iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.78650

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Edumentor: A Multi-Agent AI Study Assistant for Personalized Learning

Prof. P. Anjaiah[1], A. Vaishnavi[2], G. Srivani[3], S. Sreeya[4], CH. Soumya[5]
Dept. of CSE (AI & ML), Malla Reddy University, Hyderabad, India

Abstract: The rapid growth of digital education platforms has increased the demand for intelligent systems capable of delivering personalized learning experiences. Traditional online learning systems often provide static course structures that fail to adapt to individual student needs, learning styles, and knowledge levels. This paper presents Edumentor – Multi-Agent AI Study Assistant, an intelligent educational platform designed to provide personalized learning support using a multi-agent architecture powered by large language models. The system analyzes student learning requirements and dynamically generates customized learning roadmaps, recommended learning resources, practice quizzes, and interactive tutoring. In addition, the platform incorporates Retrieval-Augmented Generation (RAG) to enable document-based learning, allowing students to upload study materials and receive context-aware explanations. The system is implemented using a modular multi-agent framework where specialized agents perform tasks such as student analysis, curriculum planning, resource discovery, quiz generation, and tutoring. A vector database is used to store semantic embeddings of uploaded documents, enabling efficient similarity-based retrieval during question answering. The platform integrates modern AI technologies with an intuitive web interface to create a flexible and adaptive learning environment. The results demonstrate that the proposed system can effectively assist learners by providing structured learning guidance, improving access to educational resources, and supporting interactive knowledge exploration.
Keywords: Multi-Agent Systems, Generative AI, Personalized Learning, Retrieval-Augmented Generation, Educational AI, Intelligent Tutoring Systems.

I. INTRODUCTION

The advancement of artificial intelligence has significantly transformed modern education by enabling intelligent learning systems capable of adapting to individual student needs. Online learning platforms provide access to large volumes of educational content; however, many of these systems follow a static structure that does not account for variations in student knowledge levels, learning goals, or preferred learning styles. As a result, learners

Personalized learning has emerged as an important concept in modern educational technology. It aims to tailor learning experiences based on individual characteristics such as prior knowledge, available study time, and learning preferences. Achieving effective personalization, however, requires intelligent systems capable of analyzing student profiles and dynamically generating learning strategies.

Recent developments in large language models (LLMs) and generative AI have opened new possibilities for intelligent tutoring and automated educational support. These models can understand complex queries, generate explanations, and assist learners with interactive problem solving. When combined with structured workflows and specialized agents, they can support multiple educational tasks such as curriculum planning, question generation, and concept explanation.

Another emerging technique is Retrieval-Augmented Generation (RAG), which combines information retrieval with language generation. RAG allows AI systems to access external knowledge sources, retrieve relevant information, and generate responses grounded in factual content. In educational systems, this capability enables students to upload study materials such as lecture notes or textbooks and receive context-aware explanations based on those documents.

To address these challenges, this paper proposes Edumentor – Multi-Agent AI Study Assistant, an intelligent educational platform designed to support personalized learning through a multi-agent architecture. The system employs several specialized AI agents responsible for analyzing student needs, generating learning roadmaps, recommending educational resources, creating quizzes, and providing tutoring support. Additionally, a RAG-based document question answering module allows students to interact with their own learning materials.

The proposed system aims to:

- Provide personalized learning roadmaps based on student profiles
- Recommend relevant educational resources

- Generate quizzes to reinforce understanding
- Offer AI-based tutoring assistance
- Enable document-based learning through RAG

By integrating multi-agent AI techniques with modern retrieval systems, the platform creates a flexible and adaptive environment that enhances the learning experience for students.

II. RELATED WORK

Intelligent tutoring systems have been widely studied to improve personalized learning experiences. Early educational systems mainly relied on rule-based methods to guide students through predefined learning paths. Although these systems provided structured learning support, they lacked adaptability and were unable to effectively process natural language queries.

Recent advancements in artificial intelligence have enabled the development of learning systems based on large language models and generative AI. These systems can provide automated explanations, generate educational content, and assist learners in understanding complex concepts. Additionally, Retrieval-Augmented Generation has been used to improve response accuracy by retrieving relevant information from external knowledge sources.

