End-to-End Deployment of the Educational AI Hub for Personalized Learning and Engagement: A Case Study on Environmental Science Education

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Abstract
This study introduces an end-to-end framework for deploying conversational AI-enabled educational assistants, focusing on personalized support for students across diverse subject areas, including Business, Culture, Environmental Sciences, History, Politics, and Science, as outlined in our evaluation framework. The system leverages advanced conversational AI technologies to provide targeted, course-specific learning experiences by facilitating access to complex data and integrating seamlessly with Learning Management Systems (LMS) like Canvas. Key metrics—information retrieval accuracy, question-answering accuracy, and hallucination accuracy—were selected to rigorously evaluate the system's ability to retrieve relevant contexts, generate accurate responses, and identify unanswerable questions. Additionally, the Educational AI Hub agents utilize innovative document parsing methods, such as the Nougat technique, to interpret content accurately, enabling adaptable academic support tailored to individual learning needs and extending to quantitative fields through code execution capabilities. This study also emphasizes the importance of accessibility, inclusivity, and user privacy. The results showcase the potential for enhanced engagement and improved understanding of environmental concepts and software tools, demonstrating the significant impact of conversational AI in educational settings, especially in disciplines involving complex data interactions. A case study, presented at the 12th International Congress on Environmental Modelling and Software, illustrates the Educational AI Hub's effectiveness in enhancing student engagement and delivering personalized learning experiences in environmental sciences education.

Keywords: Artificial Intelligence (AI), Natural Language Processing (NLP), Large Language Models (LLM), Generative Pre-training Transformer (GPT), Personalized Learning, Document Parsing Techniques

Software Availability

Name	Educational AI Hub
Developers	Ramteja Sajja, Yusuf Sermet
Contact information	https://hydroinformatics.uiowa.edu
Cost	Free
Software required	Web Browser

Program language	JavaScript, HTML, Node.js, Python
Software Availability	https://hydroinformatics.uiowa.edu/lab/academicaihub/

1. Introduction

Bridging the communication gap in education requires a multifaceted approach that integrates technology, innovative teaching methods, and targeted skill development. Effective communication is crucial in various educational contexts, from conflict management in medical training to language proficiency in the workplace. For instance, structured conflict management sessions using role-play and high-fidelity simulation have proven effective in teaching anesthesiology residents' essential communication skills, highlighting the importance of practical, experience-based learning (Sinskey, 2021). Similarly, in developing countries like India, there is a pressing need to enhance English communication skills to meet organizational demands, suggesting that academia and industry must collaborate to provide real-world learning experiences and embrace new teaching technologies (Priya, 2022). The integration of technology in K-12 education has also been shown to improve communication and engagement.

Professional development sessions that focus on technology use can help teachers better engage students, thereby enhancing the overall learning experience (Downing, 2021). Additionally, innovative teaching methods such as the flipped classroom approach, which offers flexibility and encourages discussion, have been effective in helping students understand complex subjects like construction and statics, further emphasizing the role of interactive and visual learning aids (Tedjokoesoemo, 2022). In marketing education, a project-based learning approach that incorporates design thinking can bridge the gap between theory and practice, fostering essential soft skills like communication, creativity, and collaboration, which are critical for professional success (Patrício, 2022). These strategies can be particularly impactful in environmental sciences, where understanding complex, multidisciplinary topics and using advanced tools are essential for addressing real-world environmental challenges.

The field of environmental sciences is inherently complex and multidisciplinary, requiring students to engage with a broad spectrum of knowledge that spans geology, biology, chemistry, and physics, often integrated through sophisticated software tools (Lee, 2023; Ramirez et al., 2022). Traditional educational methods in this domain have relied heavily on theoretical instruction and static resources, which can fail to capture the dynamic and interactive nature of environmental issues and processes (Winkler & Söllner, 2018; Ewing et al., 2022). This educational approach often leaves a gap in student engagement and understanding, particularly in applying theoretical knowledge to solve practical, real-world problems (Holmes et al., 2019). Moreover, the rapid evolution of environmental technologies and methodologies necessitates a learning approach that can adapt quickly and provide students with the latest information and tools, a need not fully met by conventional educational models (Sajja et al., 2023c).

To address these challenges, the introduction of AI in educational settings, particularly through the educational assistant AI framework, offers a promising solution. The framework can transform the learning experience by providing interactive, adaptive, and personalized educational support (Sajja et al., 2023a). Specifically, in environmental sciences education, there is a critical need for tools that can not only deliver information but also interpret complex data sets, visualize and communicate data using novel methods (Sermet and Demir, 2022), simulate environmental processes, and provide hands-on experience with industry-standard software (Li and Demir, 2022). Educational AI systems must be capable of handling the diverse and often complex queries typical of environmental sciences, necessitating advanced capabilities in NLP and contextual understanding (Yusuf and Demir, 2021).

Recent advancements in AI, such as the AI Hub for water quality management using ChatGPT (Samuel et al., 2024a), and the AI-DE system for on-demand analysis of water quality data (Vald et al., 2024), demonstrate the potential of AI technologies in environmental data interpretation and management. These systems leverage large language models (LLMs) and natural language processing (NLP) to provide user-friendly interfaces for complex environmental data, making them accessible and comprehensible to a broad audience (Samuel et al., 2024b). Such technologies highlight the transformative potential of AI in making specialized knowledge accessible, particularly in environmental sciences where data interpretation is critical for informed decision-making.

Adaptive learning technologies are revolutionizing education by tailoring instructional content to individual learners' needs, abilities, and interests, thereby enhancing learning efficiency and engagement. These technologies leverage artificial intelligence to dynamically adjust course material, providing both automated and instructor-led interventions to accelerate learner performance (Capuano & Caballé, 2020). For instance, a study involving ninth-grade Algebra I students demonstrated that personalized problems aligned with students' interests in sports, music, and movies led to faster and more accurate problem-solving, particularly benefiting those struggling within the tutoring environment (Walkington, 2013).

Additionally, adaptive learning technologies are being employed in bioengineering education through initiatives like the National Science Foundation's VaNTH Engineering Research Center, which developed the courseware authoring and packaging environment (CAPE) to make authoring adaptive learning activities accessible to educators (Howard, 2003). In higher education, adaptive learning platforms such as Realizeit have shown that the interaction of various elements—knowledge acquisition, engagement, growth, and communication—plays a crucial role in the learning process, with significant variability observed based on course length, subject area, and instructional design (Dziuban et al., 2018). Overall, adaptive learning technologies offer a promising approach to personalized education, though their implementation must be carefully considered to maximize their potential benefits while accounting for opportunity costs.

Current educational challenges in engagement and personalization are multifaceted, involving both pedagogical and technical aspects. One significant challenge is the need for systems that can provide personalized learning experiences from the start, as traditional methods relying on historical data or quizzes are insufficient for immediate personalization (Lee & Ferwerda, 2017). The rise of e-learning and gamification (Demiray et al., 2023) has heightened students' expectations for personalized experiences that recognize their skills and preferences, yet many educational games still use a "one-fits-all" approach, which fails to cater to individual learning styles and needs (Terzieva, 2019). Additionally, the design and implementation of personalized learning models are complicated by the diverse requirements of businesses and educational goals set by the state, necessitating a careful balance between these factors and the technologies used for personalization (Petrova, 2020).

Online learning platforms face the challenge of managing diverse content types and user interactions, requiring a comprehensive framework to normalize and utilize this data effectively for personalized recommendations that align with users' learning objectives and deadlines (Turrin, 2017; Kaynak et al., 2024). Furthermore, context-aware technologies, while promising, struggle with integrating sound pedagogical foundations and ensuring learner involvement, which is crucial for effective learning. Enhancing personalization through social and collaborative learning approaches, such as forming groups based on sociological preferences and structuring activities according to experiential learning models, has shown positive impacts on learner engagement and performance (Mayeku, 2022). The integration of generative AI in hackathons is emerging as a significant area of study, with research indicating positive outcomes in enhancing student engagement and learning experiences (Sajja et al., 2024). Overall, addressing these challenges requires innovative solutions that combine advanced technological capabilities with robust pedagogical strategies to create engaging and personalized learning environments.

This paper presents a research study on the development and implementation of an Educational AI Hub system, with a particular focus on its application in environmental sciences education. The study explores how the system addresses key educational challenges such as engagement and personalization by integrating advanced adaptive learning technologies. These technologies facilitate personalized, context-aware learning experiences tailored to individual student needs, which are especially crucial in fields like environmental sciences that involve complex data and processes. The system’s seamless integration with Learning Management Systems (LMS) is a central feature, enabling direct incorporation of smart assistants into the LMS to streamline access and usability for both students and educators.

The research includes a case study presented at the 12th International Congress on Environmental Modelling and Software, where the Educational AI Hub's impact and potential were discussed. This case study incorporates feedback from instructors who attended the conference, providing insights into the perceived effectiveness and practical applications of the system. The paper will examine the system's architecture and features, as well as the feedback from these professionals, to assess the system's potential for broader adoption in educational settings, particularly in disciplines requiring dynamic and interactive learning environments.

The structure of this paper is as follows: Relevant Work section delves into the existing literature, emphasizing gaps in the current knowledge. The Methods section articulates the approaches, detailing the design choices and implementation of the system. The results section presents our findings and interprets their significance. The discussion section presents the strengths and limitations of our study, potential future directions, and summarizes our contributions to the field. Finally, the Conclusion section provides final remarks and outlines future research directions.

