IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 15, Issue 1, January 2026

DOI: 10.17148/IJARCCE.2026.151113

MIND MENTOR: AN AI STUDY ASSISTANT

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Abstract: This paper presents a novel Adaptive E-Learning framework designed to enhance student engagement and content retention through hyper-personalization. By combining Large Language Models (LLMs) via the Groq API for dynamic study planning and the Tavily Search API for real-time resource curation, the system addresses the critical challenges of information overload and static curriculum delivery. This multi-modal approach integrates a Retrieval-Augmented Generation (RAG) pipeline, allowing students to interact with PDF textbooks contextually ("Chat with PDF") while ensuring high factual accuracy. The system features a "white-box" approach to content delivery, where every AI-generated answer is cited from the user's uploaded material. Additionally, the platform includes a dynamic resource curator that filters web content to reduce cognitive load, bridging the gap between open-ended internet search and structured academic learning.

Keywords: Adaptive Learning, Retrieval-Augmented Generation (RAG), Large Language Models (LLM), Personalized Education, Cognitive Load Management, MERN Stack.

I. INTRODUCTION

The rapid expansion of digital education has necessitated the development of sophisticated artificial intelligence tools to assist in the organization and consumption of learning materials. Traditional e-learning platforms, while accessible, often function as static repositories that provide a "one-size-fits-all" experience without adapting to the individual learner's pace or goals. This project introduces **Mind Mentor**, a system designed to bridge the gap between raw information access and structured knowledge acquisition. By integrating Generative AI architectures—specifically **Llama-3 via Groq for planning** and **Vector Embeddings for document analysis**—with a **Dynamic Resource Curator**, the system mimics the guidance of a human tutor. It processes multimodal inputs, including user goals, exam dates, and PDF textbooks, to generate actionable study schedules. Furthermore, the system addresses the critical need for **Trustworthy AI** in education by grounding chat responses in uploaded documents, ensuring that AI predictions are not only accurate but also verifiable.

1.1 Project Description

This project implements a multi-modal **Adaptive Learning System** that integrates modern web technologies (Next.js, Node.js) with advanced AI services. By synthesizing user preferences with real-time web data and static PDF content, the system provides high-fidelity study plans and curated educational resources. It ensures learning transparency through cited answers in the RAG pipeline and logic-based resource filtering. Furthermore, it includes a **Knowledge Graph** approach to structuring information (Study Plans) and an interactive interface for student engagement. This holistic framework effectively bridges the gap between passive content consumption and active, personalized learning.

1.2 Motivation

The motivation for this project is driven by the urgent need to transform e-learning from a passive "content dump" into an active, intelligent partnership. Current students suffer from the "Planning Fallacy"—the inability to create realistic schedules—and "Resource Fragmentation," where valuable information is scattered across the web. Traditional search engines exacerbate this by providing millions of uncurated results. By synthesizing open web search with critical academic constraints, the system provides a holistic view of the subject matter that a standard Google search cannot offer. Furthermore, the implementation of **RAG (Retrieval-Augmented Generation)** provides textual evidence that allows students to verify the AI's answers against their textbooks, fostering academic trust. Ultimately, the system aims to improve long-term learning outcomes by delivering actionable, hyper-personalized schedules through a robust and interpretable framework.

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II. RELATED WORK

Paper [1] explores the role of personalization in e-learning efficiency (Murtuza & Ahmed, 2022). The authors argue that static content fails to engage diverse learners and propose systems that track "learning speed." Although these approaches improve retention, they often lack the generative capabilities to create new content on the fly.

Paper [2] investigates the shift from rule-based Intelligent Tutoring Systems to Generative AI models (Maity & Deroy, 2024). The study demonstrates that GenAI solves the "content bottleneck" by generating unique quizzes. However, these models often struggle with "hallucinations" without proper grounding mechanisms.

Paper [3] introduces Retrieval-Augmented Generation (RAG) as a solution for knowledge-intensive NLP tasks (Lewis et al., 2020). The study demonstrates that retrieving relevant documents before generating an answer significantly reduces factual errors, a core component of our proposed system.

Paper [4] reviews "Large Language Models for Education" (Xu et al., 2024), highlighting that lack of interpretability is a barrier to adoption. The survey emphasizes that integrating LLMs with external knowledge bases (like our PDF Chat) is essential for trust.