Researchers have also explored multi-agent architectures in AI systems where multiple specialized agents collaborate to perform different tasks. Such systems have shown promising results in complex applications including recommendation systems and intelligent assistants.

However, many existing educational AI systems focus on a single functionality such as tutoring or resource recommendation. The proposed Edumentor – Multi-Agent AI Study Assistant integrates multiple AI agents with document-based knowledge retrieval to provide a comprehensive and personalized learning support platform.

III. EXISTING SYSTEM

Traditional online learning platforms provide structured educational content through predefined courses and modules. However, these systems generally lack personalization and do not adapt to individual student characteristics such as knowledge level, learning goals, or learning styles. Students are often required to independently search for resources, create study plans, and evaluate their own progress. Additionally, many existing platforms do not provide integrated tutoring support or intelligent interaction with user-uploaded learning materials, limiting their ability to deliver personalized learning experiences.

IV. PROPOSED SYSTEM

The proposed system, Edumentor – Multi-Agent AI Study Assistant, introduces an intelligent educational platform that provides personalized learning assistance using a multi-agent AI architecture. The system analyzes student profiles and dynamically generates customized learning roadmaps, recommended learning resources, quizzes, and tutoring support. Additionally, a Retrieval-Augmented Generation (RAG) module allows students to upload study materials and receive context-aware answers based on those documents. By integrating multiple AI agents with a vector-based retrieval system, the platform offers a flexible and adaptive learning environment.

V. SYSTEM ARCHITECTURE

The architecture of Edumentor – Multi-Agent AI Study Assistant consists of multiple interconnected components that work together to provide personalized learning support. The system integrates a multi-agent AI framework with Retrieval-Augmented Generation (RAG) to assist students in learning efficiently.

The user interacts with the system through a web interface built using Streamlit, where students provide details such as topic, knowledge level, learning goals, and preferred learning style. This information is used to create a student profile that guides the learning process.

The core functionality of the platform is implemented using a multi-agent framework based on the Phi Agent Framework. Different agents perform specific tasks such as student analysis, learning roadmap generation, resource recommendation, quiz generation, and tutoring assistance.

For document-based learning, the system incorporates Retrieval-Augmented Generation. Uploaded documents are processed and stored as vector embeddings in ChromaDB. During query processing, relevant document segments are retrieved and used as contextual information for generating responses.

Large language models accessed through the Groq infrastructure generate explanations, quizzes, and recommendations, enabling the system to deliver adaptive and interactive learning support.

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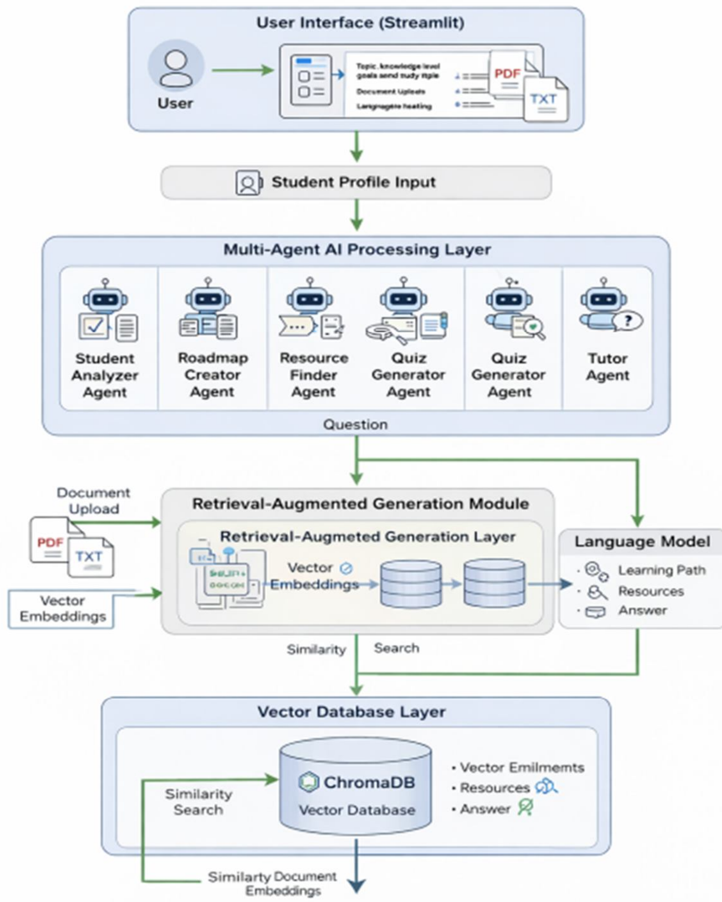


