Development of an Intelligent Learning Assistance System for Military Curriculum Using Python and Generative AI

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Abstract— **This article details the development and workflow of an AI-powered learning assistance system designed for military educational institutions, utilizing NLP and intelligent information retrieval techniques, to analyze PDF documents. The system, built with Python and libraries like Google Generative AI and scikit-learn, facilitates personalized learning and teaching by summarizing content, generating question-and-answer responses, and creating multiple-choice questions with answer keys. Experimental results, particularly with historical content like the Nine Armies' War, demonstrate the system's ability to accurately summarize key events and extract strategic military tactics in a structured format, enhancing user comprehension. The system adapts to individual learning needs, promotes interactive learning, and improves learning efficiency compared to traditional methods. While limitations such as technological access disparities and AI training data dependencies exist, the research concludes that integrating AI into learning assistance significantly enhances educational effectiveness. Future work will focus on transforming the system into a practical application for educational assessments, conducting real-world testing in educational and military settings, and expanding its application across various academic disciplines.**

Keywords—*artificial intelligence, learning assistance system, retrieval-augmented generation, term frequency-inverse document frequency*

I. INTRODUCTION

The use of technology in education plays a crucial role in enhancing the quality of education in Thailand under the National Education Plan 2017-2026, emphasizing creating equal educational opportunities, developing educational quality, promoting participatory education management, and administration [1]. This includes enhancing ICT infrastructure, digital literacy, quality and standardized learning media production, and developing teachers' knowledge and skills in digital technology for effective learning management in educational institutions.

The training and education management of Army personnel aligns with the national education plan by improving military education curricula. The Royal Thai Army (RTA) has established the training and education policy for 2023-2027, requiring military educational institutions, including the Army Non-Commissioned Officer School (ANCOS), Chulachomklao Royal Military Academy (CRMA), Phramongkutklao College of Medicine (PCM), and the Royal Thai Army Nursing College (RTANC), to modernize their teaching methods in response to rapid technological advancements. The policy promotes discussion-based learning at all levels to encourage knowledge-sharing and critical thinking skills among personnel. Information technology systems are integrated into training and education, emphasizing active learning and work-based learning approaches [2]. Additionally, teaching methods are continuously improved to ensure modernity and effectiveness, prioritizing the learners' needs.

The CRMA, as a military educational institution of the RTA responsible for higher education programs, must improve and develop its curriculum to be appropriate, advanced, modern, and meet the standards set by the Council of Military Academic Education and the Ministry of Higher Education. This is to prepare personnel for military service in the RTA. The Military Science Division (MSD-CRMA) is the main unit responsible for providing military academic knowledge to cadets under the CRMA curriculum. Most military-related courses are conducted through large-scale, lecture-based teaching. However, this method does not effectively stimulate or motivate students, making it difficult to engage all learners and failing to meet individual learning needs. Additionally, there are challenges in course preparation, as instructors' content delivery does not always align with Army policies, the learning potential of students, or their specific needs. Furthermore, while discussion-based learning is being introduced to encourage idea-sharing and experience exchange, it is still in its early stages and does not fully integrate with active learning methodologies.

Research findings indicate that military educational institutions still face limitations in terms of tools and systems [3]. Despite advancements, these systems do not fully support collaborative learning, discussions, or experience-sharing among students. Additionally, the current teaching methods lack flexibility for modern instructional design, which emphasizes a learner-centered approach. Furthermore, the learning management systems developed tend to be repetitive, leading to reduced engagement and interest in learning. To address these challenges, the development of intelligent learning innovations is essential to meet individual learning needs [4]. The integration of digital media technology, particularly AI, in learning design focuses on creating an adaptive learning environment that aligns with students' knowledge and capabilities [5]. Additionally, utilizing digital media technology to enhance teaching and learning ensures that content is relevant to students' needs and potential. This approach improves learning efficiency, enabling students to apply acquired knowledge and skills effectively in problem-solving. The ultimate goal is to equip students with practical skills applicable to both education and real-world military operations, in accordance with RTA policies and the national education plan.