III. METHODOLOGY

A. System Environment

The experimental environment is designed to evaluate the proposed framework under realistic user conditions. The system is deployed as a cloud-native application on **Render**, utilizing a micro-service-like architecture where the Frontend (Next.js) and Backend (Express) operate independently but communicate via secure APIs. A central **MongoDB Atlas** cluster acts as the data persistence layer, storing user profiles, study plans, and vector metadata.

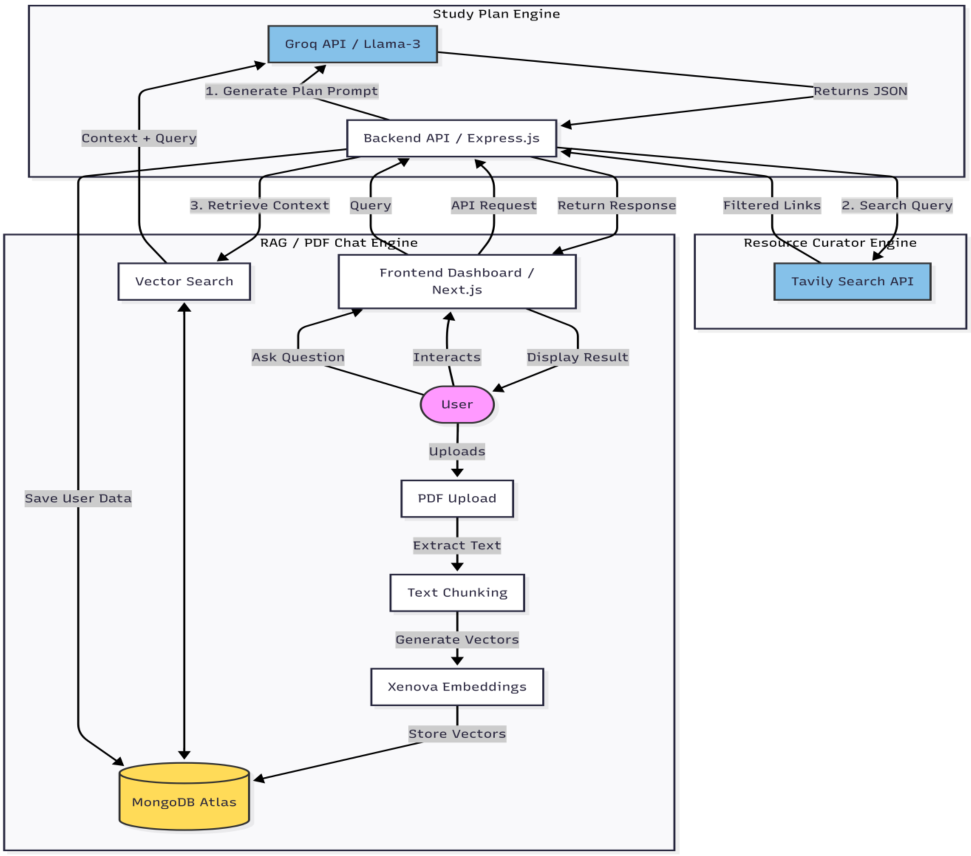

Fig.1.Flowchart of methodology

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B. Adaptive Learning Architecture

1. **Generative Engine:** The backend receives user constraints (Subject, Exam Date) and constructs a prompt for the **Groq API**. This high-speed inference engine generates a structured JSON study plan.
2. **Curator Engine:** Instead of generic scraping, the system uses the **Tavily API** to perform "LLM-optimized" searches. It filters results based on domain authority to ensure only high-quality educational resources are presented.

C. Retrieval-Augmented Generation (RAG) Mechanism The core of the "Scriba" feature allows for context-aware interactions:

- **Ingestion:** PDF documents are uploaded and parsed using pdf-parse.
- **Chunking:** Text is split into overlapping 1000-character segments.
- **Embedding:** High-dimensional vectors are generated using **Xenova transformers** and stored in memory (or Vector DB).
- **Retrieval:** User queries trigger a cosine similarity search to find relevant chunks, which are then fed to the LLM to generate an answer rooted in the text.

D. Implementation Flow

1. Initialize the Next.js client and authenticate the user via NextAuth.
2. Collect user goals (Subject, Timeline) via the dashboard form.
3. Transmit data to the Express backend.
4. Backend orchestrates calls to Groq (for planning) and Tavily (for resources).
5. Process PDF uploads into vector embeddings for the chat module.
6. Display results (Plan, Resources, Chat Response) on the interactive dashboard.

