

SMART EDUCATIONAL AGENT FOR LEARNING SUPPORT EMPLOYING LARGE LANGUAGE MODELS THROUGH LANGCHAIN

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ABSTRACT

The rapid development of Artificial Intelligence (AI) and Large Language Models (LLMs) has created new opportunities for providing personalized and context-aware learning support to university students. This study presents a Smart Educational Agent designed to support learning through the integration of Large Language Models with the LangChain framework. The proposed system processes educational content and stores it in a vector-based knowledge base using Qdrant, enabling relevant information to be retrieved according to students' queries. The system provides three major learning functions: multiple-choice test generation, academic learning plan generation, and context-based question answering. Retrieval-Augmented Generation (RAG) is employed to retrieve relevant educational information and provide contextual information to the language model before generating responses. An experimental methodology was adopted, and the system was evaluated through functional laboratory tests using educational content and simulated student queries. The evaluation focused on the accuracy, contextual understanding, information retrieval, response relevance, and resource-generation capability of the proposed agent. The results demonstrated that the Smart Educational Agent was able to generate relevant multiple-choice questions, structured academic learning plans, and context-grounded responses based on the available educational content. The findings indicate that the integration of LLMs, LangChain, Qdrant, and RAG can provide an effective approach for developing intelligent learning-support systems. The proposed agent can assist students in practicing subject knowledge, organizing their learning activities, and obtaining responses based on relevant educational resources.

Keywords: *Artificial Intelligence, Large Language Models, Smart Educational Agent, LangChain, Retrieval-Augmented Generation.*

1. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has created new opportunities for improving teaching and learning processes. In particular, Large Language Models (LLMs) have demonstrated the ability to understand natural language, process large amounts of information, and generate human-like responses.[1] Their application in education can support students by providing explanations, answering questions, generating learning materials, and assisting with academic activities. Unlike traditional educational software that generally follows predefined rules, AI-based systems can interact with learners dynamically and provide responses according to the context of their queries and available learning resources.[2]

The increasing use of LLMs in education has also led to the development of intelligent educational agents that can provide more personalized learning support. Such agents can assist students with different learning requirements by generating educational content, recommending learning activities, and responding to subject-related questions.[3] However, general-purpose language models may produce responses that are not sufficiently aligned with specific educational materials and may sometimes provide inaccurate or unsupported information. Therefore, integrating LLMs with educational knowledge bases is important for improving the relevance and contextual grounding of generated responses. Retrieval-Augmented Generation (RAG) provides an effective approach by retrieving relevant information from a knowledge base and supplying it to the language model before generating the final response.[4]

In this context, frameworks such as LangChain provide an effective environment for developing applications based on LLMs.[5] LangChain supports document processing, information retrieval, prompt management, and interaction between language models and external knowledge sources.[6] By combining LangChain with a vector database, educational documents can be processed and stored in a form that allows relevant information to be retrieved according to the semantic meaning of a student's query. This enables the development of educational agents that can provide responses based on specific learning materials rather than relying only on the general knowledge of the language model.[7]

The proposed Smart Educational Agent is designed to provide learning support to university students by integrating Large Language Models with LangChain and a structured educational knowledge base.[8] The system provides three major learning functions: multiple-choice test generation, academic planning generation, and context-based question answering.[9] The multiple-choice test generation function allows students to practice their understanding of a subject by generating questions and answer options from available educational content. The academic planning function generates structured learning plans based on subject requirements, while the question-answering function uses Retrieval-Augmented Generation to retrieve relevant educational information and provide context-based responses.[10]

For effective retrieval of educational information, the proposed system uses Qdrant as a vector database for storing processed educational content. When a student submits a question, the system identifies relevant information from the knowledge base and incorporates the retrieved context into the prompt provided to the Large Language Model through LangChain.[11] This process helps the agent generate responses that are more closely related to the uploaded educational materials. Prompt engineering is

also applied to guide the language model in producing appropriate and meaningful educational responses.

The development of such a Smart Educational Agent can provide students with flexible and accessible learning support beyond conventional classroom interactions. It can assist learners in practicing subject knowledge, organizing their academic activities, and obtaining explanations based on relevant educational resources. The proposed approach therefore aims to demonstrate how Large Language Models, LangChain, vector-based knowledge retrieval, and RAG can be combined to develop an intelligent learning-support system. The effectiveness of the proposed agent is examined through functional laboratory tests focusing on the quality of generated multiple-choice questions, academic learning plans, and context-grounded responses to student queries.