2. Related Work

Adaptive learning platforms have demonstrated significant effectiveness in enhancing student engagement and performance across various educational settings. These platforms personalize learning pathways, catering to individual student needs, which has been shown to improve learning outcomes. For instance, a study on a grade 3 mathematics curriculum revealed that students using an adaptive personalized e-learning platform showed marked improvements in academic performance and satisfaction, particularly those who initially had lower performance levels (Sayed et. al., 2023). Similarly, in a Numerical Methods course, the behavioral interactions of students with the adaptive platform and their performance on adaptive assessments were strongly associated with overall course success (Yalcin et. al., 2023).

In dental education, adaptive lessons significantly improved student engagement, motivation, perceived knowledge, and exam performance during the COVID-19 pandemic (Yakin & Linden, 2021). Furthermore, in a civil engineering technology course, increased time spent on adaptive content correlated with higher correct response rates (Barclay et. al., 2020). Lastly, a study comparing dental students' performance using an Adaptive Learning Platform (ALP) in a blended learning environment found that those using the ALP summatively scored significantly higher on final exams (Alwadei et. al., 2020). Recent tools can generate flashcards and quizzes automatically on any topics asked (Sajja et. al., 2023b).

AI-based educational tools, particularly virtual teaching assistants, are revolutionizing the educational landscape by addressing various challenges and enhancing learning experiences. These tools leverage advanced natural language processing (NLP) and machine reading comprehension (MRC) technologies to create intelligent systems capable of answering course-specific questions and providing personalized assistance. For instance, an AI-augmented intelligent educational assistance framework based on GPT-3 has been developed to generate course-specific intelligent assistants, improving access to information and reducing the logistical workload for instructors (Sajja et. al., 2023a). Additionally, an AI Virtual Teaching Assistant with Smart Search and Feedback has been developed to supplement traditional teaching methods by providing a Q&A system with high accuracy in question mapping (Cheung et. al., 2022). The application of popular virtual assistants like Amazon Alexa and Google Assistant in education has also been explored, highlighting their potential to engage students and support the learning of foreign languages (Pereira, 2022).

Learning analytics has become a pivotal component in modern education, driven by the growth of information and communication technologies and the emergence of big data. This field leverages data from learning management systems (LMS) and virtual learning environments (VLEs) to analyze student interactions and improve learning outcomes through data-driven decision-making (Stokes & Fudge, 2023). The integration of educational, administrative, and online data sources has allowed learning analytics to flourish, providing a transparent and cost-effective means to enhance educational quality management (De Witte & Chénier, 2022). Modern educational data analysis systems, often based on deep learning algorithms, are designed to help students develop good study habits and higher-order thinking abilities (Zeng, 2022). Recent learning analytical tools using AI are tracking student progression and student engagement while using a virtual assistant or smart assistants (Sajja et. al., 2023c).

The advancements in multimodal large language models (MLLMs) such as GPT-4 Vision and their applications in hydrology (Kadiyala et al., 2024) demonstrate the potential of AI to interpret complex environmental data, such as flood management and water quality monitoring. These technologies highlight the importance of integrating visual and textual data for comprehensive environmental analysis and decision-making, setting a precedent for their use in educational tools. Additionally, the application of ChatGPT for achieving satisfactory performance on the Fundamentals of Engineering (FE) Environmental Exam underscores the evolving capabilities of AI in educational contexts, particularly in enhancing students' understanding and performance in technical subjects (Pursnani et al., 2023).

The positive outcomes associated with AI-based educational tools and virtual teaching assistants underscore the need for a system that can create and deploy these assistants easily across various subjects in higher education. Virtual assistants have shown significant potential in improving student engagement and learning outcomes by providing personalized, context-specific support. However, creating and deploying these assistants remains a challenge due to the complexities involved in their development and integration with existing educational infrastructures. The system aims to address this gap by offering a framework that simplifies the creation and deployment of virtual assistants for any subject. By leveraging advanced NLP and MRC technologies, the system can generate intelligent, course-specific assistants capable of providing tailored educational support.

Furthermore, the seamless integration of the system with LMS through the LTI 1.3 protocol ensures secure and efficient deployment, making it accessible to a wide range of educational institutions. This capability is expected to enhance the learning experience for students while reducing the workload for educators, allowing them to focus more on instructional activities. The end-to-end deployment proposed in this paper ensures that the system can be adopted and integrated within existing educational systems, providing a streamlined process from document retrieval to the initialization of course-specific virtual assistants. By addressing the current limitations and challenges faced by educators and learners, the system has the potential to offer a comprehensive solution that enhances both teaching and learning experiences.

3. Methodology

The architecture of the Educational AI Hub system is designed to provide a seamless, intuitive experience for both instructors and students across various Learning Management Systems (LMS). While the system is compatible with all major LMS platforms, this paper uses Instructure Canvas as an example to illustrate the end-to-end workflow and design. This includes the process of setting up and populating the system with course-specific content, as well as detailing how the system interacts within the LMS environment.

3.1. End-to-End Workflow Architecture

The end-to-end workflow begins with the Request Educational AI Hub Service functionality, where instructors specify the documents and features required for their course's instance. Through this service, instructors have the autonomy to tailor the system's capabilities to their pedagogical needs, ensuring that the assistance provided is relevant and effective. Following the selection process, our custom-developed LMS Document Retrieval system comes into play, retrieving the designated documents and data from the selected sources within the LMS. These files and information are then processed using the sophisticated parsing techniques described in subsequent sections, with the aim of creating a rich, course-specific knowledge base.

This stage of the process involves parsing the retrieved documents to isolate and encode the information into a structured format. Utilizing state-of-the-art parsing and embedding generation techniques, we construct a knowledge base that serves as the foundation for system's interaction with users. Once the knowledge base has been established, the Educational AI Hub instance for the course is initialized. This instance is a culmination of tailored selections and processed content, ready to provide students with an intelligent, responsive educational aid within their learning environment. As illustrated in Figure 1, this integrated workflow not only enhances the customization and relevance of the system but also ensures a seamless transition from data collection to the deployment of a fully functional virtual assistant, thereby enriching the educational experience for both instructors and students.

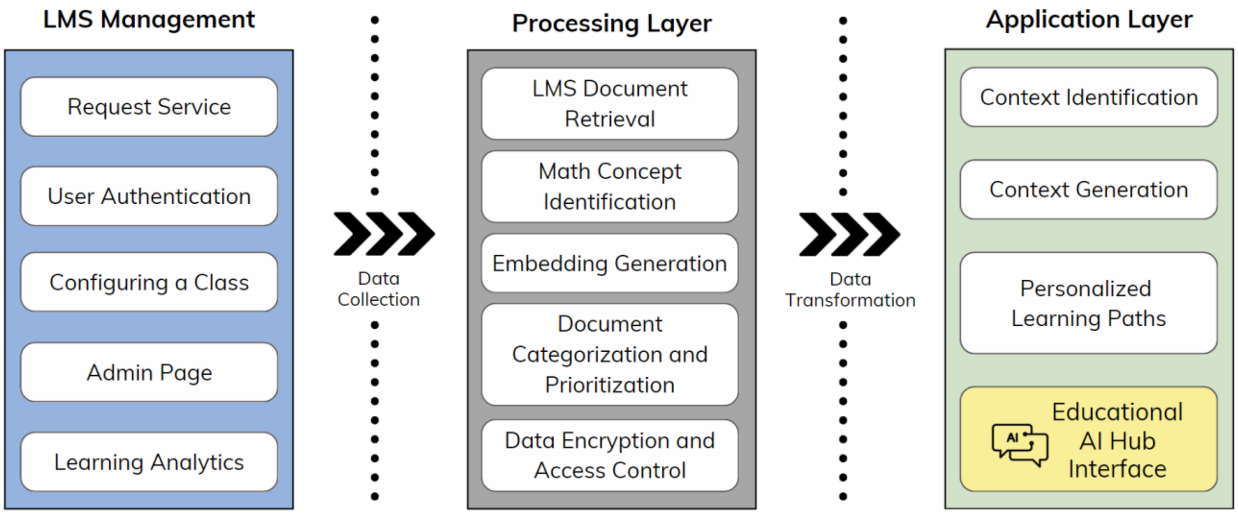

Figure 1: End-to-End System Architecture

3.2. LMS Integration

The integration of the Educational AI Hub within the LMS is facilitated through a third-party extension configuration on the course's page using the LTI 1.3 protocol for OAuth. When the app is launched, an OAuth request is generated, linking the LMS user's authentication with the system. Upon successful authorization, the user is seamlessly transferred to their personalized instance. This two-step authentication process ensures that users can securely access their instance while preserving the integrity and privacy of the educational content. The integration is designed to be unobtrusive and user-friendly, providing a straightforward pathway for users to engage with the system's suite of functionalities without navigating away from their familiar LMS environment.

