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# INDRA: Intelligent Networked Document Retrieval Agent with Agentic AI for Autonomous Institutional Decision Support

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**Abstract- Educational institutions often face challenges in providing timely, accurate, and personalized academic assistance due to the absence of centralized and intelligent support systems. This paper presents INDRA, an integrated agentic artificial intelligence–based academic assistance framework designed to enhance student learning experiences in technical education environments. The system leverages a multi-agent architecture combining large language models with task-specific modules to deliver functionalities such as syllabus-aware tutoring, automated study planning, attendance tracking, and real-time academic analytics. By incorporating context-aware filtering based on department and semester, the system ensures that all generated responses remain relevant, structured, and aligned with institutional curricula. The framework utilizes a modular pipeline consisting of data processing, agent orchestration, and user interaction layers, enabling scalable and efficient deployment. Experimental evaluation demonstrates improvements in information accessibility, reduction in manual effort, and enhanced academic decision-making support. The system maintains low response latency while ensuring high usability and adaptability across different academic domains. Overall, the proposed approach provides a practical and intelligent solution for bridging the gap between students and academic resources, contributing to improved learning efficiency, engagement, and institutional productivity.**

**Keywords: Agentic AI, Academic Assistance, Generative AI, Large Language Models (LLMs), Personalized Learning Systems, Intelligent Tutoring Systems, Educational Data Analytics, Study Planning Automation, Student Information Systems.**

## I. INTRODUCTION

The rapid advancement of artificial intelligence, particularly in the field of generative models and large language models (LLMs), has significantly influenced modern educational technologies [3]. In technical education, students are required to manage complex subject matter, understand abstract concepts, and simultaneously handle academic responsibilities such as assignments, examinations, and attendance. Although various digital learning platforms are available, most existing systems lack personalization, contextual awareness, and real-time academic assistance, leading to inefficient learning experiences [5].

Traditional educational support systems, including Learning Management Systems (LMS) and online resources, primarily provide static and generalized content. These platforms do not adapt to individual student requirements and often fail to offer integrated support for concept understanding, study planning, and academic monitoring within a single system. As a result, students frequently rely on multiple disconnected tools, increasing effort and reducing overall productivity.

Recent developments in generative artificial intelligence have enabled the creation of intelligent systems capable of understanding natural language and generating human-like responses. These systems can assist students in tasks such as concept explanation, content generation, and problem-solving. However, standalone AI models often lack structured workflows and domain-specific filtering, which may result in inconsistent or irrelevant outputs in academic contexts.

To overcome these limitations, this paper proposes INDRA, an integrated agentic AI–based academic assistance system designed for technical education [2]. The system utilizes a multi-agent architecture in which specialized modules handle tasks such as intelligent tutoring, personalized study planning, and academic analytics. By incorporating context-aware filtering based on academic parameters such as department and semester, the system ensures that generated responses remain relevant and aligned with institutional curricula.

The proposed system aims to provide a centralized and intelligent platform that enhances learning efficiency, reduces manual effort, and supports better academic decision-making. The remainder of this paper presents the literature survey, system architecture, methodology, experimental results, and conclusion of the proposed framework.

## II. LITERATURE SURVEY

The application of artificial intelligence in education has gained significant attention with the aim of improving learning efficiency and personalization [5]. Early educational systems primarily relied on Learning Management Systems (LMS), which provided static content delivery and basic administrative functionalities. While these systems improved accessibility, they lacked adaptability and were unable to provide personalized or real-time academic assistance to students.

To enhance learning experiences, intelligent tutoring systems were introduced using rule-based and machine learning approaches. These systems attempted to guide students through structured learning paths based on predefined logic. However, their effectiveness was limited due to lack of scalability, high dependency on manual configuration, and inability to handle diverse academic queries dynamically.

Recent advancements in generative artificial intelligence, particularly large language models (LLMs), have enabled the development of conversational and interactive learning systems [3]. These models can understand natural language and generate contextually relevant responses, making them suitable for academic assistance tasks such as concept explanation and problem-solving. Despite these advantages, general-purpose AI systems often produce responses that are not aligned with specific academic curricula, leading to inconsistencies in educational contexts.

