A Framework for Constructing Concept Maps from E-Books Using Large Language Models: Challenges and Future Directions

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Abstract
Concept maps have been widely used in education to organize and represent information hierarchically. However, traditional methods for constructing concept maps often depend on human experts, which can be costly and time-consuming. The emergence of large language models (LLMs), such as GPT-4, has transformed concept construction and reasoning tasks by offering automated and scalable solutions. This paper introduces a novel framework for generating concept maps of e-books with three key components: section segmentation, key concept extraction, and relationship identification. Additionally, the paper highlights challenges and future opportunities to enhance LLM-driven concept map generation for educational applications.

Keywords
E-book, LLM, ChatGPT, Concept Map.

1. Introduction

In the digital age, e-books have become widely used for education. Their portability, accessibility, and search functionality have made them popular resources across diverse domains [2,3,4]. However, their inherently linear structure often falls short of meeting the needs of learners who benefit from a more interconnected and structured view of complex content [2,3,5].

Concept maps are useful tools to address these challenges. They are visual representations that organize and represent knowledge by highlighting relationships between key concepts. These maps have been widely recognized for their ability to enhance comprehension, retention, and critical thinking skills by providing learners with a structured and interconnected view of content [6]. For instance, they enable learners to identify overarching themes and gain insights into the hierarchical structure of information. Such cognitive aids are particularly valuable in domains requiring a systems-level understanding. Additionally, concept maps are utilized as navigational tools in e-books, allowing learners to interact with the material more effectively. In these methods, concept maps are displayed as an interactive interface, where learners can click on individual nodes to directly access the corresponding pages or sections related to each concept [1].

Traditionally, the construction of concept maps has relied on manual processes, which are time-consuming and resource-intensive. This has limited the scalability of concept maps, especially in large-scale educational contexts. While researchers have made strides in automatically extracting concepts from teaching materials using NLP methods [7,8], these methods still rely on human labeling and lack interactivity generation capabilities.

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The advent of large language models (LLMs) has introduced a transformative potential for automating concept map generation. Leveraging their advanced contextual understanding, LLMs can produce meaningful content with minimal human oversight, and existing studies have demonstrated that LLMs are capable of a wide range of tasks beyond text summarization, translation, and refinement. Such versatility highlights their potential for automatically generating concept maps.

2. Related Work

Concept maps have long been employed in the education area as a means to organize information and improve students' comprehension hierarchically. Constructing a concept map typically involves multiple tasks, such as concept extraction and relation identification [9]. Researchers have recently made strides in automatically completing these tasks from textual data using NLP methods.

Traditional concept extraction methods rely on Term Frequency-Inverse Document Frequency (TF-IDF), Latent Dirichlet allocation (LDA) topic model, co-occurrence statistics, and neighboring document analysis. For example, TextRank [17] is a well-known method that uses a co-occurrence graph to rank key concepts. ExpandRank [18] leverages neighborhood documents to improve key concept extraction. In addition, many approaches incorporate external knowledge sources to enrich concept extraction, such as Wikipedia and Knowledge Base [14, 15].

While concept extraction focuses on identifying standalone terms or phrases, constructing concept maps involves defining relationships between concepts. Early work in this area used textbook structures to organize extracted concepts and construct prerequisite relationships using features from Wikipedia [15]. [19] derived prerequisite relations from ontologies, translating interactions among instances into relationships. Similarly, Liang et al. proposed an optimization-based framework to uncover concept prerequisites from course dependencies [21]. Gordon et al. introduced a cross-entropy approach and an information-flow approach for discovering concept dependency relations automatically from a text corpus [20]. Pan et al. proposed a representation learning-based method to learn the concepts and focused on generating prerequisite relations among concepts on a Massive Open Online Courses (MOOCs) corpus [7, 8].

The release of large language models like GPT-4, recognized for their remarkable general capabilities, has been considered by researchers as the spark of artificial general intelligence and has introduced transformative possibilities for concept map construction. LLMs excel in understanding and processing language, making them ideal for generating concept maps [10]. LLMs have been evaluated for their adaptability in creating knowledge representations for education [13, 16, 23]. For instance, de Paiva et al. used ChatGPT to extract Category Theory concepts from academic papers, showcasing its ability to identify mathematical entities [22]. Recently, Li et al. [11] and Chen et al. [12] utilized LLMs to analyze learning material texts to identify knowledge concepts and their interrelationships. However, their work uses knowledge concepts to predict student performance or assist collaborative problem-solving. And none of them evaluate the effectiveness of LLM-generated concepts and relationships.