2. LITERATURE REVIEW

Kim et,al (2025) Evaluation and feedback are central to the learning process, making it essential to analyze learners' incorrect answers and generate tailored questions or supplementary materials that address their weaknesses and improve learning outcomes. This paper presents CQELedu, a web application designed to generate questions based on learning materials and analyze incorrect responses to create error-driven follow-up questions. The proposed system leverages GPT-4o mini and LangChain to generate both subjective and objective questions from user-provided materials. The system analyzes incorrect answers and generates customized follow-up questions, helping learners identify and address gaps in understanding. The relevance, accuracy, and response time of the generated questions are assessed both quantitatively and qualitatively to evaluate system performance. Experimental results demonstrate high cosine similarity scores for relevance, validating the relevance of the generated questions to the learning materials. The accuracy of the system is reflected in the applicability of the questions derived from incorrect answers. Additionally, the system exhibits improved response time compared to existing methods, highlighting its efficiency. Thus, CQELedu is well-suited for supporting dynamic learning environments, particularly in standardized testing contexts such as certification exams and school assessments. Future research should explore the integration of learning materials from diverse fields, the implementation of multilingual support, and the scalability potential, aiming to expand the applicability of CQELedu across various educational domains.[12]

Lu et,al (2025) With the rapid development of generative artificial intelligence (GenAI), agents based on foundation models (FMs) have gradually acquired capabilities, such as multimodal perception, retrieval-augmented generation, reasoning and planning, interaction, and evolution. This study proposed a fundamental concept and framework for FM-based pedagogical agents. Centering on the FM as the technological core, the framework primarily consisted of several functional modules, including educational task setting, educational task planning, realization and expansion of educational capabilities, memory and reflection on educational content, and interactive collaboration and dynamic evolution. These modules support interaction with diverse entities and facilitate dynamic evolution, encompassing human-computer interaction, multi-agent interaction, and environment interaction. Building upon the proposed framework, this study adopted project-based learning tasks as an application scenario. It elaborated on the roles of pedagogical agents functioning as assistant agents and peer agents across various phases, such as personalized driving question formulation, collaborative project plan design, collaborative project work completion, and multi-role evaluation of project works, along with the associated supporting technologies. Furthermore, this study discussed the future development and prospects of pedagogical agents.[13]

Li et,al (2025) This study focuses on developing educational agents capable of understanding and adapting to learners' complex cognitive behaviors. We propose a “Reverse Turing Test” (RTT) framework to evaluate AI's ability to perceive human cognition and construct an adaptive teaching agent, “Xiaohang,” based on Multimodal Large Language Models (MLLMs). The research employs four key methods: RTT, multimodal data perception, adaptive teaching strategies, and memory-reflection mechanisms. RTT captures learners' cognitive states through interactive dialogues, multimodal perception collects multidimensional data (text, speech, images), adaptive strategies adjust teaching plans based on real-time feedback, and memory-reflection mechanisms optimize subsequent teaching outcomes. Experiments conducted in project-based learning (PBL) scenarios demonstrate that Xiaohang significantly enhances the quality of problem formulation, creativity in solution design, and task completion efficiency, validating its effectiveness in improving educational outcomes.[14]

Nouzri et,al (2024) The intersection of Artificial Intelligence (AI) and education is transforming learning and teaching, with Generative AI (GenAI) and large language models (LLMs) offering new possibilities. AI and LLMs personalize learning through adaptive study guides, instant feedback, automated grading, and content creation, making resources more accessible and tailored to individual needs. Notably, LLM-based chatbots, such as OpenAI's ChatGPT, serve as virtual assistants, ideal for language practice. However, these chatbots often limit themselves to teaching vocabulary through role-playing conversations or providing instant feedback based on model-generated content, which may lead to exposure to inaccuracies. This overlooks the holistic nature of Language Learning (LL), which requires pedagogy, effective methods, reliable content, and a supportive teacher-student relationship. Therefore, relying on a single chatbot is inefficient for the entire learning process. In this paper, a Multi-Agent System (MAS) is proposed, where each agent specializes in a specific function, working together to provide personalized, adaptive learning support. This approach breaks down the complex learning process into manageable parts. It employs the Business Process Model and Notation (BPMN), translated into agent-based modeling and LLMs to create dynamic, tailored learning environments. By simulating interactions similar to human tutoring, this model ensures real-time adjustments to meet each student's evolving needs.[15]

