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A Comprehensive Survey of an Agentic AI Powered Multimodal RAG Learning System

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Abstract: Modern-day education has changed due to the utilization of artificial intelligence by implementing adaptive learning systems tailored towards individual students. Traditional learning methods generally present the same content to every learner without considering individual learning speed, understanding, or preferences. To address this limitation, this project proposes Data Spark Assistant – An Agentic AI Powered Multimodal RAG Learning System, an intelligent learning platform that delivers personalised educational support using Artificial Intelligence (AI). The system combines Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), Natural Language Processing (NLP), and Agentic AI to analyse learner performance and generate customised study materials. Through intelligent quizzes and assessments, the platform identifies each learner's strengths, weaknesses, and knowledge gaps. Based on this analysis, it recommends personalised lessons, practice questions, and learning resources that help students improve in weaker areas. By integrating adaptive learning techniques with AI-driven content generation, the proposed system creates an interactive and personalised learning environment. This approach enhances learning efficiency, encourages self-paced study, promotes critical thinking, and supports better academic performance.

Keywords: Adaptive Learning, Agentic AI, Retrieval-Augmented Generation (RAG), Large Language Models (LLMs), Natural Language Processing (NLP), Knowledge Gap Analysis, User Profiling, Multimodal Learning.

I. INTRODUCTION

The rapid advancement of digital technologies has transformed many sectors, including education. Traditional learning methods often provide identical educational content to all learners, regardless of their individual abilities, interests, or learning pace. As a result, students may struggle to understand complex concepts or remain unchallenged by material that is too simple. This highlights the need for intelligent educational systems that can adapt to each learner's unique requirements.

The proposed project, Data Spark Assistant – An Agentic AI Powered Multimodal RAG Learning System, is designed to provide an intelligent and adaptive learning environment for students. The system accepts user queries in multiple formats, retrieves relevant information from uploaded study materials and external knowledge sources, and generates accurate, context-aware responses. It also evaluates learner performance through quizzes and assessments to identify knowledge gaps and recommend personalised study materials. By integrating adaptive learning techniques with AI-powered content generation, the proposed system creates an engaging learning experience that supports self-paced education, improves conceptual understanding, and enhances academic performance. The platform is intended to serve as an intelligent learning assistant for both students and educators, making education more personalised, interactive, and effective.

Key Issues and Solution Proposed

The platform is designed specifically for detecting knowledge gaps among learners and creating personalized content for users. There are various techniques used by the platform in order to create adaptive content for learners. The system uses intelligent technologies, namely LangChain and API in order to generate personalized content. Users can communicate with the platform using different ways.

One of the crucial steps during the process of personalized learning includes identifying knowledge gaps in users' experience. This goal may be achieved by offering personalized quizzes for learners. Personalized adaptive quizzes allow analyzing the level of users' knowledge and skills and detecting their gaps in order to improve performance.

Another crucial issue of personalization includes assessing learners' abilities in order to generate appropriate materials. Users take various quizzes on the platform and generate personalized quizzes with various levels of difficulty according to learners' preferences. The system evaluates learners' results to detect gaps in their performance.It is necessary to mention that one of the most valuable characteristics of the platform is its ability to receive feedback from users. Feedback helps adapt personalized content in accordance with changing preferences and skills of learners.

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II. RELATED WORK

Artificial Intelligence has changed the way we learn. It makes learning fun and personal for students. Before online learning systems were not very good. They gave every student the material no matter how well they understood it or how fast they learned. This made it hard for students to stay interested and learn well.

To make it better researchers started using technologies like Natural Language Processing and Large Language Models. These technologies help create platforms that can respond to what each student needs.

Many people have done research on question generation and adaptive assessment techniques. Early systems used methods to create multiple-choice questions and evaluate student performance. These approaches helped with assessments. However they were not very good at understanding the context or creating content.

Now Artificial Intelligence-powered educational systems are more advanced. They can generate notes answer questions summarize topics and even act like tutors. These technologies have improved how learners interact with Artificial Intelligence systems. They have made personalized education more practical.

