A THREE-STEP KNOWLEDGE GRAPH APPROACH USING LLMS IN COLLABORATIVE PROBLEM SOLVING-BASED STEM EDUCATION

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ABSTRACT

This paper proposes a three-step approach to develop knowledge graphs that integrate textbook-based target knowledge graph with student dialogue-based knowledge graphs. The study was conducted in seventh-grade STEM classes, following a collaborative problem solving process. First, the proposed approach generates a comprehensive target knowledge graph from learning material contents, establishing a reference framework that represents the target knowledge structure of the course. Second, customized knowledge graphs were generated by analyzing the scientific concepts and knowledge based on the discussion dialogues, showing students' activated knowledge structures. Finally, the dialogue-based knowledge graphs were integrated into textbook-based target knowledge, to identify the activated and non-activated knowledge nodes and connections, as well as the related activated knowledge nodes and connections from other previous lectures or experiences. This three-step approach visualizes students' knowledge activation, and the learning gaps remain. This paper presented three examples of integrated knowledge graphs based on the different group formations. The findings of three different groups were discussed, and some educational implications were provided.

KEYWORDS

Knowledge Graph, Collaborative Problem Solving, STEM Education, Large Language Model

1. INTRODUCTION

STEM education, which consists of the fields of science, technology, engineering, and mathematics, has received increasing attention worldwide. STEM education aims to use knowledge and skills in integrated fields to solve real-world problems by connecting scientific knowledge and skills, technology, engineering design, and mathematical thinking and analysis (Kelley & Knowles, 2016). Due to the integrative nature and complexity of the problems involved in STEM education, learners are expected to conduct cognitive processes collaboratively, which requires skills associated with collaborative problem solving (CPS; Andrews-Todd & Forsyth, 2020). In CPS activities, students actively use their existing knowledge and construct collective understandings through collaboration with peers. This process is dynamic, as knowledge is continuously activated, discussed, and reconstructed. Capturing and analyzing student knowledge structures can provide deeper insights into how students learn and adapt their understanding, which help educators to improve instructional practices accordingly.

Knowledge graphs (KGs), which visualize the relationships between concepts, provide an overview of a course's knowledge structure. However, traditional approaches that generate KGs in educational settings primarily rely on standardized contents, such as learning materials, which makes it difficult to support collaborative learning. In this regard, it is necessary to consider students' interactions in knowledge construction processes (Yamada et al., 2016). However, the quality of creating knowledge maps integrating social interactions largely depends on students' knowledge understanding and social skills. Therefore, students would benefit from a standard map alongside their actual understanding maps to visualize their learning gaps.

To address this limitation, this paper proposes a three-step KG approach that integrates STEM knowledge from learning materials and student discussion dialogues during CPS activities. The three-step approach first constructs a comprehensive KG based on the learning materials, which serves as a reference framework representing the target knowledge. Simultaneously, it generates customized KGs representing the concepts and knowledge acquired or applied during student CPS activities, which are viewed as an activated knowledge structure. By integrating dialogue-based KGs with textbook-based KG, the system identifies both activated and non-activated knowledge nodes, providing a visual representation of areas where students have actively engaged with the content and areas where learning gaps remain. This approach helps educators to gain a clearer understanding of how students apply and expand their knowledge during CPS activities and provides actionable insights for STEM instructional designs based on individual understanding.

2. THEORETICAL BACKGROUND

2.1 CPS-Based STEM Education

STEM education integrates multiple fields, including science inquiry, technology literacy, engineering design, and mathematical thinking. Science inquiry includes activities that engage students in scientific contexts and the application of scientific knowledge in real-world situations (Lou et al., 2011; Herro et al., 2017). Engineering design is used to connect all STEM fields, allowing students to apply scientific knowledge, technical skills, and analytical processes to solve problems (Lou et al., 2011; Newhouse, 2016). Technology is used to improve technological literacy, while mathematical thinking focuses on mathematical analysis and reasoning skills during learning activities (Lou et al., 2011). In summary, students are required to apply their scientific knowledge, engineering design principles, and mathematical reasoning to solve authentic problems, all while interacting with technology (Newhouse, 2016).

