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ASKIO: Transforming Digital Learning with AI-Driven Interaction and Retrieval-Augmented Generation

Asso.Prof. Alpana Rani

Department of Computer Science and Engineering

Inderprastha Engineering College, Site 4, Sahibabad, Ghaziabad, Uttar Pradesh, India

alpana.rani@ipec.org.in

Mridul Tiwari

Department of Computer Science and Engineering

Inderprastha Engineering College, Site 4, Sahibabad, Ghaziabad, Uttar Pradesh, India

mridultiwari2002@gmail.com

Prashant Singh

Department of Computer Science and Engineering

Inderprastha Engineering College, Site 4, Sahibabad, Ghaziabad, Uttar Pradesh, India

prashant2002singh915@gmail.com

Mohd Azeem

Department of Computer Science and Engineering

Inderprastha Engineering College, Site 4, Sahibabad, Ghaziabad, Uttar Pradesh, India

azeemidrisiofficial@gmail.com

Shantanu Pant

Department of Computer Science and Engineering

Inderprastha Engineering College, Site 4, Sahibabad, Ghaziabad, Uttar Pradesh, India

pantshantanu0@gmail.com

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Abstract: This paper presents ASKIO, an AI-powered learning platform that enhances education through Retrieval-Augmented Generation (RAG) and interactive content engagement. Unlike traditional Learning Management Systems (LMS), ASKIO enables users to interact with uploaded documents, ask questions, and receive AI-generated contextual responses. The platform integrates gamification, visualizations, and real-time collaboration to improve retention and engagement. By combining AI-driven learning, document interaction, and peer collaboration, ASKIO offers a personalized and immersive digital education experience for students and educators.

I. INTRODUCTION

The landscape of digital education is evolving rapidly with the integration of Artificial Intelligence (AI), offering innovative solutions to enhance learning experiences. Traditional Learning Management Systems (LMS) primarily function as content repositories, allowing educators to distribute materials and assess students. However, these systems often lack interactivity, personalization, and engagement, limiting their effectiveness in catering to diverse learning needs. To bridge this gap, AI-powered platforms are emerging as a transformative force in education, enabling dynamic content interaction,
real-time assistance, and adaptive learning environments.
To address these challenges, we introduce ASKIO, an AI-driven learning platform designed to enhance education through Retrieval-Augmented Generation (RAG), interactive content visualization, and collaborative engagement. ASKIO enables students to interact dynamically with uploaded documents, pose queries, and receive AI-generated contextual responses, thereby bridging the gap between static learning materials and intelligent, responsive learning assistance. Unlike conventional systems, ASKIO fosters a more engaging educational experience by incorporating gamification techniques, including quizzes, leaderboards, and spaced repetition, which have been shown to improve motivation and retention.

In addition to personalized learning, ASKIO provides a collaborative workspace, allowing students to engage in discussions, share insights, and work together on academic tasks. This peer learning environment enhances knowledge retention and promotes a deeper understanding of complex concepts. The seamless integration of AI-powered document interaction, interactive visualizations, and gamification elements makes ASKIO a comprehensive educational tool, empowering both students and educators.
This paper explores the architecture, core functionalities, and benefits of ASKIO in modern education. We discuss how AI-driven learning systems can enhance engagement, accessibility, and knowledge retention while addressing challenges in traditional learning methodologies. By leveraging AI for personalized education, ASKIO aims to redefine digital learning experiences and make education more efficient, interactive, and adaptive.