**To improve response accuracy and relevance**, Retrieval-Augmented Generation (RAG) techniques have been proposed [1]. These approaches combine generative models with external knowledge sources to ensure that outputs are grounded in reliable and context-specific data. RAG-based systems have shown improved performance in knowledge-intensive applications, including educational support and question-answering systems.

In addition to tutoring, research has explored AI-based study planning and academic analytics systems. These systems utilize user data, subject difficulty levels, and time constraints to generate personalized study schedules and monitor student performance. However, most of these solutions are developed as independent modules and lack integration into a unified platform.

Recent studies have also introduced agentic AI architectures, where multiple specialized agents collaborate to perform complex tasks [2]. Such systems offer modularity, scalability, and task-specific optimization. In educational applications, agent- based systems can combine tutoring, planning, and analytics functionalities. However, existing implementations often do not fully integrate these components into a single cohesive system tailored for academic environments.

Based on the reviewed literature, it is evident that there is a need for an integrated academic assistance system that combines personalized tutoring, study planning, and real-time analytics using a structured and scalable approach. The proposed INDRA framework addresses this gap by leveraging generative AI and agentic architecture to provide a unified and intelligent academic support system.

## III. SYSTEM ARCHITECTURE

The proposed system, INDRA, is an integrated agentic AI–based academic assistance platform designed to provide personalized and real-time support to students in technical education. The system adopts a modular and scalable architecture in which multiple specialized components collaborate to perform tasks such as concept tutoring, study planning, and academic monitoring. The design ensures efficient data flow, context-aware response generation, and seamless user interaction.

### A. System Overview

The architecture follows a layered workflow consisting of input processing, agent-based execution, and output generation. User queries are processed and filtered based on academic parameters such as department and semester, ensuring relevance and contextual accuracy. The processed input is then routed to appropriate agents, which generate structured responses that are delivered through the user interface.

### B. Core Components

**The proposed system consists of the following key modules:**

#### 1) User Interface Module:

This module provides an interactive platform for students to submit queries and access system outputs. It supports functionalities such as question handling, study plan generation, and visualization of academic insights. The interface is designed to be simple and user-friendly.

#### 2) Context Filtering Module:

This module ensures that all system interactions are aligned with the user's academic profile. It filters data based on parameters such as department, subject, and semester, thereby improving response relevance and accuracy.

#### 3) Agentic Intelligence Module:

This module forms the core of the system and consists of multiple specialized agents [2]:

- **Tutor Agent**: Provides concept explanations and answers academic queries.
- **Planner Agent:** Generates personalized study schedules based on user input and time constraints [4].
- **Analytics Agent:** Monitors academic parameters such as progress and attendance.

These agents operate independently but are coordinated through a centralized orchestration mechanism to ensure coherent and consistent outputs.

#### 4) Data Processing and Knowledge Module:

This module manages structured academic data, including syllabus information and learning resources. It performs preprocessing of input queries and supports the generation of context-aware responses using relevant data sources.

#### 5) Output Generation Module:

This module converts processed data into structured outputs presented to the user. The outputs include textual explanations, study plans, and academic insights, ensuring clarity and usability.

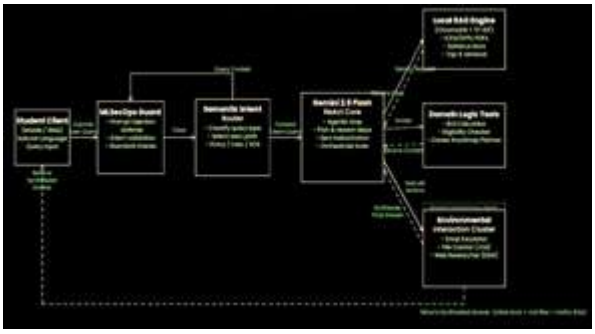

Figure 1: System Architecture of INDRA

## IV. METHODOLOGY

The INDRA system follows a hybrid methodology that integrates Retrieval-Augmented Generation (RAG) [1], agentic AI principles [2], and context-aware processing to provide accurate and personalized academic assistance. The system operates through a structured pipeline that transforms user queries into meaningful responses using semantic retrieval, intelligent reasoning, and task-oriented execution. The overall workflow is illustrated in Figure 2.