Three important factors in STEM education include the integration of the four STEM fields, instructional practices based on STEM approaches, and problem-solving in authentic contexts (Kelley & Knowles, 2016). CPS is particularly helpful in STEM education for solving complex and real-world problems. CPS contains two domains, the social domain which refers to collaboration, and the cognitive domain which refers to problem-solving (Hesse et al., 2015). CPS has several advantages compared to individual problem-solving, such as integrating others' contributions into one's own thinking by sharing knowledge, experiences, and ideas (Hesse et al., 2015; Care et al., 2016).

Many previous studies have demonstrated the benefits of the CPS learning approach for improving students' performance in STEM-related subjects, particularly when supported by instructor scaffolding and intervention (Lin et al., 2020; Kim & Tawfik, 2023). Integrating CPS within STEM education not only helps students enhance their problem-solving skills but also facilitates the development of integrated STEM knowledge across the four disciplines (Kelley & Knowles, 2016).

The complex and interdisciplinary nature of CPS in STEM education requires systems that effectively analyze students' knowledge acquisition. Traditional textbook-based knowledge, while comprehensive, is limited in capturing students' dynamic understanding of STEM concepts during CPS activities. The difficulty of the textbook contents has influence on students' selection of learning strategies and their learning behaviors (Chen et al., 2019). Textbooks provide static information that does not include the various pathways students use to solve problems, particularly in real-world contexts that demand integration across multiple STEM fields (Kelley & Knowles, 2016). To effectively support students' learning, it is important to consider the extensive information during CPS, where students actively construct understanding through interaction and dialogue with their peers.

2.2 Knowledge Graph in CPS-based STEM Education

KG has been widely applied in various fields, including STEM education, to enhance teaching and learning processes. KG refers to "a graph of data intended to accumulate and convey knowledge of the real world, whose nodes represent entities of interest and whose edges represent potentially different relations between these entities" (Hogan et al., 2021). In STEM education, authentic problem-solving requires a high demand for specialized domain knowledge. A critical factor in STEM problem-solving is clarifying how knowledge is structured and organized to improve effective and efficient retrieval of relevant knowledge and information. Therefore, KG shows great potential in supporting various learning activities such as problem-solving and personalized instructional design in STEM education, since it can provide a structured way to organize, analyze, and visualize complex information.

Several studies have utilized knowledge graphs in STEM education to improve the learning environment. For example, Kim & Tawfik (2021) visualized and examined how individuals develop their knowledge structures during CPS processes in STEM education. Their results indicated that different types of knowledge structures affect the success of problem-solving. Traditional KG generation approaches rely more on standardized content, such as learning materials, which fails to consider students' social interactions. To integrate social interactions into KGs, Yamada et al. (2018) developed a concept map system where students can use their own or others' statements to create knowledge maps. Based on this concept map system, Onoue et al. (2020) developed a social knowledge map tool into integrate individual knowledge maps to a collective one. Although their studies emphasized the social interactive elements among learners, these knowledge maps are generated by the students themselves and do not support the students' knowledge construction skills, such as providing them with a standard map for reference.

Regarding this issue, Zheng et al. (2022) proposed an automatic KG construction approach using deep neural networks to enhance computer-supported collaborative learning. They generated activated and non-activated KGs automatically using data from online discussion transcripts. The results indicated that the information containing activated and non-activated KGs improved students' collaborative knowledge building, group performance, social interaction, and shared regulation. However, although they identified both the target and students' actual knowledge structures, the activated and non-activated knowledge structures are separately visualized. This separation may lead to a lack of comprehensive understanding of the knowledge, as students fail to understand the connections between different information. Moreover, previous studies mainly relied on online chat data, while beneficial for automation, it is difficult to be used in face-to-face educational settings.

In CPS-based STEM education, student dialogue data provides valuable insights into their cognitive and social processes, revealing their real-time thinking and reasoning processes, and application of knowledge (Care et al., 2016). Therefore, to bridge the gap of using real, face-to-face dialogue data to construct KGs, this study proposed a novel approach to integrate textbook data and in-person dialogue data into one KG, which visualizes activated and non-activated target knowledge and activated prior knowledge related to the topic. This approach could provide a more comprehensive understanding of students' knowledge construction processes and support more effective and personalized learning interventions.

