthers & Hundhausen, 2003), the quality of a map proposition was scored in two dimensions: (a) relevance or importance, and (b) accuracy. The rubrics are provided in Table A1.

The scoring of each proposition included three steps: (1) assessing the proposition's relevance or importance; (2) evaluating the proposition's scientific accuracy; (3) multiplying the accuracy score by the corresponding relevance score, which resulted in a quality score for the proposition. Finally, the scores for all the propositions in a map were summed up to obtain a quality score on the map.

2.5.2 | Inquiry task report

The inquiry task report was analysed to examine each group's task performance in three aspects: the formulated hypotheses, reasoning, and the conclusion. The assessment rubrics are presented in Table B1. Each *formulated hypothesis* was assessed in terms of its relevance (or importance) and plausibility. Each *reasoning* was assessed in terms of the relevance (or importance) of the provided evidence and the accuracy of the causality. The score of each hypothesis or each reasoning was obtained by multiplying its relevance score and accuracy score. Next, summing the scores for all hypotheses and all pieces of reasoning resulted in an overall score for formulated hypotheses and reasoning, respectively.

The *conclusion* was presented in the concluding paragraph in each group's report. It typically consisted of several sentences articulating the group's explanation of the inquiry problem, that is, validated hypotheses stating the causal relationships. Following Janssen et al. (2010), Van Drie et al. (2005), and Chen et al. (2018), the conclusion was assessed in two dimensions: (1) the accuracy of the conclusion and (2) the degree to which the conclusion is consistent with previous reasoning. A conclusion developed by consulting two ecology scientists was used as a reference when scoring the conclusions made by students. The overall score for the conclusion was attained by summing up the two-dimension scores.

2.5.3 | Survey on student perceptions

A survey was administered to collect students' perceptions of their learning experience, that is, their responses to two open-ended questions: (1) What was the biggest difficulty you encountered during inquiry learning in this study; and (2) What are the benefits of constructing a concept map for your inquiry task?

2.6 | Data analysis

To answer RQ1, we investigated whether students formed different types of propositions in their concept maps and whether their concept maps could be categorized into different styles based on the dominant type of propositions in the map. To answer RQ2, we investigated whether and how students constructing different styles of concept maps differed in their inquiry task performance and the quality of their maps. Below are the details of the method.

First, two researchers independently scored the quality of each proposition in each map and obtained the quality score of each map. *Second*, the two researchers independently assessed students' task reports in terms of hypothesising, reasoning, and conclusion. *Third*, the two researchers observed the propositions presented in student-constructed maps and identified three types of propositions (see the details in Section 3.1). Based on the dominant type of propositions formed in a concept map, they identified three styles of concept maps (see the details in Section 3.1). The identified proposition types and map styles were further confirmed by the other researchers of this study. Accordingly, the two researchers independently categorized all proposition into the three types and categorized all concept maps into three styles.

The inter-rater agreement coefficients (Cohen's kappa) were 0.94 for scoring of the propositions; 0.80 for assessing the hypotheses, 0.86 for assessing the reasoning, and 0.86 for assessing the conclusion in task reports; 0.99 for categorizing propositions; and 1.0 for categorizing maps, suggesting substantial agreement between the two raters. Furthermore, the differences and inconsistencies in the results were discussed and resolved.

Fourth, Shapiro–Wilk test and Kolmogorov–Smirnov tests were used to check whether the dependent variables are distributed normally. A non-normal distribution was found for the quality of the propositions presented in student-constructed concept maps. Thus, a Kruskal-Wallis non-parametric test was used to explore the difference in quality among three types of the propositions. *Fifth*, considering the small sample size of concept maps clustered into each style of concept maps, a Kruskal-Wallis non-parametric test was used to explore the differences among the three styles of concept maps in their quality and in student task performance associated with the three styles of concept maps. As significant differences were found, the post-hoc non-parametric pairwise Mann–Whitney-Wilcoxon test was conducted to compare every two styles of concept maps. *Sixth*, the Chi-squared test was conducted to test the homogeneity of student perceptions of learning experience.

Lastly, the two researchers coded the survey data. One analysed all students' responses and identified a set of themes emerging from the responses. The identified themes were then discussed and refined by all the authors. After a consensus was reached, the two researchers coded students' responses independently, and the inter-coder reliability reached 0.89. Furthermore, all discrepancies in their coding results were discussed and resolved.

3 | RESULTS

3.1 | Three types of propositions and their difference in quality

3.1.1 | Three types of propositions

Three types of propositions were identified through direct observation of the propositions presented in student-constructed maps: knowledge-oriented proposition, problem-oriented proposition, and mixed proposition, which are outlined in Table 1. Most of the propositions formed in student-constructed concept maps fell into the first two types; only 16 out of 237 propositions (6.75%) were mixed propositions.

A *knowledge-oriented proposition* presents a piece of subject knowledge as two concepts and the relationships between them (e.g., "Green algae *consume* PO_4 and NO_3"). A *problem-oriented proposition* presents a small part of the problem situation as two specific changes or events and the causal relationships between them (e.g., "The increase in PO_4 and NO_3 in the pond *led to* the increase in green algae"). The causal relationship identified in a problem-oriented proposition may also indicate relevant knowledge that supports the causal relationship. For example, the proposition "The increase in PO_4 and NO_3 in the pond *led to* the increase in green algae" implies that PO_4 and NO_3 are prerequisite for the growth of green algae. A *mixed proposition* presents a problem-related concept and a specific change along with the relationship between the two (e.g., "Green algae *led to* the decrease of dissolved oxygen").

3.1.2 | Difference in quality among the three types of propositions

After scoring all propositions formed in all the maps, we explored whether there were any differences in the quality of the three types of propositions. Table 2 presents the descriptive statistics and Kruskal-Wallis test results. Kruskal-Wallis test showed no quality differences among the three types of propositions (χ^2 (2, $N = 237$) $= 1.966$, $p = 0.374$).

3.2 | Three styles of concept maps and their difference in quality

3.2.1 | Three styles of concept maps

In this study, students formed three types of propositions in their concept maps. The dominant type of proposition in a concept map could be identified if it appeared significantly more frequently than other types of propositions. Given that a concept map generated by students in this study consisted of 8.8 propositions on average, the dominant type of proposition could be identified if it appeared three times more frequently than other types of propositions in a concept map. Further, based on the dominant type of proposition identified in a concept map, the style of the concept map could be determined. The principles for identifying the dominant type of proposition in a concept map and determining the map style are specified as follows and demonstrated in Table C1.