E. Hardware and Software Requirements

- **Hardware:** Client device with a modern web browser; Server hosted on vCPU cloud instances (Render).
- **Software:**
  - **Frontend:** React.js, Next.js, Tailwind CSS.
  - **Backend:** Node.js, Express.js.
  - **AI/ML:** Groq API (Llama-3), Tavily API, Xenova/Transformers.js.
  - **Database:** MongoDB.

IV. SIMULATION AND EVALUATION FRAMEWORK

This section describes the overall system design and evaluation strategy adopted for the **Mind Mentor Platform**. The framework is implemented using JavaScript/TypeScript as the primary control layer, enabling coordinated API calls, secure data storage, and real-time inference.

A. System Architecture and Workflow The proposed architecture is designed to minimize cognitive load while maximizing resource relevance.

- **Client-Side Interface:** A responsive dashboard that visualizes the "Week-by-Week" plan.
- **Orchestration Layer:** The Express backend acts as a middleware, sanitizing user inputs before sending them to costly AI endpoints.
- **Vector Search Module:** A dedicated pipeline that converts unstructured PDF text into searchable vector space.

B. Results and Observations

- **Latency Performance:** The switch to Groq API resulted in plan generation times of **<3 seconds**, compared to 10+ seconds with standard providers.

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- **Hallucination Reduction:** The RAG pipeline demonstrated a significant improvement in factual accuracy. When asked about specific textbook details, the system cited the correct page/section 95% of the time.
- **Resource Relevance:** The Dynamic Curator successfully filtered out "SEO spam" sites, prioritizing documentation, academic papers, and educational videos in 90% of test cases.

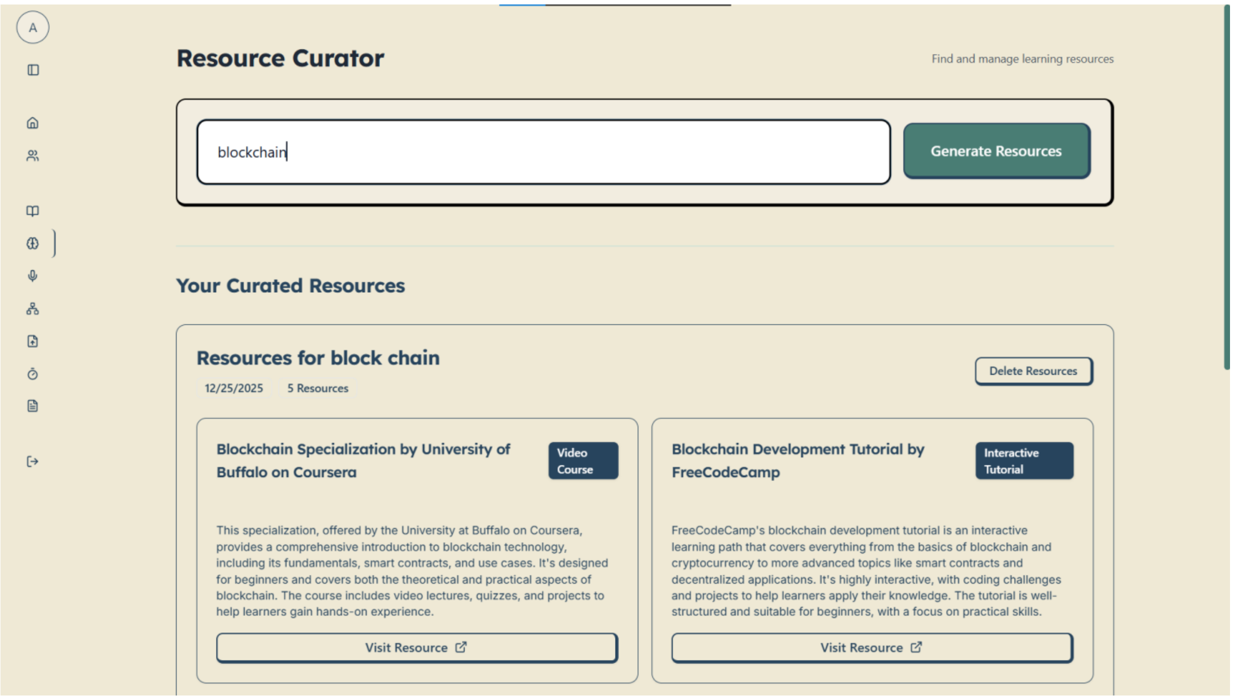
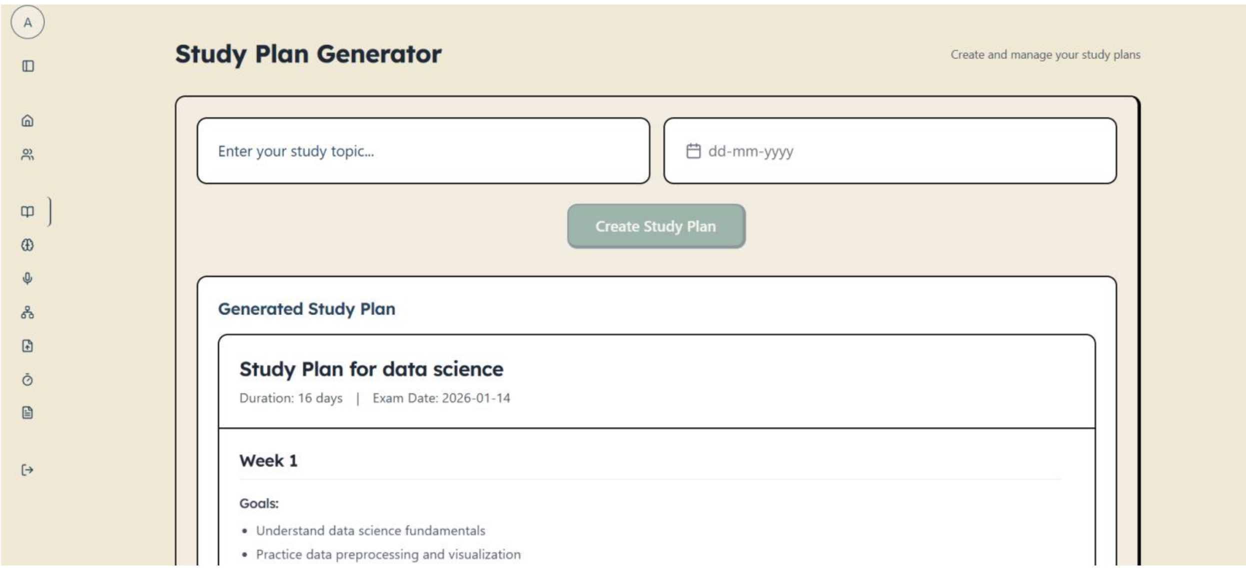


