Majumdar, R. et al. (Eds.) (2025). Proceedings of the 1st International Conference on Learning Evidence and Analytics. Asia-Pacific Society for Computers in Education

A Framework for Using LLMs and RAG to Realize the Automatic Generation of Learning Materials from Lecture Slides

Kota HASHIYADA[a*], Wei SHI[b] & Chengjiu YIN[b]
[a] *Graduate School and Faculty of Information Science and Electrical Engineering, Kyushu University, Japan*
[b]*Research Institute for Information Technology, Kyushu University, Japan*
*hashiyada.kota.923@s.kyushu-u.ac.jp

Abstract: In real-world education, the use of PowerPoint slides or similar types of files is becoming more popular. Such slides are easy to distribute to students. Some online courses also provide slides to their students. These files typically contain the key points of each lecture. However, such slides may not be sufficient for students. Students often need to find their desired knowledge from reference materials, consume much of their time. With the development of Large Language Models (LLMs), a form of generative AI specialized in text generation, the automatic creation of such educational materials has become possible. In this paper, we present a framework for generating personalized and detailed learning materials using LLMs and Retrieval-Augmented Generation (RAG), addressing the limitations of traditional lecture slides that lack depth. Furthermore, we apply the VARK model to detect students' learning styles. The learning materials will be generated to accommodate students' diverse learning styles. The system operates in five steps: (1)extracting a section structure from slides using LLMs like Copilot, (2) teacher review and refinement of the structure, (3) storing reference materials in a vector database using Dify, (4) generating detailed materials with RAG based on the structure and knowledge base, and (5) evaluating the output through teacher checks and learner feedback. The generated content can be further customized into VARK-specific formats, such as diagrams for visual learners or audio for auditory learners. The proposed method demonstrates that combining LLMs with RAG can enhance the quality and adaptability of educational content.

Keywords: Generative AI, Large Language Model (LLM), Retrieval-Augmented Generation (RAG), Personalized Learning, VARK Style,

1. Introduction

In modern school education, all students are usually given the same lecture materials, regardless of their understanding, learning pace, or personal learning style. Many lecture materials are presented as slides with keywords and brief explanations. However, this format limits learning resources for students who need a deeper understanding and detailed information. This uniform approach does not meet the needs of all students. To address this issue, this study aims to develop a system that automatically generates learning materials from lecture slides based on each student's level of understanding and learning style. This study specifically considers the VARK learning model to define students' learning styles, which classifies learners based on their preference for Visual, Auditory, Reading/Writing, or Kinesthetic learning.

This study aims to establish a method for automatically generating detailed learning materials using Large Language Models(LLMs). We first use generative AI to extract the structure and key knowledge points from the lecture slides and then give more details to generate learning materials. However, LLMs sometimes create incorrect information, a problem known as "hallucination." To reduce this issue, this study proposes using Retrieval-Augmented Generation (RAG). RAG is a method that improves accuracy by retrieving and incorporating external information. Furthermore, the learning materials generated by our system will be customized according to each student's learning styles, which are defined by using the VARK framework(https://vark-learn.com/introduction-to-vark/the-vark-modalities/). We believe that such customized materials can enhance students' learning performance. The following sections of this paper are organized as follows: Section 2 presents the related work, Section 3 explains our framework, Section 4 describes an experiment to discuss how the composition of the knowledge database influences the generation result, and Section 5 concludes our research. Although this study aims to personalize educational content, no student learning data was used; all materials utilized in the system were instructional resources obtained with permission from the teacher.

2. Related Work

2.1 Generative AI and Education

The integration of Artificial Intelligence-Generated Content (AIGC) into education has prompted a growing body of empirical research on its effectiveness. In particular, many studies have focused on the relationship between AIGC and factors such as learning motivation and self-efficacy, often reporting positive outcomes. A study by Yin (Guo, J, et al., 2024) found that learners who used AI chatbots showed higher motivation compared to those who learned through traditional methods. Lee (Guo, J, et al., 2024) reported that review activities supported by AI chatbots enhanced students' sense of self-efficacy. Similarly, Kim found that students using chatbots in English language learning demonstrated greater motivation to learn. AIGC has also been shown to support active learning and improve learning outcomes across various subjects. According to Yilmaz (Guo, J, et al., 2024), the use of ChatGPT in programming education helped enhance students' computational thinking skills and motivation, while also promoting critical thinking and creativity. Moreover, findings from qualitative studies highlight that AIGC can offer engaging and effective learning experiences. For instance, in an interview-based study by Acosta-Enriquez (Guo, J, et al., 2024), students positively evaluated ChatGPT-generated content as a helpful learning aid and reported increased engagement and confidence in solving problems. These results suggest that AIGC has strong potential as an effective educational support tool that can enhance both learner motivation and academic performance.