If the number of problem-oriented propositions—the number of knowledge-oriented propositions ≥3 in a concept map, then the dominant type of proposition in the concept map is problem-oriented and the map style is problem-oriented concept map (PCM);

Else if the number of knowledge-oriented propositions—the number of problem-oriented propositions ≥3 in a concept map, then the dominant type of proposition in the concept map is knowledge-oriented and the map style is knowledge-oriented concept map (KCM);

Else no dominant type of proposition is identified in a concept map and the map style is mixed concept map (MCM).

In this way, three styles or categories of concept maps were identified: KCM, PCM, and MCM. The KCMs mainly consisted of knowledge-oriented propositions representing the subject knowledge required to solve the problem or explain the phenomenon as a set of concepts (e.g., green algae, oxygen) and the relationships between the concepts (e.g., "Green algae *produce* oxygen via photosynthesis"). Some KCMs included a few problem-oriented propositions. Figure 3 presents an example of a KCM containing ten knowledge-oriented propositions and two problem-oriented propositions.

The PCMs mainly consisted of problem-oriented propositions representing the problem situation as a number of changes (e.g., green algae increased) and the causal relationships between the changes (e.g., "The increase in PO_4 and NO_3 *led to* the increase in green algae in the pond"). Some PCM included a few knowledge-oriented propositions. Figure 4 presents an example of a PCM containing seven problem-oriented propositions and three knowledge-oriented propositions.

The MCMs consisted of a similar number of knowledge-oriented propositions and problem-oriented propositions plus some mixed propositions. Figure 5 presents an example of an MCM containing one problem-oriented proposition, one knowledge-oriented proposition and three mix propositions.

Among all 27 groups, 11 (40.7%) groups constructed KCMs, another 11 (40.7%) groups constructed PCMs, and the rest 5 (18.5%) groups constructed MCMs. Therefore, KCMs and PCMs were identified as the two major concept-mapping styles. Detailed information about the style of each map is provided in Table A1.

Table 3 presents the descriptive statistics for the three styles of maps, in terms of the number of knowledge-oriented propositions, number of problem-oriented propositions, mixed propositions, and the total number of propositions in the map. The majority of the propositions included in KCMs were knowledge-oriented (with a mean value of 7 out of all 7.82 propositions); the majority of the propositions in PCMs were problem-oriented (with a mean value of 8.82 out of all 10.09 propositions); while the MCMs consisted of comparable

TABLE 1 Main features of three types of propositions.

Aspects		Knowledge-oriented proposition	Problem-oriented proposition	Mixed proposition
Proposition component	Node	Representing a basic concept relevant to the problem	Representing a change that had occurred in the problem situation	Representing a concept/variable, or a change in value of the variable
	Link	Representing the relationship between linked concepts	Representing the sequence of (or causal relationship between) linked changes	Representing the causal relationship between linked nodes
	Linking words	Specifying the nature of the relationship	Specifying the nature of the relationship in most cases Specifying the knowledge underlying the causal relationship in two cases only	Specifying the nature of the relationship
Proposition content		Representing a piece of the subject knowledge relevant to the problem	Representing a small part of the problem situation	Representing a concept/variable and its relationship with a change in the problem situation
Example		“Green algae consume PO4 and NO3.”	“The increase in PO4 and NO3 in the pond led to the increase in green algae.”	“Green algae led to the decrease of dissolved oxygen.”

TABLE 2 Descriptive statistics and Kruskal-Wallis test for the quality of three types of propositions.

Proposition type	N	Mean (SD)	Kruskal-Wallis test
Knowledge-oriented proposition	101	1.43 (1.10)	χ^2 (2, $N = 237$) $= 1.966$ ($p = 0.374$)
Problem-oriented proposition	120	1.69 (1.29)	
Mixed proposition	16	1.63 (1.21)	

number of knowledge-oriented propositions and problem-oriented propositions. Compared to KCMs and PCMs, MCMs contained more mixed propositions. Among the three styles of concept maps, there are significant differences in the number of knowledge-oriented (F (2, 24) $= 20.739$, $p = 0.000$) and problem-oriented (F(2, 24) $= 48.123$, $p = 0.000$) propositions. However, there is no significant difference in the number of total propositions among the three styles of concept maps (F(2, 24) $= 1.589$, $p = 0.225$).

3.2.2 | Difference in quality among the three styles of concept maps

The quality of the student-constructed concept maps was assessed by scoring the propositions presented in the maps. Table 4 presents the descriptive statistics and Kruskal-Wallis test results for the quality of the three styles of maps. The Kruskal-Wallis test revealed that there was significant difference in quality among the three styles of concept map (χ^2 (2, $N = 27$) $= 7.969$, $p = 0.019$); further, the *post-hoc* Mann-Whiteney U-Test showed that the PCMs demonstrated significantly higher quality than KCMs ($U = 8.500$, $p = 0.036$).

3.3 | Inquiry task performance

The descriptive statistics and Kruskal-Wallis test results for the inquiry task performance are presented in Table 5, with the detailed profiles presented in Table D1. The Kruskal-Wallis test revealed that there was significant difference among the task performance associated with the three styles of concept maps; and the *post-hoc* Mann-Whiteney U-Test showed that the groups constructing PCMs outperformed those constructing KCMs and MCMs in hypothesising, reasoning, drawing a conclusion, and the overall performance ($t_{20} = 3.302$, $p = 0.004$).

3.4 | Student perceptions of learning experience

Within the 80 participants, 76 of them completed the survey, which collected student responses to two open-ended questions. We analysed the responses from 36 students constructing KCMs and 30 students constructing PCMs. A response covering more than one theme was split into several responses. Accordingly, there were 76 responses to the first survey question and 72 responses to the second survey question. Among them, the themes mentioned in the responses by more than two students were outlined for analysis.

Table 6 presented the survey results on learning difficulties perceived by students. The major difficulties reported by the two clusters of students (i.e., 36 constructing KCMs, 30 constructing PCMs) were related to processing a lot of data and reasoning with the data. The Chi-squared test results showed there were no significant differences in the distribution of perceived learning difficulties between the two clusters of students (χ^2 (4, $N = 66$) $= 5.636$, $p > 0.05$). However, compared to students from the PCM cluster, students from the KCM