Figure 1: System Architecture of Edumentor — Multi-Agent AI Study Assistant

VI. IMPLEMENTATION

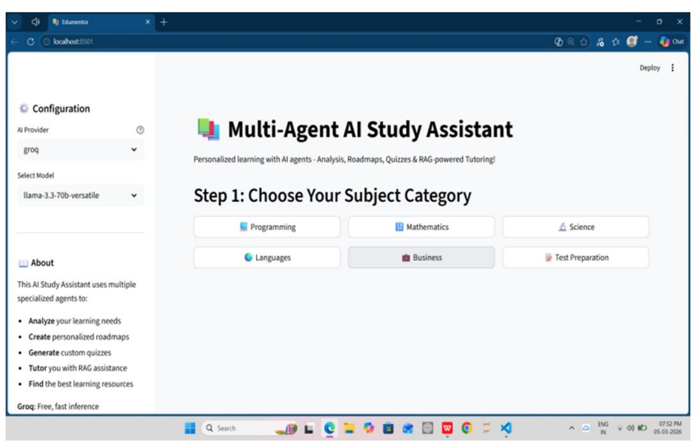
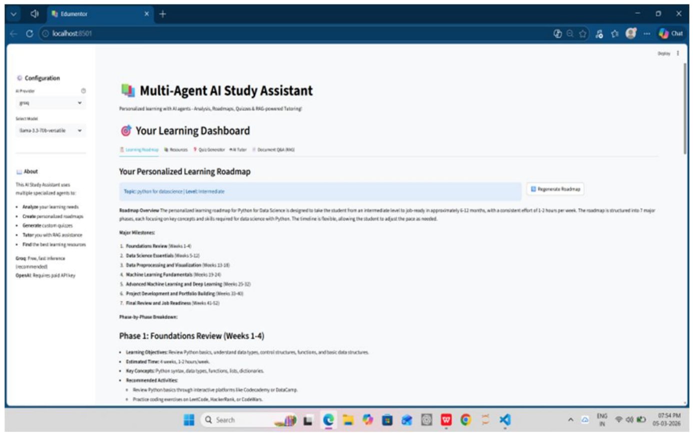


Figure 2: User Interface of the Edumentor – Multi-Agent AI Study Assistant showing subject category selection for personalized learning.



.**Figure 4:** Personalized learning dashboard displaying the AI-generated learning roadmap based on the user's inputs.

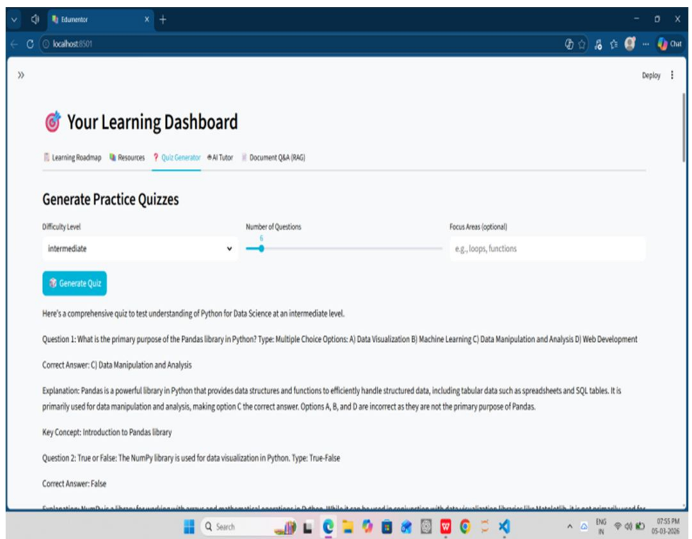


Figure 6: Quiz generation module that automatically creates practice questions based on the selected topic and difficulty level.