3. METHOD

3.1 Participants

The participants were 114 seventh-grade students at a junior high school in China. The experiment was conducted in a CPS-based STEM course, and the duration was four weeks.

Before the course, the students were required to take a pre-test to investigate their prior knowledge. During the course, students were provided with laptops and digital textbooks to learn the contents and solve problems through collaboration. Due to missing data, final data were collected from 106 participants.

3.2 Design of the CPS-Based STEM Lessons

The theme of the course was "Solutions around us," including four sub-themes: (a) The Formation of Solutions, (b) Various Types of Solutions, (c) Using Solutions Safely, and (d) Limnic Eruption. Specifically, theme (a) focused on introducing the definition and formation of solutions. Theme (b) covered the classification of solutions, as well as the applications and effects of acidic and alkaline solutions. The related knowledge was expected to be acquired through discussions on examples of using acid and alkali solutions in daily life. Theme (c) focused on the characteristics of solutions by discussing the effects of acid rain on human health. Finally, theme (d) introduced a novel topic based on a natural disaster caused by carbon dioxide. Students were expected to clarify the mechanism of this disaster by integrating their prior knowledge and newly acquired knowledge in this course. Each theme was addressed in a separate textbook weekly.

3.3 Data Collection and Analysis

First, a pre-test was conducted to assess students' prior knowledge. The pre-test (100 full marks) consisted of multiple-choice questions, fill-in-the-blank questions, and short-answer questions concerning conceptual knowledge about the composition and characteristics of solutions, the meaning and application of pH values, and the applications of solutions in daily life.

Students were divided into different performance groups based on their pre-test scores. The top 25% of the pre-test scores were classified into the high group (21 students), the bottom 25% were classified into the low group (low group, 28 students), and the others were in the middle group (57 students).

We conducted a preliminary content analysis of the integrated KGs from different groups, focusing on the features of knowledge nodes, relationships, and structural information. By comparing the knowledge graphs of each group, we identified the different patterns of knowledge node activation, the relationships between nodes, and the overall structural differences of the graphs.

3.4 Knowledge Graph Extraction

We propose a systematic approach utilizing Large Language Models (LLMs) to automate the extraction and integration of KGs from learning materials and student discussion dialogues. This approach provides educators with more intuitive insights into how effectively students engage in discussion centered around the taught knowledge. The method involves the following three key steps. The process of this three-step KG extraction approach is presented in Figure 1.

3.4.1 Extraction of Hierarchical Knowledge Graph from Learning Materials

The first step focuses on extracting a hierarchical KG from the provided learning materials (Li, et al., 2024). LLMs are employed to process textual content from lecture slides or relevant documents, identifying key knowledge entities and their interrelationships, with a predefined set of entity types (i.e., concept and instance in this study).

- **Entity Identification**: LLMs initially identify and categorize entities based on their types. Each identified entity is labeled by its entity type and a description that captures its attributes and role within the learning material.
- **Hierarchical Structure Formation**: Following entity identification, LLMs are instructed to analyze the relationships between these entities to determine their hierarchical structure. This involves establishing parent-child relationships, ensuring that the resulting structure forms a tree-like hierarchy that reflects the dependencies and organizations of the knowledge presented in the learning materials.

The output of this process is a hierarchical knowledge graph that represents the structured understanding of the learning material.

3.4.2 Extraction of Knowledge Graph from Student Discussion Dialogues

To capture the activated knowledge during student dialogues, LLMs were used to extract KGs from student group dialogue transcripts. The extraction process is similar to that used for the learning materials, but it is for the context of the discussions without strict limitation of tree-like structure.

- **Entity and Relationship Extraction**: Entities mentioned by students during discussions are identified and categorized. Relationships between these entities are established based on the dialogue sequences, highlighting how students interact with and relate to the concepts.

The resulting KGs from student discussion dialogue provide insight into how students used and understood the knowledge within the learning materials during their CPS activities.

3.4.3 Integration and Analysis of Combined Knowledge Graphs

The final step is the integration of the hierarchical KG extracted from the learning materials and the KGs extracted from student dialogues. This integration allows for an analysis of how the lecture content is reflected in student dialogues and to what extent students activate the relevant knowledge.