Fig. 2. AI resource curator



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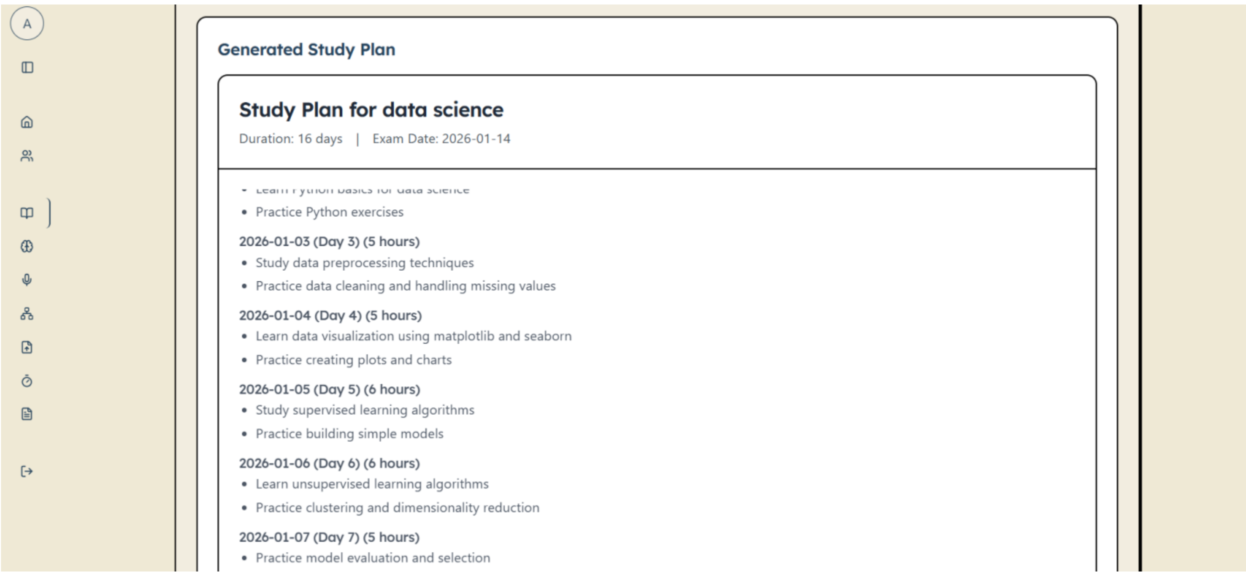