3. Framework

As shown in Figure 1, we propose a framework for LLM-based e-book concept map construction. Specifically, the process involves e-book section segmentation, key concept extraction from each section, and relationship identification between concepts for each section. Finally, it merges and refines the results of each section to create a comprehensive concept map for the e-book. The prompts we used can be seen in Figure 2.

The first step in constructing concept maps involves segmenting the e-book content into distinct sections using LLM. The objective is to break down the material into units that facilitate concept

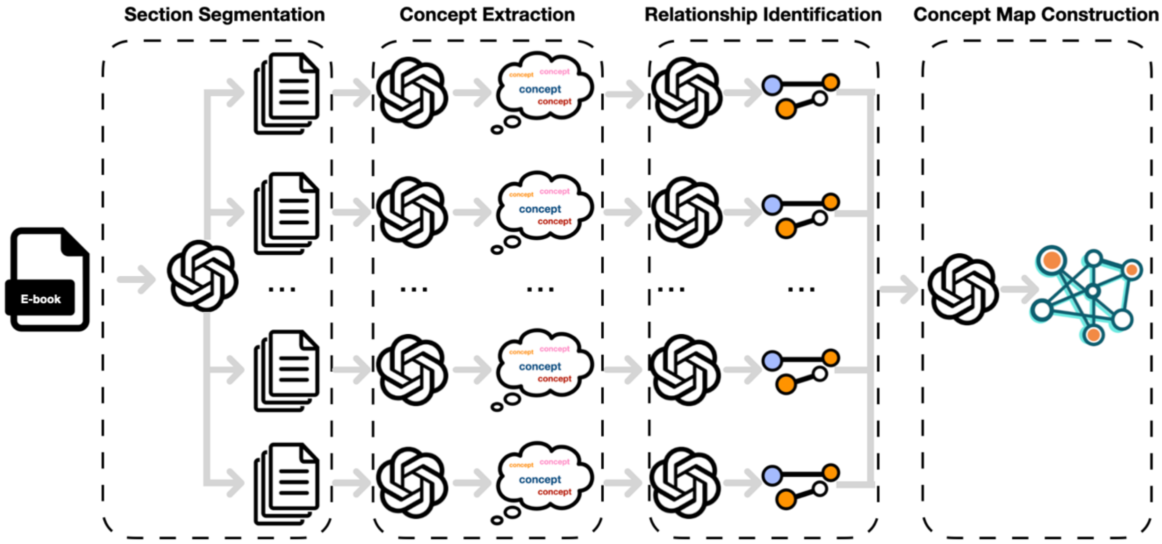

Figure 1: The Framework for LLM-based E-book concept map construction.

extraction. This structured segmentation ensures that each section contains logically connected content, setting the stage for accurate concept extraction and relationship identification. E-book lectures typically have inherent structure, such as chapters and headings, which is helpful for segmentation tasks. After the section segmentation, the LLM is prompted to identify the main concepts within each specified segment. The process involves carefully designed prompts that direct the LLM to identify key concepts within the section and obtain a set of knowledge concept entities K = {k1, k2, ..., kn}. After identifying the main concepts, the LLM proceeds to map relationships between them. These relationships are fundamental in constructing a concept map, as they provide the connective structure that illustrates how concepts interrelate. The LLM's ability to contextualize relationships is enhanced through example-based prompting and iterative refinement. This step is crucial for ensuring that the generated concept map accurately represents the material's underlying structure. With the concepts and relationships identified for each section, the next step is to construct the concept maps. These maps are visualized as directed graphs, where nodes represent concepts and edges represent relationships. Once all section-level concept maps are generated, they are aggregated into a unified concept map representing the entire e-book content. During this aggregation, cross-section relationships are identified to ensure coherence and connectivity across the material.

4. Evaluation

4.1. Dataset

We evaluated LLMs based on our framework to have an initial understanding of their capabilities by evaluating their performance on concept map construction. We collected lecture files from an Introductory Python Programming course at our university. A total of 12 lecture files were used in this study. The content covers the basics of Python programming, including functions, variables, strings, lists, branches, loops, and so on.

4.2. Preliminary Results

We tested GPT4o because of its affordability and widespread adoption. We compare the results generated by GPT and those generated by the instructor.

Please construct a concept map based on the content of the e-book.
 # Input
E-book PDF File {File}
You may use four steps to do it, and please show the results of each step.

