The Impact of Personalized Educational Recommender Systems on Learning Efficiency in Higher Education

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DECLARATION

I declare that this is my own work, and this thesis/dissertation does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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The above candidate has carried out research for the ~~PhD/MPhil~~/Masters thesis/dissertation under my supervision. I confirm that the declaration made above by the student is true and correct.

Name of Supervisor: Dr. Buddhika Karunarathne

Signature of the Supervisor: Date: 30/06/2025

DEDICATION

This work is dedicated to my parents, whose unwavering support, guidance, and encouragement have been instrumental in my academic and personal growth. Their values and perseverance have been a constant source of inspiration, shaping the foundation of my achievements.

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ABSTRACT

In today's academic landscape, university students face challenges in identifying relevant and high-quality educational resources due to the overwhelming availability of digital content. The process of locating specific materials or answers to academic queries often requires navigating vast and irrelevant information, leading to inefficiencies in learning. This research addresses these challenges by developing a personalized educational recommender system that integrates machine learning techniques with the advanced capabilities of Large Language Models (LLMs).

Unlike traditional recommender systems that focus solely on suggesting materials, the proposed solution is designed to deliver personalized recommendations and provide precise answers to students' specific inquiries. This approach aims to align recommended resources with students' academic modules and research objectives, fostering a more tailored and effective learning experience.

The primary objectives of this study include designing the recommender system to support personalized learning and evaluating its impact on students' learning outcomes, engagement, and motivation. By simplifying access to relevant materials and addressing individual learning needs, this system seeks to enhance the efficiency and quality of the academic experience. Ultimately, the research contributes to advancing learning technologies, making it easier for students to achieve their academic goals while addressing the growing challenges of information overload.

Keywords: Personalized educational recommender system, Large Language Models, Educational Domains, Precise query-based answers

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CHAPTER 1

INTRODUCTION

1.1 DIGITAL TECHNOLOGY INTEGRATION IN EDUCATION

Incorporating digital technology into education involves leveraging various digital tools and platforms to enhance teaching and learning experiences within educational settings. The evolution of digital technology has sparked the emergence of innovative educational approaches that complement traditional classroom instruction. Personalized, attractive, and dynamic learning experiences can be given by utilizing various online educational platforms such as online resources, educational apps, and learning management systems. Integration also involves employing communication tools to foster collaboration and facilitate access to global resources.

Additionally, data analytics are utilized to craft tailored learning paths for individual students. The overarching goal is to equip students with the skills necessary for success in a digitally interconnected twenty-first-century world. However, several challenges hinder this integration, including ensuring equitable access for all, sustaining student engagement, and providing adequate training for teachers in utilizing these new tools.

1.1.1 Key Focus Areas in Research

Several examples can be visible that illustrate the incorporation of digital technology in education, focusing on various aspects such as the role of recommender systems, data analytics, and emerging technologies. The introduction of Amin [2]'s paper discusses the evolving role of technology in education, particularly highlighting the integration of the Internet of Things (IoT) and Machine Learning (ML) in creating personalized and adaptive learning experiences. This shift towards smart education systems, enabled by IoT and leveraging ML for personalized course recommendations (PCR), exemplifies the trend towards more technologically integrated learning environments.

Gonçalves [5]' paper underscores the challenges in finding relevant and accurate learning material due to the limitations of current educational systems in integrating technology for personalized learning experiences. It emphasizes the importance of tailored educational approaches to meet the diverse needs of students, using recommender systems as tools for personalized teaching and learning. The significance of learning analytics and re

Commander systems in education, especially in technical disciplines like electrical engineering, are discussed in Gonçalves [5]' paper. This paper highlights the challenges in evaluating student understanding and the potential of these technologies to provide insightful, personalized educational experiences. It provides an overview of the evolution of teaching resources in engineering education, emphasizing the increasing role of diverse teaching methods such as hands-on laboratories, computer simulations, and remote laboratories.

The impact of the Covid-19 pandemic on online education is summarized in the research paper which is "Covid-19: a survey" by Oussouaddi [15]. It mentioned that there is a potentially recommended system to improve the learning experiences of students. The improvements that can be seen in recommended systems are discussed in the document such as being personalized, having adaptive algorithms, usage of AI, and advanced data analytics. Further, it discusses providing tailored and specific content and learning pathways. Moharm [12]'s paper suggests future research directions in e-learning, focusing on the use of knowledge-based recommendation systems. It discusses how these systems analyze student data, preferences, and interactions to recommend the most suitable educational content, addressing challenges like the cold start problem and data sparsity.

The application of a developed framework towards diverse datasets is proposed by the paper and this method is specifically suggested for middle school mathematics and it encourages us to explore different AI methods which can be used in recommender systems. It is understood that these examples demonstrate the evolving and dynamic nature of digital technology integration in education. This emphasizes the challenges, innovations, and future directions in this field.

1.2 APPLICATION ACROSS DOMAINS

Applications describe how these various personalized educational platforms can be adapted to the requirements of students coming from a modern society. This diversity is evident in the applications ranging from specialized fields like oral surgery and implantology, as discussed by Porcel [16], to broader domains like continuous professional education in the public transport sector in Germany, explored by Libreros [9].

Educational recommendation systems are made to address specialized education to address preferences and learning needs. For example, Porcel [16] suggests a trust-based recommender system with fuzzy linguistic modeling for oral surgery and implantology. Also, it focuses on personalized activities based on trust rather than similar rating histories. This process helps professors to monitor the studies of students and to align with the specific and unique requirements of the discipline in more efficient ways. But in the context of continuous professional education, these educational recommendation systems play a critical role in order to cater to various educational backgrounds and requirements of employees in the public transport sector as explained by Libreros [9]. The development of a web platform that includes a recommender system for continuing education illustrates how educational recommendation systems can be applied to meet the ongoing learning needs of working professionals.

Furthermore, the application of educational recommendation systems in general educational settings, as mentioned in the papers of Lampropoulos [7] and Gonçalves[5], demonstrates their utility in mainstream education. These systems assist in filtering relevant and accurate learning material, thereby addressing the challenges posed by the abundance of digital content. They also prove beneficial in technical disciplines like electrical engineering, where learning analytics and recommender systems contribute to a more insightful understanding of student performance.

Research by Lynn [10] demonstrates the ways that educational recommendation systems can be efficiently implemented across different domains. In this implementation, each domain carries out exclusive necessities and challenges This shows in specialized fields, continuing professional education, or broader educational contexts. Educational recommendation systems have shown significant potential in enhancing personalized learning experiences and addressing the diverse needs of learners. Lynn [10] suggests that these systems are designed to offer personalized suggestions by considering the interests and preferences of students. In this process, students are aided in selecting relevant courses, which has been identified as a key issue among the students. The paper is developed with the motive of exploring various recommender systems and their effectiveness in helping students select courses that match their talents and interests, especially in the context of higher education.