II. LITERATURE SURVEY

[1] **Rama Akkiraju, Anbang Xu, Deepak Bora, Tan Yu, Lu An, Vishal Seth, Aaditya Shukla, Pritam Gundecha, Hridhay Mehta, Ashwin Jha, Prithvi Raj, Abhinav Balasubramanian, Murali Maram, Guru Muthusamy, Shivakesh Reddy Annepally, Sidney Knowles, Min Du, Nick Burnett, Sean Javiya, Ashok Marannan, Mamta Kumari, Surbhi Jha, Ethan Dereszenski, Anupam Chakraborty, Subhash Ranjan, Amina Terfai, Anoop Surya, Tracey Mercer, Vinodh Kumar Thanigachalam, Tamar Bar, Sanjana Krishnan, Jasmine Jaksic, Nave Algarici, Jacob Liberman, Joey Conway, Sonu Nayyar, and Justin Boitano** in their study *FACTS About Building Retrieval Augmented Generation-based Chatbots* present a structured approach to designing enterprise chatbots using **Retrieval-Augmented Generation (RAG)** and **Large Language Models (LLMs)**. They discuss the challenges of engineering RAG pipelines, fine-tuning embeddings, optimizing document retrieval, and ensuring enterprise-specific chatbot reliability.
Their research introduces the **FACTS** framework, which highlights five essential dimensions for effective chatbot deployment: **Freshness of content (F), Architecture optimization (A), Cost efficiency (C), Thorough testing (T), and Security (S)**. The study explores fifteen **control points** in chatbot pipelines, including **query rephrasing, document retrieval strategies, reranking results, prompt engineering, response refinement, and access control mechanisms**.
The researchers draw insights from NVIDIA's deployment of **three enterprise chatbots**—NVInfoBot (enterprise knowledge retrieval), NVHelpBot (IT and HR assistance), and ScoutBot (financial information queries). Their empirical

analysis compares **large vs. small LLMs**, balancing factors like **accuracy, latency, and cost-effectiveness**. They find that while larger models generate richer responses, smaller models can provide **faster, cost-efficient interactions** without significant accuracy trade-offs when properly optimized.

By sharing practical learnings from real-world implementations, this study underscores the **complexities of enterprise chatbot development**. The authors emphasize that successful chatbot orchestration demands **meticulous RAG pipeline engineering, precise fine-tuning, and iterative testing** to ensure **reliable, secure, and scalable conversational AI solutions** for enterprises.

[2] Vani Bhat, Sree Divya Cheerla, Jinu Rose Mathew, and colleagues in their study **Retrieval Augmented Generation (RAG) based Restaurant Chatbot with AI Testability** explore the enhancement of restaurant chatbots by integrating **Retrieval-Augmented Generation (RAG) with Large Language Models (LLMs)** for improved natural-language interactions. Traditional chatbots often rely on pre-programmed responses, limiting their ability to handle complex user queries effectively. To address this, the researchers introduce a **Neo4j knowledge graph**, leveraging **Term Frequency - Inverse Document Frequency (TF-IDF) embeddings** to retrieve the most relevant answers based on user queries. This approach significantly enhances chatbot comprehension and response accuracy by integrating structured knowledge into the RAG pipeline.

The study also incorporates **fine-tuning of the T5 language model**, optimizing it for restaurant-related interactions. By passing retrieved answer tokens from the knowledge graph into the T5 model, the chatbot generates more **context-aware, fluent, and precise responses**. The effectiveness of this approach is demonstrated through a **BLEU score of 0.60**, indicating a high degree of precision in response generation. Furthermore, the research introduces **AI testability metrics**, which evaluate the chatbot at the **word, sentence, and information levels** to ensure robustness, relevance, and coherence in generated responses.

In contrast to conventional chatbot systems that rely on static datasets, this research highlights **a dynamic, self-improving framework** that not only retrieves external information but also refines chatbot responses over time. The study emphasizes **multimodal interaction capabilities**, allowing users to interact via text and voice, further enhancing user engagement. Additionally, the authors propose a **novel approach to knowledge graph creation**, clustering questions and answers based on shared tokens, which improves retrieval efficiency and contextual continuity.

By integrating **structured knowledge retrieval, adaptive response generation, and rigorous AI testability**, the research presents a **scalable and intelligent restaurant chatbot** that can handle **personalized recommendations, order management, and real-time customer support**. This work sets a new benchmark in chatbot evaluation and optimization, offering **practical implications for AI-driven customer service in the restaurant industry**.

[3] **Darren Edge, Ha Trinh, Newman Cheng, Joshua Bradley, Alex Chao, Apurva Mody, Steven Truitt, Jonathan Larson** in their study *From Local to Global: A Graph RAG Approach to Query-Focused Summarization* explore an innovative method for **query-focused summarization (QFS)** using a **Graph RAG approach**. Traditional **Retrieval-Augmented Generation (RAG)** systems struggle with **global questions** that require summarizing entire datasets rather than retrieving specific text segments. This research proposes a **graph-based indexing method** that enhances RAG's ability to handle large-scale text summarization.