(1) E-book section segmentation: break down the material into units that facilitate concept extraction.

(2) Key concept extraction from each section: identify the main concepts within the specified unit.

(3) Relationship identification: map relationships between concepts.

(4) Merge and refine: merge and refine the results of each section to create a comprehensive concept map for the e-book.

Figure 2: Example Prompts for concept map construction.

Table 1
Performance of concept extraction.

	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12	Mean
Precision	0.75	0.93	0.92	0.78	0.75	0.86	0.5	0.9	0.86	0.38	0.71	1	0.8
Recall	0.79	0.88	0.85	0.54	1	1	1	0.9	1	1	1	0.83	0.86
F1	0.77	0.90	0.88	0.64	0.86	0.92	0.67	0.9	0.92	0.55	0.83	0.91	0.83

4.2.1. Section Segment

The evaluation results show that GPT-4o exhibited exceptional accuracy in section segmentation. Across 12 lectures, it divided the content into 57 sections, averaging 4.75 sections per lecture. Notably, the segmentation of 10 out of 12 lectures was perfectly aligned with the instructor's structure. This high level of accuracy can be attributed to the inherent structure of e-books, such as outlines and chapter headings provided on the page, which provided clear guidance for GPT-4o's section segmentation. Minor discrepancies occurred in two lectures: in one case, GPT added an extra section, and in another, it omitted a section. These deviations were related to the course's pedagogical design.

4.2.2. Concept Extraction

Table 1 summarizes the results of concept extraction across 12 e-books. GPT generated a total of 138 concepts compared to the 111 concepts in the Ground Truth identified by the instructor. Overall, GPT demonstrates strong performance, achieving an impressive average F1 score of 0.83. With a Precision of 0.8, the model exhibits notable accuracy in generating relevant concepts, while its Recall of 0.86 highlights its ability to capture most of the original concepts effectively.

Notably, in 6 out of the 12 e-books (50%), GPT fully covered all the concepts in the Ground Truth, showcasing its great capability to align with human-labeled content. Moreover, GPT generated extra concepts in 11 of the 12 e-books, totaling 27 additional concepts, with an average of 2.45 extra concepts per e-book. However, upon careful examination, these additional concepts were often highly relevant to the topic and enriched or expanded the scope of the extracted concepts.

Conversely, missing concepts were identified in 5 of the 12 e-books, amounting to a total of 18 omissions. However, these omissions are not always totally wrong. In many cases, the missing concepts were either integrated into other concepts or expressed differently due to adjustments in the concept hierarchy.

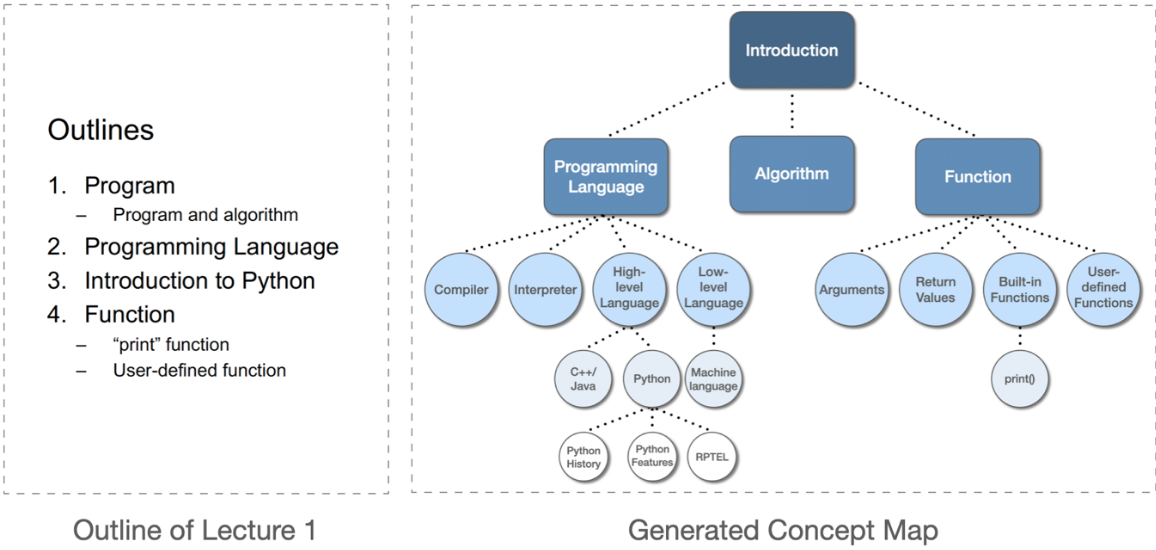

Figure 3: An example of an LLM-generated e-book concept map.