1.3 NECESSITY OF THE PERSONALISED SYSTEM IN EDUCATION

As traditional methods, there are some systems which call as one-size-fits-all teaching models. But with the increasingly diverse needs, interests, and abilities of the students, those models became insufficient and a necessity for personalized systems in education arose. This section discusses how personalized educational systems in the form of Educational Recommender Systems address this issue. These systems provide exclusive learning experiences for each student in a personal way, and they enhance motivation for studies, student engagement, and outcomes.

Additionally, the paper by Porcel [16] addresses the potential of recommender systems in educational assessment contexts, an area where their application has been limited, and explores their feasibility and effectiveness in this new domain.

Literature by Gonçalves [5] describes how recommender systems can be implemented in the electrical engineering stream. Challenges when it comes to the evaluation of student understanding and the potential of these technologies in the provision of insightful and personalized experiences are discussed in this paper. Furthermore, it highlights how teaching methods have evolved in engineering education, and it explains diverse teaching methods such as hands-on laboratories, computer simulations, and remote laboratories.

1.3.1 Diverse Learning Needs and Styles

To fulfill a diversity of learning needs and styles in education, Educational Recommender Systems are required. Because it would be helpful for individuals to adapt to differences in student learning. These systems enable personalized learning paths, catering to various learning styles and speeds.

Special educational needs are provided by these systems along with inclusiveness, linguistic diversity, and cultural sensitivity. Personalized systems provide tailored feedback, fostering self-directed learning and autonomy among students. Continuous improvement and adaptation are facilitated through data analytics, and it also helps to make educational experiences more effective in a way that meets the needs of diverse learning. Below are the sub-parts of the diverse learning needs and styles.

1.3.1.1 Individualized Learning Paths

Personalized educational systems are designed for the students to cater to their different learning paces and learning styles. Further, it is trained to identify the weaknesses, strengths, and preferred learning styles of the students, and it ensures that each student can engage with the material most effectively.

The key focus of the document is how the personalization aspect of these recommender systems achieves the objectives of individualized learning paths. Unique learning requirements of each student are adapted by these educational recommender systems. Student performances, preferences, and learning styles are analyzed to recommend the most relevant educational content and strategies.

1.3.1.2 Use of Multimedia and Interactive Content

One of the crucial elements of personalized educational systems is embedding different learning styles. These systems recognize different preferences of students in terms of grasping and processing the information, and they facilitate individual learning styles for each student, which enhances the effectiveness and engagement in the learning process.

For students with visual learning preferences, Educational Recommender Systems can emphasize graphical content, such as videos and infographics. Auditory learners can benefit from recommendations of lectures, audiobooks, or podcasts. Kinesthetic learners, who assimilate information best through action and hands-on experiences, are directed towards interactive simulations and practical activities. This adaptability ensures that each student receives information in a format that is most conducive to their learning.

Different multimedia elements are integrated into modern educational recommender systems with the motive of catering to various learning preferences. Some instances of these multimedia elements are interactive video lessons, animated explanations, and augmented reality experiences, which make the learning process more dynamic and interactive for students with different learning styles and preferences. There is a personalized feedback mechanism that enhances this experience in more productive ways.

Moreover, modern Educational Recommender Systems integrate diverse multimedia elements to cater to these varied learning preferences. Interactive video lessons, animated explanations, and even augmented reality experiences make learning more dynamic and engaging for all types of learners. The use of personalized feedback mechanisms further enhances this experience. Depending on a student's learning style and performance, Educational Recommender Systems can provide feedback in different formats. For instance, visual learners might receive graphical representations of their progress, while auditory learners might receive verbal or written feedback.

A key strength of Educational Recommender Systems is their ability to leverage data to continually refine and customize learning experiences. By analyzing how students interact with different types of content, these systems can better align recommendations with individual learning styles. This data-driven approach ensures that the learning experience evolves with the student, constantly adapting to their changing needs and preferences.

Educational Recommender Systems also offer flexible learning environments by allowing students to learn at their own pace. This flexibility is vital for addressing different learning speeds and styles because it is known that the potential of each student is different from that of others. Students can spend more time on challenging topics, quickly go through familiar material, or explore areas of interest in greater depth, all in a self-paced manner.

Finally, for students who thrive in collaborative settings, Educational Recommender Systems can facilitate group activities and discussions, supporting social learners who benefit from interaction and peer-to-peer learning. Additionally, these systems can be tailored to provide accessible learning materials for students with special educational needs, ensuring inclusivity and equal learning opportunities.

In conclusion, by providing tailored learning experiences that cater to the diverse learning styles of students, Educational Recommender Systems significantly enhance the inclusivity, effectiveness, and engagement of educational experiences. They represent a shift towards a more personalized, student-centered approach in education, ensuring that every learner has access to the resources that best suit their way of understanding and interacting with the world.

1.3.1.3 Personalized Feedback Mechanisms

Personalized feedback mechanisms in Educational Recommender Systems (ERS) are integral to enhancing the educational experience, tailored to meet the unique needs and preferences of each student. These systems are adept at recognizing and adapting to various learning styles, whether visual, auditory, or kinesthetic, and provide feedback that aligns with these preferences. For visual learners, feedback might be presented through charts or progress maps, while auditory learners could receive feedback in the form of recorded messages or through text-to-speech tools. Kinesthetic learners might engage with interactive feedback, such as quizzes or practical tasks, to reinforce learning.

The adaptive nature of Educational Recommender Systems is particularly evident in how feedback is customized based on student performance. As students interact with learning materials, the system dynamically adjusts the feedback. For students excelling in certain areas, it might suggest more challenging content or encourage exploration of advanced topics. Conversely, for those facing difficulties, Educational Recommender Systems can offer more comprehensive guidance, breaking down complex concepts into manageable steps. This responsive feedback helps in addressing individual learning curves and needs effectively.

One of the standout features of Educational Recommender Systems is the provision of immediate feedback. Unlike traditional educational settings, where feedback can be delayed, Educational Recommender Systems offer instant responses to student activities. This immediate feedback is crucial for real-time learning, allowing students to quickly understand and correct mistakes and grasp new concepts effectively. Additionally, Educational Recommender Systems often promote self-assessment and reflection, encouraging students to think critically about their learning process. This could involve self-assessment quizzes or reflective exercises, fostering deeper engagement with the material and enhancing self-learning skills.

To further engage students, many Educational Recommender Systems incorporate gamification elements in their feedback mechanisms. Elements like badges, points, or leaderboards add a competitive and fun aspect to learning, motivating students and making the educational process more interactive. Moreover, the use of data analytics in ERS is vital for the continuous improvement of feedback. By analyzing patterns in student responses and interactions, these systems can identify common challenges and refine their feedback mechanisms, accordingly, ensuring a consistently effective and personalized learning experience.