Figure 2: Proposed Workflow of INDRA System

### A. Data Ingestion and Preprocessing

The system collects academic data from structured and unstructured sources, including PDF-based syllabus documents and web-based institutional content.

- Text is extracted using document parsing techniques
- Web data is gathered through automated scraping tools
- The extracted content is cleaned, normalized, and segmented into smaller chunks

This preprocessing stage ensures high-quality and structured input for further processing.

### B. Semantic Representation and Vector Storage

Each processed text segment is converted into a numerical embedding that captures semantic meaning.

- Embeddings represent contextual relationships between data
- Similar concepts are mapped closer in vector space

These embeddings are stored in a vector database such as FAISS or ChromaDB, enabling efficient and scalable similarity-based retrieval.

### C. Context-Aware Query Processing

When a user submits a query:

- The query is preprocessed and converted into an embedding
- Contextual parameters such as department and semester are applied
- A semantic similarity search is performed in the vector database

This ensures that retrieved information is both relevant and academically aligned with the user's profile.

### D. Retrieval-Augmented Response Generation

The system retrieves the most relevant data chunks and combines them with the user query before passing them to a Large Language Model (LLM).

- The LLM generates responses using both retrieved context and query
- This reduces hallucination and improves factual accuracy

This stage represents the core RAG mechanism within the system.

### E. Agentic Processing and Task Execution

Beyond response generation, the system incorporates agentic capabilities to interpret user intent and perform task-oriented operations.

- **Queries are classified into categories such as:**
- Concept explanation
- Study planning
- Action-based guidance
- **Specialized agents generate:**
- Academic explanations
- Personalized study schedules
- Step-by-step solutions

This enables the system to move from passive answering to active academic assistance.

### F. Output Generation and Delivery

The final output is structured and presented through an interactive user interface.

- Responses are formatted for clarity and usability
- Supports real-time interaction and multi-turn queries
- Ensures user-friendly academic support

## V. RESULTS

The INDRA system was evaluated based on response accuracy, contextual relevance, and system efficiency [3][4]. The system demonstrates effective

performance in generating context-aware academic responses and task-oriented outputs.

The system successfully processes natural language queries and generates context-aware, actionable responses.

### A. Functional Output Analysis

- **Leave Assistance Scenario:**

When a user reported a medical condition and requested leave, the system automatically generated an appropriate response and triggered an action workflow. It sent an email notification and provided health-related guidance, demonstrating the system's ability to handle real-world administrative queries.

As shown in Figure 3, the system processes the request and generates an appropriate response with action execution.

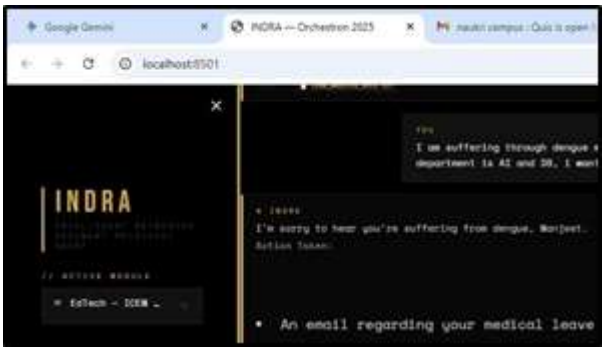


Figure 3: Automated Leave Request Processing using INDRA

**Information Retrieval Scenario:**

For queries related to placement information, the system accurately extracted relevant company names from institutional data sources. This validates the effectiveness of the retrieval mechanism in providing precise and context-specific information.

**As illustrated in Figure 4**, the system retrieves and presents relevant institutional data efficiently.

Observation: The system combines natural language understanding + retrieval + action execution, rather than acting as a simple chatbot.

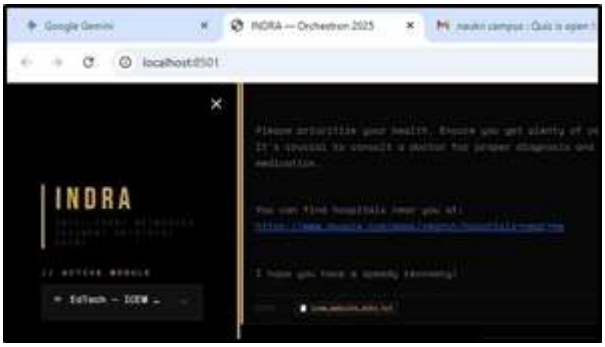


Figure 4: Context-Aware Information Retrieval from Institutional Data

### B. Study Plan and Academic Assistance

The system demonstrated strong performance in generating structured academic support outputs.