4.2.3. Relationship Identification

GPT generated a diverse range of relationships, which we carefully reviewed. Since no constraints were placed on the generation process, the resulting relationships sometimes lacked clear logical structure or coherence. It generated a total of relationships, including 154 hierarchical relationships and 70 other relationships. For hierarchical relationships, GPT performed well in most cases, accurately identifying connections that aligned with the internal structure of the chapters or content. However, GPT also produced several relationships that, while seemingly plausible at first glance, offered little meaningful insight. These extraneous relationships, though not entirely incorrect, did not contribute significantly to enhancing the conceptual understanding and may have added unnecessary complexity to the overall map. To refine this process, future improvements could involve introducing constraints or guiding rules to ensure the relationships generated are more focused, meaningful, and aligned with the specific needs of the concept map. This would help balance creative exploration with logical coherence, maximizing the utility of the extracted relationships.

4.2.4. Concept Map Construction

The final step involved having GPT use its generated concepts and relationships to construct a concept map. We observed that the resulting map primarily employs hierarchical relationships, with most of the content being accurate and well-organized. Figure 3 showcases an example of a generated concept map. Interestingly, we noticed that the structure of the concept map generated by GPT differed from the original e-book structure designed by the instructor. For example, in Lecture 1, the e-book's structure was organized as follows: (1) Program, (2) Programming Language, (3) Introduction to Python, and (4) Function. In contrast, GPT's concept map adhered more closely to the logical and content-based relationships within the knowledge rather than strictly following the e-book’s predefined order. This divergence suggests that GPT is capable of reinterpreting content to create maps that emphasize conceptual connections and hierarchy. While the instructor’s structure is pedagogically motivated, the GPT-generated map offers an alternative perspective that focuses on content flow and interrelationships, potentially enhancing understanding by presenting concepts in a way that mirrors their logical and thematic linkages.

5. Discussion

The evaluation of large language models in concept map construction underscores their significant potential for advancing educational content creation and content analysis. Across the four stages of the framework, LLMs demonstrated notable accuracy, producing well-structured and coherent concept maps that closely aligned with the source e-book. Their ability to integrate these distinct tasks highlights their versatility and efficiency. While many NLP-based approaches can perform tasks such as concept extraction or relationship identification, they are often task-specific, requiring separate models for each step of the concept map construction process. This fragmented approach limits their scalability and efficiency. Furthermore, traditional methods frequently lack context awareness, which can lead to semantic drift—a phenomenon where knowledge concepts with similar semantics but from unrelated domains are incorrectly generated or linked [14]. LLMs, however, effectively address this challenge by leveraging their advanced contextual understanding to maintain semantic consistency and ensure the relevance of extracted concepts within a given domain. The unique strengths of LLMs to optimize resource utilization make them outperform smaller, task-specific models in adaptability for diverse application domains and data-limited settings. By unifying multiple tasks under one framework, LLMs reduce the complexity of the process and improve overall coherence, positioning themselves as indispensable tools for concept map generation and reasoning.

Despite these advantages, several challenges and areas for improvement remain. In the following section, we delve deeper into these challenges and propose actionable insights to guide future developments in leveraging LLMs for concept map construction.

5.1. Challenges

5.1.1. Misalignment with Educational Goals

Based on our observation, one significant challenge is the misalignment between LLM-generated results and pedagogical intentions. Although the concepts generated by GPT are often drawn directly from e-book content, some of these concepts may not align with the educational priorities or the core objectives of the lesson. For instance, GPT might include concepts that are mentioned in passing within the material but are not critical to the intended teaching focus. This divergence can dilute the map's effectiveness as a teaching tool, highlighting the need for mechanisms to guide LLMs toward emphasizing key educational priorities while minimizing peripheral or non-essential concepts.

5.1.2. Balancing Human Oversight and Automation

Another key issue is the balance between human oversight and full automation. While GPT is powerful, it is not yet capable of consistently producing flawless results. Therefore, generating accurate concepts and relationships often requires iterative refinement, which calls for human interaction at various stages. A human-in-the-loop approach is essential, not only to correct errors but also to ensure that the generated content aligns with teaching objectives. Although such an approach can increase time and labor costs if every step of the process requires human intervention, on the flip side, GPT can serve as a valuable assistant, enabling teachers to refine and enhance the educational design. Striking the right balance between GPT autonomy and human involvement remains a critical area for improvement.