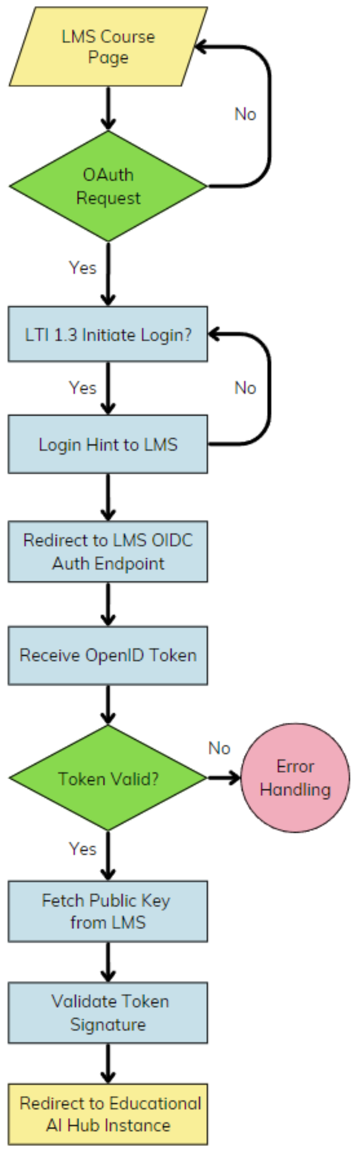

Figure 2: Integration workflow of the Educational AI Hub for LMS

Through the LMS integration architecture, the system becomes an integral component of the course's digital space, accessible directly through the LMS interface. This architecture not only exemplifies the technological synergy between the system and the LMS but also reflects our commitment to enhancing educational workflows through the thoughtful application of technology. By leveraging the robust security and seamless user experience provided by the LTI 1.3 protocol, we ensure that the system remains both highly functional and secure, meeting the needs of modern educational environments.

The integration flowchart, as shown in Figure 2, visualizes the step-by-step process of integrating and accessing the Educational AI Hub instance through the LMS. It starts with the LMS course page where the system applications are listed, followed by the initiation of an OAuth request which begins the authentication process. Upon successful authorization, the LTI

1.3 login is initiated, and a login hint is sent back to the LMS. The LMS then redirects to its OpenID Connect (OIDC) Authentication endpoint. At this stage, the LMS sends an OpenID token to the system. The token's validity is checked, and if valid, the system fetches the public key from the LMS to validate the token's signature. Upon successful validation, the user is finally redirected to their personalized Educational AI Hub instance. This comprehensive flow ensures a secure, efficient, and user-friendly experience, providing seamless access to the system while maintaining high standards of security and data integrity.

3.3. LMS Applications

Integrating advanced technological tools into Learning Management Systems (LMS) is a critical step towards modernizing educational environments. The system, with its suite of applications, is designed to seamlessly mesh with the existing infrastructure of an LMS such as Canvas, Blackboard, or Moodle. This integration allows for a cohesive experience where the system's functionalities become a natural extension of the course's digital space. The system is designed to integrate smoothly as a third-party application within the LMS, fitting seamlessly with course modules, assignments, and other content areas. This integration ensures that the tools are accessible when needed, without disrupting the course layout or user experience. Instructors can easily access various features of the system from their course interface, streamlining the management of course-related tasks.

Applications for Instructors and Students: For students, a course-specific Educational AI Hub instance can be made available, providing tailored support and resources directly related to their coursework. This personalization enhances the learning experience by offering targeted assistance, fostering a more engaging and interactive educational journey. Instructors, on the other hand, are provided with a more generalized instance, giving them the flexibility to manage multiple courses or tailor the assistant to suit different educational needs. Additionally, the Learning Analytics Dashboard becomes a critical tool, presenting actionable insights into student engagement, performance, and overall course dynamics. These insights enable instructors to make data-driven decisions that can positively impact the learning outcomes. Lastly, the Request Educational AI Hub Service application streamlines the process of obtaining assistance, ensuring that support is just a few clicks away. This application can be crucial for instructors seeking to optimize the system to their course's specific requirements or to resolve any queries related to its functionality.

As depicted in the accompanying screenshot (Figure 3), the instructor's view within the LMS is organized and intuitive, with clear access points to the system's functionalities. Each application, whether it be the general Educational AI Hub, the Learning Analytics Dashboard, or the Request Educational AI Hub Service, is represented as a distinct element within the LMS course page. This design allows for quick navigation and an uncluttered environment, empowering instructors to utilize the system's full spectrum of services efficiently. This integration represents a significant step forward in educational technology, offering a suite of powerful tools that enhance the capabilities of traditional LMS platforms. By embedding these applications directly into the course environment, the system stands out as an innovative solution, driving the evolution of interactive and responsive educational experiences.

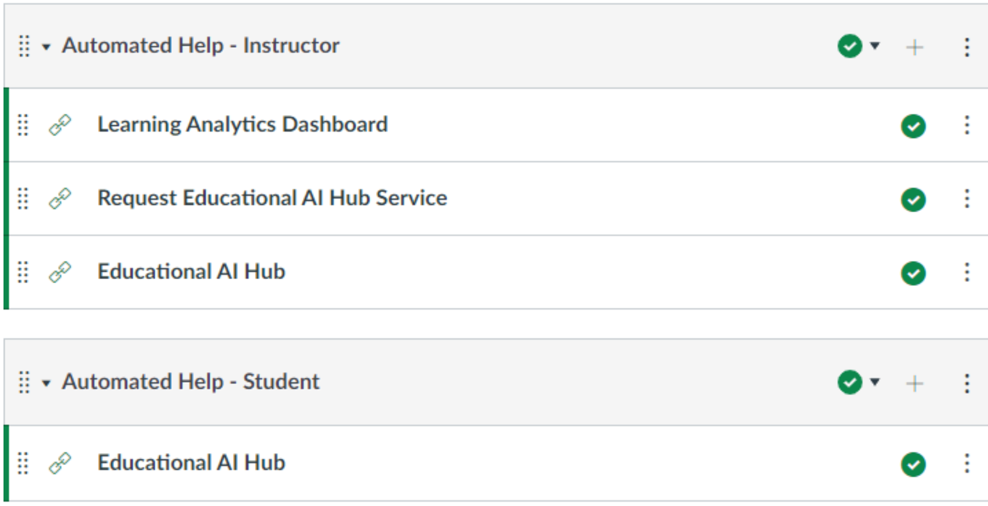

Figure 3: Educational AI Hub components and its applications in an LMS

3.4. Educational Content Accessibility and Utility

In the digital era, enhancing the accessibility and utility of educational materials is essential for meeting the evolving demands of teaching and learning. Our workflow is carefully designed to address this need, using advanced technologies and methodologies. From the initial retrieval of documents to their processing and preparation, each step in our workflow aims to transform educational materials into accessible formats that enhance learning experiences. This section outlines our approach to improving educational content, highlighting our commitment to using technology to support and enrich the teaching and learning process.

3.4.1. Document Retrieval and Preprocessing for AI Hub Integration

The initial stages of integrating educational content into the system involve a meticulous process of document retrieval and preprocessing. This phase is crucial for ensuring that the educational materials are not only systematically collected but also prepared for subsequent analysis and transformation, thereby maximizing their utility within the system. This section details the strategies and methodologies employed in the acquisition and initial handling of these documents, emphasizing the efficiency and systematic approach that underpins the seamless integration of instructional content.

Retrieval of Instructional Content: The process begins with the precise acquisition of educational resources, identified by instructors for their relevance and importance to the system's operational scope. To facilitate this, we developed a specialized library that connects directly with Learning Management Systems (LMS) through their APIs, with Canvas used as an example in this paper. This custom library serves as the primary channel for retrieving a wide range of instructional materials, including assignments, quizzes, general files, and modules. By leveraging the Canvas API as an illustration, our system automates the collection of these materials, enabling the swift and efficient retrieval of the necessary documents from the LMS. This automation ensures that the system consistently receives the most relevant and up-to-date materials as specified by the instructors, maintaining alignment with the instructional objectives and course content. The same process applies to other LMS platforms, demonstrating the system's flexibility and broad applicability.

Initial Processing and Structured Organization: Following the acquisition of educational resources, we move to the initial processing stage, which involves the organized storage and categorization of the retrieved documents. Each document is carefully tagged with its corresponding location within the LMS, such as "assignments," "quizzes," "files," or "modules." This methodical categorization reflects the organizational structure of the course content, enhancing the efficiency of document retrieval and utilization within the system. This approach ensures the contextual integrity of the educational materials, providing a coherent and intuitive interaction experience for both instructors and students. Our structured approach to document retrieval and preprocessing aims to create a cohesive and integrated learning experience. Using a custom-developed library with the Canvas API, we establish a robust and scalable foundation for managing course content. This methodology facilitates the smooth integration of educational materials into the system, allowing us to adapt to the changing needs of the educational community. This approach seeks to leverage technology to enhance accessibility and engagement in educational environments.

3.4.2. Document Conversion Technologies in Educational Material Processing

The digital transformation of educational materials, particularly those with complex mathematical expressions and scientific data, poses challenges in maintaining their semantic integrity and accessibility. To improve the learning experience through technology, we assessed various document conversion technologies to find solutions that streamline the process of converting academic content into digital formats. This section outlines our evaluation of different methodologies, leading to the strategic selection of the most effective approach for our goals.

YOLO Image Detection and MathPix: Our initial approach into document conversion technologies involved utilizing the YOLO (You Only Look Once) (Redmon et. al., 2016) v3 model, a renowned deep learning algorithm designed for real-time object detection, to identify and extract mathematical formulas from a variety of documents. The process required assembling a dataset of 158 documents, with formulas manually highlighted, to train the model over 300 epochs. This preparation was essential for optimizing the model's formula detection capabilities. Figure 4 illustrates a validation example showcasing the accuracy of the model's predictions.