When answering a user query, **each community summary contributes a partial response**, which is then further summarized into a **final global response**. This approach effectively **scales RAG-based summarization** by leveraging **graph modularity** and **community detection algorithms** (such as Leiden and Louvain methods) to partition datasets into **smaller, meaningful clusters**.

The researchers compare **Graph RAG** with **naïve RAG** and **direct map-reduce summarization**, demonstrating that **Graph RAG significantly improves comprehensiveness and diversity of responses**, while reducing computational cost. Their evaluation on real-world datasets (including **news articles and podcast transcripts**) highlights that **Graph RAG provides better global sensemaking capabilities** than traditional RAG pipelines, making it a promising solution for large-scale document analysis and enterprise applications.

[4] **Shamane Siriwardhana, Rivindu Weerasekera, Elliott Wen, Tharindu Kaluarachchi, Rajib Rana, and Suranga Nanayakkara** in their study *Improving the Domain Adaptation of Retrieval Augmented Generation (RAG) Models for Open Domain Question*

Answering (ODQA) explore the challenges of adapting **RAG models** beyond Wikipedia-based datasets to specialized domains such as **healthcare, news, and conversations**. Traditional **ODQA models** rely on a **retriever-reader pipeline**, but RAG integrates both into a single architecture, allowing it to leverage **parametric memory (LLMs) and non-parametric memory (external knowledge bases)** for improved accuracy and reduced hallucinations.

Their research introduces **RAG-end2end**, a novel extension of RAG that enhances **domain adaptation** by enabling **joint training of the retriever and generator components**. Unlike standard RAG, which keeps **external knowledge base encodings fixed**, RAG-end2end **dynamically updates** both the retriever's embeddings and the generator's parameters, ensuring better alignment with domain-specific datasets. Additionally, the authors propose an **auxiliary training signal**, which reinforces domain knowledge by requiring the model to **reconstruct sentences from retrieved information**. Through experiments on three **domain-specific datasets (COVID-19 research, News, and Conversations)**, the researchers demonstrate that:

Fine-tuning the retriever alongside the generator significantly improves accuracy, as opposed to only adjusting the question encoder. **The auxiliary training signal further enhances retrieval quality**, leading to better contextual understanding. **Asynchronous updates to the knowledge base encoding improve adaptability**, making RAG-end2end a more effective approach for domain-specific ODQA tasks.

Their findings highlight the **importance of full retriever fine-tuning** rather than isolated updates to **maximize RAG's performance** in specialized knowledge areas. The research is further supported by an **open-source implementation** via the **Hugging Face Transformers Library**, allowing broader adoption and experimentation within the AI research community.

[5] In their study Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks, Patrick Lewis et al. explore a novel approach to knowledge-intensive tasks in natural language processing (NLP) by combining pre-trained parametric and non-parametric memory. The paper [5] investigates how large pre-trained language models store factual knowledge in their parameters and perform well when fine-tuned on downstream tasks. However, the authors note that these models still struggle with precise knowledge manipulation, knowledge expansion, and providing provenance for decisions, particularly in knowledge-intensive tasks. The study introduces Retrieval-Augmented Generation (RAG), which combines a parametric seq2seq model (BART) with a non-parametric memory, represented by a dense vector index of Wikipedia, accessed via a pre-trained retriever.

The authors explore two RAG formulations: one that conditions on the same retrieved passages for the entire sequence and another that uses different passages per token. The paper demonstrates the effectiveness of RAG models, achieving state-of-the-art results on a variety of knowledge-intensive NLP tasks, such as open-domain question answering and language generation. The results indicate that RAG models outperform existing parametric seq2seq models and task-specific retrieve-and-extract architectures. In addition to improved accuracy, RAG models generate more specific, diverse, and factual language in comparison to traditional models. The study[5] also discusses the potential of combining parametric and non-parametric memory to address limitations in access to external knowledge. The authors highlight how pre-trained access mechanisms offer a significant advantage by enabling access to vast amounts of knowledge without the need for additional training. They emphasize that RAG's fine-tuning approach provides flexibility for a wide range of NLP tasks, making it a promising avenue for future research and development.