Yun, X. (2024) Large language models are widely applied in educational scenarios. Students can engage in personalized and interactive learning through intelligent learning assistants installed on various devices. Among these applications, integrating large language models (LLMs) with knowledge graphs to achieve complex reasoning is a key issue. Traditional methods often solve multi-hop query problems based on individual technologies, leading to insufficient accuracy and comprehensiveness in answering complex questions. This paper proposes an intelligent agent framework called K12-Agent, which uses retrieval-enhanced generation, fine-tuning of LLMs integrated with knowledge graphs, and collaborative reasoning to enhance the initiative of the agent in interactions with students. Compared to traditional methods, K12-Agent has improved the accuracy by 15% and the recall rate by 13% when facing complex student questions. Additionally, K12-Agent is more adaptable to the expression methods of younger students, making it more user-friendly.[16]

Jung et,al (2026) Human-Building Interaction (HBI) has emerged as a key domain within building science - typically encompassing civil/architectural engineering and architecture - in the past decade, as its potential to improve building performance by integrating human dynamics into the control of buildings. Educating students in HBI presents unique challenges due to its interdisciplinary nature. It requires multiple skills, including programming (e.g., Arduino and Python), wiring circuits with sensors, and understanding diverse domains, including thermal comfort, lighting, indoor air quality and more. We aim to address this challenge by developing an artificial intelligence (AI) learning assistant,

incorporating web-based multi-agent frameworks for HBI education. In this study, we highlight this assistant's expandability, accessibility, and enhanced usefulness compared to general-purpose large language models (LLMs). Specifically, this assistant is supported through both LangChain and LangGraph, to combine the flexible integration of diverse LLM capabilities with the structured orchestration of complex workflows, thereby enabling adaptive and educational interactions for HBI education. We showed its usefulness in supporting Arduino programming by comparing its response with those generated by a generalpurpose LLM model using systematic evaluation criteria. This research and development effort will contribute to advancing educational innovation in HBI as well as interdisciplinary subjects in architecture, engineering, and construction by lowering technical barriers for students, fostering interdisciplinary skill development, and creating a scalable framework where AI supports experiential learning and empowers learners to transition from passive knowledge absorption to active problem-solving and innovation.[17]

León-Paredes et,al (2025) This work presents the development of NOVA, an educational virtual assistant designed for the Parallel Computing course, built using a Retrieval-Augmented Generation (RAG) architecture combined with Large Language Models (LLMs). The assistant operates entirely in Spanish, supporting native-language learning and increasing accessibility for students in Latin American academic settings. It integrates vector and relational databases to provide an interactive, personalized learning experience that supports the understanding of complex technical concepts. Its core functionalities include the automatic generation of questions and answers, quizzes, and practical guides, all tailored to promote autonomous learning. NOVA was deployed in an academic setting at Universidad Politécnica Salesiana. Its modular architecture includes five components: a relational database for logging, a vector database for semantic retrieval, a FastAPI backend for managing logic, a Next.js frontend for user interaction, and an integration server for workflow automation. The system uses the GPT-4o mini model to generate context-aware, pedagogically aligned responses. To evaluate its effectiveness, a test suite of 100 academic tasks was executed—55 question-and-answer prompts, 25 practical guides, and 20 quizzes. NOVA achieved a 92% excellence rating, a 21-second average response time, and 72% retrieval coverage, confirming its potential as a reliable AI-driven tool for enhancing technical education.[18]