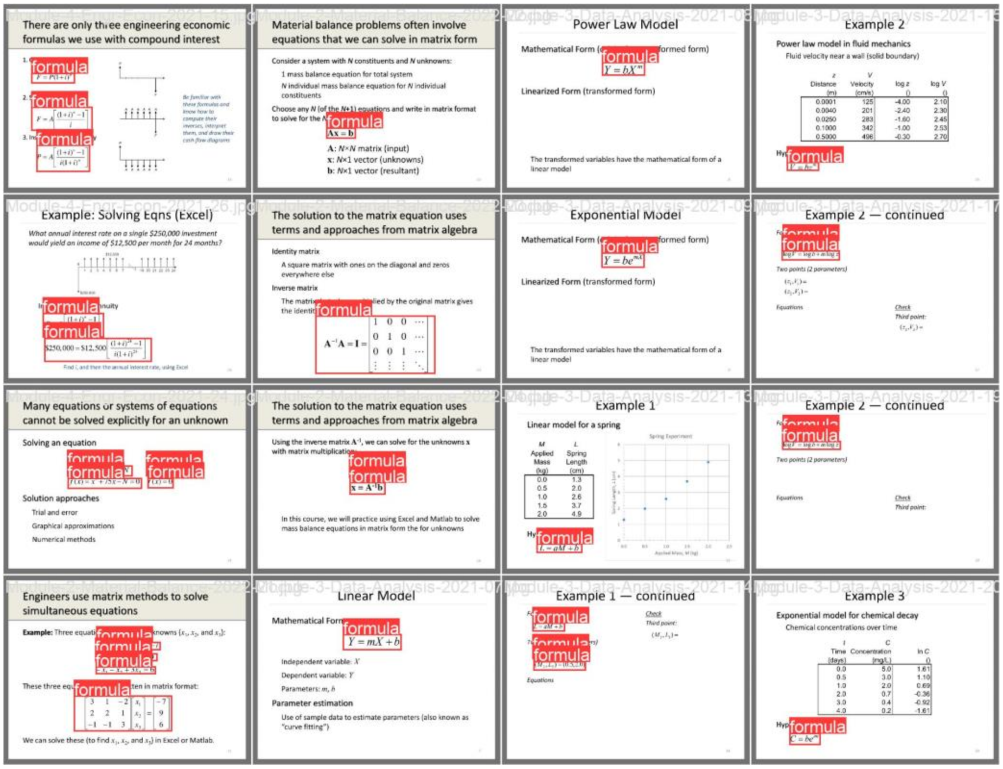

Figure 4: Validation example

Upon successful training, we employed the YOLOv3 model to detect formulas within documents, subsequently using MathPix as a conversion tool to transform these elements into digitally accessible formats. MathPix's ability to convert PDFs into searchable, exportable, and machine-readable text proved invaluable, ensuring that mathematical formulas and tables were accurately rendered in MathPix Latex format. Figure 5 demonstrates the model's prediction capabilities, highlighting the conversion of detected formulas into digital text. This dual-step process, though promising, revealed complexities and inefficiencies that prompted us to seek a more streamlined solution for our document conversion needs.

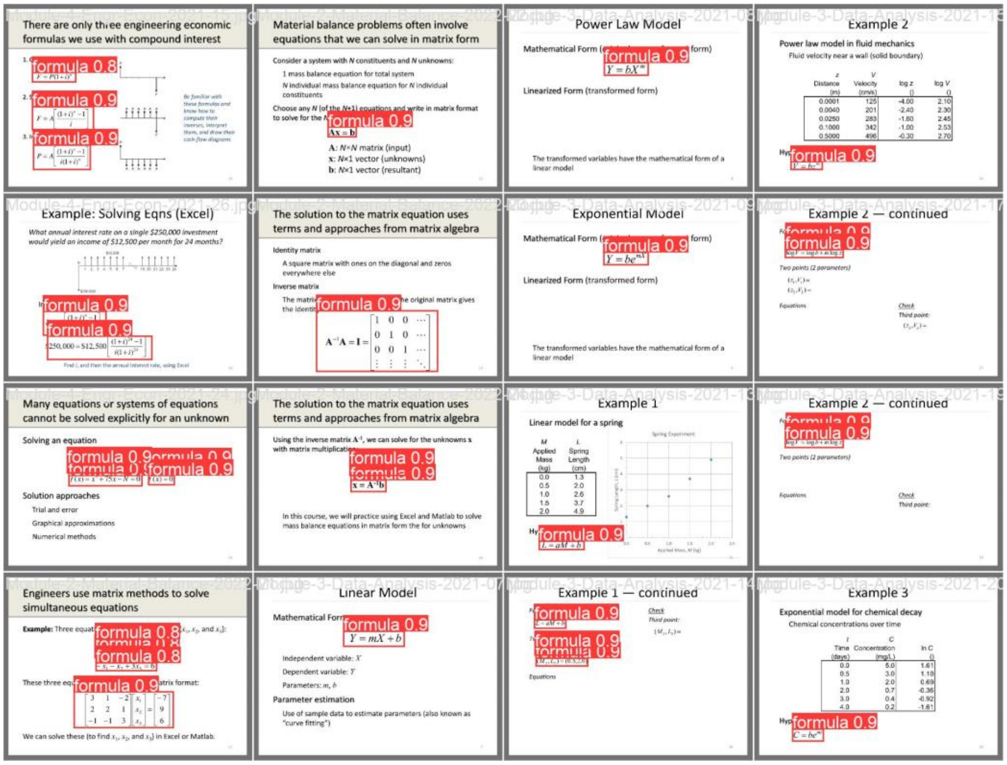

Figure 5: Model Prediction presenting the accuracy of the YOLOv3's predictions.

Nougat: A Streamlined Solution: The transition to Nougat (Blecher et.al., 2023), a cutting-edge technology developed by Meta, marked a pivotal shift in our approach to document conversion. Nougat's Neural Optical Understanding for Academic Documents system utilizes a Visual Transformer model for Optical Character Recognition (OCR), directly converting PDFs of course content, including textbooks, lecture notes, and slides, into MathPix Markdown. This direct conversion process maintains the semantic integrity of the content, offering a significant advantage over the multi-step process of YOLO and MathPix.

Choosing Nougat was driven by its straightforwardness, ease of use, and the efficiency it added to our workflow. By eliminating manual steps in the formula detection and conversion process, Nougat significantly reduced the resources required to make educational materials digitally accessible. Its ability to directly produce MathPix Markdown format streamlined the integration of materials into our system, enhancing our system's capability to understand and interact with the course content effectively.

To support the computational demands of this conversion process, we utilized cloud-based compute services, particularly leveraging GPU resources. These services provided the necessary computational power to handle large volumes of educational documents efficiently, ensuring timely processing and delivery of content. The scalability of cloud infrastructure allowed us to accommodate varying workloads, from routine updates to intensive processing tasks, thereby maintaining the system's responsiveness and reliability. The use of GPUs was particularly crucial during the data collection phase from the LMS, as they significantly accelerated the processing speed compared to traditional CPUs.

Processing these documents using Nougat, which involves complex OCR and content extraction tasks, is computationally intensive. Relying solely on CPUs would have slowed down the setup of the Educational AI Hub instance for a given course, leading to delays in making the educational resources available to students and instructors. By utilizing GPUs, we ensured that the system could quickly and accurately prepare course-specific content, enhancing the overall efficiency and user experience. To illustrate the capabilities of Nougat, Figure 6 presents the textbook source file in PDF format, and Figure 7 displays the parsed text extracted from the same textbook, "Engineering Fundamentals and Problem Solving," 7th Edition, by Mickelson et al. (2017). These examples demonstrate the technology's effectiveness in preserving the semantic integrity and format of complex educational materials.

As you can see from the example, even though the stated interest is the same, 12% in this case, the change in the compounding period changes the sum. Thus, to compare different alternatives, we must know the *stated* or *nominal* annual interest rate and the compounding period. We can also define an *effective annual rate,* often called *annual percentage rate* (APR), for comparison purposes. The annual percentage rate (APR) is then the interest rate that would have produced the final amount under annual (rather than semiannual, monthly, or other) compounding.

Then, continuing with Example Problem 8.1 part (b), with a nominal interest rate of 12% and semiannual compounding, the APR can be found as follows:

$$F = \$12{,}750.73 = 8{,}000(1 + APR)^4 = 8{,}000\left(1 + \frac{0.12}{2}\right)^8$$

or

$$(1 + APR)^4 = \left(1 + \frac{0.12}{2}\right)^8$$

then

$$APR = \left(1 + \frac{0.12}{2}\right)^2 - 1 = 0.123\,6 \qquad (12.36\%\ \text{APR})$$

Considering part (c) with 12% nominal and monthly compounding, the APR is found from

$$\$12\,897.81 = 8\,000(1 + \text{APR})^4 = 8\,000\left(1 + \frac{0.12}{12}\right)^{48}$$

$$\text{APR} = \left(1 + \frac{0.12}{12}\right)^{12} - 1 = 0.126\,8 \qquad (12.68\%\ \text{APR})$$

Financial institutions sometimes "intentionally confuse" nominal and APR values in their advertising. They may state the nominal rate and simply call it the APR if this makes the rate appear to be a better deal. APR is always going to be larger than nominal interest if the compounding period is less than one year when the APR value is computed as previously defined. Since you know how to compute APR, you can always check it out.

Figure 6: Textbook source file in pdf format (Mickelson et al., 2017)

3.4.3. Post-processing and Embeddings Generation

In the next stage of our workflow, after converting educational documents into MathPix Markdown format using Nougat, we focus on parsing and embedding generation to enhance the accessibility and utility of the processed content. This section describes the post-processing steps and methods used to create embeddings from the transformed documents, preparing them for integration into our system.

Post-processing of Converted Documents: After converting documents to MathPix Markdown, we enter a post-processing phase to extract and separate mathematical expressions encoded in LaTeX. Using regular expressions (regex), we carefully parse the text to identify these LaTeX formulas. This detailed parsing process ensures that the formulas, crucial for scientific and mathematical content, are accurately preserved for future use. To facilitate easy reference and retrieval, each formula is assigned a unique identifier (ID), such as "formula_0". This ID replaces the original LaTeX formula in the text, acting as a placeholder that maintains the document's structure and meaning while allowing for separate access to the formulas. This method simplifies the management of mathematical expressions in the documents and improves the clarity and ease of navigation of the processed content.