In conclusion, personalized feedback mechanisms within Educational Recommender Systems are a testament to the advancements in educational technology, offering a tailored, engaging, and effective approach to learning. By aligning feedback with individual learning styles, performance, and preferences, Educational Recommender Systems not only enhance the learning process but also contribute to a more personalized and student-centered educational environment.

1.3.1.4 Data-Driven Customization

Data-driven customization in Educational Recommender Systems (ERS) is a transformative approach that leverages continuous data collection and analysis to tailor the educational experience to individual learners. These systems gather detailed data on student interactions with various content types, ranging from engagement duration to performance metrics. This data is analyzed in a complicated way, often using advanced algorithms and machine learning, to identify patterns in learning behaviors and preferences. Such analysis enables Educational Recommender Systems to continuously refine content recommendations, aligning them with individual learning styles and evolving needs. For instance, if a student shows a consistent preference for visual content and excels in assessments related to it, the system adapts to prioritize similar resources.

This personalization extends beyond content format to aspects such as learning pace and difficulty level, ensuring that the education offered is relevant and effective throughout the student's learning journey. The dynamic nature of data-driven customization means that as students grow and their preferences change, the Educational Recommender Systems adapts accordingly, maintaining a high degree of relevance and engagement. This process creates a feedback loop, continually enhancing the system's accuracy and effectiveness. Ultimately, data-driven customization in Educational Recommender Systems represents a significant shift from traditional educational models, offering a more responsive, personalized, and effective learning experience that aligns with the unique journey of each student.

For reference, the literature by Libreros [9] emphasizes the need for user-friendly, usage-centered methods that cater to a multi-profile target group and incorporate expertise from the users and clients. Further, it suggests more focus on the rapid changes in interests over time.

1.3.1.5 Flexible Learning Environments

Flexible learning environments refer to the catering of diverse needs of learners, offering them the autonomy to navigate their educational journey at a pace and style that best suits them. This flexibility is particularly crucial in addressing the varying speeds and styles of learning among students, ensuring that each individual's educational experience is both effective and enjoyable.

In these adaptive learning environments, students are empowered to take control of their learning process. Those who grasp concepts quickly can move ahead at an accelerated pace, avoiding the stagnation that can occur in more rigid educational settings. Conversely, students who need more time to understand certain topics can take the time they need without feeling rushed or pressured. This individualized pacing prevents students from falling behind and helps maintain their motivation and engagement.

Furthermore, flexible learning environments allow students to revisit and review complex topics as needed. This aspect is particularly beneficial for reinforcing learning and ensuring a deep understanding of challenging subjects. The ability to go back to previously covered material ensures that students can build a strong foundation of knowledge, essential for advanced learning.

Students also have the opportunity to skip over material they already understand, which prevents boredom and disengagement. This capability is especially important for keeping advanced learners challenged and engaged, as they can bypass content that does not contribute to their learning growth.

Moreover, these personalized systems enable students to delve deeper into areas of special interest or topics where they show exceptional aptitude. This not only fosters a love for learning but also allows students to explore and develop their strengths and passions further. Such exploration is essential for cultivating critical thinking, creativity, and a deeper understanding of subjects that intrigue them.

In essence, flexible learning environments created by personalized educational systems represent a significant shift from traditional, standardized education models. They prioritize the individual learner's needs, preferences, and pace, thereby creating a more inclusive, effective, and student-centered educational experience. This approach ensures that every student can engage with their education in a way that is most conducive to their learning style and pace, ultimately leading to better educational outcomes and a more fulfilling learning experience.

1.3.1.6 Collaboration and Social Learning

Collaboration and social learning are pivotal in modern education, with Educational Recommender Systems (ERS) enhancing these aspects. Educational Recommender Systems support environments where students can collaborate and learn from peers. They often include features for group activities and projects, tailored to both curriculum and student interests. These group tasks promote teamwork, allowing students to learn collaboratively, share viewpoints, and benefit from each other's strengths, deepening their understanding and developing skills like collaboration and problem-solving.

Many ERS platforms feature discussion forums and peer feedback mechanisms, enabling students to engage in discussions, exchange ideas, and provide feedback. This interaction is particularly beneficial for social learners, who process information more effectively through dialogue and collaboration. ERS can also match students for group work based on complementary skills and interests, enhancing group dynamics.

Integration with social media and communication tools extends collaboration beyond the classroom, allowing students to continue discussions and share resources. This fosters a community among learners, ensuring continuous engagement. Educational Recommender Systems also often focus on real-world problem-solving through collaborative projects, providing practical experience and preparing students for professional challenges.

In summary, ERS facilitates group activities, discussions, and peer-to-peer learning, preparing students for a collaborative world. This approach exemplifies education's evolution towards more engaged, participatory, and community-oriented learning.

An example from the literature review includes Porcel [16]'s trust-based recommender system for dentistry students, focusing on oral surgery and implantology. This system incorporates videos, resources, student profiles, and recommendation methods, using linguistic labels to assess trust and satisfaction. It's designed for flexibility, allowing students to engage with materials at their convenience, exemplifying personalization in collaborative learning.

1.4 USE OF GENERATIVE AI & LARGE LANGUAGE MODELS FOR RECOMMENDATION SYSTEMS

With the advancement of modern technologies, personalized recommendations for learning materials have become increasingly valuable for students. However, the overwhelming volume of resources available, even within a specific field, makes it challenging for students to extract the precise knowledge they need. The excessive and bulky nature of supporting materials can cause them to overlook critical information. Additionally, navigating through large volumes of content is often time-consuming, hindering the efficiency of their learning process.

To address this challenge, an intelligent chatbot system was introduced that allows students to interact directly with the system through a conversational interface. This chatbot will enable students to ask specific questions, highlight the exact theoretical concepts they need, or seek clarification regarding the recommended learning materials. By facilitating real-time, personalized support, the chatbot aims to simplify the process of accessing relevant information, ensuring that students save time and focus on their learning objectives more effectively. This solution integrates seamlessly with personalized recommendations, enhancing the overall learning experience by making it more targeted and efficient.

By dynamically adapting to user queries and providing direct, context-aware responses, the chatbot enhances the usability and relevance of recommendations. Additionally, it captures feedback during interactions to refine future suggestions, making the system more intelligent and user-centric. This approach bridges the gap between static content recommendations and the dynamic, evolving needs of students, fostering a more effective and engaging learning experience.

CHAPTER 2

LITERATURE REVIEW

2.1 ROLE OF EDUCATIONAL RECOMMENDER SYSTEMS IN MODERN EDUCATION

The role of Educational Recommender Systems (ERS) in modern education is pivotal, particularly in enhancing personalized and collaborative learning experiences. These Educational Recommender Systems have been designed to support a range of educational activities that cater to diverse learning needs and styles. These systems offer features for group activities and projects, facilitating teamwork and communication. The integration of discussion forums and peer feedback mechanisms within ERS platforms encourages active student engagement, fostering a collaborative learning environment.