2.2 Retrieval and Knowledge Composition in Retrieval-Augmented Generation

RAG introduces an information retrieval process that enhances the generation process by searching for relevant objects from an available vector database. This approach achieves higher accuracy and robustness. Retrieval involves identifying and obtaining relevant information based on information needs. Specifically, information resources are viewed as a store of key-value pairs, where each key corresponds to a value (the key and value can be the same). When a query is given, the top k most similar keys are searched using a similarity function, and the corresponding values are retrieved. Fusion-in-Decoder (FiD) (G. Izacard, et al., 2021) and Retrieval-Augmented Language Model (REALM) (K. Guu, et al., 2020) identify the top k most relevant chunks of articles based on the query. Each chunk is then sent along with the question to a LLM to generate k responses. These responses are combined into the final answer. SKR (Y. Wang, et al., 2023) observed that using RAG does not always benefit question answering. SKR explored ways for the model to evaluate relevant knowledge and then adapt the use of external resources. In this study, we also examine how changes to the structure of reference materials stored in knowledge affect the generated content. We discuss which knowledge structures provide better answers.

3. Learning Materials Generation Framework

The goal of this study is to establish a method for generating detailed learning materials from slide presentations and reference documents using LLMs and RAG. This section introduces the proposed method, outlines the framework, and describes its implementation. Figure 1 shows the overview of our framework, and our system is created using Dify, which is an engine for generative AI applications. (https://dify.ai/) Figure 2 shows the workflow of using Dify to create our system.

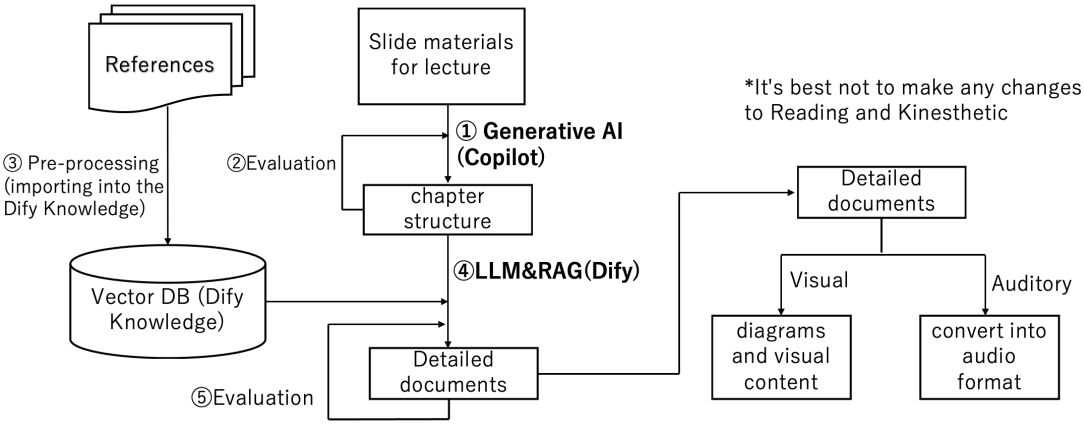

Figure 1. Framework Overview

Figure 2. Workflow of defining our system

The following steps explain how to use our system to generate learning materials.

①. Extracting Section Structure Using Generative AI
Using generative AI such as Copilot, the lecture content is converted into a logical section structure. In this study, lecture slides in PowerPoint format were uploaded to Copilot, and prompts were entered manually to extract section structures.

②. Teacher Review
The extracted section structure is reviewed by teachers, allowing them to identify any misalignment between the generated structure and the instructor's intentions. Based on the feedback, prompts or parameters can be adjusted, and the content can be regenerated if necessary.

③. Preprocessing (Storing into Vector Database)
The curated reference materials are stored in a local vector database. In this study, the knowledge function of Dify was used to store lecture slides and reference documents.

④. Material Generation Using LLM and RAG
The section structure and the content in the vector database are then combined using LLM and RAG. In this study, the Dify platform's workflow function was used to implement this process. The flow consists of the following stages:

- START: The user must input required variables such as `chapter_title`, `section1`, and `file`, and optionally `section2` through `section5`. These are derived from the Copilot output. The `file` corresponds to the uploaded PowerPoint slides.
- KNOWLEDGE RETRIEVAL: In this step, the system searches the knowledge base for related content based on the input variables and questions. The database structure and search settings can be adjusted flexibly to include various reference documents.

⑤. Evaluation

After generating the detailed materials, two types of evaluations are conducted. First, teachers such as course instructors or professionals with relevant knowledge review the materials and correct any errors or inappropriate content. Second, user feedback is collected after learners use the materials. Based on this feedback, prompts and the database can be refined, and the materials regenerated to improve quality.

⑥. Learning materials modification based on students' VARK styles

We describe the process of converting the generated detailed learning materials into personalized content based on individual VARK learning styles. In the VARK framework, students are divided into four types. **Visual learners** acquire knowledge most effectively through visual input. In this study, we promote effective learning by using generative AI to create visual materials such as charts and figures. For example, tools like ChatGPT and GitHub Copilot can be used to convert textual content into visual formats. **Auditory (or Aural) learners** benefit most from listening. In our approach, we encourage auditory learning by converting generated materials into an audio format. This can be achieved through AI-based text-to-speech software such as VoxBox or Voice Space. **Reading/Writing learners** prefer learning through reading and writing. For these learners, the generated textual materials are already in a form that supports their learning preferences and can be used directly without modification. **Kinesthetic learners** learn best through physical movement and hands-on experiences. They benefit from activities that involve body movement, such as using gestures while learning. In this study, we chose not to modify the generated materials for kinesthetic learners. As with the Reading/Writing style, the existing generated materials can be effectively used as-is for this learning type.