- **Overlay Analysis**: The overlap was determined between the hierarchical KG and the student discussion graphs to identify which knowledge nodes were activated during the discussions.

- **Identification of Additional Knowledge Entities**: Beyond identifying overlaps, the student dialogues were analyzed to detect any additional knowledge entities mentioned by students that were not part of the lecture. These entities could represent prior knowledge, personal examples, or concepts from other lectures.

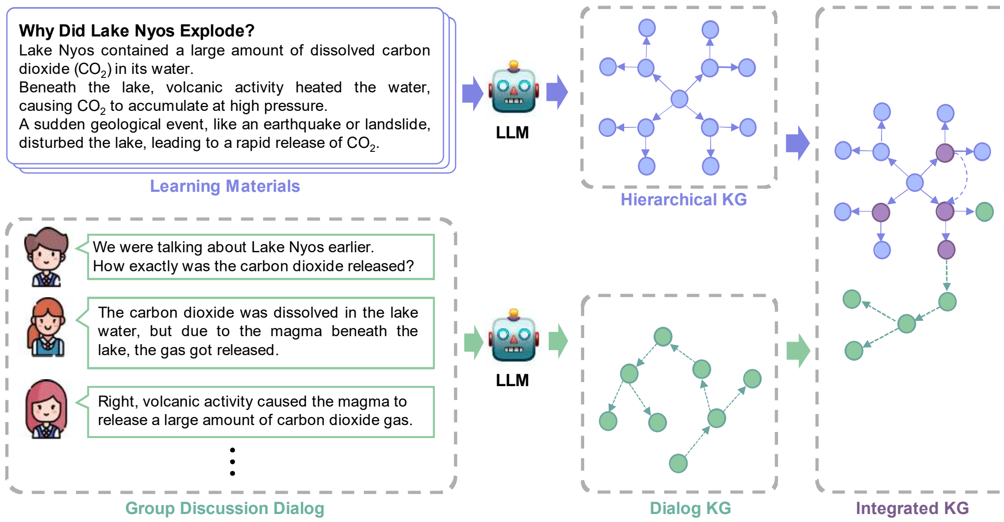

Figure 1. Three-step approach of knowledge graph extraction integrating learning materials and discussion dialogues

4. RESULTS AND DISCUSSION

4.1 Elements and Representations of Integrated Knowledge Graphs

We generated KGs that integrated both learning materials and student discussion dialogues using the three-step KG extraction approach. The examples of the KGs regarding theme (d) are shown in Figure 2.

The first and second layers, starting from the center, represent the standard (target) knowledge structure extracted from the learning materials.

- **Blue nodes**: The blue nodes in the first layer represent target but non-activated knowledge, which was not mentioned during the dialogues.
- **Purple nodes**: The purple nodes in the second layer represent target and activated knowledge, indicating the knowledge in both the learning materials and student dialogues.

The third layer consists of additional knowledge that emerged during the discussions but was not part of the provided learning materials. Since a critical factor in STEM education is the integration of different types of knowledge, including background knowledge and newly acquired knowledge, we further categorized this layer into two nodes:

- **Green nodes**: The green nodes in the third layer represent students' previous knowledge, which has appeared in previous lectures.
- **Yellow nodes**: The yellow nodes in the third layer represent students' background knowledge that is not covered in any provided learning materials, including the information from the Internet or the instances related to the specific knowledge.

In addition, the solid blue lines represent the relationships between the standard (target) knowledge (extracted from the learning materials), the blue dashed lines represent the activated knowledge relationships by the students (from both the learning materials and dialogues), and the green dashed lines indicate the relationships between the knowledge constructed by students (from the dialogues).