However many existing systems still have problems like providing information. Large Language Models depend on trained data. They may sometimes provide responses. This is especially bad in environments where accuracy's very important.

In (2024)[2] K.V. Parekh, N. Saxena and M. A. Ansari, presented RAG chatbots have also been beneficial in academic advising, as highlighted in, where the team developed an LLM-based chatbot that extracts student data from transcripts to provide targeted advice. Students were provided with quality advice on choosing courses, monitoring graduation requirements, and optimizing learning paths by having upfront access to previously hard-to-find information. Outside of research and counseling, also demonstrates how RAG-based LLMs can be leveraged to provide accurate and timely information about queries regarding admissions, programs, faculties, and campus facilities. A study introduced OpenRAG, an open-source retrieval-augmented generation framework for online learning platforms. This framework can generate customized learning paths based on individual students' needs and preferences, thus improving engagement and reducing comprehension times. Apart from student-facing applications, demonstrated how RAG-powered chatbots can help overcome issues with prolonged usage of e-books.

The TP AI Assistant architecture was developed, leveraging various Azure services. To start off, subject leaders uploaded training materials to SharePoint Online, before Azure Logic App copied them to a secure Storage Account, ensuring centralized access, indexing, and retrieval while minimizing manual effort and errors. After which, the Logic App ran an indexer of AI Search to make uploaded documents retrievable.[4] A ChatGPT-like web application (see Fig. 1) was then designed and hosted on Azure with Agentic Artificial Intelligence functionality the App Service. Users must authenticate via Microsoft Entra ID to securely access the platform. When a question was posed, AI Search retrieved relevant responses from the indexed data, which are processed by Azure OpenAI and delivered back through the web app.[4]

Their method leverages pre-trained language models (LMs) to generate questions that match a student's current knowledge state and desired difficulty level. This paper focuses on reverse language translation tasks using data from Duolingo for the purpose of predicting whether a student will answer a question based on the LM-KT description. The authors then trained a question-generation model to dynamically generate questions of a specified difficulty, thereby improving upon the adaptability of online education. Results indicate fine-grained control over question difficulty while holding fluency and novelty. The study emphasizes the potential of language models in personalized education and adaptive curriculum design.

To solve these problems researchers introduced Retrieval-Augmented Generation. This combines information retrieval techniques with Artificial Intelligence models. Retrieval-Augmented Generation-based systems first find information from trusted documents or databases. Then they generate responses based on that information. This method helps improve the accuracy and reliability of Artificial Intelligence-generated answers.

Retrieval-Augmented Generation has gained attention in domains where factual correctness is essential. Even though Retrieval-Augmented Generation has shown results its use in systems is still limited. Many Artificial Intelligence learning assistants continue to rely on general-purpose Large Language Models.
These models may not properly understand content or institutional study materials. In some cases these systems cannot effectively use documents, lecture notes or custom learning documents provided by students and teachers. As a result there is often a mismatch between the generated answers and the actual educational resources required for learning.
The proposed system, "DataSpark Assistant: An Agentic Artificial Intelligence Powered Multimodal Retrieval-Augmented Generation Learning System" is designed to address these limitations. The DataSpark Assistant generates

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responses, from uploaded and verified documents. This approach ensures that the information provided to students is accurate and relevant.

By restricting the system to document-based retrieval the chances of misleading answers are significantly reduced. Another important feature of the proposed project is its ability to handle types of learning resources. The DataSpark Assistant can process text documents, images and user queries.

The DataSpark Assistant is designed to process multiple forms of input, including text documents, images, and natural language queries. By integrating Agentic Artificial Intelligence, the system can understand user requirements, retrieve relevant information, analyse learning needs, and provide intelligent academic assistance. This enables learners to receive accurate, context-aware, and personalised support throughout their learning system journey.