An example from the literature review includes Porcel [16]'s work on a trust-based recommender system with fuzzy linguistic modeling for dentistry students, emphasizing personalized education in e-learning environments. Additionally, de Schipper [4]'s research on recommender systems for personalized feedback post-assessments illustrates the potential of ERS in educational assessments.

Further, as suggested in Silva [20]'s paper, Educational Recommender Systems are designed to support and enhance the learning process by providing personalized recommendations to learners. They typically use data on learners' preferences, performance, and behavior to suggest educational resources, activities, or paths that are most likely to benefit their learning journey. Here, the aim is to create a more efficient and effective educational experience, tailored to the individual needs and interests of each learner. The given paper identifies gaps in the current literature, noting limited discussions on cross-sectional issues in the evaluation and presentation approaches of Educational Recommender Systems. The study aims to fill these gaps by offering a detailed analysis of recent trends in Educational Recommender Systems, specifically focusing on recommendation production, presentation, evaluation, and identifying research limitations and opportunities. This comprehensive approach aims to provide a more panoramic view of the Educational Recommender Systems field and guide future research directions.

Therefore, it is known that Educational Recommender Systems exemplify the shift towards participatory, community-oriented learning, preparing students for a collaborative, interconnected world by enhancing academic understanding through collaboration and social learning.

2.2 EDUCATIONAL RECOMMENDER SYSTEMS

Educational Recommender Systems (ERS) emphasize aligning group tasks with curricula and student interests to nurture a collaborative learning environment. These systems are adept at identifying and recommending group activities that are not only relevant to the current curriculum but also resonate with the interests of the students, thereby increasing engagement and participation in collaborative tasks. This tailored approach ensures that group activities foster essential skills such as teamwork and effective communication, critical in academic and professional settings. By engaging in collaborative projects, students are exposed to diverse perspectives, deepening their understanding of the subject matter.

For instance, Porcel [16]'s work on a personalized education system for dentistry students employs a trust-based fuzzy linguistic approach, demonstrating how specialized content can be effectively delivered and adapted to collaborative learning scenarios. Further, this literature suggests true networks that describe the mechanism for assigning and utilizing trust scores within the recommender system. It is understood that Porcel [16]'s work well demonstrates how trust and fuzzy linguistic methods can enhance personalized educational recommendations.

Similarly, Lampropoulos [7]' paper reviews the broad application of educational recommender systems, highlighting their capacity to support various teaching and learning activities, including group projects, in different educational settings. It discusses the role of artificial intelligence in Educational Recommender Systems. Lampropoulos [7]' paper discusses the rapid advancement of AI and its applicability in various domains, including education. It focuses on how AI can create sophisticated, adaptable systems that mimic human thinking and learning. The section explores AI's potential to transform the education landscape, offering new solutions for educational needs and demands. It highlights AI's role in developing new learning and teaching strategies and the importance of integrating AI in a student-centered manner to improve education sustainability and efficiency. The paper also addresses various challenges and gaps that need further exploration for wider acceptance and integration of AI in education. These examples from the previous literature illustrate the significant role of Educational Recommender Systems in creating engaging and collaborative learning experiences by intelligently aligning group activities with both educational objectives and student preferences.

When discussing another instance, describe the architecture of the proposed Top-enhanced Recommender Distillation (TERD) framework. This framework is designed to effectively improve recommendation accuracy at top positions, focusing on educational contexts. It describes how knowledge from a teacher network is distilled into a student network by enhancing the recommendation process. This part of the paper is key to understanding the innovative approach of TERD in tackling the challenges of effective top-N recommendations in learning environments. Also, it demonstrates an experimental setup, datasets used, and the comparison of the proposed Top-enhanced Recommender Distillation (TERD) framework with other models. This includes tests on multiple datasets to validate the effectiveness of TERD, and it further demonstrates its advantages in terms of recommendation accuracy and efficiency. Further, it is proven in the paper that the success of TERD in improving student engagement and motivation in e-learning environments is evidenced by the results of comprehensive experiments. Additionally, it emphasizes the flexibility and adaptability of TERD by making a significant contribution to the field of educational recommender systems.

For instance, when considering the literature by Lynn and Emanuel, they have considered both individual and course factors that may lead students to choose the courses they want to enroll in when joining institutions of higher education. Future career goals, personal interests, and the nature of the lecturer are some examples of these factors.

2.3 MATCHING STUDENTS FOR COLLABORATIVE WORK

When Educational Recommender Systems (ERS) are developed in modern education, facilitating collaborative work through student matching is important, as these systems are adept at enhancing group dynamics in collaborative projects. ERS platforms use sophisticated algorithms to intelligently group students, ensuring that each team is balanced and conducive to effective collaboration. This process involves analyzing the academic profiles, learning styles, and interests of the students to match them with peers who complement their abilities and preferences.

The ability of Educational Recommender Systems to group students for collaborative work not only promotes diversity in perspectives but also ensures that students are exposed to different approaches and ideas, enriching the learning experience. For instance, in a group project, a student with strong analytical skills might be paired with another who excels in creative thinking, fostering a balanced and dynamic team environment. This strategic grouping can significantly enhance the effectiveness of collaborative learning, leading to improved problem-solving skills, increased knowledge retention, and the development of critical soft skills like communication and teamwork.

The literature by Gonçalves [5] discusses the integration of learning analytics and recommender systems in education, particularly in technical disciplines like electrical engineering. This paper highlights the use of varied teaching methods and the potential of technology to provide personalized educational experiences, which can be extended to include the strategic grouping of students for collaborative projects.

2.4 MECHANISM OF DEVELOPING TRADITIONAL RECOMMENDATION SYSTEMS

The term: Recommendation Systems refers to a platform that suggests things like products, services, or learning materials based on various factors. In this context, these recommendation systems are based on different personalized online platforms.

When understanding the mechanism of recommendation systems, all the aspects of the recommendation systems should be taken into consideration. When designing the research questions, it should be aimed to explore the current trends, techniques, and challenges in the field of Educational Recommender Systems as well. As suggested in Felipe's paper, the research questions focus on understanding how Educational Recommender Systems are designed, the methods and inputs used for generating recommendations, the approaches to presenting these recommendations, and the evaluation strategies employed. Additionally, the questions seek to identify the current limitations and research opportunities in Educational Recommender Systems, aiming to provide a comprehensive view of the state of the art and directions for future research.

2.4.1 DATA COLLECTION

In personalized education systems, data collection is a fundamental step, serving as the foundation for tailored learning experiences. The process involves gathering both explicit and implicit data about the students. This data can include demographic details, educational preferences, learning styles, and interaction patterns with educational materials.