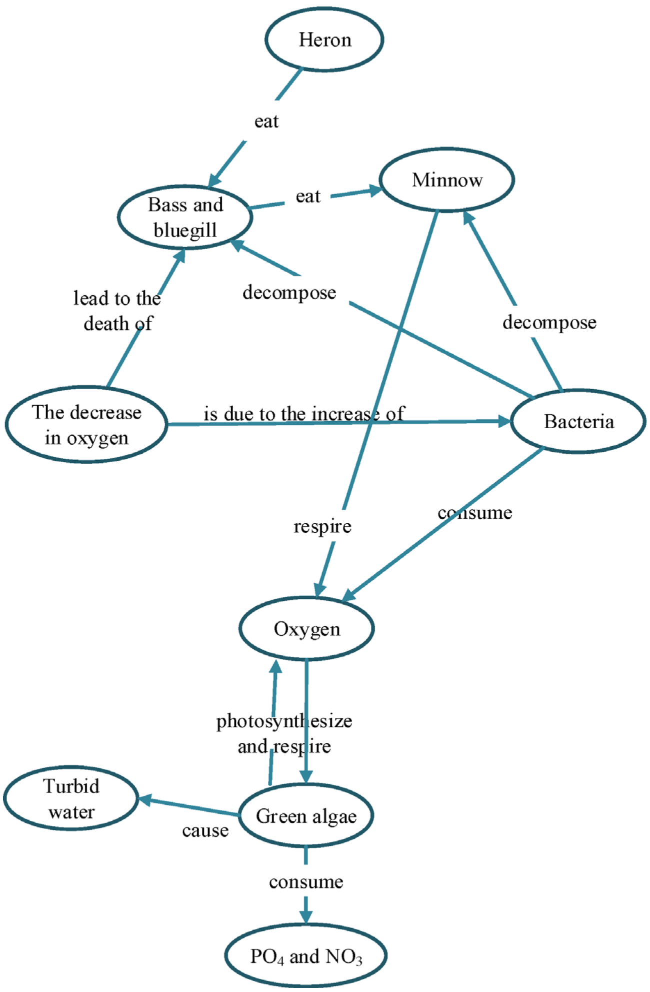

FIGURE 3 An example of a knowledge-oriented concept map (KCM).

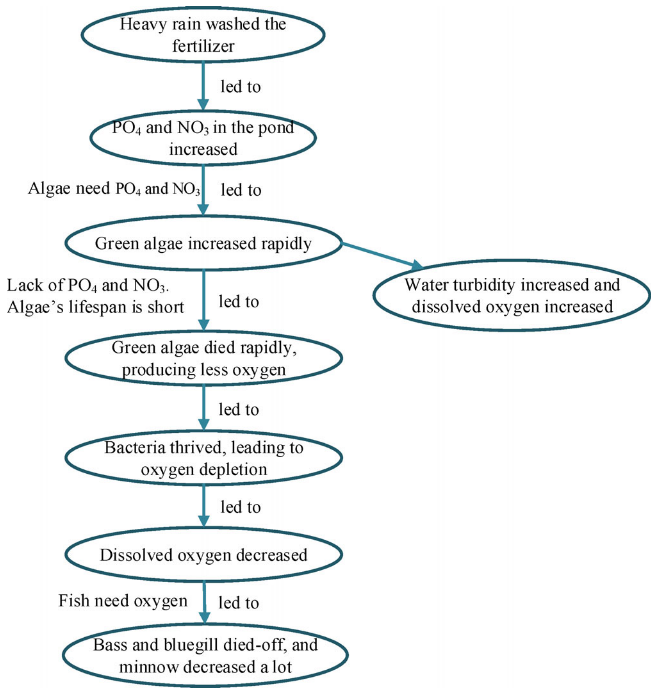

FIGURE 4 An example of a problem-oriented concept map (PCM).

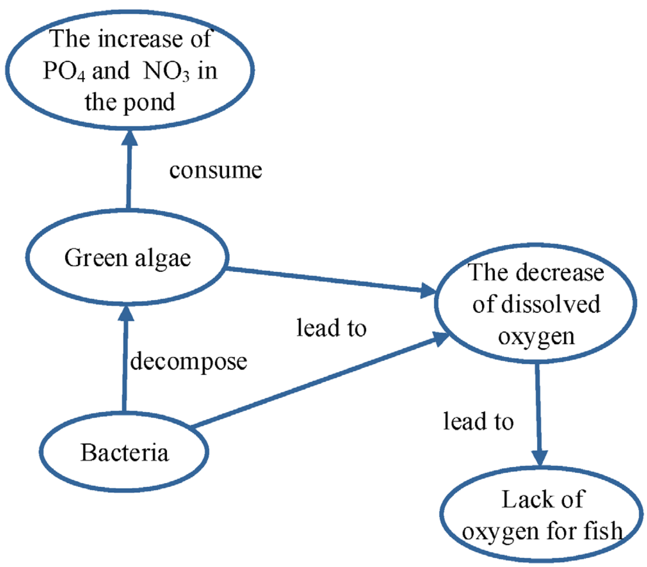

FIGURE 5 An example of a mixed concept map (MCM).

cluster reported more difficulties in generating hypotheses and in drawing concept maps.

Table 7 presented the survey results on the benefits of concept mapping. The results of Chi-squared test showed that there were no significant differences in the distribution of student perceptions of the benefits of concept mapping (χ^2 (4, $N = 63$) $= 7.334$, $p > 0.05$). Although both clusters of students reported the benefits in terms of visualizing complex relationships and fostering clear thinking and reasoning, students from the PCM cluster perceived more benefits of concept mapping in terms of identifying related variables, representing ongoing changes, and fostering reflection.

4 | DISCUSSION

4.1 | Proposition types and mapping styles

Three types of propositions were found in the concept maps constructed by the students during the inquiry task, that is, knowledge-oriented propositions, problem-oriented propositions, and mixed propositions, with most of the propositions in the maps falling into the first two categories. On the basis of the dominant types of propositions in the maps, three concept mapping styles were identified, that is, KCMs, PCMs, and MCMs, with most of the maps falling into the first two styles.

The students constructing KCMs focused on representing the subject knowledge required to solve the problem as a set of concepts and the relationships between the concepts (e.g., "Fish need oxygen"). KCMs are quite similar to traditional concept maps, which have been

TABLE 3 Descriptive statistics for three styles of concept maps.

Map style	N	Mean (SD)			
		N of KPs in the map	N of PPs in the map	N of MPs in the map	N of propositions in the map
KCM	11	7 (2.97)	0.55 (0.82)	0.27 (0.65)	7.82 (3.09)
PCM	11	0.82 (1.33)	8.82 (2.64)	0.45 (0.93)	10.09 (2.74)
MCM	5	3 (2.45)	3.4 (2.07)	1.4 (1.14)	8 (4.24)

Abbreviations: KP, knowledge-oriented proposition; MP, mixed proposition; PP, problem-oriented proposition.

TABLE 4 Descriptive statistics and Kruskal-Wallis test for the quality of the three styles of concept maps.