The system incorporates Retrieval-Augmented Generation (RAG) to improve the quality and reliability of AI-generated responses. Instead of relying only on the knowledge stored within a Large Language Model (LLM), the RAG framework retrieves relevant information from uploaded study materials and trusted knowledge sources before generating responses. This approach ensures that the answers are more accurate, up-to-date, and relevant to the learner's query. By integrating advanced AI technologies with adaptive learning mechanisms, the DataSpark Assistant overcomes many of the limitations of existing educational systems. The platform encourages self-paced learning, strengthens conceptual understanding, and promotes critical thinking through interactive and personalised educational support.

III. METHODOLOGY

The intended aim of this research is to develop an AI-based educational ecosystem to generate new insights into educator-student interactions, develop an on-going, continually re-designing approach towards education that closely mimics the interactivity and reasoning that take place in an effective educator-tutor relationship. Therefore, the method of operation is structurally based on five (5) connected phases that employ human-like reasoning to simulate the way a human would reason as a tutor.

A. Intelligent User Profiling

The first step for personalizing content for a learner begins with developing a deep understanding of their cognitive profile based on past experiences and self-reported interests. An Agentic Profiling Module records more than just a student's name. By synthesizing past experiences with a student to derive their cognitive state of knowledge using the knowledge scaffolding function, the agent can determine the appropriate level of knowledge for a beginner (Zawacki-Richter, 2019) and make suggestions for activities accordingly.

The Agent also utilizes multimodal affinity analysis to identify the preferred method that a student learns best through, i.e. whether they learn best through visual representation (diagrams), auditory representation (lectures) or written representation (structured text) (Taneja et al., 2025). The agent then deploys activities according to the preferred method of the student.

Fig. 1: Intelligent User Interface

B. Diagnostic Quizzes and Adaptive Assessment

The goal of the agent in administering an adaptive assessment is to provide the learner with appropriate, personalized and contextually relevant learning materials and activities at the time that the learner is engaged in the learning process.

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Adaptive assessment, unlike traditional assessments which provide fixed, standardised feedback on performance based on normative comparisons of performance on the assessment (i.e., performance relative to peers), is a method of gathering, analyzing and assessing real-time feedback about the learner while they are in the learning process (Deci, 2001). The agent generates diagnostic assessments that enable the learner to establish their current level of content knowledge and skills; they are also designed to provide the agent with insight into how best to support the learner's successful completion of the assessment process as they progress through the learning process.

C. Multimodal User Responses

In order for a system to be truly human-like, it must look beyond just the "right/incorrect" answer. The Human-Computer Intelligent System will perform a Semantic Gap Analysis on the end-user responses received by the Intelligent Agent; this Phase looks specifically at the "Why" behind an erroneous answer from the user & determine if the user is having issues with the actual concept or just a term within their specific subject area through process of Semantic Gap Analysis (Zawacki-Richter, et al, 2019).

Fig. 2: Generated Form to Collect Data

The collection of qualitative data regarding the manner in which any student interacts with the system is critical for this overall Phase to be successful, this is where the integration of "Multimodal" components is utilized. This includes gaining insight into how a student is utilizing a diagram to interact with the learning material or how long did they spend reviewing a video segment; therefore providing the Agent with what is referred to as a "heat map" of learning challenges that exist for students (Seo, et al, 2021).

D. Agentic Content Generation - RAG Process

After a Lag (Knowledge Gap) is identified, the RAG (Retrieval Augmented Generation) process begins with the system initiating an Autonomous Retrieving process to close the Gap using the following processes:

Sequential & Vector Indexing of Educational Inputs: The indexing process occurs chronologically (to preserve the narrative flow) & semantically (to find hidden associations); this ensures that the information retrieved from the Knowledge Base does not feel like a collection of fragmented pieces of Educational Data (Taneja, et al., 2025).

RAG Process Using Knowledge Graphs: The function of using Knowledge Graphs provides the foundation upon which the RAG process occurs.