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(12.36% APR)

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(12.68% APR)

Financial institutions sometimes “intentionally confuse” nominal and APR values in their advertising. They may state the nominal rate and simply call it the APR if this makes the rate appear to be a better deal. APR is always going to be larger than nominal interest if the compounding period is less than one year when the APR value is computed as previously defined. Since you know how to compute APR, you can always check it out.

Figure 7: Parsed text from the textbook (Mickelson et al., 2017)

Generation of Embeddings: The core text of the documents, after parsing and removal of direct LaTeX expressions, undergoes an embedding generation process. Using OpenAI's "text-embedding-3-large" model, we convert the textual content into high-dimensional vectors, known as embeddings. These embeddings capture the semantic essence of the text, allowing for detailed analyses and applications that utilize the content's inherent meanings and themes. The embeddings, along with the extracted LaTeX formulas, are carefully stored in a structured format. This format includes various fields that detail each document comprehensively, ensuring that all relevant information is preserved and accessible for future use. This format comprises several fields designed to encapsulate the comprehensive details of each document, including:

- **fileType**: Indicates the original source or location from which the document was retrieved.
- **fileName**: The name of the file, preserving its original designation for easy identification.
- **text**: The English representation of the document's content post-embedding, retaining the essence of the text in its vectorized form.

- **latexFormula**: A dedicated field housing all LaTeX formulas extracted from the document, ensuring their accessibility and usability for academic and educational purposes.

This structured approach to storing processed documents and their associated embeddings and formulas facilitates their efficient retrieval and utilization within the system. By replacing LaTeX formulas in the text with identifiable placeholders and preserving these formulas in a separate field, we ensure the integrity and richness of the academic content are maintained, while also rendering the material more flexible and adaptable for digital educational applications.

3.5. Data Security and Privacy

Security and privacy are paramount considerations in the design of the Educational AI Hub system. To safeguard user data and ensure compliance with relevant regulations, the system employs robust technical measures. Data transmission is protected using SSL (Secure Sockets Layer) encryption, ensuring that all communications between users and the system are kept confidential and secure. Furthermore, the system's databases are secured with advanced security protocols, including encryption at rest, to prevent unauthorized access and ensure the integrity of stored data. The system implements the OAuth (Open Authorization) framework for secure user authentication and authorization. This framework ensures that only authorized users have access to sensitive information, protecting user credentials from interception and misuse. Regular security audits and vulnerability assessments are conducted to identify and mitigate potential security risks. This proactive approach aids in maintaining a secure environment and protecting user data from evolving threats.

In terms of compliance, the system adheres to the Family Educational Rights and Privacy Act (FERPA) guidelines, ensuring that student data is handled with the utmost care. Strict access controls and data handling procedures are implemented to protect the privacy of student records and educational information. The system follows the principle of data minimization, collecting only the information necessary for its functionality and educational purposes. This approach reduces the risk of data breaches and enhances user privacy. User consent mechanisms are included in the system to ensure transparency and trust. Users are informed about the types of data collected and the purposes for which it is used, and explicit consent is obtained for data collection and processing. The system's security protocols are aligned with industry best practices, including regular updates to security measures, continuous monitoring for potential threats, and immediate response to any security incidents.

3.6. Case Study Design

The Educational AI Hub system was presented at the 12th International Congress on Environmental Modelling and Software, providing a platform to showcase its features and potential impact on environmental sciences education. This presentation aimed to gather qualitative feedback from a diverse audience, including instructors, domain experts, and educational professionals, to assess the system's design, functionality, and potential effectiveness in real-world educational settings. During the presentation, we outlined the key features of the system, including its advanced AI and NLP capabilities, seamless integration with LMS platforms like Canvas, and its specific applications for environmental sciences education.

The audience was informed about the system's ability to handle complex environmental data, support personalized learning experiences, and facilitate engagement with quantitative subjects through features like code execution and document parsing. Feedback from the conference participants was collected through discussions and Q&A sessions following the presentation. Participants provided valuable insights into the system's design and potential applications, highlighting the importance of its features in addressing the unique challenges of teaching environmental sciences. They noted the system's potential to enhance student engagement and understanding by providing interactive and personalized learning experiences and emphasized the value of integrating such technologies into traditional educational frameworks.

3.7. Evaluation Criteria and Metrics

Our evaluation framework focuses on three essential metrics to comprehensively assess the system's capabilities: information retrieval accuracy, question-answering accuracy, and hallucination accuracy. These metrics were carefully chosen to evaluate the system's effectiveness in retrieving relevant contexts, producing accurate answers, and correctly identifying unanswerable questions. Importantly, these metrics directly inform the performance of core functionalities like flashcards, notes, and quizzes. By ensuring that the system retrieves accurate information, we bolster the reliability of these educational tools, which depend on precise data extraction and response generation. This evaluation verifies the robustness of VirtualTA's knowledge engine in delivering dependable learning support.

To conduct this evaluation, we utilized the SQuAD2.0 (Rajpurkar et. al., 2018) dev dataset, which comprises 11,862 questions and 1,213 documents (contexts). To gain insights into the system's performance across different knowledge domains, we categorized the SQuAD2.0 dataset into six main subject areas: Business, Culture, Environmental Sciences, History, Politics, and Science. This categorization allowed for a more detailed analysis of the system's question-answering abilities within specific content areas, ensuring a broad and balanced evaluation across distinct topics. As shown in Table 1, the dataset includes a variety of question counts across these categories, allowing us to assess the system's performance in retrieving relevant information and generating accurate answers within each subject area.

Main Category	**Total Questions**
Business	1109
Culture	1465
Environmental Sciences	1678
History	2850
Politics	1640
Science	3120
Total	11862

Table 1: Distribution of Questions Across Main Categories

Information Retrieval Accuracy: This metric measures the system's ability to select the most relevant context for each question. Information retrieval accuracy is a crucial component of the pipeline, as an accurately retrieved context ensures a higher chance of providing the correct answer. Additionally, accurate context retrieval enhances the quality of flashcards, notes, and quizzes generated by the system, as these features rely on precise information retrieval. To calculate this metric, we retrieved the top-5 contexts for each question based on cosine similarity between the question and context embeddings, comparing these with the ground truth to verify if the correct context was included in the top-5 results.

Question-Answering Accuracy**:** This metric assesses the system's performance in generating accurate answers from the retrieved contexts. To evaluate this, we use a two-step verification process. First, we utilize an LLM-based verification, where the language model analyzes the question, ground truth, and generated answer to confirm if the generated response aligns with the expected answer. This automated verification allows for efficient and scalable checking of answer quality. Following this, we perform manual checks to ensure that the answers align closely with the expected responses, adding a layer of human validation to support the reliability of the system. This combined approach enhances the system's credibility in generating accurate study aids and instructional content, verifying that it provides dependable responses across various educational scenarios.

Hallucination Accuracy**:** Hallucination accuracy evaluates the system's ability to recognize when a question is unanswerable based on the provided context and to abstain from answering when necessary. This is crucial in the context of SQuAD2.0, where some questions deliberately lack answers in the given context. By tracking the system's error rate for unanswerable questions, we assess how effectively it avoids generating unsupported or "hallucinated" answers. Ensuring a high rate of accurate abstentions supports the trustworthiness of the system in educational settings, reinforcing its utility as a dependable learning assistant.

By integrating these metrics, our evaluation framework provides a holistic view of the system's strengths and limitations in retrieving relevant information, accurately answering questions, and abstaining appropriately from unanswerable ones. These evaluations form the foundation for assessing the knowledge engine's performance across various domains, ensuring that it can reliably support VirtualTA's functionalities like flashcards, notes, and quizzes, each of which contributes to an effective and accurate educational experience.

4. Results

The integration and deployment of the Educational AI Hub system includes a comprehensive set of features and applications designed to enhance both teaching and learning experiences. This section highlights the key features and user interaction applications, demonstrating how the system caters to the diverse needs of students and instructors in a dynamic educational environment.

4.1. Key Features of the Educational AI Hub

The system includes a suite of features designed to enhance the educational experience. It offers personalized learning paths, advanced content support, and prioritizes accessibility to create an inclusive and secure learning environment. The system is tailored to meet the diverse needs of students and instructors, making it a valuable resource in the educational process.

4.1.1. Personalization and Adaptive Learning

The core feature of the system is its ability to provide personalized and adaptive learning experiences. By analyzing user interactions, the system can understand the user's emotional state and adjust its responses accordingly. This ensures that the support provided is appropriate and helpful, whether the student is feeling confused, frustrated, or engaged.

Emotion-Sensitive Interaction: Utilizing a nuanced understanding of various emotional states—from anger to joy, and from fear to love—the system adjusts its tone and level of detail in explanations. For example, a user displaying signs of frustration may receive calming messages and simplified explanations, whereas a curious user might be presented with additional learning resources.

Customizable Learning Tools: The system empowers users to tailor their study methods by generating quizzes and flashcards on preferred course topics. It acknowledges that each student has unique learning preferences and adapts accordingly, offering flexibility in how educational content is engaged with.

Emotional Analysis Tree: The system harnesses a comprehensive emotional analysis tree that includes a spectrum of emotions such as anger, sadness, surprise, joy, love, and fear, with deeper levels of granularity, as outlined in the provided context. By identifying specific emotions within these categories, the system can deliver responses that are not only accurate in content but also empathetic in nature. We utilized the emotional tree discussed in the *pyemotionwheel* repository for classification and grouping of emotions, enabling more nuanced and empathetic interactions (Rosebrock, 2023). This capability is illustrated in Figure 8, which depicts the emotional tree used in the system, highlighting its broad range of emotional categories and subcategories that inform the system's adaptive responses.