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II. RELATED THEORIES AND RESEARCH

The Retrieval-Augmented Generation (RAG) technique allows Large Language Models (LLMs) to retrieve data from external databases and combine it with user input, enhancing both accuracy and breadth of knowledge [6]. This capability is particularly beneficial in educational applications, such as chatbots. By leveraging RAG, chatbots can accurately and comprehensively respond to student inquiries by extracting relevant information from teaching materials, manuals, or other sources [7]. For instance, Intelligent Tutoring Systems (ITS) can utilize RAG-enabled chatbots to teach complex subjects like physics or chemistry. These chatbots can access vast databases containing text, images, and videos to provide detailed explanations. Additionally, RAG allows chatbots to customize responses based on student needs by analyzing learning history, identifying strengths and weaknesses, and tailoring questions, exercises, and assessments accordingly [8]. This personalized approach can increase student motivation. However, developing an effective educational chatbot using RAG requires careful consideration of key factors, such as selecting appropriate databases, designing natural interaction patterns, and conducting continuous evaluations to enhance performance [9].

Term Frequency-Inverse Document Frequency (TF-IDF) is used in RAG for retrieval. Although TF-IDF is a traditional technique, it is still useful for matching words and calculating the relevance between search terms and documents. Currently, TF-IDF remains an effective text analysis tool and is used in various contexts, such as screening hate speech against foreigners on Twitter in conjunction with other word embedding techniques [10], analyzing consumer sentiment in restaurants and shops by considering word importance and creating data visualizations [11], and detecting Thai fake news as part of data preparation for artificial intelligence models [12].

RAG is an architecture that combines information retrieval with context-aware text generation which utilizing the LLMs such as GPT, BART, or T5 along with external knowledge sources like Wikipedia or domain-specific databases [13]. The process starts with a user query, followed by the retriever module fetching relevant information using sparse or dense retrieval methods via vector stores like FAISS or LlamaIndex. The retrieved data is then passed to the generator module to produce accurately evidence-based responses. RAG excels at generating complex and context-rich answers, making it ideal for applications such as automated question-answering, intelligent learning assistants, and deep knowledge retrieval. It also supports various data modalities, including text, educational materials, audio, video, and knowledge graphs. TF-IDF is a statistical technique for measuring the importance of a term within a document relative to a collection of documents [14]. At its core, it functions by ranking documents according to keyword relevance. Often used with inverted indexing, TF-IDF enables fast and efficient search operations, particularly in keyword-based retrieval systems and large-scale unstructured text processing, such as news or Wikipedia content. In summary, RAG and TF-IDF have distinct advantages. TF-IDF is suitable for rapid keyword-based retrieval, while RAG is better for generating precise, contextually rich responses.

III. SYSTEM MODEL

Development of the learning assistance system for lesson content using artificial intelligence to develop the AI-assisted learning content management system tailored to individual learning needs for students in military educational institutions. This system is designed and written in Python, utilizing key libraries such as Google Generative AI, Colorama, Scikit-learn, and PyPDF2. To use the Gemini AI model, the following steps are required for integration and configuration:

1. API Key Configuration: The command genai.configure (api_key) is used to set your personal API key obtained from GenAI. This allows the client to authenticate and send requests to the GenAI server for content generation.

2. Text Generation Settings: A configuration dictionary named generation_config is defined to specify how the model should generate responses. Key parameters include

2.1 Temperature: Controls the randomness of the output.

2.2 top_p: Sets the cumulative probability threshold for token sampling.

2.3 top_k: Limits the number of highest probability tokens considered for generation.

2.4 max_output_tokens: Specifies the maximum length of the generated output.

3. Model Initialization: The Gemini AI model is initialized using genai. GenerativeModel(), where the model name (e.g., "gemini-2.0-flash-exp") and the generation configuration (generation_config) are provided as parameters.