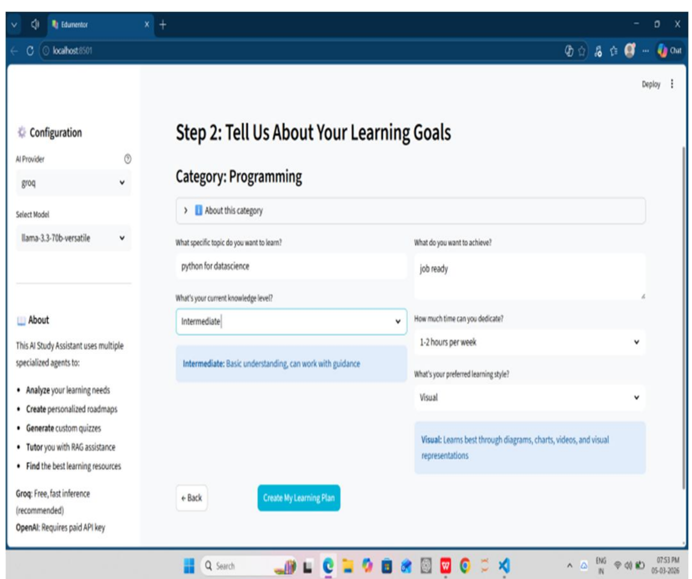


Figure 3: Learning goal input interface where users provide topic, knowledge level, time availability, and preferred learning style.

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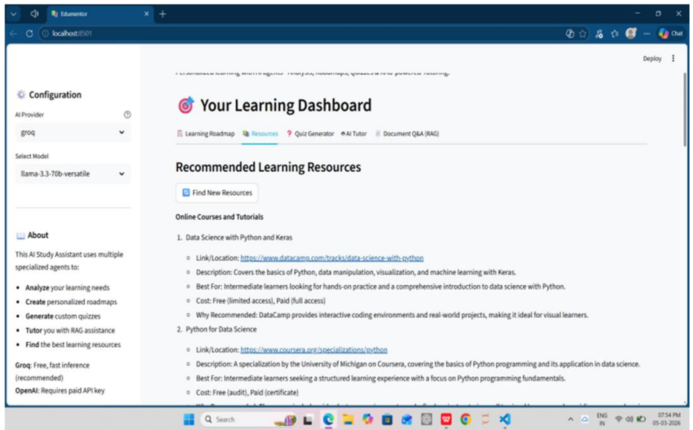

Figure 5: Resource recommendation module presenting curated online courses and tutorials for the selected topic.

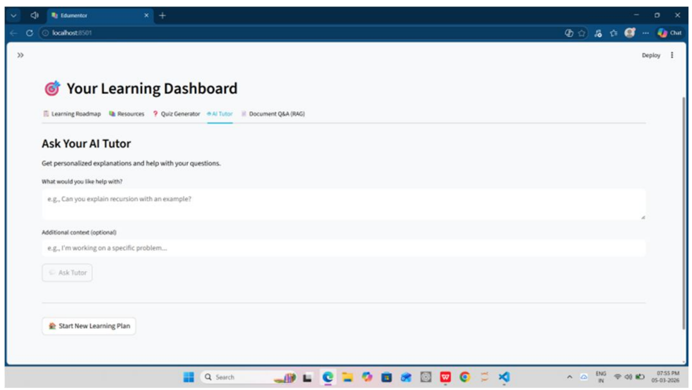

Figure 7: AI tutoring interface allowing users to ask questions and receive personalized explanations from the AI tutor.

VII. EVALUATION AND RESULT

A. Experimental Setup

The proposed system was evaluated to analyze its ability to generate personalized learning assistance and respond to user queries effectively. The platform was deployed locally using a Python environment and accessed through a web interface developed with Streamlit. The system integrates multiple AI agents that operate sequentially to perform tasks such as student analysis, roadmap generation, resource recommendation, quiz generation, and tutoring assistance.