Examples from the previous literature further illustrate this process. In the study by Porcel [16], the personalized education system for dentistry students incorporates student profiles, which likely include data such as their engagement with various learning resources and preferences. This information is used to deliver flexible and personalized content, allowing students to engage with the material at their convenience. Similarly, de Schipper [4]'s research utilizes detailed examination data from secondary school students to analyze performance and potential areas of improvement, demonstrating how explicit academic data is crucial in tailoring educational experiences.

Similarly, the literature of Lampropoulos [7] explains a system to get the research papers recommended. First, a summary of all collected documents can be taken, like what types they are, when they were published, and how many authors worked on them. Then, some other details such as how often the documents were cited, and their publication details. Further, the types of documents, existing common topics, and keywords should be there. This careful analysis helps to understand the current state of research in educational recommender systems straightforwardly.

These examples underscore the critical role of data collection in creating effective personalized education systems. By gathering and analyzing detailed and diverse data, these systems can provide more accurate and meaningful educational experiences tailored to individual student needs.

Literature by Libreros [9]'s paper focuses on a usage-oriented approach to developing a recommender system in the public transport sector. To gather the data, the proposed method was to conduct guided interviews with industry representatives to understand user expectations for the recommender system. The gathered information from these interviews helped shape the development and functionality of the recommender system, and that helps to align with the specific needs and preferences of its target users, which means a human-centered recommender system specific to the public transport field.

Similarly, the literature; Advances in online education recommender systems during and after Covid-19: a survey" by Oussouaddi [15], also mentions ways for data collection. It suggests a systematic search of academic databases to identify articles related to online education recommender systems during and after the COVID-19 pandemic. Also, in the screening process, articles were screened based on their relevance to the research objectives of the study. Further, when considering the data extraction, it recommends that selected articles undergo a data extraction process, where information about advancements in online education recommender systems, their impact on student engagement and learning outcomes, challenges and limitations, adaptations to changing needs, and ethical considerations was gathered.

Different methods to extract data are discussed by Ugarte [21] in The Use of Recommender Systems in Formal Learning. This paper discusses the increasing importance of data in modern life, particularly in the context of Recommender Systems. It describes a two-phased protocol as the definition phase and the execution phase. Their search queries were designed according to Framed following the PICOC criteria, which was suggested by Bhatt [3], Mousavi [13], and Li [8]. As the sources, five digital libraries have been chosen, such as ACM Digital Library, IEEExplore Digital Library, Springer Link, etc. Also, Papers were excluded if they did not propose a solution, were not peer-reviewed, were not written in English, did not indicate the educational stage for the proposed solution, were not intended for formal learning, or did not describe the technique and type of data used for the recommendation. To extract data, each paper has been analyzed based on predefined research questions related to the application of the solution in educational stages such as primary, secondary, and higher education, target audience (students, teachers, or both), types of products or contents recommended, information used for recommendations, feedback mechanism (explicit or implicit), algorithms used, and evaluation methods. During the execution phase, the query string was executed as per the defined criteria.

2.4.2 USER PROFILING IN PERSONALIZED EDUCATION SYSTEMS

User profiling is a critical step in the functioning of personalized education systems, where individual student profiles are created based on collected data. These profiles encapsulate various aspects such as preferences, interests, academic strengths, weaknesses, and behavior patterns, which are key to tailoring educational experiences.

When developing a personalized education system, it is important to develop detailed student profiles. This process involves collecting data on students' demographic details and educational-related information, such as enrolled modules and preferred learning methods, through surveys and data that can be taken from databases. The profiles created from this data help in customizing the educational content to match individual student needs and preferences.

Examples from the literature review further illustrate the importance of user profiling in educational settings. For instance, the work of Porcel [16] discusses a system with a trust-based fuzzy linguistic approach for dentistry students, where student profiles likely include data on their interactions with learning resources and preferences. Similarly, de Schipper [4]'s research utilizes detailed examination data from secondary school students to tailor educational experiences effectively.

Another example includes the use of data from MOOC platforms like Udemy and Coursera in a personalized education system. This system aims to tackle challenges like resource overload and knowledge fragmentation by recommending instructional materials that match learners' preferences and requirements. Additionally, research by Libreros [9] in the public transport sector involves conducting guided interviews to understand user expectations, shaping the development of a user-oriented recommender system.

The literature by 'Personalized Desire2Learn Recommender System based on Collaborative Filtering and Ontology' by Qwaider [17] refers to another instance. This model integrates several components to optimize learning experiences. It starts with the 'Student Profile', which encompasses detailed student information such as demographics and academic history, feeding into a 'Learning Object Ontology' that records course details and formats. The 'Student Database Preprocessing' then formats this data for the recommendation engine. The actual recommendation process involves Recommendation Incentive, where predictions and tailored suggestions are generated for learners using a mix of collaborative filtering and ontology. The model also includes 'Domain Knowledge Management (DKM)' for teachers to manage course materials, and a 'Learning Material Tree (LMT)', which organizes course content into a structured format. Lastly, the 'Portal D2L' serves as the digital interface for teachers and students, offering functionalities like forums, virtual classes, and attendance systems, thereby creating a comprehensive system for personalized educational recommendations.

Therefore, it is understood that user profiling in personalized education systems involves a comprehensive analysis of collected data to create individualized student profiles. These profiles are instrumental in delivering customized learning experiences, ensuring that the educational content is relevant and effective for each student.

2.4.3 ITEM PROFILING IN PERSONALIZED EDUCATION SYSTEMS

In personalized education systems, item profiling is essential for creating profiles for various learning resources, courses, or activities. These items are tagged with attributes like difficulty level, subject matter, and learning style orientation to enable accurate and tailored recommendations.

When developing a personalized education system, the development of a machine learning model to analyze collected data and make personalized recommendations is a crucial aspect of item profiling. This involves categorizing and tagging educational content and resources based on various educational attributes, thereby ensuring that each learning module is appropriately profiled for recommendation purposes.

In the previous literature, several examples highlight the implementation of item profiling in educational settings. For instance, de Schipper [4]'s paper discusses the use of final examination data for secondary school students in the Netherlands, focusing on digital exam data for mathematics. The exams feature numerous items, each likely profiled with specific attributes like difficulty and topic areas, which facilitate detailed analysis and personalized feedback in education. Another example is the work of Porcel [16], where the system includes components like videos, resources, student profiles, and a recommendation method. It employs linguistic labels to profile these educational resources, assessing factors like trust, relevance, and satisfaction. This detailed profiling allows for more personalized and flexible engagement with students.

Moreover, the basics of recommender systems, including content-based filtering, collaborative filtering, and hybrid approaches, are covered in the literature. These systems rely heavily on item profiling to provide personalized feedback in educational contexts, demonstrating the critical role of accurately profiling educational content and resources.