Li et,al (2026) As large language models (LLMs) continue to advance, they have demonstrated remarkable performance across a wide range of tasks. However, their application in highly specialized scientific domains—such as quantum physics—remains limited, particularly in educational settings where precision and domain expertise are crucial. Given the abstract nature and mathematical rigor of quantum theory, delivering accurate AI-assisted support in this field is both technically demanding and educationally valuable. To address these challenges, we propose a retrieval-augmented generation (RAG) framework that incorporates a domain-specific knowledge base constructed from authoritative quantum physics textbooks. Our approach introduces customized strategies at both the preretrieval and postretrieval stages to enhance the relevance of retrieved content, mitigate hallucinations, and improve factual accuracy and contextual alignment. This tighter integration between retrieval and generation substantially improves the system's ability to produce reliable and pedagogically meaningful responses. To enable rigorous and systematic evaluation, we present PhysicBench—the first comprehensive benchmark specifically designed for quantum physics question answering in RAG systems. Unlike existing datasets, which are either scarce or ill-suited to this domain, PhysicBench supports fine-grained evaluation across key components of the RAG pipeline, including document retrieval, ranking effectiveness, and answer generation accuracy. It fills a critical gap in current resources and provides detailed metrics for performance analysis at each stage. Experimental results show that our proposed system significantly outperforms LLM-only baselines, highlighting the effectiveness of domain-aware

RAG approaches. Overall, this work contributes both a robust technical solution and a much-needed benchmark to advance research in AI-powered education and intelligent question answering within the field of quantum physics.[19]

Baur et,al (2025) Large language models are increasingly applied in health care for documentation, patient education, and clinical decision support. However, their factual reliability can be compromised by hallucinations and a lack of source traceability. Retrieval-augmented generation (RAG) enhances response accuracy by combining generative models with document retrieval mechanisms. While promising in medical contexts, RAG-based systems remain underexplored in orthopedic and trauma surgery patient education, particularly in non-English settings. The chatbot integrated OpenAI's GPT language model with a Qdrant vector database for semantic search. Its corpus consisted of 899 curated German-language documents, including national orthopedic guidelines and patient education content from the Orthinform platform of the German Society of Orthopedics and Trauma Surgery. After preprocessing, the data were segmented into 18,197 retrievable chunks. Evaluation occurred in two phases: (1) human validation by 30 participants (orthopedic specialists, medical students, and nonmedical users), who rated 12 standardized chatbot responses using a 5-point Likert scale, and (2) automated evaluation of 100 synthetic queries using the Retrieval-Augmented Generation Assessment Scale, measuring answer relevancy, contextual precision, and faithfulness. A permanent disclaimer indicated that the chatbot provides general information only and is not intended for diagnosis or treatment decisions. The chatbot demonstrated strong performance in delivering orthopedic patient education through an RAG framework. Its deployment on the national Orthinform platform has led to more than 9500 real-world user interactions, supporting its relevance and acceptance. Future improvements should focus on expanding domain coverage, enhancing retrieval precision, and integrating multimodal content and advanced RAG techniques to improve robustness and safety in patient-facing apps.[20]

Tsirini, V. (2025) Rapid technological and social changes, coupled with increasing time pressures, have defined a new reality for modern societies and extend to heavily affect the educational process. For example, educators often struggle with time limitations that restrict their capacity to redesign the teaching material in a more engaging, creative, and responsive way that better addresses the individuals' learning requirements. At the same time, rapid technological advancements such as the advent of Generative AI, have become deeply embedded in everyday life and have fundamentally transformed learners' cognitive patterns and educational preferences (e.g. younger learners, who have typically grown up in digital environments, naturally prefer learning experiences that incorporate technology that allows them to interact with the learning content instead of passively receiving information). These evolving patterns of both educators and learners impose the need for the development of educational tools that benefit from advanced technologies and enable adaptability to the diverse learning preferences while efficiently supporting teachers in delivering personalized content. Towards this direction, in the present thesis we explore how Generative and (agentic) Artificial Intelligence can empower the next generation of education software design, bridging this gap and ensuring that the teaching and learning processes remain effective and relevant in the face of ongoing societal and technological shifts. In particular, we developed a series of AI-based tools that dynamically adjust the learning content into different formats, meeting each user's unique learning preferences. These tools employ the use of Large Language Models (LLM) and Retrieval Augmented Generation (RAG) in the context of AI agents and AI flows, that enable the retrieval of information from the given education curriculum and the provision of grounded responses in multimodal forms. For example, we introduce agentic designs that: • enable the creation of interactive quizzes and quests, gamifying the educational content while empowering knowledge learning and assessment, • allow for the effective development of learning plans and

summaries (with visual and audio support) for addressing the time pressure bottlenecks as well as for covering for the diverse learners' cognitive styles. • empower the interactive Q&A sessions, fueled by agentic tools that can handle multimedia input and leverage planning and reasoning in order to assist the learner address inquiries on the learning subjects of their preferences, in a grounded and reliable way Combined with a prototype implementation of such AI agents, we also provide details on the architectural backbone and functional interplay of these tools and conclude this study by sharing ideas for prospect future further research.[21]