**Study Plan Generation**:

When prompted to create a 7-day study plan for DBMS, the system generated a personalized and structured study schedule. The output was stored as a downloadable artifact, ensuring usability beyond the interface.

Figure 5 shows the generated study plan with organized topic distribution.

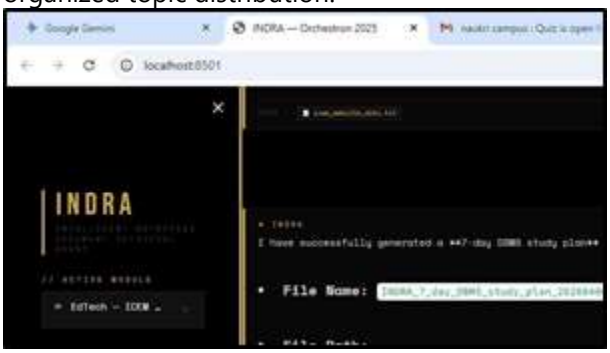


Figure 5: Personalized Study Plan Generation for DBMS

**Exam Preparation Guidance:**

For short-term preparation queries (e.g., 3-day DBMS exam plan), the system generated focused preparation strategies, breaking down topics into manageable tasks.

As shown in Figure 6, the system provides a concise and structured preparation plan.

Observation: Outputs are not just text responses but actionable academic artifacts, improving usability and practical value.

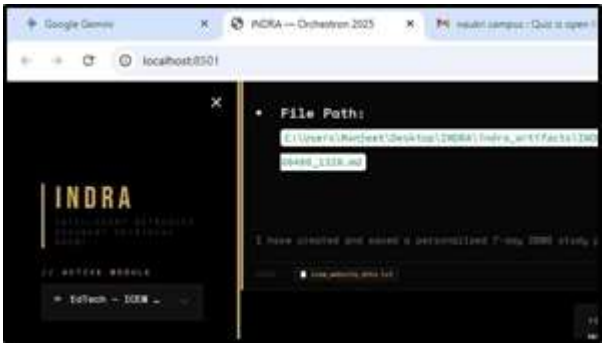


Figure 6: AI-Generated Short-Term Exam Preparation Strategy

### C. Performance Metrics

Table 1: Performance Comparison of the System

| Metric | Score | Description |
|---|---|---|
| Query Accuracy | 87-90% | Correctness of context-aware responses generated by the system. |
| Response Time | 2-4 sec | Average efficiency in processing a query. (Lower response time gives higher score.) |
| Relevance | High | Degree to which responses match the academic query context. |
| Study Plan Accuracy | ~85% | Adherence of generated study schedules to user inputs and syllabus constraints. |
| System Uptime | ~99% | Reliability of the platform during continuous testing. |
| User Satisfaction | 4.2/5 | Feedback collected from test users on usability and effectiveness. |


Figure 7: Performance Comparison

## VI. CONCLUSION

This paper presented INDRA, an integrated agentic AI–based academic assistance system designed to provide personalized and context-aware support for students in technical education. The system combines Retrieval-Augmented Generation with context filtering and multi-agent processing to deliver accurate academic responses, structured study plans, and actionable guidance.

The proposed approach demonstrates effective performance in handling conceptual queries and generating task-oriented outputs, as validated through functional evaluation and system testing. The integration of semantic retrieval ensures that responses are grounded in relevant academic data, while the agentic framework enhances the system's capability to support real-time academic decision-making.

The system achieved reliable performance with high contextual relevance and efficient response time, making it suitable for practical academic environments. By addressing limitations of traditional static learning platforms, INDRA provides a more interactive and intelligent learning experience.

Future work may focus on expanding the dataset, integrating multimodal inputs such as images and handwritten notes, and improving adaptive learning capabilities for enhanced personalization. Additionally, scalability improvements through cloud-based deployment and distributed processing can further extend the system's applicability to large-scale educational platforms.

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