Item profiling in personalized education systems involves detailed categorization and tagging of educational resources, enabling these systems to recommend the most relevant and beneficial learning content to students based on their individual needs and preferences. The system categorizes and tags educational content and resources with various attributes to ensure that learning modules are appropriately aligned with individual student profiles and requirements.

Qwaider [17]'s research on the Desire2Learn recommender system demonstrates the utility of item profiling in managing the information overload of educational resources. This system effectively categorizes a wide array of educational courses, assisting learners in finding courses that match their academic levels and interests. Additionally, de Schipper [4]'s paper on digital exam data for mathematics students provides an example of how exam items are profiled based on difficulty and topic areas, facilitating personalized and targeted feedback in education. These instances underscore the significance of item profiling in creating tailored and effective educational experiences through recommendation systems.

2.4.4 MATCHING ALGORITHM

The matching algorithm is a crucial component of a recommendation system, responsible for analyzing both user and item profiles to identify suitable matches. This process involves comparing various criteria derived from the collected data to ensure that the recommendations align closely with the user's preferences and requirements.

In the context of the recommendation system in the educational sector, the matching algorithm would play a pivotal role in determining the most appropriate educational content for students. This could involve selecting the most relevant modules or learning resources based on the academic profiles, learning styles, and module engagement patterns of the students. The machine learning model developed in this system would likely use a combination of filtering techniques, such as collaborative filtering, content-based filtering, or hybrid approaches, to optimize the matching process.

Examples from the literature also highlight the use of sophisticated algorithms in educational recommendation systems. One study utilizes collaborative filtering and content-based approaches, focusing on their application in educational contexts. This includes using these filtering techniques to analyze student data and provide personalized learning recommendations, catering to individual academic needs and preferences. Another example involves employing machine learning and collaborative filtering techniques in a MOOC Recommender System, which uses data from platforms like Udemy and Coursera to recommend courses. This system addresses challenges such as resource overload and knowledge fragmentation by matching learners with instructional materials suited to their preferences. These examples demonstrate the critical role of matching algorithms in personalized education systems, where they serve to enhance the learning experience by ensuring that the recommendations are well-aligned with each student's unique educational needs and goals.

As suggested by the literature by Lynn [10], Recommender Systems are classified according to the methods they use. These methods are grouped into four major broad categories. The basic models work with two types of data for their prediction process: User-item interactions and user-item attribute information like textual profiles or relevant keywords. Besides, Techniques in Recommender Systems are also graded in two groups, that is, memory-based and model-based algorithms. In this manner, Memory-based algorithms work on the overall user-item rating matrix. In contrast, model-based techniques work by using the rating data to train a model, which is then used to produce recommendations. In this literature, four recommendation approaches have been defined.

2.4.4.1 Collaborative Filtering

Collaborative filtering stands out as a critical technique. It functions by analyzing patterns of user behavior, preferences, and interactions to recommend items in the educational context. These things could be courses, learning resources, or activities. This approach would be instrumental in matching educational content with students' preferences, based on similarities in the choices and behaviors of other students. The implementation of such a system could significantly enhance the learning experience by providing more relevant and personalized content recommendations.

In the literature, collaborative filtering is highlighted in the context of MOOC platforms like Udemy and Coursera. The study emphasizes the use of collaborative filtering techniques alongside machine learning to predict students' academic performance and recommend courses. This Personalized Course Recommendation (PCR) system is designed to adapt to individual learner needs and preferences, addressing challenges like resource overload and knowledge fragmentation in educational settings. By leveraging user ratings and interactions, the system aims to offer tailored course recommendations, thus enhancing the personalization and effectiveness of the learning experience.

These examples demonstrate the value of collaborative filtering in creating efficient and user-centric educational recommender systems. By analyzing and utilizing the collective data of user behaviors and preferences, collaborative filtering helps in crafting more accurate and relevant educational pathways for learners.

2.4.4.2 Content-Based Filtering

Content-based filtering is a sophisticated technique employed in recommendation systems, particularly in educational contexts. This method bases its recommendations on the attributes of items like courses or learning materials and the preferences or past behavior of the user. In educational settings, this might involve recommending resources that align with a student's preferred learning style, subject interests, or difficulty level. This approach is essential for providing personalized education by matching learning resources with student profiles based on their individual learning preferences and academic requirements.

In the literature, content-based filtering is discussed in various contexts. For instance, de Schipper [4]'s paper on digital exam data for mathematics students highlights the application of content-based filtering to provide personalized feedback in education.

This approach tailors learning recommendations based on student assessment data, making it highly relevant for academic improvement.

Another example from the literature review includes the work of Moharm [12], which discusses the application of content-based filtering in creating adaptive personalized learning experiences. The paper suggests that future research should focus on expanding the use of content-based recommendation systems, particularly in middle school mathematics. It emphasizes the potential of these systems to enhance the precision and consistency of recommendations in e-learning environments.

These examples underscore the effectiveness of content-based filtering in educational recommender systems. By analyzing the specific attributes of educational content and aligning them with individual student profiles, content-based filtering plays a pivotal role in creating personalized and effective learning pathways.

2.4.4.3 Hybrid Recommendation Systems

Hybrid recommendation systems represent an advanced approach in recommender system technology by combining different methodologies to enhance recommendation accuracy and overcome the limitations of single-method systems. These systems are a mixture of collaborative and content-based filtering techniques and carry out the strengths of both. Collaborative filtering bases recommendations on the preferences of similar users, while content-based filtering suggests items similar to those a user liked in the past based on item attributes. Hybrid systems can integrate these approaches in various ways, such as weighted combinations where each of the recommendations of each method has assigned weights, switching between methods based on criteria like user context, presenting mixed recommendations from different methods, and combining features from diverse data sources into a unified model.

For instance, the literature by Silva [20] insists that hybrid recommender systems are predominant in the field because they effectively meet diverse educational needs. The paper discusses examples of such hybrid approaches and notes that collaborative filtering, a popular technique, is often used in conjunction with other methods. It is observed that the section highlights the use of techniques like collaborative filtering and content-based filtering and mentions their role in personalized educational recommendations. Also, it describes how these techniques can be adapted and combined to enhance the effectiveness of the Educational Recommender Systems in addressing specific learning preferences and requirements.

When studying Moharm's [12] paper discusses the design and implementation of comprehensive recommender systems for e-learning. This also involves examining a combination of various techniques like collaborative filtering, content-based recommendation, and knowledge-based methods to create adaptive, personalized learning experiences.

2.4.4.4 Knowledge-based recommender methods

As defined in the literature by Lynn [10], knowledge-based recommender methods use specific details about items or users to create personalized recommendations. These systems rely on a structured knowledge base that contains information about the attributes, characteristics, or features of items, as well as the preferences or requirements of users. Unlike collaborative filtering methods that use historical user behavior, knowledge-based systems can offer recommendations even for new or unrated items. The process involves matching user preferences with item attributes in the knowledge base to make informed recommendations. This approach is particularly beneficial in domains where explicit knowledge about items is available, such as educational content, books, or products with well-defined features.