RESEARCH GAP: Based on the studies reviewed, existing research has demonstrated the potential of Large Language Models and educational agents for question generation, adaptive learning, personalized teaching, knowledge-based reasoning, and multi-agent educational support. However, most existing systems focus on specific educational scenarios such as language learning, project-based learning, K–12 education, or specialized subjects, while limited attention has been given to a general-purpose learning support agent for university students that combines multiple academic functions within a single framework. Although LangChain has been used for question generation and LangChain/LangGraph for specialized learning assistance, there is still a need for an integrated system that combines educational content management, multiple-choice test generation, personalized academic planning, and context-based question answering. Furthermore, the use of a dedicated vector database with Retrieval-Augmented Generation (RAG) to ground responses specifically in uploaded university-level learning materials remains insufficiently explored. Therefore, the present study addresses this gap by developing a Smart Educational Agent using LLMs, LangChain, Qdrant, and RAG to provide context-aware and personalized learning support to university students.

3. OBJECTIVES

1. To develop a Smart Educational Agent using Large Language Models and LangChain.
2. To integrate educational content into a knowledge base for learning support.
3. To generate multiple-choice tests and personalized academic learning plans.
4. To provide context-based answers using Retrieval-Augmented Generation (RAG).

4. METHODOLOGY

In this research, a Smart Educational Agent was implemented to provide learning support to university students using Artificial Intelligence and Large Language Models (LLMs). An experimental methodology was adopted to evaluate the agent's ability to process educational information, understand student queries, and generate context-aware learning resources. The functional requirements were defined considering the need to process previously stored educational content and provide appropriate responses according to the user's request.

To address these requirements, the LangChain framework was implemented to manage document processing, contextual information, and interaction with the Large Language Model. Educational documents are processed and stored in a vector database, Qdrant, which enables relevant information to be retrieved according to the semantic similarity of a student's query. The OpenAI API was used to connect the system with the Large Language Model, while prompt engineering was applied to guide the generation of appropriate and context-specific responses.

The proposed Smart Educational Agent supports three main learning functions: multiple-choice test generation, academic planning generation, and question answering based on retrieved educational information. The multiple-choice test service generates questions and answer options from the available educational content, while the academic planning service produces a structured learning plan according to the subject requirements. These functions were used to evaluate the agent's capability to generate useful educational resources.

For context-based question answering, the system employs the Retrieval-Augmented Generation (RAG) technique. When a student submits a query, LangChain processes the question and retrieves relevant information from the educational knowledge base through Qdrant. The retrieved context is then incorporated into the prompt provided to the Large Language Model, allowing the agent to generate a response grounded in the relevant educational content. This process enables the system to provide more focused and contextually relevant answers.

The system was evaluated through functional laboratory tests using educational content and simulated student queries. The evaluation examined the accuracy of generated content, contextual understanding, and resource-generation capability for the multiple-choice and academic planning services. For the RAG-based question-answering service, information retrieval, context grounding, and response relevance were also examined. The resulting outputs were used to assess the effectiveness of the Smart Educational Agent in providing learning support through LangChain and Large Language Models.

5. RESULTS

To fully understand the performance of the proposed Smart Educational Agent and its effectiveness in providing learning support, a comprehensive evaluation was conducted based on specific functional tests. The evaluation focused on the ability of the agent to support students through large language models integrated with the LangChain framework. Here, we present and exemplify three use cases:

Multiple-Choice Test Generation: In this test, we evaluated the agent's ability to generate a multiple-choice test based on the educational content provided through the knowledge base, as shown in Figure 4. The results highlighted the following aspects:

- **Accuracy of Answers:** The agent demonstrated the ability to generate relevant multiple-choice questions and corresponding answers based on the educational content, reflecting its capability to address the topics presented accurately.
- **Contextual Understanding:** The agent appropriately maintained the context of the uploaded subject content while generating questions and answers, demonstrating its ability to provide responses related to the specific learning material.
- **Resource Generation Capability:** The agent successfully generated multiple-choice questions as an educational resource, providing students with an additional means of practicing and assessing their understanding of the subject matter.