Map style	N	Mean (SD)	Kruskal-Wallis test	*Post-hoc* tests (Mann-Whiteney U test)
KCM	11	12.05 (4.32)	χ^2 (2, $N = 27$) = 7.969 ($p = 0.019$)	PCM > KCM*
PCM	11	17.50 (4.46)		
MCM	5	11.20 (3.70)		

*$p < 0.01$.

TABLE 5 Descriptive statistics and Kruskal-Wallis test for inquiry task performance.

Aspect	Map style	N	Mean (SD)	Kruskal-Wallis test	*Post-hoc* tests (Mann-Whiteney U test)
Hypotheses	KCM	11	9.86 (4.47)	χ^2 (2, $N = 27$) = 9.577 ($p = 0.008$)	PCM > KCM* PCM > MCM**
	PCM	11	13.91 (3.81)		
	MCM	5	6.70 (3.25)		
Reasoning	KCM	11	12.32 (6.00)	χ^2 (2, $N = 27$) = 10.184 ($p = 0.006$)	PCM > KCM** PCM > MCM**
	PCM	11	20.54 (5.91)		
	MCM	5	11.00 (4.64)		
Conclusion	KCM	11	10.36 (2.25)	χ^2 (2, $N = 27$) = 9.711 ($p = 0.008$)	PCM > KCM** PCM > MCM*
	PCM	11	13.45 (2.58)		
	MCM	5	9.46 (2.74)		
Total score (Overall performance)	KCM	11	32.55 (11.39)	χ^2 (2, $N = 27$) = 12.132 ($p = 0.002$)	PCM > KCM** PCM > MCM**
	PCM	11	47.91 (10.35)		
	MCM	5	27.16 (9.31)		

*$p < 0.05$; **$p < 0.01$.

widely used for representing learners' understanding of subject knowledge (e.g., Ruiz-Primo et al., 2001; Schwendimann & Linn, 2016).

The students constructing PCMs focused on representing the problem situation as ongoing changes and the causal relationships between the changes. The PCMs shared some similarities with causal chains or loop diagrams, which are beneficial to dynamic thinking and reasoning (Derbentseva et al., 2007; Slof et al., 2013). Although a prior study indicated that concept maps are not well suited to represent the problem contextual information such as the temporal aspects of phenomena (Tripto et al., 2018), our study demonstrated student use of concept maps to represent problem situation.

The MCMs included relatively more mixed propositions, compared to KCMs and PCMs. The mixed propositions, which were not reported in previous literature, generally revealed students' vague understanding of the relationships between variables (e.g., "Green algae led to the decrease of dissolved oxygen").

4.2 | Quality of concept maps

The study found that the quality of the PCMs was higher than that of the other two styles of maps. This finding is consistent with previous studies indicating that students drawing KCMs represented insufficient parts of the problem; they placed more emphasis on organizing the concepts than on investigating the dynamics of the problem (Khajeloo & Siegel, 2022; Öllinger et al., 2015). The survey results also show that students constructing KCMs perceived more difficulties in constructing a concept map for inquiry learning.

The students constructing PCMs demonstrated their potential to make expert-like thinking and causal reasoning about ecosystems, that is, focusing on the dynamics of the system (e.g., a number of changes) and the mechanisms of the system (e.g., the causal relationships between the changes) (Grotzer et al., 2013). Among the three types of propositions identified in the student-constructed concept maps in this study, there was no statistical difference in the proposition

TABLE 6 Students' perceptions of learning difficulties.

Themes	Examples	Frequency: Students constructing KCMs (*N* = 37) *K* (%)	Frequency: Students constructing PCMs (*N* = 30) *K* (%)
Difficulty in reasoning with data	*The compiled evidence could not support our hypotheses.*	13 (35.14%)	15 (50.00%)
Difficulty in processing a lot of data	*There was so much information and data that it was hard to process and synthesize them.*	9 (24.32%)	9 (30.00%)
Difficulty in drawing a concept map for inquiry	*The concept map cannot represent the problem in its entirety.*	9 (24.32%)	3 (10.00%)
Difficulty in generating hypotheses	*Formulate hypotheses.*	5 (13.51%)	1 (3.33%)
Difficulty in investigating the root cause of the problem	*We could only find the surface cause, but could not find the root cause.*	1 (2.70%)	2 (6.67%)

Note: *N* = total number of responses (One participant might write more than one response, or one response might covey more than one theme). *K* = number of responses to each theme/category. % = the percentage of responses.

TABLE 7 Students' perceptions of the benefits of concept mapping.

Themes	Examples	Frequency: Students constructing KCMs (*N* = 29) *K* (%)	Frequency: Students constructing PCMs (*N* = 34) *K* (%)
Fostering clear thinking and reasoning	*The concept map helped us think in a clear way and reason from the surface level to the deep level.*	13 (44.83%)	15 (44.12%)
Visualizing complex relationships	*The concept map helped clarify the relationships between intertwined variables.*	10 (34.48)	8 (23.53%)
Identifying related variables	*The concept map helped us filter out major variables related to the big fish die-off problem and exclude irrelevant variables.*	0 (0.00%)	2 (5.88%)
Representing ongoing changes	*Constructing a concept map helped us visually externalize the sequence of events.*	0 (0.00%)	3 (8.82%)
Fostering reflection	*It (concept mapping) helped us find missing points.*	0 (0.00%)	2 (5.88%)
No clear benefits	*Concept mapping did not help us a lot.*	6 (20.69%)	4 (11.76%)

Note: *N* = total number of responses (One participant might write more than one response, or one response might covey more than one theme). *K* = number of responses to each theme/category. % = the percentage of responses.

quality. Also, there was no statistical difference in the number of propositions between KCMs and PCMs. Compared to other students, those placing more emphases to problem-oriented propositions (i.e., constructing a PCM) obtained a higher score on the overall quality of their maps. The results indicate that when constructing a concept map by placing more emphases on ongoing changes and the causal relationships between the changes, students formed more relevant and accurate propositions, showing their better understanding or conceptualization of the inquiry problem. This may influence how they approach and investigate the problem (Öllinger et al., 2015).

4.3 | Inquiry task performance

The study reveals that the two clusters of students constructing KCMs and PCMs, respectively, showed significant differences in inquiry task performance. The students constructing PCMs outperformed those constructing KCMs in hypothesising, reasoning, and drawing conclusions. A possible reason for the difference is that the students constructing PCMs performed better in conceptualizing the problem situation, which directly helped them formulate and test hypotheses (Eseryel et al., 2013; Öllinger et al., 2015). As indicated in these students' responses to the survey, "Constructing a concept map helped us visually externalize the ongoing changes." The propositions presenting problem situation in the map can be well transformed into a hypothesis. Further, the problem information included in the propositions provides clear evidence for testing the hypotheses. The promising association between the construction of PCMs and the better inquiry task performance is consistent with prior research highlighting the importance of focusing on ongoing changes over time to facilitate reasoning about ecosystems dynamics in inquiry learning (Grotzer et al., 2013; Khajeloo & Siegel, 2022). The more quantified concepts and dynamic propositions students incorporate in their concept maps, the more their dynamic thinking will be stimulated (Derbentseva et al., 2007).