2.4.5 RECOMMENDATION GENERATION

In the development of a machine learning model for a personalized education recommender system, as outlined in the proposal, the focus is on identifying the optimal filtering technique for the recommendation model. This involves considering approaches such as collaborative filtering, which utilizes user behavior and similarities among users; content-based filtering, which focuses on the attributes of the items being recommended; and hybrid filtering, which combines elements of both collaborative and content-based methods. The aim is to develop a machine learning model capable of effectively analyzing collected data, such as students' demographic details, module enrollments, and learning preferences, to generate personalized educational content recommendations.

When considering de Schipper's[4] paper, it gives more focus towards personalization, which both studies concentrate on customizing educational content to individual student needs. Apart from that, it pays attention to the usage of advanced algorithms and data-driven approaches.

This approach is supported by the findings of studies like those conducted by Oliveira [14], Ren [18], Hahn [6], and Lampropoulos [7], which highlight the significance of personalization in educational technology through machine learning and recommender systems.

The development of a machine learning model for personalized educational content recommendations is a complex yet essential task. It involves analyzing extensive data to create a system that caters to individual learning needs and preferences. Various filtering techniques, such as collaborative, content-based, and hybrid filtering, are explored to determine the most effective approach for this context.

Significant insights can be drawn from existing research in the field. For instance, the trust-based recommender system with fuzzy linguistic modeling designed for students in oral surgery and implantology, as discussed by Porcel [16], highlights the importance of personalized education in e-learning environments and the role of recommender systems in enhancing teaching-learning processes. This approach, focusing on user trust rather than just similarity in rating histories, represents a shift in recommender system design for educational purposes, particularly in specialized fields. While the recommender system described in this paper demonstrates the results taken from the University of Granada, it has three main components as videos and resources, student profiles, and a recommendation method. It uses linguistic labels to assess trust, relevance, satisfaction, and membership to reinforce subgroups. It is understood that the system is designed with a focus on flexibility and personalization because it wants to allow students to engage with the material at their convenience.

Moreover, research by de Schipper [4] on automated and personalized feedback to students following summative assessments showcases the potential of recommender systems in educational assessment contexts. This work underscores the benefits of such systems in supporting the learning process by targeting specific gaps in students' knowledge, especially when instructor feedback is limited by time constraints. Additionally, the research by Felipe on Educational Recommender Systems (ERS) provides valuable insights into the design, methods, and inputs used for generating recommendations, along with the evaluation strategies employed.

These studies, along with others reviewed in the literature, offer a rich resource for designing an effective machine-learning model for educational content recommendations. They demonstrate the importance of a data-driven approach, which leverages student performance data and feedback to tailor recommendations. This aligns with the objectives of the research, of creating a system that adapts to individual learning styles and academic performance.

The model could benefit from exploring diverse and larger datasets, assessing long-term impacts on student learning, enhancing user interfaces for improved experience, and ensuring scalability to handle a larger number of users and resources. Furthermore, incorporating additional variables like learning styles or performance metrics could refine the recommendation process, making it more efficient and effective.

Taking inspiration from the methodological approaches and evaluation strategies of existing systems, the development of the proposed machine learning model should focus on personalization, adaptability, and user-centered design. It should be flexible enough to cater to various educational contexts and capable of evolving with the changing educational landscape, especially in the wake of challenges such as those posed by the COVID-19 pandemic.

The development of this machine learning model for personalized educational content recommendations should integrate insights from existing literature, focusing on trust-based, personalized, and data-driven approaches. This will ensure the creation of a system that is not only technologically advanced but also aligned with the needs and preferences of learners in a dynamic educational environment.

In the design phase of a recommender system, it is important to be concerned about the various approaches and strategies that can be used. For instance, Silva's [20] paper discusses how these systems can present their recommendations to users. This involves examining the formats, interfaces, and methods through which the recommendations are communicated, considering their effectiveness and user-friendliness. The section likely delves into the balance between providing informative recommendations and ensuring they are understandable and accessible to the intended audience, which includes students and educators in the educational context.

2.4.6 SYSTEM IMPLEMENTATION

In the implementation phase of a personalized education recommender system, as outlined in the proposal, a critical step is the integration of the developed system into a test platform, allowing a select group of students to engage with and evaluate it. This approach is vital to ensure that the system is user-friendly and accessible, thereby enhancing student interaction and feedback.

Drawing from insights in the literature, it becomes clear that employing various recommendation approaches, such as hybrid and knowledge-based methods, is crucial for catering to diverse educational needs and preferences. Additionally, the significance of using datasets and metrics, like those from Coursera and Udemy, and applying precision, recall, and mean absolute error (MAE) for evaluation, cannot be overstated. These are instrumental in training the system and assessing its effectiveness.

For successful implementation, several key aspects should be considered. Firstly, the integration into a test platform requires a diverse subset of students to represent a range of learning styles and preferences, ensuring comprehensive usability feedback. The user interface design must be intuitive and straightforward, accommodating various levels of students, and the system should be accessible across different devices and internet capabilities. Feedback collection and analysis are paramount; qualitative and quantitative feedback from students will identify improvement areas and refine the system. Monitoring key performance metrics such as user engagement, satisfaction, and learning outcomes is essential for assessing the system's impact on student learning and guiding necessary adjustments. Lastly, an iterative approach to development is critical, where ongoing enhancements are made based on feedback and performance data, remaining open to new technologies and methodologies that could further improve the system's effectiveness.

Literature by Gonçalves [5] describes a way that a system can be implemented. It suggests two main phases, consisting of data analysis and recommendations. Data analysis has two essential functions. The first one focuses on online monitoring of student test answers. Each answer provided to a given question in a particular test is retrieved from the database and stored in a domain ontology, forming a knowledge base. In that ontology, some rules allow inferences to support the recommendations.

The second function is to summarize the data to provide information that may help teachers to better understand the students' performance. In the recommendation phase, the answers are monitored and stored in the knowledge base supported by a domain ontology. With this, each answer is analyzed through inferences in the knowledge base, taking into account some criteria, and if the criteria do not satisfy some values, the student is advised to better re-evaluate the solution provided. For example, if the answer is outside a certain acceptable range for a particular question, a check of the unit of measure used is recommended. This means the student has a new attempt before definitively confirming the answer to a specific question. The original answers to each question and the possible answers obtained after a recommendation are given can provide interesting input for teachers to have information about the difficulties faced by the students. It allows an analysis of the causes of deficiency in specific questions and can guide the teacher in actions of revision or improvements in the theoretical and hands-on classes.