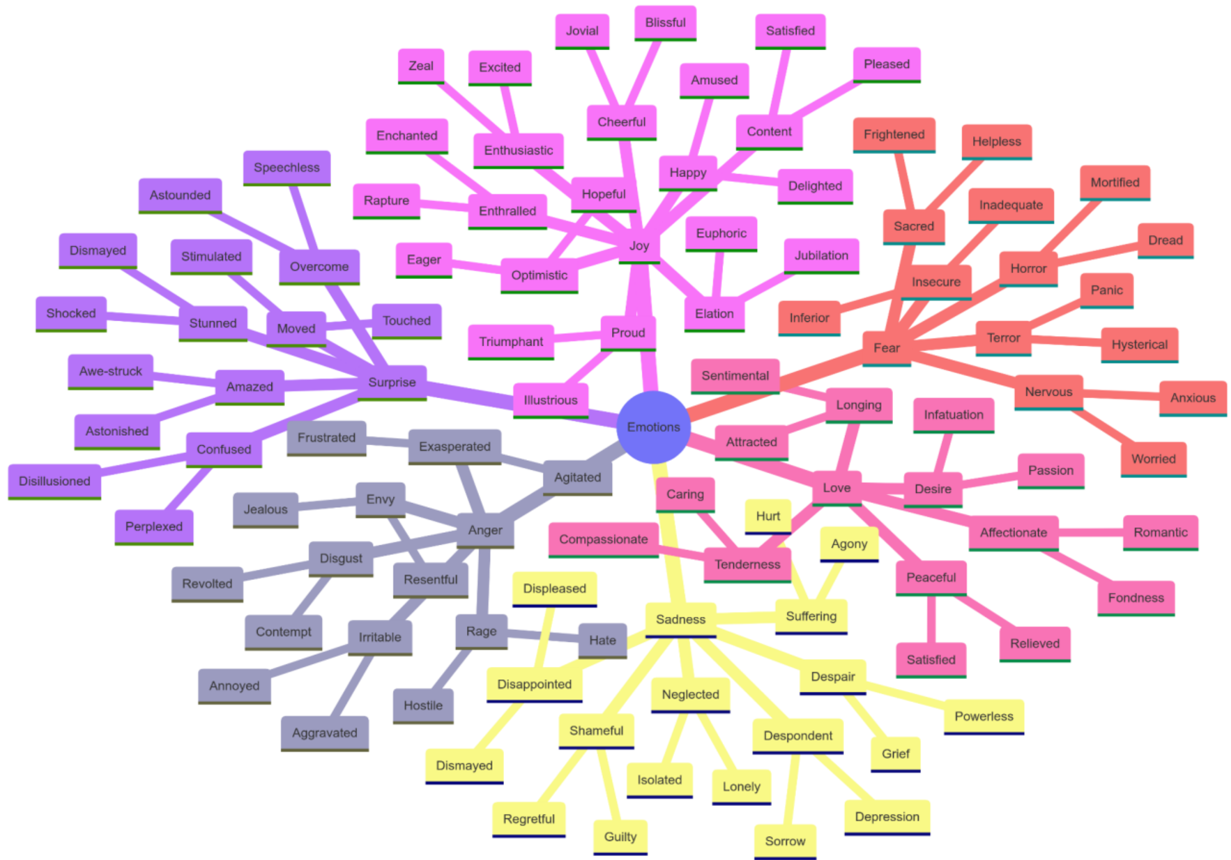

Figure 8: Emotional tree used in Educational AI Hub

4.1.2. Quantitative Content Support

The system’s capacity to support quantitative content is a cornerstone feature, particularly in fields where numerical accuracy is crucial. Our novel parsing techniques ensure that mathematical expressions—equations, formulas, and tables—are preserved without loss of context when transitioning from course materials to the digital learning environment. With the ability to accurately store and utilize such content, the system keeps quantitative discussions domain-specific, respecting the notational conventions unique to each course. This is particularly beneficial when instructors adopt custom notations or methodologies, as it allows students to engage with materials in a format that is consistent with their in-class learning. By mirroring the instructor's approach, the system minimizes student confusion and solidifies the connection between the virtual assistant and the course content.

Moreover, the system enhances user interaction by allowing numerical problem-solving to be directly accessed by students. For example, if a course module includes specialized formulas for calculating engineering stress or statistical variance, the system can interpret these formulas and present them to students for practice and application. This direct interaction with course-specific problems not only aids in reinforcing learning outcomes but also prepares students for exams and practical applications beyond the classroom. The quantitative content support provided by the system represents a significant advancement in digital learning platforms. By ensuring fidelity to course-specific quantitative material and enabling direct problem-solving capabilities, the system offers a sophisticated and contextually aware tool that meets the rigorous demands of academic programs heavy in mathematics and data analysis.

4.1.3. Accessibility and Inclusivity

The system demonstrates a strong commitment to accessibility and inclusivity, ensuring that every student and instructor, irrespective of individual challenges and learning preferences, can fully engage with the educational offerings. Recognizing the diversity of users, the system is meticulously designed with features that foster an inclusive learning environment. Text-to-speech functionality is a core component, ensuring that information is available in auditory form. This is a crucial aspect that makes the system usable for individuals with visual impairments and reading disorders. The capacity of users to adjust font sizes according to their needs further exemplifies the system's adaptability. Such a feature not only serves those with visual impairments but also addresses the diverse requirements for reading comfort, potentially mitigating the strain of prolonged screen time. High contrast options within the system interface cater to users with color vision deficiencies, providing the necessary visual clarity for content distinction and navigation ease. The intention behind these visual accommodations is to ensure that no user is at a disadvantage due to the presentation of digital content. Through these deliberate design choices, the system emerges as an accessible, inclusive educational platform, consciously equipped to support a wide range of learning and interaction needs.

4.2. Application and User Interaction

Educational technology has significantly changed the landscape of learning and teaching, with a strong focus on enhancing user interaction through digital tools. The system reflects this evolution by providing specialized applications that address the specific needs of both students and instructors within a learning management system.

4.2.1. Applications for Students

Students interact with the system through a chat interface that serves as a virtual hub for learning and inquiry. Figure 9 showcases this interactive platform, which includes the following features:

- **Questions and Answers**: This tool empowers students to seek clarifications on complex topics and receive immediate, contextually relevant responses.
- **Summarization**: It provides succinct summaries of dense material, aiding in quick comprehension of essential information.
- **Flashcard Generation**: This feature supports active recall practices by generating study flashcards from the course content.
- **Quizzes**: Students can assess their knowledge through customized quizzes, reinforcing learning objectives.
- **Coding Sandbox**: This interactive environment allows students to write, execute, and troubleshoot code, fostering practical programming skills.

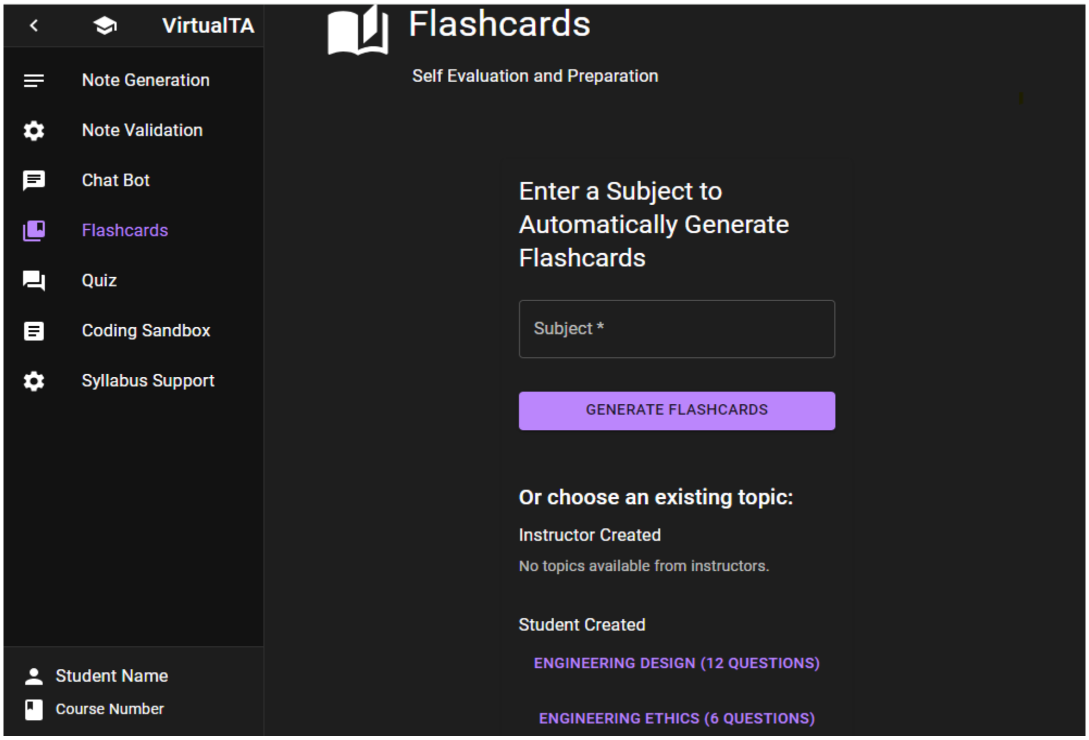

Figure 9: Educational AI Hub interface for students

4.3. Applications for Instructors

For instructors, the system offers a suite of tools designed to streamline course management and enhance student engagement.