In summary, using the Gemini AI model requires a valid API key and careful configuration of the generation parameters to ensure effective and appropriate output generation.

Fig. 1 illustrates the steps in the design of the system's workflow where the user can create a message or prompt for the system to process and generate the desired content. This system utilizes Retrieval-Augmented Generation (RAG), which integrates retrieval and text generation processes to provide accurate and well-supported answers. The system consists of three main components:

1. User Interaction

1.1 The user inputs a query (question or search text) through the system interface.

1.2 The system forwards the query to the retrieval module (Retriever).

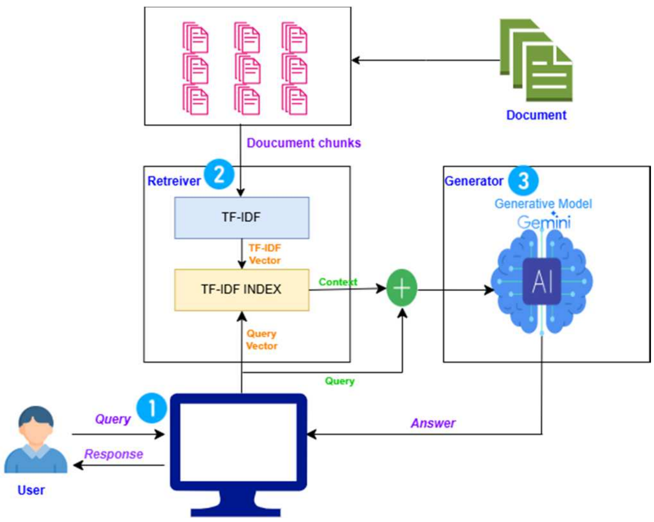

Fig. 1. Diagram of the learning assistance system for lesson content using artificial intelligence.

2. Retriever (Information Retrieval Module)

2.1 Documents stored in the database are divided into document chunks to enhance search efficiency.

2.2 The system applies TF-IDF, a technique that assigns weight to words in documents to prioritize important terms.

2.3 The retrieval process consists of the following steps:

2.3.1 Compute word values in documents as TF-IDF vectors.

2.3.2 Store these vectors in a TF-IDF index.

2.3.3 Convert the user's query into a query vector.

2.3.4 Compare the query vector with the TF-IDF index to retrieve the most relevant information.

2.4 Once the most relevant document is found, its content is sent to the Generator module as context.

3. Generator (Answer Generation Module) This module uses an advanced generative model such as Gemini AI to process information. The Generator module operates as follows:

3.1 Receives the query and context (retrieved data).

3.2 Processes the data to generate an answer.

3.3 Sends the final response back to the user through the interface.

The system workflow begins when the user submits a query. The Retriever module searches for relevant information using TF-IDF. Once the relevant documents are retrieved, they are passed to the Generator module along with the original query. The Gemini AI model processes this data to generate an accurate and well-supported response, which is then delivered to the user.