IV. Proposed System

The proposed DataSpark Assistant – An Agentic AI Powered Multimodal RAG Learning System is designed to provide an intelligent, adaptive, and personalised learning experience by combining Agentic AI, Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), and multimodal data processing.

The system is activated when a user submits a query through the User Interface (UI). The input may be in the form of text and can also include images or audio, enabling multimodal interaction. Before users can interact with the system, an offline document ingestion process is performed. During this phase, study materials in formats such as PDF, DOCX, and TXT are uploaded into the system. The documents are processed by extracting the text, removing unnecessary content, cleaning the data, and dividing it into smaller text chunks. These chunks are then converted into embeddings, which are numerical vector representations that capture the semantic meaning of the text.

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The generated embeddings are stored in a FAISS (Facebook AI Similarity Search) Vector Database, allowing the system to perform fast and efficient semantic searches. This indexing process enables the assistant to retrieve information based on meaning rather than simple keyword matching.

After receiving the input, the system forwards the request to the Retrieval Agent, which searches for relevant information from the knowledge base to generate an accurate and context-aware response. After the Retrieval Agent returns the chunks of information to the Answer Agent (which is powered by an OpenAI LLM) the Answer Agent generates an answer from the chunks of information returned by the Retrieval Agent.

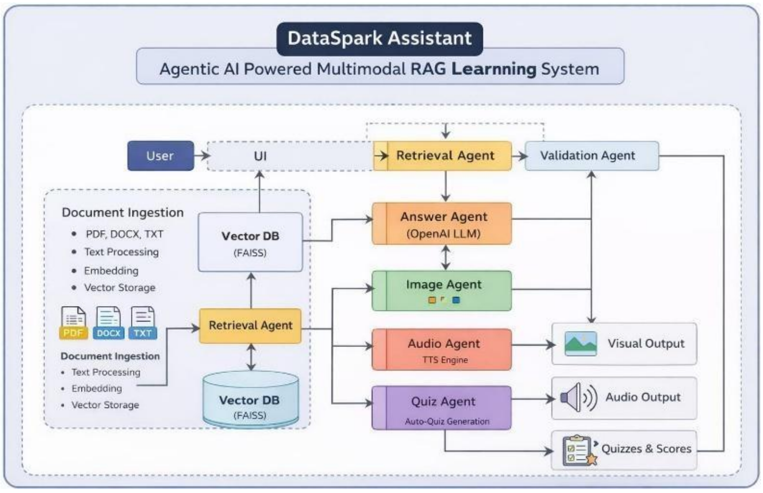

Fig. 3: Flow Chart of the proposed RAG chatbots

Ingesting Documents into the RAG System requires chunking the documents into smaller chunks so that they can be easily processed and embedded into an array of numbers (high-dimensional vectors). The chunks are stored in the Vector Database (VD) when the document upload process is complete.

Once a user submits a question, they need to have their question embedded (i.e., loaded into the VD as a query) and then find the top K most similar chunks to the user's question based on how similar the embedding of the question is to the stored embeddings in the VD (most likely using some form of fast ANN index such as the ones provided by FAISS). The LLM generates an answer to the user's question, which is based on the retrieved documents.

This report contains details on data formats (raw text, chunks, embeddings, etc.) algorithms (chunking, embedding models, ANN search) and aspects of the system (e.g., VD, top K retrievals, context assembly). The proposed system also addresses several important challenges associated with Retrieval-Augmented Generation (RAG). These include scalability, which ensures efficient retrieval from large document collections; low latency, which enables fast response generation; and common error modes, such as handling out-of-domain queries and reducing hallucinations by grounding responses in retrieved documents. In addition, the system incorporates privacy and security mechanisms, including Personally Identifiable Information (PII) protection, data encryption, and secure storage practices to safeguard user information.

V. COMPARATIVE ANALYSIS

The primary objective of this study is to compare the proposed DataSpark Assistant – An Agentic AI Powered Multimodal RAG Learning System with traditional learning methods in terms of learner engagement, adaptability, personalisation, and overall learning effectiveness. The comparison aims to evaluate whether an AI-driven learning environment can provide a more efficient and interactive educational experience than conventional teaching approaches.