In contrast, the students constructing KCMs only represented the subject knowledge and did not adequately conceptualize the problem in their maps. Previous studies have shown that insufficient problem representation might have been detrimental to identifying the significant variables and thus affect their task performance (Öllinger & Goel, 2010). This also indicates that making the subject knowledge explicit is not enough to promote task performance (Öllinger et al., 2015; Ruiz-Primo et al., 2001). Although the KCM students mentioned the benefits of concept mapping for visualizing complex relationships and fostering clear thinking, they reported their difficulties in generating hypotheses. Although some KCM groups demonstrated their understanding of the subject knowledge about bacteria consuming oxygen, they did not formulate the hypothesis that the increase in bacteria had led to the decrease in oxygen in the water. Without representing the problem situation, KCMs are insufficient to support hypotheses formulation and evidence-based reasoning to investigate the problem (Wang et al., 2017; Wang et al., 2022). A prior study also revealed that the quality of KCMs is not a significant predictor of inquiry task performance (Chen et al., 2021).

4.4 | Limitations of the study

This research has the following limitations. *First*, the association between students' concept mapping styles and their inquiry task performance investigated in this study does not imply causality. Further studies are needed to investigate the effects of constructing different styles of concept maps on inquiry learning through controlled experiments. *Second*, the small sample size may influence the results of the study. Future studies will be conducted with more participants to improve the statistical power. *Third*, in a group task context, both group discussion and collaborative concept mapping may affect group task performance. Future studies can be conducted to differentiate between the impact of collaborative concept mapping and the impact of group discussion.

5 | CONCLUSIONS

This research analysed the content of concept maps constructed by secondary students to facilitate inquiry learning in a virtual ecosystem. Three types of propositions formed by linked concepts and linking words in the concept maps were identified, namely knowledge-oriented propositions, problem-oriented propositions, and mixed propositions, with most of the propositions demonstrating the first two types. Based on the dominant type of propositions formed in the concept maps, three styles of concept maps were identified: (1) KCMs, mainly consisting of knowledge-oriented propositions plus a few problem-oriented ones; (2) PCMs, primarily consisting of problem-oriented propositions plus a few knowledge-oriented ones; and (3) MCMs, comprising a comparable number of the three types of propositions. Compared to those constructing KCMs, students constructing PCMs formed higher-quality propositions in their concept maps and performed better in the inquiry task in terms of hypothesising, reasoning, and drawing a conclusion.

The findings have several implications for research and practice in applying concept maps to support inquiry learning. *First*, analysing student-constructed concept maps can help understand students' thinking processes, which are difficult to communicate but crucial to inquiry learning. Findings from analysing student-constructed concept maps may provide useful insights into how concept mapping can be guided to foster effective thinking in inquiry learning. *Second*, in addition to conventional KCMs, students in inquiry learning can be encouraged to construct PCMs or formulate problem-oriented propositions in concept maps to foster effective thinking and reasoning about the problem. *Third*, concept mapping is not a one-off learning activity; students need guidance and practice to realize the full potential of concept mapping to facilitate complex thinking (Eshuis et al., 2022; Roessger et al., 2018).

AUTHOR CONTRIBUTIONS

Juanjuan Chen: Data curation; formal analysis; writing – original draft. **Minhong Wang:** Conceptualization; supervision; validation; writing – review and editing. **Tina Grotzer:** Resources; validation; writing – review and editing. **Chris Dede:** Resources; validation; writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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REFERENCES

Bell, T., Urhahne, D., Schanze, S., & Ploetzner, R. (2010). Collaborative inquiry learning: Models, tools, and challenges. *International Journal of Science Education*, *32*(3), 349–377. https://doi.org/10.1080/09500690802582241

Berland, L. K., & Reiser, B. J. (2009). Making sense of argumentation and explanation. *Science Education*, *93*(1), 26–55. https://doi.org/10.1002/sce.20286

Bleckmann, T., & Friege, G. (2023). Concept maps for formative assessment: Creation and implementation of an automatic and intelligent evaluation method. *Knowledge Management & E-Learning*, *15*(3), 433–447. https://doi.org/10.34105/j.kmel.2023.15.025

Brinson, J. R. (2015). Learning outcome achievement in non-traditional (virtual and remote) versus traditional (hands-on) laboratories: A review of the empirical research. *Computers in Education*, *87*, 218–237. https://doi.org/10.1016/j.compedu.2015.07.003

Bybee, R. W. (2002). Scientific inquiry, student learning, and the science curriculum. In N. S. T. Association (Ed.), *Learning science and the science of learning*. National Science Teachers Association Press.

Cañas, A. J., Novak, J. D., & Reiska, P. (2012). Freedom vs. restriction of content and structure during concept mapping—Possibilities and limitations for construction and assessment. In *Concept maps: Theory, methodology, technology—Proceedings of the 5th international conference on concept mapping*. University of Malta.

Chen, J., Wang, M., Dede, C., & Grotzer, T. (2021). Analyzing student thinking reflected in self-constructed cognitive maps and its influence on inquiry task performance. *Instructional Science*, *49*(3), 287–312. https://doi.org/10.1007/s11251-021-09543-8

Chen, J., Wang, M., Grotzer, T. A., & Dede, C. (2018). Using a three-dimensional thinking graph to support inquiry learning. *Journal of Research in Science Teaching*, *55*(9), 1239–1263. https://doi.org/10.1002/tea.21450

Chu, H. C., Hwang, G. J., Tsai, C. C., & Tseng, J. C. R. (2010). A two-tier test approach to developing location-aware mobile learning systems for natural science courses. *Computers in Education*, *55*(4), 1618–1627. https://doi.org/10.1016/j.compedu.2010.07.004

Conradty, C., & Bogner, F. X. (2012). Knowledge presented in concept maps: Correlations with conventional cognitive knowledge tests. *Educational Studies*, *38*(3), 341–354. https://doi.org/10.1080/03055698.2011.643100

Cox, R. (1999). Representation construction, externalised cognition and individual differences. *Learning and Instruction*, *9*(4), 343–363.

de Jong, T., Linn, M. C., & Zacharia, Z. C. (2013). Physical and virtual laboratories in science and engineering education. *Science*, *340*(6130), 305–308. https://doi.org/10.1126/science.1230579

de Vries, E. (2006). Students' construction of external representations in design-based learning situations. *Learning and Instruction*, *16*(3), 213–227. https://doi.org/10.1016/j.learninstruc.2006.03.006