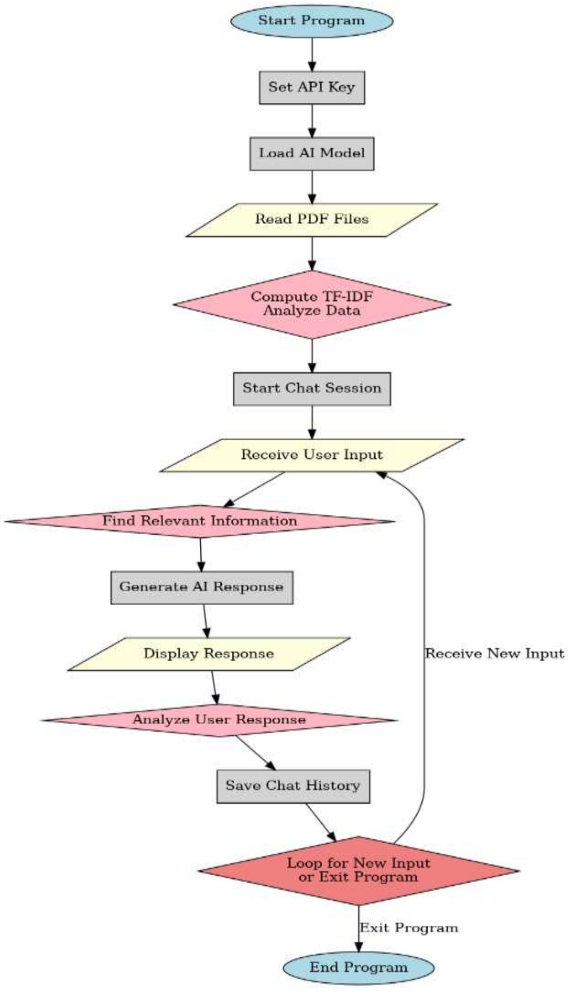

Fig. 2. Flowchart of the learning assistance system for lesson Content Using Artificial Intelligence.

Fig. 2 illustrates the system's operation, starting with system setup, loading the AI model, and loading the desired PDF document. Once these steps are completed, student users can utilize commands via the prompt to ask and answer content-related questions, as well as request summaries of specific topics. For instructor users, the system can generate multiple-choice questions with answer keys. The system also records user command history. After completing each command, the program returns to the user prompt, allowing the user to input another command. The program will terminate when the user exits the Python program. The details of the flowchart are as follows:

1. Initial Setup: The researcher imports necessary libraries to ensure the system operates efficiently, especially those related to file management, text processing, and communication with the Gemini AI model API. Additionally, an API key is set up to allow proper access to the AI model, along with important parameters like temp, top_p, top_k, and max_output_tokens, which affect the quality of the generated text.

2. PDF File Reading Function: The system is designed to automatically read content from PDF files through the read_pdf_file function, which uses PyPDF2 to open the files and extract data from each page. This content is then used for analysis and responding to queries. The researcher incorporates error-handling mechanisms using a try-except structure to prevent issues with missing or unreadable files.

3. Reference Document Preparation: The researcher defines a list of reference documents that the system will use as its database for answering learners' questions. These documents, in PDF format, are imported into the system via predefined file paths. Choosing documents relevant to the lesson ensures that the system can provide accurate and academically aligned answers.

4. Relevant Information Retrieval: The system uses TF-IDF to calculate the importance of words in each document. It then calculates the similarity between the user's query and all documents, selecting the top 5 most relevant documents to serve as references in generating the response. This process allows the system to present content that closely matches the learner's question.

5. Session Initialization: The researcher has designed the system to interact with users via a chat session. An initial greeting message is provided by the AI to create a friendly learning environment. This setup helps ensure that the user can interact with the system in a natural and smooth manner.

6. Question Set Definition: To maintain a continuous and efficient conversation, the researcher has defined a set of questions for the AI to ask the user. These questions are designed to cover important topics in the lesson and promote deeper learning.

7. Tracking Conversation Topics and Context: The system has been developed to track the conversation topic and context through key variables such as current_topic (to store the current topic), conversation_history (to record previous interactions), and asked_questions (to check the questions the AI has already asked). This structure helps the AI interact with the user in alignment with previous content and avoid asking repetitive questions.

8. Conversation Loop: The conversation process has been designed to operate in a loop. It begins by receiving input from the user, checking if the user wishes to exit the program. The system then searches for relevant information from the reference documents and creates a prompt to send to the

Gemini model, which generates a response that is presented to the user. The system also logs the conversation history, analyzes the user's answer, and updates the topic to ensure effective interaction.

9. Program Termination: When the user opts to exit the program, the system closes the chat session and terminates its operations smoothly. This design ensures that the user can use the system without confusion or errors.