4. Evaluation of the Usefulness of Knowledge Configuration

4.1 Evaluation Method

To examine in detail how modifications to the knowledge database influence the generated learning materials, we conducted a comparative experiment using training content provided by Insource Co., Ltd., titled "ChatGPT Training". Specifically, we generated learning materials using GPT-4o under two conditions: one that included the Insource training materials as part of the knowledge base, and one that excluded them.

However, since the material only covers the curriculum overview and does not include detailed educational content, its importance as knowledge content is limited. Nevertheless, it contains many technical terms related to "generative AI," and it was meaningful to evaluate the impact these terms have on Dify's search and generation behavior. One particular concern was that if Dify failed to properly reference the Insource content, it might instead automatically generate related explanations based on publicly available online sources. Evaluating this behavior was therefore a key part of the comparison. As a practical example, we also tested lecture slides on generative AI prepared by a university instructor. Specifically, pages 2 and 3 of the slides, which discuss artificial intelligence, machine learning, and generative AI, were used as input to generate new materials. We then classified the resulting generated text into three categories for evaluation, focusing on whether hallucinated content was present.

- K: Content based on the registered knowledge base
- N: Content generated based on internet sources
- O: Other (e.g., structurally necessary filler text or content with no substantial meaning)

4.2 Results and Discussion

The evaluation results are summarized in Table 1 and Figure 3. A comparison between the "with Insource" and "without Insource" conditions revealed that the proportion of knowledge-based content (K) was higher in the without Insource condition. This trend suggests that although the Insource materials contained many relevant terms related to generative AI, they lacked sufficient concrete descriptions usable in actual responses. As a result, the system tended to draw more from internet sources when the Insource materials were included. From this, we conclude that to effectively reduce hallucinations in generated content, it is essential to carefully curate the composition of the knowledge base.

Table1. Citation Ratio

	K	N	O
with insource	0.54545455	0.18181818	0.27272727
without insource	0.7826087	0.04347826	0.17391304

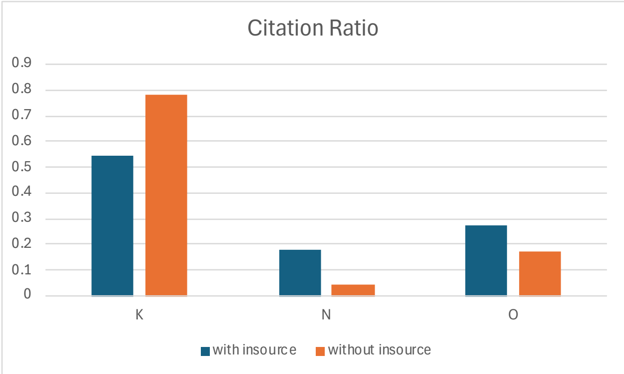

Figure 3 Citation Ratio

5. Conclusion

In this study, we developed a method for creating educational materials using LLMs and RAG. The results showed that by using Copilot, ChatGPT, and Dify, it was possible to generate reference materials corresponding to PowerPoint (PPT) slides. Additionally, using RAG helped reduce hallucinations. We conducted experiments to verify the usefulness of this material generation method. By utilizing RAG, we were able to suppress the occurrence of hallucinations during generation to a certain extent, although not completely. We found that the materials included in the knowledge database affected the generated content. In this study, we applied the VARK model to define students' learning styles. By providing content in multiple formats, such as diagrams, audio, and text, the system effectively supported different learning styles and helped meet the individual needs of each student. However, the effectiveness of the teaching materials has not yet been verified, and we plan to prioritize conducting evaluation experiments to demonstrate improvements in learning efficiency in the future.
The primary objective of this study was to bridge the gap between reference materials and slide-based lecture content. The purpose of this study is to bridge the gap between reference materials and slide lectures. There are two future development plans. First, to utilize OpenAI's API to build a one-stop pipeline that can consistently execute material generation. Second, to generate customized educational materials optimized for each learner's style, ability, and interests. Through these incremental improvements, we aim to enhance the usability and flexibility of this system and maximize its practicality and educational effectiveness in educational settings.

References

Guo, J. (2024, December). Harnessing Artificial Intelligence in Generative Content for Enhancing. Motivation in Learning. ScienceDirect.
G. Izacard and E. Grave, (2021) "Leveraging passage retrieval with generative models for open domain question answering," in EACL.
K. Guu, K. Lee, Z. Tung et al., "REALM: retrieval-augmented language model pre-training," ICML, 2020.
Y. Wang, P. Li, M. Sun, and Y. Liu, (2023) "Self-knowledge guided retrieval augmentation for. large language models," in EMNLP Findings.