User: Create a test of 3 multiple-choice questions on information security principles.

Assistant: Here is a test of 3 multiple-choice questions on information security principles:

Question 1:
Which principle ensures that data is accurate, complete, and has not been altered by unauthorized parties?

- a) Confidentiality
- b) Integrity
- c) Availability
- d) Non-repudiation

Question 2:
What is the main purpose of access control in information security?

- a) To encrypt data during transmission
- b) To ensure that only authorized users can access resources
- c) To protect data from physical damage
- d) To increase system processing speed

Question 3:
Which of the following is an example of a technical safeguard?

- a) Security awareness training
- b) Firewall
- c) Security policy document
- d) Employee code of conduct

User:

Fig 4. Multiple-Choice Test Generation Service.

Academic Planning Generation: In the second test, we evaluated the ability of the Smart Educational Agent to create a detailed academic learning plan based on the subject content, and the result generated is shown in Fig 5. The following aspects stood out:

- **Accuracy of Responses:** The academic plan generated by the agent covered the major aspects of the subject content and provided a coherent structure for learning, demonstrating its ability to support academic planning.
- **Contextual Understanding:** The agent maintained the appropriate context of the subject during the generation of the academic plan, identifying relevant topics and organizing them according to the educational requirements.
- **Resource Generation Capability:** The generated academic plan provided recommendations for additional learning activities and resources, thereby supporting students in organizing their study process and enriching their learning experience.

User: Create an academic plan for a course on Information Security.

Assistant: Here is a suggested academic plan for a course on Information Security:

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Title of the Course: Information Security Fundamentals

Objective of the Course:

To familiarize students with the basic concepts of information security and the fundamentals of information security management systems.

Duration: 8 Weeks

Weekly Plan:

1. Week 1: Introduction to Information Security

- Overview of information security
- Importance and need for information security
- Threats, vulnerabilities and attacks

2. Week 2: Information Security Principles

- Confidentiality, Integrity, Availability
- Authentication and Authorization
- Non-repudiation and Accountability

3. Week 3: Risk Management

- Risk identification and analysis
- Risk assessment and evaluation
- Risk treatment and monitoring

4. Week 4: Security Controls

- Administrative controls
- Technical controls
- Physical controls

5. Week 5: Cryptography Fundamentals

- Symmetric and asymmetric encryption
- Hash functions and digital signatures
- Public Key Infrastructure (PKI)

6. Week 6: Network Security

- Firewalls and Intrusion Detection Systems
- Secure protocols (SSL/TLS, IPsec)
- Wireless and mobile security

7. Week 7: Information Security Management Standards

- ISO/IEC 27001 and its framework
- Policies, procedures and compliance
- Security audits and assessments

8. Week 8: Review and Case Studies

- Real-world case studies
- Best practices in information security
- Course review and assessment

Learning Activities:

- Lectures and discussions
- Practical exercises and labs
- Case study analysis
- Group presentations

Assessment Methods:

- Quizzes and assignments
- Mid-term examination
- Final examination
- Project/ Case study report

Recommended Resources:

- Textbook: Information Security – Principles and Practice
- NIST Special Publications
- Online resources and research articles

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User:

Fig 5. Academic Planning Generation Service.

Retrieval-Augmented Question Answering: In the third test, we evaluated the ability of the Smart Educational Agent to retrieve relevant information from the educational knowledge base and use the retrieved context to generate responses to student queries, as shown in Fig 6. The Retrieval-Augmented Generation (RAG) technique was employed to improve the contextual relevance of the generated responses. The following aspects stood out:

- **Information Retrieval:** The agent successfully retrieved relevant information from the uploaded educational content based on the student's query, demonstrating its ability to identify appropriate subject-specific information.
- **Context-Grounded Responses:** The retrieved information was provided as contextual information to the large language model, enabling the agent to generate responses based on the relevant educational content and reducing dependence on general responses.
- **Response Relevance:** The generated responses were relevant to the student's questions and aligned with the retrieved educational information, demonstrating the usefulness of RAG for providing context-aware learning support.

User: What is a firewall in information security and why is it important?