For testing the functionality of the system, the researchers created a set of questions based on the content provided to the system. The designed artificial intelligence was then tested to determine whether its responses accurately matched the given content. After that, the AI system generated questions for users to evaluate whether the generated questions aligned with the provided content.

IV. Results and Discussions

After testing the system by inputting a history of war textbook file, the system was able to accurately summarize the content, provide question-and-answer responses, and generate multiple-choice questions via the command prompt.

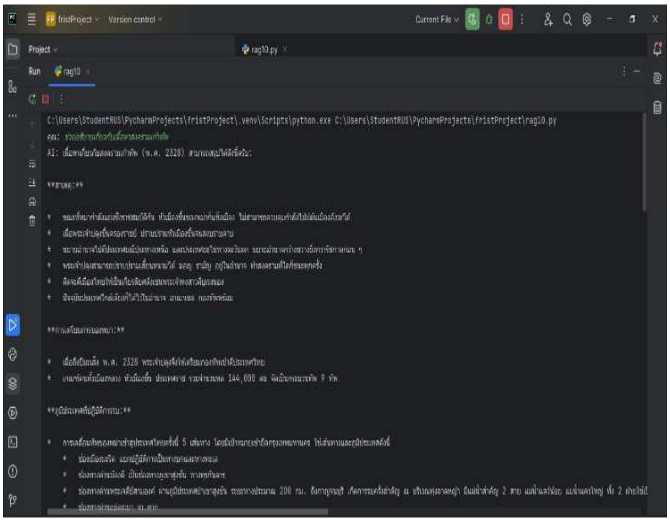

Fig. 3. Interface for generating 4-option multiple-choice questions with answers.

Fig. 3. presents the output of the system that generating 4 option multiple-choice questions with answers in the topic "Information about the Nine Armies' War". In addition, users can pose queries to the system via a command prompt. To ensure system usability, the system will undergo testing across two key areas. This includes the generation of 30 multiple-choice questions with corresponding answers, and responding to 15 content-specific inquiries for the key point extraction test. These tests will be conducted to determine the percentage accuracy of the system's responses.

TABLE I.

Test Case	Expected Outcome	Actual Outcome	Accuracy (%)
Q&A Generation	System provides correct answers	Number of correct answers generated	100
Key Point Extraction	Correctly identifies key points	Number of correctly extracted points	100

Table I. presents the test results. The system successfully generated 30 multiple-choice questions with answers in a single instance, and all provided answers were consistent with the content, resulting in a 100% accuracy rate. For the 15 question-and-answer prompts, the system's responses were entirely accurate when validated against the content, also yielding a 100% accuracy rate.

The findings indicate that the system effectively retrieves relevant information on a given topic and presents responses in a well-structured format when tested on the topic the results demonstrate that the AI accurately summarizes key historical events in a comprehensive manner, ensuring alignment with the original sources. Additionally, the system successfully extracts and summarizes strategic military tactics employed in major battles while maintaining a coherent chronological order. This ensures that the system can enhance users' ability to systematically and thoroughly and correctly understand historical content.

The study on the development of an AI-powered learning assistance system for lesson content reveals that the system enhances personalized learning experiences and improves learning efficiency. Designed to adapt learning content to individual learners' needs, the system fosters interactive learning and supports a learner-centered approach.

The authors have applied the designed model to the cadets and the personnel of Chulachomklao Royal Military Academy to assess the satisfaction of 100 users who were randomly selected, consisting of 70 cadets, 20 instructors, and 10 support personnel. A satisfaction questionnaire was used as the tool to collect data on such needs. The research instrument was checked for accuracy by experts to ensure its appropriateness and tested for language accuracy. The statistical methods used to analyze the data were percentage, mean, and standard deviation.

TABLE II.