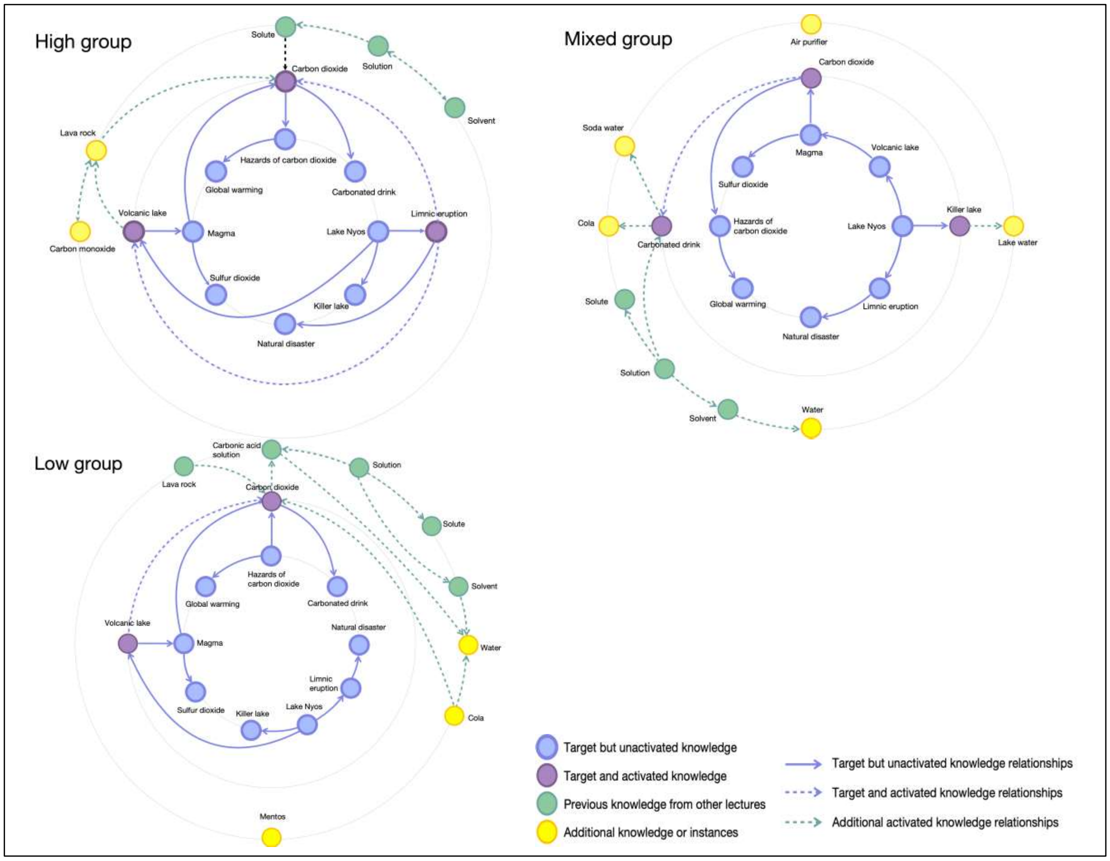

Figure 2. Knowledge graphs of three performance groups

4.2 Comparison of Knowledge Understanding of Three Performance Groups

First, regarding the target and activated knowledge, compared to the Low group, the High and Mixed groups showed more activated knowledge nodes (purple nodes). The High group had a high level of engagement with key concepts from the learning materials. Moreover, the High group showed a more comprehensive understanding of the target knowledge, effectively recalling important information during discussions. In contrast, the Low group showed fewer activated knowledge nodes, indicating an insufficient understanding of the target knowledge and challenges in connecting with provided content. In further work, instructional designs should be considered to support students with lower performance levels to engage deeply with the learning materials and construct connections between different knowledge.

As for previous and additional knowledge, the High group also showed several green nodes, representing previous knowledge from earlier lectures. For example, concepts such as "solvent," "solution," and "solute" from Theme (a)~(c) were effectively integrated into discussions about Theme (d). It indicates the ability of High group students to apply prior knowledge to new contexts, which is an important factor in STEM education (Kelley & Knowles, 2016) and CPS activities (Hesse et al., 2015). However, this group showed less background knowledge (yellow nodes) compared to other groups. This indicated that they seldom retrieve individual experience and knowledge or use real-life examples when dealing with problems.

The Mixed group showed a balance between previous and background knowledge. For example, they had more yellow nodes than other groups, such as using "Soda water" and "Cola" to understand "carbonated drink." This suggested they relied more on their real-life experience to understand scientific concepts in the learning material. The strategy of using familiar and practical examples helps link new information with individual experience and background knowledge and has the potential improve the understanding of abstract concepts (Hesse et al., 2015; Chen et al., 2024a).