Delahunty, T., Seery, N., & Lynch, R. (2020). Exploring problem conceptualization and performance in STEM problem solving contexts. *Instructional Science*, *48*(4), 395–425. https://doi.org/10.1007/s11251-020-09515-4

Derbentseva, N., Safayeni, F., & Cañas, A. J. (2007). Concept maps: Experiments on dynamic thinking. *Journal of Research in Science Teaching*, *44*(3), 448–465. https://doi.org/10.1002/tea.20153

Dmoshinskaia, N., Gijlers, H., & de Jong, T. (2021). Giving feedback on peers' concept maps in an inquiry learning context: The effect of providing assessment criteria. *Journal of Science Education and Technology*, *30*(3), 420–430. https://doi.org/10.1007/s10956-020-09884-y

Eberbach, C., & Crowley, K. (2009). From everyday to scientific observation: How children learn to observe the biologist's world. *Review of Educational Research*, *79*(1), 39–68. https://doi.org/10.3102/0034654308325899

Eggert, S., Nitsch, A., Boone, W., & Nückles, M. (2017). Supporting students' learning and socioscientific reasoning about climate change—The effect of computer-based concept mapping scaffolds. *Research in Science Education*, *47*(1), 137–159.

Eseryel, D., Ifenthaler, D., & Ge, X. (2013). Validation study of a method for assessing complex ill-structured problem solving by using causal representations. *Educational Technology Research and Development*, *61*(3), 443–463. https://doi.org/10.1007/s11423-013-9297-2

Eshuis, E. H., ter Vrugte, J., Anjewierden, A., & de Jong, T. (2022). Expert examples and prompted reflection in learning with self-generated concept maps. *Journal of Computer Assisted Learning*, *38*(2), 350–365. https://doi.org/10.1111/jcal.12615

Furtak, E. M., Seidel, T., Iverson, H., & Briggs, D. C. (2012). Experimental and quasi-experimental studies of inquiry-based science teaching: A meta-analysis. *Review of Educational Research*, *82*(3), 300–329. https://doi.org/10.3102/0034654312457206

Gijlers, H., & de Jong, T. (2013). Using concept maps to facilitate collaborative simulation-based inquiry learning. *Journal of the Learning Sciences*, *22*(3), 340–374. https://doi.org/10.1080/10508406.2012.748664

Grotzer, T. A., Kamarainen, A. M., Tutwiler, M. S., Metcalf, S., & Dede, C. (2013). Learning to reason about ecosystems dynamics over time: The challenges of an event-based causal focus. *Bioscience*, *63*(4), 288–296. https://doi.org/10.1525/bio.2013.63.4.9

Hmelo-Silver, C. E., & Azevedo, R. (2006). Understanding complex systems: Some core challenges. *The Journal of the Learning Sciences*, *15*(1), 53–61. https://doi.org/10.1207/s15327809jls1501_7

Hmelo-Silver, C. E., Duncan, R. G., & Chinn, C. A. (2007). Scaffolding and achievement in problem-based and inquiry learning: A response to Kirschner, Sweller, and Clark (2006). *Educational Psychologist*, *42*(2), 99–107. https://doi.org/10.1080/00461520701263368

Hovardas, T., Zacharia, Z., Xenofontos, N., & de Jong, T. (2022). How many words are enough? Investigating the effect of different configurations of a software scaffold for formulating scientific hypotheses in inquiry-oriented contexts. *Instructional Science*, *50*(3), 361–390. https://doi.org/10.1007/s11251-022-09580-x

Hsu, C. C., Chiu, C. H., Lin, C. H., & Wang, T. I. (2015). Enhancing skill in constructing scientific explanations using a structured argumentation scaffold in scientific inquiry. *Computers in Education*, *91*, 46–59. https://doi.org/10.1016/j.compedu.2015.09.009

Hwang, G. J., Chen, C. H., & Chen, W. H. (2022). A concept mapping-based prediction-observation-explanation approach to promoting students' flipped learning achievements and perceptions. *Educational Technology Research and Development*, *70*(4), 1497–1516. https://doi.org/10.1007/s11423-022-10106-y

Hwang, G. J., Zou, D., & Lin, J. (2020). Effects of a multi-level concept mapping-based question-posing approach on students' ubiquitous learning performance and perceptions. *Computers in Education*, *149*, 103815. https://doi.org/10.1016/j.compedu.2020.103815

Janssen, J., Erkens, G., Kirschner, P. A., & Kanselaar, G. (2010). Effects of representational guidance during computer-supported collaborative learning. *Instructional Science*, *38*(1), 59–88. https://doi.org/10.1007/s11251-008-9078-1

Jonassen, D. H. (1997). Instructional design models for well-structured and ill-structured problem-solving learning outcomes. *Educational Technology Research and Development*, *45*(1), 65–94. https://doi.org/10.1007/BF02299613

Jonassen, D. H. (2003). Using cognitive tools to represent problems. *Journal of Research on Technology in Education*, *35*(3), 362–381. https://doi.org/10.1080/15391523.2003.10782391

Jonassen, D. H. (2005). Tools for representing problems and the knowledge required to solve them. In S. O. Tergan & T. Keller (Eds.), *Knowledge and information visualization* (pp. 82–94). Springer.

Khajeloo, M., & Siegel, M. A. (2022). Concept map as a tool to assess and enhance students' system thinking skills. *Instructional Science*, *50*(4), 571–597. https://doi.org/10.1007/s11251-022-09586-5

Kim, M. C., & Hannafin, M. J. (2011). Scaffolding 6th graders' problem solving in technology-enhanced science classrooms: A qualitative case study. *Instructional Science*, *39*(3), 255–282. https://doi.org/10.1007/s11251-010-9127-4

Kyza, E. A. (2009). Middle-school students' reasoning about alternative hypotheses in a scaffolded, software-based inquiry investigation. *Cognition and Instruction*, *27*(4), 277–311. https://doi.org/10.1080/07370000903221718

Lazonder, A. W., & Harmsen, R. (2016). Meta-analysis of inquiry-based learning: Effects of guidance. *Review of Educational Research*, *86*(3), 681–718. https://doi.org/10.3102/0034654315627366

Löhner, S., Van Joolingen, W. R., & Savelsbergh, E. R. (2003). The effect of external representation on constructing computer models of complex phenomena. *Instructional Science*, *31*(6), 395–418. https://doi.org/10.1023/A:1025746813683