Assistant: Here is the answer to your question based on the retrieved information.

Retrieved Context:

[1] Source: *Network Security Essentials (5th Edition)*
A firewall is a hardware or software security system that monitors and controls incoming and outgoing network traffic based on predetermined security rules. It acts as a barrier between a trusted internal network and untrusted external networks.

[2] Source: *ISO/IEC 27002:2022 – Information Security Controls*
Firewalls are technical controls implemented to protect networks from unauthorized access. They help enforce the organization's security policy by allowing legitimate traffic and blocking malicious or suspicious traffic.

[3] Source: *Cybersecurity Fundamentals – Concepts and Practices*
Firewalls can be configured to filter packets, perform stateful inspection, and support application-level gateways. They are a critical component of defense-in-depth strategy.

Answer:

A firewall is a security system—either hardware or software—that monitors and controls incoming and outgoing network traffic based on defined security rules. It acts as a barrier between a trusted internal network and untrusted external networks.

It is important because it:

- Prevents unauthorized access to internal systems and data.
- Allows legitimate traffic while blocking malicious or suspicious traffic.
- Enforces the organization's security policies.
- Forms a critical layer of defense as part of a defense-in-depth strategy.

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User:

Fig 6. Retrieval-Augmented Question Answering Service.

Laboratory tests were conducted using educational content and simulated student queries to validate the operability of the Smart Educational Agent. The educational data verified the system's ability to process subject-related information, while the functional tests evaluated its effectiveness in providing real-time learning support. These processes played a fundamental role in determining whether the system could retrieve relevant educational information, generate appropriate responses, and provide learning resources using the large language model through LangChain. To this end, a process of uploading subject content and subsequently generating multiple-choice questions, academic learning plans, and context-based answers was carried out to validate the results produced by the educational agent. The Retrieval-Augmented Generation process was also evaluated to determine whether relevant information could be retrieved from the knowledge base and incorporated into the generated responses.

6. DISCUSSION

The use of large language models for learning support has the potential to personalize the educational experience of students through a smart educational agent. These models have the ability to process and analyze extensive educational content, understand context and semantics, and generate responses according to student queries. Through LangChain, the educational agent can utilize relevant contextual information to provide students with detailed explanations, appropriate examples, practice questions, and personalized learning recommendations.

Furthermore, learning support based on large language models can address differences in students' learning requirements and levels of knowledge. By considering the context of the educational content and the nature of the student's query, the Smart Educational Agent can provide appropriate explanations, generate additional exercises, organize learning activities, and simplify complex concepts. This can enhance the learning experience by providing individualized support and allowing students to focus on areas that require greater understanding.

The integration of Retrieval-Augmented Generation further strengthens the learning support capability of the proposed agent by allowing relevant information to be retrieved from the educational knowledge base before generating a response. This approach enables the large language model to utilize subject-specific contextual information when responding to student queries. As a result, the agent can provide more relevant and context-grounded responses based on the educational resources available in the knowledge base. The use of LangChain for contextual processing and retrieval is consistent with the architecture described in the reference study, where relevant vectors are retrieved from the knowledge base and incorporated into the prompt provided to the language model.

On the other hand, there are challenges such as the availability and quality of educational datasets used by the Smart Educational Agent. A representative and diverse educational knowledge base covering the relevant subject matter is important for generating reliable and contextually appropriate responses. Additionally, ethical, privacy, and data-security concerns must be addressed when processing student-related information. The computational requirements of large language models and the need for human supervision and validation of generated educational content are also important considerations for implementing such systems in educational environments.

CONCLUSION

The study concludes that the proposed Smart Educational Agent provides an effective approach for supporting university students through the integration of Artificial Intelligence, Large Language Models (LLMs), LangChain, Qdrant, and Retrieval-Augmented Generation (RAG). The system successfully generated relevant multiple-choice questions, structured academic learning plans, and context-based answers from educational content. The use of Qdrant enabled the retrieval of relevant information, while RAG helped generate responses grounded in the available learning materials. Functional laboratory testing demonstrated the system's ability to process educational content and provide context-aware learning support. Overall, the findings show that the proposed agent can assist students in self-learning, practicing subject knowledge, organizing academic activities, and obtaining relevant explanations. Further development can focus on expanding the knowledge base, improving personalization, and evaluating the system with real university students.

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