5.1.3. The Hallucination Problem in LLMs

Hallucination, the tendency of LLMs to generate inaccurate or nonsensical information, poses another challenge. While LLMs perform with high accuracy in concept generation and rarely produce irrelevant or false concepts, the issue becomes more pronounced when identifying relationships.

Hierarchical relationships, such as part-of relationships, are often reliable due to their grounding in the structure of the content. However, when tasked with generating other types of relationships without explicit constraints, LLMs may produce plausible but unhelpful or unreliable connections. This highlights the need for strict-designed prompts when generating complex relationships. Existing research suggests that GPT performs better when constrained to choose from predefined options rather than generating relationships freely [10]. Despite these limitations, ChatGPT's ability to generate hierarchical relationships is reliable. For purposes such as creating navigation-oriented concept maps or tools to aid reading comprehension, it already shows strong potential and could become a powerful asset in educational content creation with further refinement.

5.2. Future Directions

Looking ahead, the application of LLMs for generating e-book concept maps presents exciting opportunities. Below, we outline three key directions to enhance the development and integration of LLM-generated concept maps for e-books.

5.2.1. Fine-Tuning and Domain Adaptation

Integrating educational design principles into the LLM generation process is important. This alignment will ensure that generated concept maps better reflect instructional goals and pedagogical priorities. Fine-tuning LLMs with domain-specific datasets offers a promising avenue, enabling models to extract nuanced concepts and accurately map relationships. Incorporating specialized corpora, such as annotated academic texts or field-specific materials, can assist in generating concepts that are not only relevant to the content but also central to the instructional goals. Moreover, domain-specific fine-tuning tailored to particular subjects can enhance the precision and relevance of generated concept maps [16].

5.2.2. Concept Expansion and Categorization

Beyond the concepts explicitly written in e-books, supplementary concepts can provide valuable context and open avenues for deeper exploration [14]. For example, in Figure 3, when introducing **Built-in Functions**, while the core concept is **print()** function, it is valuable to introduce other built-in functions, such as **input()**. These supplementary concepts connect the core concept to broader contexts, encouraging curiosity and fostering a more comprehensive understanding. LLMs' ability to expand on core concepts offers a transformative approach to enhancing student understanding and engagement. By leveraging its vast knowledge base and contextual reasoning, GPT bridges the gap between narrowly focused course content and the broader spectrum of relevant knowledge, enabling students to explore beyond the standard curriculum.

To further enhance the utility of concept expansion, LLMs can categorize concepts into distinct groups, ensuring clarity and prioritization. Core concepts represent the foundational knowledge that aligns directly with course objectives, while supplementary concepts provide additional insights or alternative perspectives to deepen understanding. Advanced concepts cater to more inquisitive students, offering pathways for further exploration beyond the standard syllabus. By organizing concepts into these categories, LLMs can empower students to focus on what is essential while also providing opportunities for enrichment. For educators, this structured approach offers flexibility to tailor content based on student needs, ensuring that both the core curriculum and optional extensions are effectively addressed. Such categorization not only supports personalized learning but also ensures that the expanded knowledge remains manageable and relevant.