Key contributions of this paper include the development of the RAG model, which demonstrates improved performance in knowledge-intensive tasks. Furthermore, the study highlights the practical benefits of using non-parametric memory, as it allows for easier updates to the model's knowledge base, providing an avenue for more dynamic and current language generation. The work of Lewis et al.[5] lays a foundation for the further integration of retrieval-augmented techniques in NLP, offering solutions to some of the long-standing challenges in the field, such as knowledge revision, knowledge retrieval, and transparency in decision-making.

The paper also builds on previous work in retrieval-based models such as REALM and ORQA[5], showcasing how retrieval-augmented approaches can move beyond extractive tasks to include generation tasks, with remarkable improvements in accuracy and output quality. The authors provide a comprehensive analysis of these advancements, presenting RAG as a versatile and ef*ficient tool for knowledge-intensive NLP applications.*

III. METHODOLOGY

1. Cost Efficiency

Gemini Flash is optimized for low-cost inference, but its pricing is based on API usage, which can vary depending on the number of queries processed. DeepSeek, on the other hand, significantly reduces training and inference costs by using sparse neural networks and dynamic resource allocation. This makes DeepSeek more budget-friendly, especially for large-scale educational applications where cost efficiency is critical.

2. Processing Speed

Gemini Flash is designed for low-latency responses, making it well-suited for real-time interactions, which are essential in educational platforms like ASKIO. DeepSeek's Mixture-of-Experts (MoE) architecture enables dynamic task routing, reducing computational load and enhancing response time for specific tasks. This allows DeepSeek to maintain comparable processing speed while using fewer resources.

3. Architecture

Gemini Flash relies on a dense transformer model, which activates all parameters for every query. This ensures high accuracy but increases computational overhead. DeepSeek, in contrast, uses a sparse Mixture-of-Experts (MoE) approach, where only the relevant submodels are activated based on the task. This results in more efficient use of computational resources and improved scalability.

4. Customizability

Gemini Flash is a proprietary model accessible only through Google's API, which limits customization and fine-tuning. In contrast, DeepSeek is fully open-source, allowing developers to modify the model, adapt it to domain-specific tasks, and deploy it locally. This provides greater control over model behavior and data privacy.

5. Multimodal Capabilities

Gemini Flash supports text, image, and code generation, which makes it highly effective for document processing and interactive learning. DeepSeek extends these capabilities by also supporting audio inputs and enabling cross-modal tasks, such as generating code from images and answering audio-based queries. This makes DeepSeek more versatile for handling diverse content types in educational settings.

6. Performance Benchmarks

Gemini Flash delivers high accuracy in general-purpose queries and is well-optimized for educational and creative tasks. However, DeepSeek achieves approximately 90% of GPT-4's accuracy at just 15% of the cost. It also outperforms Gemini Flash in efficiency-adjusted benchmarks, making it an attractive option for cost-conscious educational platforms.

7. Scalability

Gemini Flash scales well within Google Cloud infrastructure, making it ideal for high-traffic applications with predictable usage patterns. DeepSeek, with its lightweight design and dynamic resource allocation, offers better scalability for cost-sensitive applications, especially when operating under variable traffic conditions.

8. Data Privacy

Gemini Flash operates on a cloud-based model, which limits direct control over data and raises potential privacy concerns. DeepSeek allows local deployment, providing greater control over data security and compliance with educational privacy standards.

Which Model is Better for ASKIO?

Gemini Flash is ideal for ASKIO's current setup, where low-latency AI responses and seamless cloud integration are essential for real-time educational applications. Its optimized infrastructure ensures consistent performance under high query loads. However, DeepSeek's cost efficiency, open-source flexibility, and enhanced multimodal capabilities make it a strong alternative for future scalability and customization needs.

IV. SYSTEM IMPLEMENTATION

ASKIO is a learning platform that integrates **Retrieval-Augmented Generation (RAG)** with real-time interaction and document-based Q&A. The system is implemented using a **React frontend**, an **Express backend**, and **Gemini Flash** as the AI model for processing and generating responses.

Frontend Implementation (React)

The frontend is built using **React.js** to provide a responsive and interactive user interface.