4.3.1. Educational AI Hub Service Set Up

The admin portal, depicted in the image below (Figure 10), is where instructors configure the Educational AI Hub service for their courses. They can select specific course materials to be made accessible and define the features they wish to include, such as assignments, discussions, or any other resources available within the LMS.

4.3.2. Learning Analytics Dashboard

A crucial tool for instructors is the Learning Analytics Dashboard, represented by the third image. This interface provides instructors with insights into student engagement and performance metrics, including:

- **Emotional Analysis**: Graphs displaying the stress, agitation, confusion, and curiosity levels among students, offering a glimpse into the emotional dynamics of the class.
- **Academic Progress**: Data on how students are interacting with different topics, their performance on assessments, and overall course progression.
- **Student List**: An overview of the students enrolled on the course.

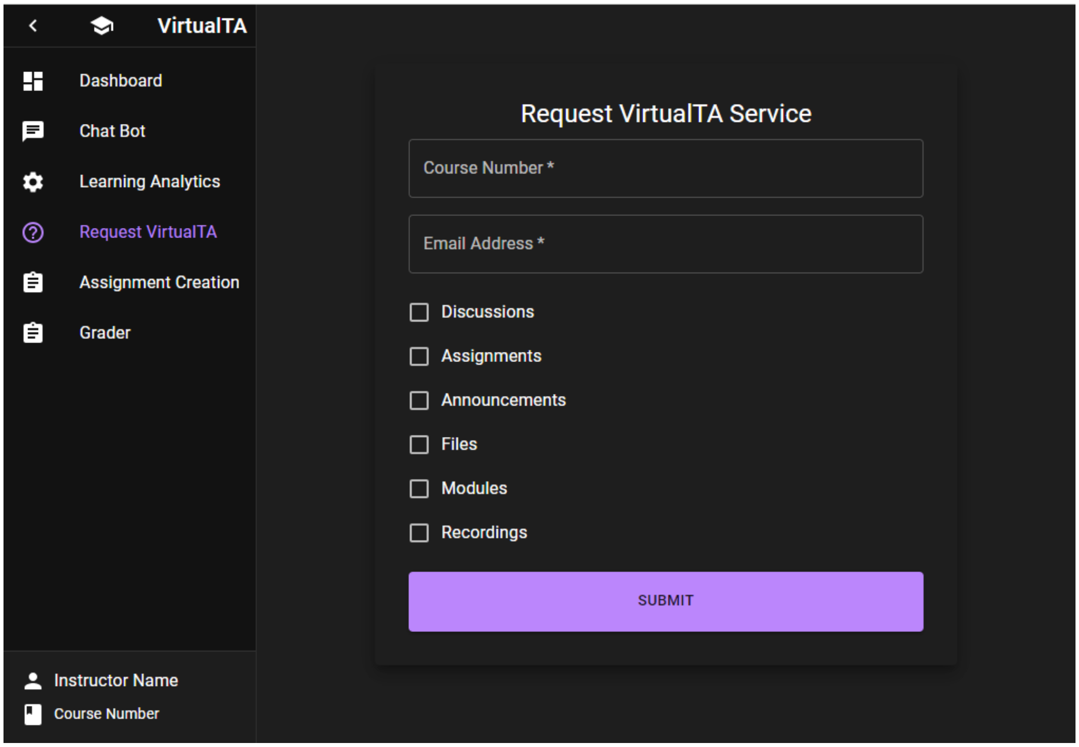

Figure 10: Setting up the Educational AI Hub Service

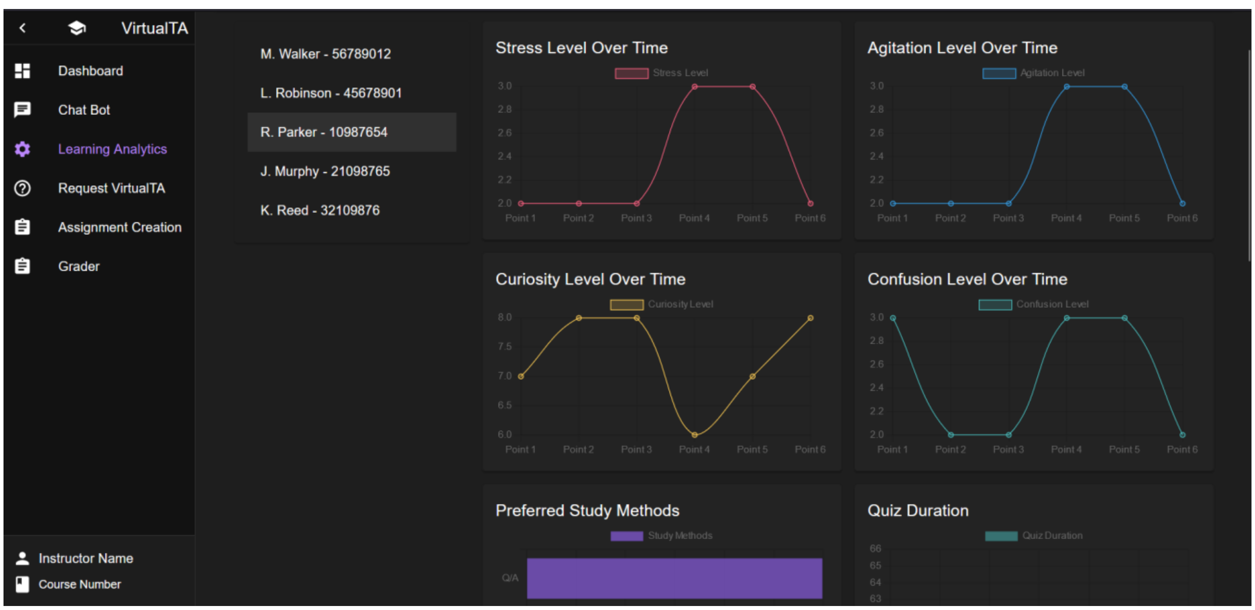

Figure 11: Learning Analytics Dashboard

4.3.3. Generalized Instance of Educational AI Hub

The generalized Educational AI Hub instance for instructors acts as a multifunctional tool, blending course management capabilities with advanced AI-assisted functionalities. As depicted in Figure 11, the Learning Analytics Dashboard helps instructors monitor and respond to the needs of their students, facilitating a more tailored and effective educational experience.

It is a broad-spectrum application that includes following functions:

- **Automates Routine Tasks**: Simplifies tasks like grading, attendance tracking, and scheduling.
- **Facilitates Content Customization**: Allows instructors to adapt the system's database to the course syllabus and educational objectives.
- **Offers Real-Time Assistance**: Provides support for instructional design and pedagogical approaches, incorporating insights from the Learning Analytics Dashboard to inform teaching practices.

4.4. Evaluation Results and Performance Analysis

In this section, we present the evaluation results of VirtualTA's knowledge engine based on the three key metrics: information retrieval accuracy, question-answering accuracy, and hallucination accuracy. These metrics allow us to measure the effectiveness of the knowledge engine in retrieving the correct context, accurately answering questions, and identifying when questions are unanswerable. The results provide insights into the performance of VirtualTA across various domains, illustrating its strengths and areas for improvement in handling a diverse range of questions and knowledge categories. This analysis underscores the engine's capability to support accurate, reliable study aids and instructional content generation, reinforcing its value in educational applications.

4.4.1. Information Retrieval Accuracy

Information retrieval accuracy reflects the system's capability to identify the most relevant contexts for each question—a foundational step for the accurate generation of educational aids such as flashcards, quizzes, notes, and question-answer responses. High retrieval accuracy ensures that the information presented is not only relevant but also aligned with the specific learning objectives, providing students with accurate materials that reinforce their understanding of key concepts.

To evaluate information retrieval accuracy, we retrieved the top-5 contexts based on cosine similarity and compared these to the ground truth contexts for each question. Table 2 presents the results across various main categories, highlighting the number of questions and corresponding accuracy percentages.

Main Category	**Accuracy (%)**	**Total Questions**
Business	88.41	1109
Culture	88.75	1465
Environmental Sciences	97.15	1678
History	67.90	2850
Politics	95.28	1640
Science	96.21	3120
Total	89.56	11862

Table 2: Information Retrieval Accuracy Across Main Categories

These results demonstrate the system's strong performance in categories like Environmental Sciences, Politics and Science, where retrieval accuracy exceeds 95%. In contrast, the History category shows lower accuracy, indicating potential challenges in retrieving relevant contexts within historically complex or varied information.

Information retrieval is crucial for downstream tasks, such as generating accurate flashcards, quizzes, and notes, where precise context is essential for creating meaningful study aids. Furthermore, in question-answering, the initial retrieval accuracy directly impacts the quality and relevance of the generated answers, contributing to a coherent and targeted learning experience. This focus on contextually accurate retrieval reinforces the system's goal of delivering reliable educational resources that cater to students' specific subject needs.

4.4.2. Question-Answering Accuracy

Question-answering accuracy assesses the system's ability to generate correct responses from retrieved contexts, directly impacting the AI's reliability in providing relevant and accurate answers to user queries. This metric is evaluated using two sub-metrics: Exact Match (EM) and manual checks, each contributing to a holistic view of the system's answer accuracy by considering both fully correct answers and an additional level of human verification for responses that may be ambiguous or partially correct.