McNeill, K. L., & Krajcik, J. (2008). Scientific explanations: Characterizing and evaluating the effects of teachers' instructional practices on student learning. *Journal of Research in Science Teaching*, *45*(1), 53–78. https://doi.org/10.1002/tea.20201

Metcalf, S., Kamarainen, A., Tutwiler, M. S., Grotzer, T. A., & Dede, C. (2011). Ecosystem science learning via multi-user virtual environments. *International Journal of Gaming and Computer-Mediated Simulations*, *3*(1), 86–90. https://doi.org/10.4018/jgcms.2011010107

Metcalf, S. J., Reilly, J. M., Kamarainen, A. M., King, J., Grotzer, T. A., & Dede, C. (2018). Supports for deeper learning of inquiry-based ecosystem science in virtual environments - comparing virtual and physical concept mapping. *Computers in Human Behavior*, *87*, 459–469. https://doi.org/10.1016/j.chb.2018.03.018

Moritz, J., Meyerhoff, H. S., & Schwan, S. (2020). Control over spatial representation format enhances information extraction but prevents long-term learning. *Journal of Educational Psychology*, *112*(1), 148–165. https://doi.org/10.1037/edu0000364

National Research Council. (2012). *A framework for K-12 science education: Practices, crosscutting concepts, and core ideas*. National Academies Press. https://doi.org/10.17226/13165

Novak, J. D., Bob Gowin, D., & Johansen, G. T. (1983). The use of concept mapping and knowledge vee mapping with junior high school science students. *Science Education*, *67*(5), 625–645. https://doi.org/10.1002/sce.3730670511

Öllinger, M., & Goel, V. (2010). Problem solving. In B. Glatzeder, V. Goel, & A. von Muller (Eds.), *Towards a theory of thinking* (pp. 3–21). Springer.

Öllinger, M., Hammon, S., von Grundherr, M., & Funke, J. (2015). Does visualization enhance complex problem solving? The effect of causal mapping on performance in the computer-based microworld Tailorshop. *Educational Technology Research and Development*, *63*(4), 621–637. https://doi.org/10.1007/s11423-015-9393-6

Olympiou, G., Zacharias, Z., & deJong, T. (2013). Making the invisible visible: Enhancing students' conceptual understanding by introducing representations of abstract objects in a simulation. *Instructional Science*, *41*(3), 575–596. https://doi.org/10.1007/s11251-012-9245-2

Park, J., Tang, K. S., & Chang, J. (2021). Plan-draw-evaluate (PDE) pattern in students' collaborative drawing: Interaction between visual and verbal modes of representation. *Science Education*, *105*(5), 1013–1045. https://doi.org/10.1002/sce.21668

Pedaste, M., Mäeots, M., Siiman, L. A., de Jong, T., van Riesen, S. A. N., Kamp, E. T., Manoli, C. C., Zacharia, Z. C., & Tsourlidaki, E. (2015). Phases of inquiry-based learning: Definitions and the inquiry cycle. *Educational Research Review*, *14*, 47–61. https://doi.org/10.1016/j.edurev.2015.02.003

Rau, M. A., Zahn, M., Misback, E., Herder, T., & Burstyn, J. (2021). Adaptive support for representational competencies during technology-based problem solving in chemistry. *Journal of the Learning Sciences*, *30*(2), 163–203. https://doi.org/10.1080/10508406.2021.1888733

Reiser, B. J. (2004). Scaffolding complex learning: The mechanisms of structuring and problematizing student work. *Journal of the Learning Sciences*, *13*(3), 273–304. https://doi.org/10.1207/s15327809jls1303_2

Roessger, K. M., Daley, B. J., & Hafez, D. A. (2018). Effects of teaching concept mapping using practice, feedback, and relational framing. *Learning and Instruction*, *54*, 11–21. https://doi.org/10.1016/j.learninstruc.2018.01.011

Ruiz-Primo, M. A., Schultz, S. E., Li, M., & Shavelson, R. J. (2001). Comparison of the reliability and validity of scores from two concept-mapping techniques. *Journal of Research in Science Teaching*, *38*(2), 260–278.

Safayeni, F., Derbentseva, N., & Cañnas, A. J. (2005). A theoretical note on concepts and the need for cyclic concept maps. *Journal of Research in Science Teaching*, *42*(7), 741–766. https://doi.org/10.1002/tea.20074

Saidin, N. F., Halim, N. D. A., Yahaya, N., & Zulkifli, N. N. (2024). Enhancing students' critical thinking and visualisation skills through mobile augmented reality. *Knowledge Management & E-Learning*, *16*(1), 1–41. https://doi.org/10.34105/j.kmel.2024.16.001

Schroeder, N. L., Nesbit, J. C., Anguiano, C. J., & Adesope, O. O. (2018). Studying and constructing concept maps: A meta-analysis. *Educational Psychology Review*, *30*(2), 431–455. https://doi.org/10.1007/s10648-017-9403-9

Schwendimann, B. A., & Linn, M. C. (2016). Comparing two forms of concept map critique activities to facilitate knowledge integration processes in evolution education. *Journal of Research in Science Teaching*, *53*(1), 70–94. https://doi.org/10.1002/tea.21244

Slof, B., Erkens, G., Kirschner, P. A., & Helms-Lorenz, M. (2013). The effects of inspecting and constructing part-task-specific visualizations on team and individual learning. *Computers in Education*, *60*(1), 221–233. https://doi.org/10.1016/j.compedu.2012.07.019

Slof, B., Erkens, G., Kirschner, P. A., Janssen, J., & Phielix, C. (2010). Fostering complex learning-task performance through scripting student use of computer supported representational tools. *Computers in Education*, *55*(4), 1707–1720. https://doi.org/10.1016/j.compedu.2010.07.016

Suthers, D. D., & Hundhausen, C. D. (2003). An experimental study of the effects of representational guidance on collaborative learning processes. *Journal of the Learning Sciences*, *12*(2), 183–218. https://doi.org/10.1207/S15327809JLS1202_2

Tang, K. S., Won, M., & Treagust, D. (2019). Analytical framework for student-generated drawings. *International Journal of Science Education*, *41*(16), 2296–2322. https://doi.org/10.1080/09500693.2019.1672906

Talbert, L. E., Bonner, J., Mortezaei, K., Guregyan, C., Henbest, G., & Eichler, J. F. (2020). Revisiting the use of concept maps in a large enrollment general chemistry course: implementation and assessment. *Chemistry Education Research and Practice*, *21*(1), 37–50. https://doi.org/10.1039/C9RP00059C

Tripto, J., Assaraf, O. B. Z., & Amit, M. (2018). Recurring patterns in the development of high school biology students' system thinking over time. *Instructional Science*, *46*(5), 639–680. https://doi.org/10.1007/s11251-018-9447-3