Evaluation	$\bar{x}$	S.D.	Evaluation results
Ease of Use	4.62	0.78	Very satisfied
Function Accessibility	4.47	0.91	Very satisfied
Answer Relevance	4.50	1.02	Very satisfied
System Response Speed	4.36	0.98	Very satisfied
Confidence in Answers	4.85	0.95	Very satisfied
Overall Satisfaction	4.50	1.04	Very satisfied
Average value	**4.55**	**0.95**	Very satisfied

The results of the study of the overall opinions of the sample group found that they were Very satisfied ($\bar{x}$ = 4.55, SD = 0.95), reflecting their satisfaction with the use of the system, as shown in Table II.

Therefore, the experimental results demonstrate that learners achieve a better understanding of lesson content and develop analytical thinking skills compared to traditional learning methods. AI-driven analysis of learner behavior and capabilities enables precise personalization of the learning process. Furthermore, the system reduces instructors' workload and enhances the effectiveness of learner support. However, certain limitations remain, such as disparities in learners' access to technology in some regions and challenges in designing a system that accommodates diverse learning styles. Additionally, reliance on AI training data may affect system accuracy, necessitating continuous improvements and further testing to ensure adaptability to diverse and up-to-date content. he findings indicate that integrating AI into learning assistance can enhance educational effectiveness in military institutions. However, ongoing system development is essential to overcome existing limitations and maximize its ability to meet learners' needs efficiently.

V. Conclusion And Future Research

In this article, we present the design and workflow of an intelligent conversational system that utilizes NLP and intelligent information retrieval techniques. The system is designed to read and analyze PDF documents, applying the TF-IDF technique to extract and process relevant information. The system operates through multiple stages, starting with program initialization, API configuration, AI model loading, and managing input and output data. When a user inputs a query, the system searches for relevant information and generates responses using an AI model from Google generative AI. The generated responses are displayed, and the system analyzes user feedback to refine future responses.

Additionally, the system records conversation history and supports continuous user interaction through a loop structure until the user chooses to exit the program. The results of this system design facilitate the development of an intelligent conversational platform capable of handling large-scale data and efficiently responding to user inquiries. By integrating data processing techniques with AI, the system reduces errors and enhances the quality of generated responses. The developed learning assistance system effectively provides relevant historical information for testing purposes, supports interactive learning, and serves as a tool that can be further developed to enhance historical education, as well as other academic disciplines and analytical research.

The intelligent conversation system developed using NLP techniques and intelligent data retrieval, such as the application of TF-IDF techniques and generative language models from Google generative AI, has the ability to analyze and extract data from PDF documents to respond to user questions more accurately and efficiently than traditional teaching methods, which may rely on the teacher's delivery alone without adjusting to the learner's characteristics. Compared to basic methods, traditional teaching may face limitations in terms of access to a large amount of data, real-time response, and the ability to analyze in-depth data. On the other hand, AI-based systems can process large amounts of data and provide relevant and on-point answers while learning from user feedback to improve future answers, which results in reducing errors in providing information and increasing the accuracy of academic communication. In addition, the system supports continuous interaction through a loop structure, promoting interactive learning and learner participation, which is different from traditional teaching methods that focus on delivering content according to a pre-determined lesson plan without being able to flexibly adjust to the learner's context or needs. From the preliminary analysis, it was found that the use of AI technology to enhance learning not only increases the efficiency of data management and answering but also promotes deep learning, supports analytical thinking skills, and enhances learning experiences that are more consistent with each learner. Preliminary results Conversational intelligence has great potential to be developed as an effective learning tool that can outperform traditional teaching methods and non-AI systems, particularly in terms of accuracy, flexibility, and support for personalized learning.

The future work will focus on the education assessment. The researchers intend to transform the proposed learning management system into a practical application. This will involve testing the system in educational institutions and military settings to evaluate and analyze its effectiveness in enhancing student learning in real-world contexts. It will shift towards further developing and refining the AI-Debate system to ensure its suitability for various academic disciplines. Additionally, efforts will be made to expand research initiatives to present this technology to a broader range of educational institutions.

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