Different learning topics from categories such as programming, mathematics, and science were used to test the adaptability of the system. Users provided inputs including the learning topic, knowledge level, learning goal, available study time, and preferred learning style. The system then generated personalized learning outputs based on these inputs.

For document-based learning evaluation, users uploaded study materials such as PDF and text files. These documents were processed using a Retrieval-Augmented Generation pipeline and stored in a ChromaDB for similarity-based retrieval.

B. Evaluation Metrics

Since the proposed system does not involve training a traditional machine learning model, its performance was evaluated using system-level metrics relevant to generative AI applications. The following metrics were considered:

1) Response Relevance – Measures how relevant the generated responses are to the user's query or learning goal.
2) Response Time – Measures the time required for the system to generate outputs such as roadmaps, quizzes, or tutoring responses.
3) Task Success Rate – Measures how successfully each AI agent performs its assigned task.
4) Retrieval Effectiveness – Evaluates the accuracy of retrieving relevant document segments during document-based question answering.

These metrics help assess both the usability and performance of the system.

C. System Performance

The evaluation results indicate that the multi-agent architecture successfully coordinates different AI agents to perform specialized learning tasks. The student analyzer agent generates structured learning profiles based on user inputs, while the roadmap creator agent produces step-by-step learning plans tailored to the student's goals and knowledge level.

The quiz generator agent creates practice questions covering different difficulty levels, allowing students to evaluate their understanding of the topic. The tutoring agent provides detailed explanations and guidance based on student queries.

The average response time for generating learning outputs was observed to be between **1.5 and 3 seconds**, depending on the complexity of the request and the type of task performed by the agent.

D. Experimental Results

The document-based question answering module demonstrated effective retrieval of relevant information from uploaded study materials. By integrating retrieval with language model generation, the system produced context-aware responses grounded in the uploaded documents.

The overall performance of the system across different modules is summarized in Table I.

Module	Avg Response Time	Task Success Rate
Student Analysis	1.8 s	100%
Roadmap Generation	2.2 s	96%
Quiz Generation	1.9 s	95%
AI Tutoring	2.3 s	94%
Document Q&A (RAG)	2.5 s	93%

The results demonstrate that the proposed system effectively integrates multi-agent AI processing with retrieval-based knowledge access to provide personalized learning assistance and interactive tutoring support.

VIII. CONCLUSION

This paper presented Edumentor – Multi-Agent AI Study Assistant, an intelligent learning platform designed to provide personalized educational support using a multi-agent architecture. The system analyzes student inputs such as topic, knowledge level, learning goals, and preferred learning style to generate customized learning roadmaps, recommended resources, quizzes, and tutoring assistance.

The platform integrates multiple specialized AI agents that collaborate to perform different educational tasks, enabling an adaptive and interactive learning experience. In addition, the system incorporates a Retrieval-Augmented Generation mechanism that allows students to upload study materials and receive context-aware answers based on those documents.

The results demonstrate that the proposed system successfully combines generative AI capabilities with document retrieval techniques to deliver personalized learning assistance. The integration of a multi-agent framework improves task specialization and enables the system to handle multiple learning functions within a single platform. Overall, the proposed system highlights the potential of AI-powered educational assistants in improving accessibility, personalization, and efficiency in modern digital learning environments

IX. FUTURE SCOPE

The proposed system can be further enhanced by incorporating additional intelligent features to improve its functionality and learning effectiveness. Some potential future improvements include:

1) Adaptive Learning Analytics: Tracking student progress and dynamically updating learning roadmaps based on performance and learning patterns
2) Voice-Based Interaction: Integrating speech recognition to allow students to interact with the system through voice commands.
3) Collaborative Learning Features: Enabling multiple users to share study materials and participate in group learning sessions.

4) Improved Resource Recommendation: Enhancing the recommendation module using advanced algorithms to provide more relevant learning materials
5) Mobile Application Support: Developing a mobile version of the platform to make the system more accessible for students on smartphones and tablets.

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