Trundle, K. C., & Bell, R. L. (2010). The use of a computer simulation to promote conceptual change: A quasi-experimental study. *Computers in Education*, *54*(4), 1078–1088. https://doi.org/10.1016/j.compedu.2009.10.012

van Amelsvoort, M., Andriessen, J., & Kanselaar, G. (2007). Representational tools in computer-supported collaborative argumentation-based learning: How dyads work with constructed and inspected argumentative diagrams. *The Journal of the Learning Sciences*, *16*(4), 485–521. https://doi.org/10.1080/10508400701524785

van Drie, J., van Boxtel, C., Jaspers, J., & Kanselaar, G. (2005). Effects of representational guidance on domain specific reasoning in CSCL. *Computers in Human Behavior*, *21*(4), 575–602. https://doi.org/10.1016/j.chb.2004.10.024

Wang, M., Cheng, B., Chen, J., Mercer, N., & Kirschner, P. A. (2017). The use of web-based collaborative concept mapping to support group learning and interaction in an online environment. *Internet and Higher Education*, *34*, 28–40. https://doi.org/10.1016/j.iheduc.2017.04.003

Wang, Q., Zhu, Y., Wei, L., & Deng, H. (2022). Visual attention pattern of middle school students during problem-solving in physics. *Mind, Brain, and Education*, *16*(2), 99–111. https://doi.org/10.1111/mbe.12313

Wörner, S., Kuhn, J., & Scheiter, K. (2022). The best of two worlds: A systematic review on combining real and virtual experiments in science education. *Review of Educational Research*, *92*, 911–952. https://doi.org/10.3102/00346543221079417

Wu, B., & Wang, M. (2012). Integrating problem solving and knowledge construction through dual mapping. *Knowledge Management & E-Learning*, *4*(3), 248-257. https://doi.org/10.34105/j.kmel.2012.04.021

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APPENDIX A

TABLE A1 Rubrics for scoring a proposition in a concept map.

Dimension	Description
Relevance or importance	Whether a proposition is relevant to the cause-and-effect analysis of the fish die-off problem. 0 = irrelevant, 0.5 = weakly relevant, 1 = relevant, 2 = highly or particularly relevant or important
Accuracy	Whether the proposition's substantive content is scientific accuracy, based on the subject knowledge as well as the set of primary relationships identified in Metcalf et al. (2018), regardless of whether the node represents an element or a process. 0 = totally inaccurate, 1 = partially accurate, 2 = absolutely accurate.

TABLE B1 Rubrics for assessing inquiry task performance.

Element	Dimension	Description
Hypothesis	Relevance or importance	Whether the hypothesis is relevant to the cause-and-effect analysis of the fish die-off problem. 0 = irrelevant, 0.5 = somewhat relevant, 1 = relevant, 2 = highly or particularly relevant or important.
	Plausibility	Whether the hypothesis is accurate. 0 = totally improbable, 1 = partially probable, 2 = absolutely probable.
Reasoning	Relevance or importance	Whether the piece of evidence is highly relevant to the corresponding hypothesis, indicating a strong evidential relationship. 0 = irrelevant, 0.5 = somewhat relevant, 1 = relevant, 2 = highly or particularly important.
	Accuracy	Whether there is a demonstration of causality. 0 = totally inaccurate, 1 = partially accurate, 2 = absolutely accurate.
Conclusion	Accuracy	Whether the conclusion is accurate, based on how close the conclusion is to the expert conclusion. Score = the number of included propositions that overlap the 9 propositions in the reference conclusion provided by experts[a]: 0 = none, 1 = 1 overlap, 2 = 2 overlaps, ..., 9 = completely overlap.
	Consistency with the reasoning	Whether the conclusion is consistent with previous reasoning. Score = the number of included propositions/the number of validated hypotheses[a] 10.

[a]The 9 propositions in the reference conclusion are: (1) Rain washes the fertilizer into the pond; (2) The added fertilizer causes the growth of algae in the pond; (3) Algae is related to the dissolved oxygen in the pond; (4) More dead algae causes the growth of bacteria in the pond; (5) The bacteria consumes a log of oxygen dissolved in the water; (6) Increased temperature causes the decrease of dissolved oxygen in the pond; (7) Low wind speed causes the decrease of dissolved oxygen in the pond; (8) Clouds affects the dissolved oxygen in the pond by blocking sunlight; (9) Low concentration of dissolved oxygen causes more large fish dying in the pond.

TABLE C1 Categorization of student-constructed concept maps.

Student group	Map style			Number of propositions in the concept map		
	KCM	PCM	MCM	Knowledge-oriented propositions	Problem-oriented propositions	Mixed propositions
G1	√			5	2	0
G2	√			6	2	2
G3	√			6	1	0
G4	√			4	0	0
G5	√			7	0	0
G6	√			11	0	0
G7	√			7	0	0
G8	√			7	0	0
G9	√			5	1	0
G10	√			5	0	0
G11	√			14	0	1
G12		√		0	9	0
G13		√		2	5	1
G14		√		0	9	0
G15		√		0	6	0
G16		√		1	12	3
G17		√		2	5	1
G18		√		0	12	0
G19		√		0	9	0
G20		√		0	12	0
G21		√		0	10	0
G22		√		4	8	0
G23			√	7	7	1
G24			√	1	2	3
G25			√	3	3	3
G26			√	3	2	0
G27			√	1	3	1
Sum						
N of groups	*N* of KCMs	*N* of PCMs	*N* of MCMs	*N* of knowledge-oriented propositions	*N* of problem-oriented propositions	*N* of mixed propositions
27	11	11	5	101	120	16

TABLE D1 Task performance of each group of students.

Student group	Performance score			
	Hypothesising	Reasoning	Conclusion	Overall
G1	15	20	15	50
G2	6.5	4.5	9	20
G3	3	6	8	17
G4	5	11	9	25
G5	18	20	12	50
G6	8	4.5	11	23.5
G7	12	20	9	41
G8	12	16	11	39
G9	12	10	13	35
G10	7	11.5	9	27.5
G11	10	12	8	30
G12	15.5	18	17	50.5
G13	8.5	18	12	38.5
G14	13.5	25.5	14	53
G15	13.5	20	12	45.5
G16	11	21	16	48
G17	14	15	10	39
G18	16	14.5	10	40.5
G19	13	19	14	46
G20	15	20	11	46
G21	23	36	16	75
G22	10	19	16	45
G23	3.5	10	9	22.5
G24	10	14	13.667	32.667
G25	3.5	9	9	21.5
G26	10	17	9	36.625
G27	6.5	5	6	17.5