As shown in Table 3, the accuracy rates vary across different subject areas, with Environmental Sciences and Politics demonstrating the highest levels of question-answering accuracy at 97.57% and 93.54%, respectively. This high accuracy reflects the system's robustness in fields where contextual understanding and precise information extraction are essential. Categories such as Science and Culture also exhibit strong performance, with accuracy rates exceeding 90%.

The History category, however, shows a relatively lower accuracy at 79.36%, which could indicate challenges in accurately interpreting historically dense or contextually diverse content. These variations highlight areas where the system performs optimally and where further improvements may enhance accuracy.

Main Category	**Accuracy (%)**	**Total Questions**
Business	88.23	1109
Culture	90.99	1465
Environmental Sciences	97.57	1678
History	79.36	2850
Politics	93.54	1640
Science	91.08	3120
Total	89.25	11862

Table 3: Question-Answering Accuracy Across Main Categories

These results underscore the system's proficiency in answering questions across a variety of subjects, which is particularly valuable in educational applications. High question-answering accuracy ensures that students receive clear and relevant responses, enhancing their understanding of complex material. This capability also supports additional learning functions, such as quiz and flashcard generation, by providing reliable answers that students can depend on for effective study and revision.

4.4.3. Hallucination Accuracy

Hallucination accuracy reflects the system's capability to recognize and abstain from answering questions that lack sufficient support within the context. This feature is particularly crucial for minimizing unsupported or "hallucinated" responses, aligning well with the requirements of datasets like SQuAD2.0, where certain questions are deliberately unanswerable within the provided context.

As shown in Table 4, the system demonstrates a strong capability in identifying unanswerable questions, with an Impossible Question Accuracy of 92.38% and a low Error Rate for Impossible Questions at 7.62%. These results underscore the system's robust handling of unanswerable questions, with a high accuracy rate for distinguishing when answers should be withheld. By abstaining from providing answers where none exist, the system demonstrates a high level of precision in distinguishing between answerable and unanswerable queries. This contributes significantly to the AI assistant's reliability, especially in educational settings where accurate, evidence-backed responses are crucial for effective learning support.

Metric	Accuracy (%)	Number of Questions
Impossible Question Accuracy	92.38	5504
Error Rate for Impossible Questions	7.62	454

Table 4: Hallucination Accuracy Metrics

This capability enhances the assistant's trustworthiness by preventing the delivery of speculative answers, thereby fostering an environment where students can depend on the assistant for accurate and well-supported information.

5. Discussions

The presentation of the Educational AI Hub system at the 12th International Congress on Environmental Modelling and Software provided a unique opportunity to gather feedback from a diverse group of instructors, domain experts, and educational professionals. The discussions following the presentation revealed several key insights into the system's potential effectiveness, usability, and areas for improvement. Participants raised several pertinent questions regarding the functionality and scope of the system. Key questions included:

Data Source Integration: Participants inquired about the potential to include textbooks as a data source within the system, questioning how such integration could enhance the breadth and depth of the educational content available to students.

Accuracy of Responses: Concerns were expressed about the accuracy of the answers provided by the system. Questions focused on the mechanisms in place to ensure that the information delivered is reliable and up to date, highlighting the importance of maintaining a high standard of accuracy in educational tools.

Academic Integrity: Participants asked how the system handles issues of academic integrity, particularly in preventing the direct provision of answers to homework assignments. This concern underscores the need for systems like Educational AI Hub to support learning without compromising ethical standards.

Gamification Potential: There was significant interest in the potential for gamification within the system to enhance student engagement. Participants suggested that incorporating game-like elements could make learning more interactive and enjoyable, thereby increasing student participation and motivation.

Student Usage Insights: Another area of interest was the system's ability to provide insights into how students are using the tool. Participants were keen on understanding how the system could track and analyze student interactions to provide educators with valuable feedback on student engagement and learning outcomes.

Expanding Features and Capabilities: There were discussions on the possibility of expanding the system's features, including enhanced contextual understanding and the application of Bloom's Taxonomy to assess students' cognitive development stages. This feedback points to a desire for the system to not only provide information but also facilitate deeper understanding and critical thinking.

The feedback received highlighted both the potential and areas for further development of the system in transforming environmental sciences education. Participants noted the value of integrating textbooks as data sources to expand the content base, thereby making the system more comprehensive. Additionally, there were discussions about the importance of developing mechanisms to verify the accuracy of responses and implement safeguards against academic dishonesty, which are crucial for maintaining the system's credibility. The interest in incorporating gamification features reflects a trend in education towards more interactive and engaging learning methods. Such features could potentially increase the system's appeal to students and enhance its overall effectiveness. Furthermore, the capability to provide educators with insights into student usage patterns was suggested to better tailor teaching strategies to meet the diverse needs of students.

5.1. Challenges and Limitations

The deployment and integration of the system presented several technical challenges, particularly the transition from LTI 1.1 to LTI 1.3 for Learning Management System (LMS) integration. This upgrade involved complex compatibility and implementation issues, necessitating extensive testing and troubleshooting to ensure smooth interoperability between the LMS and the system. Additionally, natural language processing (NLP) challenges, such as hallucination—where the AI generates responses not grounded in the provided data—and the use of open-source methods for embedding lookup, highlighted areas in need of further refinement. These technical hurdles underscore the importance of continuously improving NLP algorithms to enhance the accuracy and reliability of the system's responses.

Data security and user privacy are critical considerations in the design and implementation of the system, particularly in adhering to regulations like the Family Educational Rights and Privacy Act (FERPA). FERPA mandates strict controls over the access and disclosure of student education records, requiring robust security measures, including encryption, secure data storage, and controlled access protocols. Balancing the need for data collection and analysis to improve the system with the stringent requirements of FERPA is challenging, especially in maintaining transparency and accountability in how data is used and stored. Ensuring compliance with these regulations while still leveraging data for educational improvements remains a delicate and essential aspect of the system's operation.

The system's limitations are also evident in its dependence on the quality and comprehensiveness of its knowledge base. A more extensive and well-curated knowledge base would significantly enhance the system's ability to provide accurate and relevant information. However, building and maintaining such a knowledge base is resource-intensive and requires continuous updates to keep the information current and comprehensive. The reliance on accurate data inputs means that any gaps or inaccuracies in the data can lead to suboptimal performance, highlighting the need for rigorous content management and quality assurance processes. Furthermore, while the system utilizes advanced NLP techniques, there are inherent limitations in its ability to fully understand and respond to complex or nuanced queries, especially those requiring deep contextual understanding. Addressing these challenges is crucial for enhancing the system's overall effectiveness and relevance. Future developments should focus on expanding the knowledge base and refining NLP capabilities to overcome these limitations, thereby maximizing the potential of the system in educational settings.

6. Conclusion and Future Directions

The integration and deployment of the Educational AI Hub system showcases a significant leap forward in educational technology. The results observed from the implementation of the system highlight its potential to enhance both learning and teaching experiences, making it an indispensable tool in modern education. Through its adaptive, inclusive, and secure design, the system addresses current educational challenges and sets a new standard for digital learning platforms. The positive feedback from instructors further validates the system's impact and potential for widespread adoption in educational institutions.

To further enhance the capabilities of the system, ongoing advancements in AI and NLP technologies will be crucial. Future improvements could focus on enhancing the system’s ability to accurately interpret and respond to a wider range of user queries, ensuring more relevant and precise answers. Additionally, developing more sophisticated algorithms to seamlessly integrate and contextualize educational content within the system will provide users with richer, more interactive learning experiences.

In the field of environmental sciences education, the system is particularly beneficial for facilitating access to complex environmental data and helping students understand interdisciplinary scientific processes. This system aids in comprehending dynamic and interactive environmental issues, which are often challenging with traditional educational methods. By providing tailored support and real-time data analysis, the system enhances the educational experience in environmental sciences, making it easier for students to engage with and apply complex concepts.

Strategies for addressing the identified limitations of the system will be essential for its continued success. Key areas of focus include enhancing the system's flexibility to adapt to various educational contexts, including different subject areas and teaching methodologies. Moreover, developing advanced parsing and analysis tools to better handle complex mathematical, scientific, and technical content will ensure accurate and meaningful support for all types of educational material. The potential applications of the system's technology extend beyond its current scope. Future directions include adapting the system for use in K-12 education, vocational training, and higher education, tailoring its features to meet the specific needs of each educational level. Additionally, leveraging the system to support lifelong learning initiatives and global education programs can promote continuous education and skill development across diverse populations and geographies.

Future research will play a pivotal role in exploring the long-term impacts and scalability of the system. Key research avenues include investigating the sustained effects of the system on student engagement, comprehension, and academic performance over extended periods. Furthermore, examining the scalability of system's technology in different educational settings and identifying best practices for large-scale deployment and integration will be essential. Exploring how a system can evolve in response to emerging educational trends and technologies will ensure its continued relevance and effectiveness in a rapidly changing educational landscape.

In conclusion, the Educational AI Hub system, with its high accuracy in retrieval and question-answering, represents a significant advancement in educational technology. By offering personalized, adaptive learning experiences and facilitating efficient content generation, the system addresses the diverse needs of modern education. Ongoing development and refinement will support its continued success in enhancing educational experiences for students and instructors alike, contributing to a more informed, accessible, and effective educational landscape.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to improve the flow of the text, correct any potential grammatical errors, and improve the writing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Competing Interests

The authors declare that they have no competing interests.

Credit Author Statement

Ramteja Sajja: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, and Visualization. Yusuf Sermet: Conceptualization, Methodology, Writing - Review & Editing, Investigation, Validation, Funding acquisition, and Visualization. Ibrahim Demir: Conceptualization, Methodology, Writing - Review & Editing, Project administration, Supervision, Funding acquisition, and Resources.

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