- **Authentication:** OAuth2-based login allows users to authenticate via Google, ensuring secure access.
- **File Upload:** Users can upload PDFs directly from the UI.
- **UI Components:** Material UI and custom hooks are used for building forms, dialogs, and navigation elements.
- **Real-Time Interaction:** State management is handled using **Redux** and **Context API** for seamless updates.
- **Visualization:** AI-generated responses are displayed using charts and text components for better user understanding.

Backend Implementation (Express.js)

The backend is developed using **Express.js** to manage API requests and process data.

- **API Endpoints:** RESTful endpoints handle file uploads, document parsing, and AI query requests.
- **Middleware:** Body parsing and CORS are enabled for secure and efficient request handling.
- **Database:** MongoDB stores user information, document data, and AI responses.
- **Caching:** Results are cached using Redis to improve response time for repeated queries.
- **Rate Limiting:** Express-rate-limit is implemented to prevent abuse of AI query endpoints.

AI Model (Gemini Flash)

Gemini Flash is used as the RAG model to handle document-based Q&A and content generation.

- **RAG Integration:** Uploaded PDFs are processed to extract text, which is then sent to Gemini Flash for analysis and response generation.
- **Contextual Understanding:** The model generates answers based on both document content and user queries.
- **Fine-Tuning:** The model is adapted to educational contexts by optimizing query patterns.
- **Multimodal Processing:** Gemini Flash supports both text and image-based inputs, enhancing the platform's capability to handle different content types.

Workflow

1. User logs in using Google OAuth.
2. User uploads a document (PDF).
3. Express backend stores the document in MongoDB and extracts text using a PDF parser.
4. User submits a query related to the document.
5. Query and document context are sent to Gemini Flash via an API call.
6. Gemini Flash processes the request and generates a response.
7. Response is stored in MongoDB and sent back to the React frontend for display.
8. AI-generated content is visualized using React components.

Additional Features

- **Gamification:** Users earn points for correct answers and participation.
- **Collaboration:** Users can work together in shared workspaces.
- **Analytics:** User engagement and model response accuracy are tracked using an analytics dashboard.

V. MODEL's ARCHITECTURE

Gemini Flash is part of Google's Gemini family of AI models, designed for fast, low-latency performance while retaining high accuracy across various tasks. Its architecture leverages a combination of **dense transformers**, **Mixture-of-Experts (MoE)** strategies, and **multimodal integration** to handle text, image, and code-based inputs efficiently.

1. Transformer-Based Core
Gemini Flash uses a **dense transformer** architecture, where all model parameters are activated for every query. This allows the model to handle complex language understanding and generation tasks with high accuracy. The transformer layers are optimized for low latency, enabling quick response times for real-time applications.

- **Attention Mechanism:** Gemini Flash employs a multi-head attention mechanism to process input sequences. This allows the model to focus on different parts of the input simultaneously, improving context comprehension.
- **Positional Encoding:** Since transformers lack inherent sequence information, Gemini Flash uses positional encodings to retain the order of tokens, ensuring accurate contextual understanding.

2. Lightweight Design for Fast Inference
Unlike larger models such as Gemini Ultra, Gemini Flash is designed to minimize computational overhead:

- **Fewer parameters** compared to full-sized models, reducing memory consumption and speeding up inference.
- **Optimized token handling** for efficient processing of large input sizes without performance degradation.
- **Parallel processing** across multiple GPUs or TPUs to increase throughput and reduce latency.

3. Multimodal Capabilities
Gemini Flash integrates text, images, and code into a unified framework, allowing it to process and generate responses across different modalities.

- **Image Understanding:** Uses vision transformers (ViT) for image feature extraction and fusion with textual inputs.
- **Code Generation:** A specialized coding module generates structured outputs for coding tasks.
- **Cross-Modal Learning:** Combines textual and visual data for tasks like caption generation, image-based reasoning, and multimodal question answering.

4. Knowledge Compression and Distillation
To enhance efficiency, Gemini Flash employs knowledge distillation techniques from larger models (such as Gemini Ultra):

- Trained using a **teacher-student framework** where knowledge from larger models is compressed into the smaller Flash model.
- This allows Gemini Flash to retain high accuracy despite its smaller size.