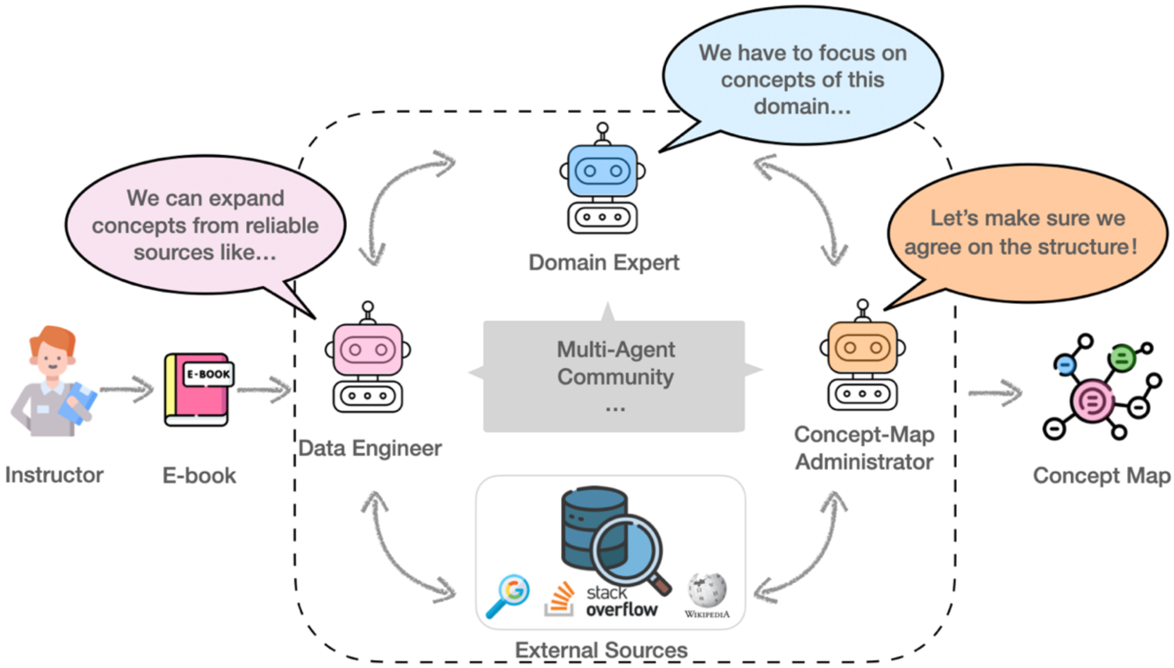

Figure 4: Collaborative Concept Map Construction Using Communicative LLM Agents.

5.2.3. Communicative Intelligent Agents for Concept Map Construction

The efficacy of LLMs heavily leans on human engagement in dialogue generation. Further refining model responses necessitates intricate user task descriptions and enriched interaction contexts, a process that remains demanding and time-intensive in the development lifecycle. Consequently, research efforts concerning intelligent agents can independently generate prompts and carry out tasks. Inspired by Zhu et al. [10], we introduced a framework for concept map construction using communicative intelligent agents, each assigned specific roles. As shown in Figure 4, we can assign specific roles for agents, such as a **Concept map administrator**, a **Domain expert**, and a **Data Engineer**, to collaborate to complete tasks iteratively.

The administrator acts as a coordinator, clarifying ambiguities and aligning the agents' work with instructional goals. The domain expert agent generates concepts and structures, ensuring coverage of core material and verifying the accuracy and relevance of expanded concepts. Also, the data engineer agent acts as a web searcher. It retrieves additional information for supplementary concepts from external sources, such as Wikipedia and Stack Overflow, to help expand concepts with real-world examples or related threads. The iterative process allows agents to consult, update, and refine their outputs based on feedback, ensuring higher accuracy and alignment with user needs.

5.2.4. Integrating with E-book Systems

Integrating concept maps into e-book systems has the potential to revolutionize digital learning. By providing learners with interactive navigation aids, it can transform static e-books into adaptive learning environments [5]. Users could click on concepts to access definitions, explore related topics, or view hierarchical structures dynamically. This interactivity would help students navigate complex material more effectively, fostering deeper understanding [2]. Additionally, incorporating user feedback loops into the system could significantly improve the quality of LLM-generated concept maps [14]. Educators and students could add missing concepts, refine incorrect relationships, or suggest alternative interpretations, creating a collaborative and iterative refinement process [6, 14]. Furthermore, tracking student interactions with the e-book system could help identify relationships between concepts that might otherwise go unnoticed, offering valuable insights for improving both the maps and the learning experience. For instance, recently, Lu et al. [24] integrated LLM-generated concept maps and student-concept-page interaction data to generate a reading path dashboard. By seamlessly integrating LLMs and e-book systems, the instructional content and student interaction data could create a more comprehensive visualization of the concept map for e-books.

6. Conclusion

In this paper, we explored the capabilities of large language models in constructing e-book concept maps and introduced a framework encompassing section segmentation, key concept extraction, and relationship identification. We evaluated the framework's performance using a real-world dataset, demonstrating the significant potential of LLMs in this task. Furthermore, we discussed the challenges and opportunities associated with leveraging LLMs for e-book concept map construction and corresponding applications. For future work, we plan to evaluate the framework on larger and more diverse datasets. Additionally, extending this study to include other LLMs could provide valuable insights into their comparative performance and generalizability.

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Declaration on Generative AI

During the preparation of this work, the author(s) used GPT-4o in order to: Grammar and spelling check. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take full responsibility for the publication's content.

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