The purpose of this project (an early phase study) was to compare an AI-developed/customized learning system versus traditional educational methods regarding learners' engagement and adaptability.

The following outlines the procedures to compare the AI (custom-built learning experience) vs. traditional education (standardized curriculum), utilizing the same metrics (engagement measures) to evaluate learnings.

Step 1: Quantitative Data (Participation/Engagement Measure)

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Quantitative data (time spent on site and feedback measures) demonstrated that learners had engaged with the content created by the (AI) learning systems (i.e., engagement was found). In total, the quantitative data showed that an AI-developed/customized (individualized) learning experience is more engaging than conventional teaching.

Step 2: Qualitative Data (Learner/Participant Feedback)

User engagement was measured through indicators such as: participation in the learning activities, time spent engaged in learning activities, the frequency of interaction with the systems, etc. In addition to the quantitative evaluation, a qualitative analysis was conducted to understand learners' experiences and opinions regarding the use of the AI-powered learning system. Participants were asked to provide feedback on the effectiveness, usability, and overall learning experience offered by the DataSpark Assistant. Their responses were analysed to identify the strengths and potential improvements of the proposed system.

The qualitative findings revealed several significant benefits of incorporating Artificial Intelligence into the learning process:

1. Flexibility:

Participants reported that the system effectively adapted learning materials, quizzes, and assessments according to their individual learning pace, knowledge level, and academic objectives.

2. Knowledge Gap Identification:

The AI-powered assistant successfully identified learners' weak areas through intelligent assessments and performance analysis. Based on the identified knowledge gaps, the system recommended personalised study materials, practice exercises, and quizzes to improve conceptual understanding.

3. Interactive Learning Experience:

Students found the contextual quizzes, AI-generated explanations, and conversational interactions engaging and informative. The immediate feedback provided by the system encouraged active participation, self-paced learning, and better understanding of complex concepts.

REFERENCES

[1] An Empirical Evaluation of Retrieval, Reranking, and Similarity for a Q&A-Based Retrieval Augmented Generation System, Harun Elkiran, Jawad Rasheed, in proceedings of IEEE Access, Year: 2026 | Volume 14 | Journal Article | Publisher: IEEE, **DOI:** 10.1109/ACCESS.2026.3664852

[2] A Comparative Study of Retrieval-Augmented Generation (RAG) Chatbots, K.V. Parekh, N. Saxena and M. A. Ansari, in Proceedings of the 2025 International Conference on Automatics, Robotics and Artificial Intelligence (ICARAI), Year: 2025 | Conference Paper | Publisher: IEEE,**DOI:** 10.1109/ICARAI67046.2025.11137956

[3] Advanced AI-Powered Platform for Student Learning and Academic Enhancement, G. Mounika, A. Gaddi, P. Gaddi, K. Varun, and K. Vihar in Proceedings of the 2025 International Conference on Visual Analytics and Data Visualization (ICVADV), Year: 2025 | Conference Paper | Publisher: IEEE, **DOI:** 10.1109/ICVADV63329.2025.10961252

[4] Exploring Student Engagement and Personalized Learning with a Retrieval-Augmented Generation (RAG) Chatbot, H. Zhang, B. Z. J. Teo, E. G. H. Goh, K. Subramaniyan, and K. H. Lee in Proceedings of the 2025 International Conference on Artificial Intelligence and Education (ICAIE), Year: 2025 | Conference Paper | Publisher: IEEE, **DOI:** 10.1109/ICAIE64856.2025.11157971

[5] Development of Interactive Assistance for Academic Preparation Using Large Language Models, P. Kumar, Haresh M, Hayagreevan V in Proceedings of the 2025 International Conference On Computational Communication and Information Technology (ICCCIT), Year: 2025 | Conference Paper | Publisher: IEEE, **DOI:** 10.1109/ICCCIT62592.2025.10928137