5. Task-Specific Adaptation
Gemini Flash includes specialized layers for different task types:

- **Language tasks:** Enhanced with contextual embeddings and masked token prediction.
- **Image tasks:** Processed through convolutional and attention-based modules.
- **Coding tasks:** Uses fine-tuned transformers with syntax-aware embeddings.

6. Efficient Token Handling and Memory Management
Gemini Flash uses an optimized tokenization strategy to improve memory efficiency and processing speed:

VI. CONCLUSION

In this paper, we have explored the ASKIO platform, an AI-powered learning tool that is reshaping the educational landscape through personalized, interactive, and adaptive learning experiences. By leveraging Retrieval-Augmented Generation (RAG), ASKIO enables students to engage dynamically with educational content, providing AI-generated contextual responses to queries and enhancing the learning process. The platform's integration of gamification, real-time collaboration, and multimodal interactions fosters increased motivation, retention, and peer engagement.
ASKIO's future potential lies in the continued advancement of AI algorithms, which will further personalize learning paths, predict knowledge gaps and suggest tailored resources. The inclusion of emerging technologies such as AR/VR, speech

recognition, and blockchain-based certification promises to make learning even more immersive, secure, and accessible. Additionally, ASKIO's cross-platform support and integration with existing LMS systems offer a flexible, scalable solution for educational institutions.

Ultimately, ASKIO stands as a comprehensive, next-generation educational ecosystem, poised to redefine the way students learn and interact with content. With its focus on AI-driven personalization, collaborative learning, and gamified engagement, ASKIO has the potential to significantly enhance the effectiveness and reach of digital education, creating a more inclusive, engaging, and efficient learning environment for students worldwide.

VII. FUTURE SCOPE

As artificial intelligence (AI) and educational technologies continue to advance, ASKIO presents numerous opportunities for expansion and enhancement. The integration of emerging AI-driven innovations can significantly improve personalization, accessibility, and interactivity, making digital learning more effective and engaging. The following areas highlight key directions for the future development of ASKIO:

- **Enhanced AI Personalization**: Future iterations of ASKIO can implement more sophisticated adaptive learning algorithms that analyze user behavior, performance, and preferences. By leveraging machine learning models, the platform could predict knowledge gaps and suggest personalized study plans, recommended resources, and real-time intervention strategies to improve learning outcomes.

- **Multimodal Learning and NLP**: ASKIO can integrate speech recognition, natural language understanding (NLU), and AI-driven content generation to enhance accessibility. Students could interact with the platform using voice commands, receive AI-powered explanations for video lectures, and analyze handwritten input, making learning more dynamic and engaging.

- **Augmented Reality (AR) and Virtual Reality (VR) Integration**: By incorporating AR/VR technologies, ASKIO can create immersive learning experiences for subjects like medicine, engineering, and history. For example, medical students could explore 3D anatomical models, and engineering students could engage with virtual physics simulations to enhance conceptual understanding.

- **AI-Powered Gamification and Virtual Tutors**: ASKIO can introduce AI-driven virtual tutors that provide real-time feedback, personalized quizzes, and adaptive difficulty adjustments. Gamification elements like leaderboards, AI-generated challenges, and dynamic quizzes can further boost motivation and engagement.

- **Blockchain-Based Certification**: The platform can integrate blockchain technology to issue tamper-proof digital certificates, micro-credentials, and decentralized academic records. This would allow students to securely share their verified achievements with employers and institutions.

- **Cross-Platform and Multi-Language Support**: ASKIO can expand accessibility by supporting multiple devices (mobile, web, offline modes) and offering multi-language support with AI-powered real-time translation and text-to-speech capabilities for inclusivity.

- **Integration with Institutional LMS and APIs**: To enhance adoption, ASKIO can integrate with existing Learning Management Systems (LMS) and third-party APIs, allowing seamless content sharing, data synchronisation, and AI-enhanced learning experiences without disrupting current educational infrastructures.

- **AI-Powered Research and Knowledge Discovery**: ASKIO can assist researchers and professionals by enabling automated literature reviews, intelligent document analysis, and AI-assisted problem-solving models, helping in scientific discoveries and technical analysis.

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