The Low group showed more green nodes, indicating a tendency to rely on learning materials from earlier lectures and make connections between similar concepts. For example, they mentioned the previous concept of "Carbonic acid solution," which is similar to "Carbonated drink," and "Lava rock", which is closely related to "Magma," in their discussion. Although these similar concepts appeared in the discussion, the Low group students failed to connect them coherently. It may lead to the construction of fragmented knowledge. The results suggested that while they can retrieve information from different lectures, they have difficulty integrating it for effective problem-solving.

The different patterns of knowledge construction across the High, Mixed, and Low groups indicated different levels of knowledge activation and integration. Student with different levels of prior knowledge showed different patterns of using learning strategies. For example, students with sufficient prior knowledge used cognitive strategies more effectively during individual thinking, while students who lack prior knowledge focused more on social strategies and engaged in cognitive strategies through group contribution (Chen et al., 2024b). The study conducted by Kim and Tawfik (2021) indicated that different types of knowledge structures had a significant effect on the success of problem-solving in STEM learning. Therefore, the findings from integrated KGs reveal the need to use targeted instructional strategies. For the High group, to improve engagement and deeper learning, it is suggested to introduce more challenging tasks that go beyond the current content. These challenging tasks aim to encourage high-level students to explore more complex, interdisciplinary problems, finally enhancing their ability to connect and apply multiple knowledge sources. On the contrary, the Low group may benefit more from scaffolded support that recalls foundational concepts and makes meaningful connections to the learning materials. Activities that focus on improving basic understanding could help bridge knowledge gaps and improve comprehension.

Overall, the findings indicate that the integrated KGs of textbook-based and dialogue-based approach complement the one-size-fits-all approach in CPS-based STEM education. By understanding the distinct ways in which different groups construct and activate knowledge, educators can develop more effective teaching strategies to activate the non-activated target knowledge.

5. CONCLUSION

This study introduces a three-step KG approach that integrates textbook-based knowledge with knowledge acquired through student dialogues during CPS activities in STEM education. The study was conducted in seventh-grade STEM classes. The integrated KGs were generated from the learning materials and 106 students' dialogue data. The findings demonstrated that different groups of students, which were categorized by their prior knowledge levels, showed different patterns of knowledge activation, integration, and structures. The High group showed active engagement with key concepts and effectively integrated prior knowledge from previous lectures into new contexts, while their use of real-life examples was limited. The Mixed group showed a more balanced knowledge structure, using both prior knowledge and real-life experiences to understand new concepts. The Low group tended to retrieve similar concepts from earlier lectures but struggled to connect these similar concepts. This study highlights the potential of generating KGs by considering both learning materials and students' discussion dialogue. The integrated KGs provide deeper insights into students' learning processes that were not possible with traditional methods alone, such as understanding how students negotiate meaning, identify and bridge knowledge gaps, which are important CPS processes.

Our approach provides some implications for STEM education. For example, it allows teachers to understand students' knowledge activation, making it easier to provide personalized instructions. For high-performers, more complex interdisciplinary problems can be designed to deepen their understanding, while for lower-performers, customized support can be provided to bridge learning gaps. In addition, the use of KG provides a structured way to visualize how students connect concepts from different STEM disciplines. By analyzing the details of knowledge nodes, it can help students see the relationships between scientific, mathematical, and engineering principles, leading to a more comprehensive understanding of STEM subjects.

This study has several limitations. First, the current approach provides a static visualization of knowledge activation and integration without accounting for the evolution of students' real-time knowledge structures or across multiple CPS activities. In future work, it is expected to combine various data sources, such as online chat data, and behavioral data (e.g., learning logs or eye-tracking), to develop a dynamic or real-time knowledge structure visualization tool. Second, the effectiveness of the KGs depends on the quality and depth of student dialogues. In cases of shallow discussions, the extracted KGs might not accurately represent students' understanding. In the future work, it is necessary to conduct further assessments to examine the effectiveness of the approach and provide personalized learning paths and interventions based on the findings.

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