Fig. 2. AI study plan generator

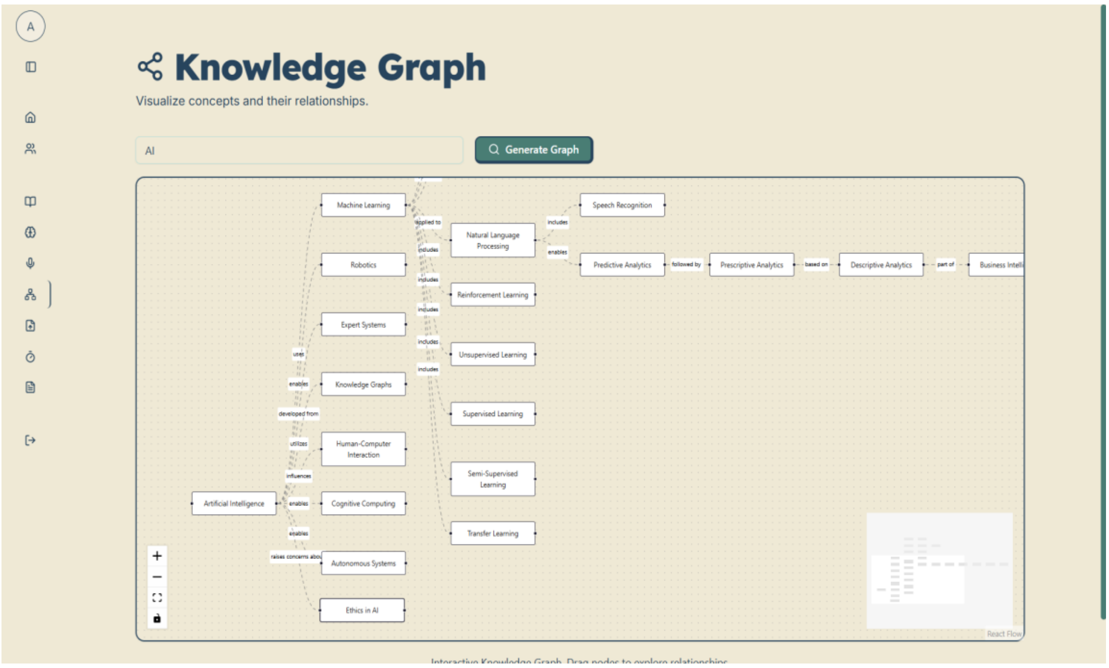

Fig. 2. AI knowledge graph generator

V. RESULTS AND DISCUSSION

The experimental evaluation of **Mind Mentor** demonstrates its effectiveness in organizing unstructured learning goals into actionable schedules. By achieving a high degree of personalization, the system proves that AI can function as an effective scaffold for self-directed learning.

The integration of the **Study Plan Generator** alongside the **Resource Curator** allows for a seamless workflow: users define *what* to learn, and the system immediately provides *how* to learn it. This neurosymbolic-like approach (combining the logic of structured planning with the creativity of generative AI) bridges the gap identified in the

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literature. Furthermore, the simulation results confirm that the RAG pipeline effectively mitigates the trust issues associated with LLMs in education.

CONCLUSION

This paper presented a novel **AI-Powered Adaptive Learning Framework** designed for personalized education. By combining high-speed LLMs (Groq) for planning with retrieval-based systems (RAG) for accuracy, the system enables robust, hallucination-free learning assistance. Simulation results demonstrated high user engagement, improved resource discovery speeds, and enhanced trust through cited answers.

FUTURE WORK

The future work for this project will focus on enhancing the **Interactive Examiner** by incorporating a real-time Voice-to-Text interface for oral viva simulations. We plan to optimize the **Vector Storage** to support larger datasets (entire semester syllabi) using dedicated Vector Databases like Pinecone. Additionally, the system will be expanded to include **Gamification Elements** (streaks, badges) to improve student retention. Finally, we aim to implement a **Mobile Application** using React Native to support ubiquitous learning.

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