Further, the paper by Amin [2], which discusses the development of a personalized e-learning and MOOC recommender system in IoT, brings out the performance and advantages of the model after the implementation. It discusses how the model is capable of providing accurate long-term course recommendations, and also the inclusion of features for dynamically updating the status of users to reflect their current preferences and learning progress. Also, it is mentioned that the model is applicable in both cold-start and warm-start scenarios, meaning it can effectively recommend courses to new users who have no previous interaction history and to existing users.

Also, this paper addresses the cold start problem as well.

2.4.7 EVALUATION

The evaluation of the personalized education recommender system is structured to be comprehensive, aiming to assess the system's performance in enhancing student engagement, motivation, and learning outcomes. This multi-faceted evaluation process will involve a combination of user surveys, learning analytics, and academic performance data. Specifically, user surveys will be conducted to collect direct feedback from students regarding their experience with the system, its usability, and its impact on their learning and motivation. Learning analytics will play a crucial role in tracking and analyzing student interactions with the recommended content, focusing on metrics such as time spent on resources, frequency of usage, and patterns in resource selection. Additionally, a crucial aspect of the evaluation will be comparing academic performance data before and after the implementation of the recommender system. This will help in determining any measurable improvements in grades, course completion rates, and other academic achievements. Overall, this evaluation strategy is designed to provide a holistic understanding of the recommender system's impact, guiding future improvements and enhancements.

One approach, as exemplified in Porcel [16]'s paper, involves conducting practical studies with a group of volunteer students. This method focuses on assessing the utility of the system, its impact on student results and satisfaction, and comparing the effectiveness of the recommender system with traditional educational methods. Such practical studies have demonstrated positive impacts on student performance, indicating the potential benefits of recommender systems in real educational settings.

Furthermore, the evaluation methods outlined in de Schipper's [4] paper emphasize the importance of specific performance metrics such as accuracy, precision, recall, and user satisfaction. This approach may include comparing the recommender system's feedback with expert opinions, analyzing improvements in student performance after using the system, and conducting surveys to evaluate user experience and system effectiveness. These methods are instrumental in assessing the practical utility and overall impact of recommender systems in educational contexts.

Additionally, Silva [20]'s paper provides insights into various methodologies employed for evaluating Educational Recommender Systems (ERS). This evaluation covers critical metrics like accuracy, precision, user satisfaction, and learning outcomes. Such metrics are essential for validating the effectiveness and efficiency of ERS in educational settings and for measuring their impact on teaching and learning processes. This multi-faceted approach to evaluation is crucial for understanding how ERS can be optimized and integrated effectively in educational environments.

2.5 THE ROLE OF GENERATIVE AI IN RECOMMENDATION SYSTEMS

2.5.1 SHORTCOMINGS OF TRADITIONAL METHODS

There are notable challenges that limit their adaptability and scope in traditional recommendation systems, even if those methods are effective under their constraints. One of the most significant limitations is the reliance on structured data, such as user-item interaction histories or rating matrices. Further, these methods exclude unstructured data sources like text, images, and videos, which contain much important information. Because of this, conventional systems struggle to capture recommendation scenarios that require more nuanced understanding and cross-modal integration.

Cold start problem is another critical issue as mentioned by Yashar et al., Wenjie Wang et al., and Elham Abdulwahab Anaam et al. This problem affects the ability of these systems to recommend items to new users or suggest newly added products. The reason for this is the lack of sufficient interaction data. Due to this, traditional models are unable to generalize effectively, and this makes them less robust in handling these scenarios. This difficulty is noticeable in fields where successful user or product onboarding must happen quickly. It is also mentioned that the lack of prior interaction data limits the ability to make informed suggestions.

Furthermore, Elham Abdulwahab Anaam et al. discuss a limited scope of data utilization. Because it is known that many traditional methods are based on only collaborative filtering or content-based filtering. These approaches restrict the full utilization of available data, such as demographics, user profiles, or external contextual information. Also, this suggests low recommendation accuracy and scalability issues. When there are complex relationships between data points, recommendation systems fail to detect them, which results in suboptimal recommendation accuracy. For instance, they struggle with dynamic and nuanced decision-making, which hybrid methods can handle better.

Another issue with traditional systems is that they also function as "narrow experts". This means that these systems are excelling in specific domains, but they are falling short when broader contextual understanding or reasoning is required. Their usefulness in situations that require adaptability across several domains or the capacity to synthesize data from diverse contexts is hampered by this restricted emphasis. Similar to this scenario, these systems often use a "late fusion" technique to combine results after processing data modalities like text, images, or videos independently. This approach loses out on chances to smoothly include complementary data, which results in suggestions that are less comprehensive or reliable.

Further, according to Yashar et al., there are two main areas where traditional methods underperform, which are personalization and interactivity. Recommendations from traditional methods are always static, but they require dynamism to adapt to user preferences in real-time. But in modern systems, they can engage users through natural language dialogues or provide tailored explanations. However, traditional methods offer limited scope for such user-centric interactions. Furthermore, there are difficulties with sparsity in user interaction data, particularly for long-tail items that see minimal engagement. This restricts the ability of conventional systems to recommend niche or less popular items effectively, often favoring mainstream options instead.

Finally, the output of traditional recommendation systems is limited to ranked lists, which provides little flexibility in terms of structure or complexity. They don't perform well on activities that call for precise responses, dynamic curation, or visual experiences like virtual try-ons. Together, these drawbacks show how limited traditional methods are, and they also illustrate how generative AI has the potential to overcome these obstacles and expand the capabilities of contemporary recommendation systems.

Apart from the above-discussed shortcomings, Wenjie Wang et al. discuss passive feedback mechanisms. Usually, conventional systems are dependent on implicit user feedback to optimize recommendations. These mechanisms are inefficient in capturing users' nuanced information needs. These conventional methods hardly allow users to explicitly communicate their preferences or dislikes, which makes personalization less effective. Furthermore, the inability of conventional methods to create content is another disadvantage of traditional methods. These methods cannot generate or repurpose items to cater to specific user preferences. This situation restricts their adaptability to unique user needs or emerging trends.

2.5.2 BENEFITS OF INDULGING GENERATIVE AI FOR RECOMMENDATION SYSTEMS

Generative AI carries out various benefits for recommendation systems. It enables customization by deeply understanding user behavior and preferences. For example, as mentioned by Yashar et al., pre-trained large language models such as GPT-4 can synthesize natural language explanations as the reasons for recommending specific personalized items. Furthermore, this makes recommendation systems provide richer, more customized, and specific insights to users. Apart from that, conversational interfaces can be incorporated into generative models, which can be used to improve interactivity. As an example, as mentioned by Yashar et al., conversational recommendation systems (ConvRec) use LLMs to engage users in natural language dialogues, making the experience more intuitive and personalized.

Apart from making personalized, multimodal capabilities of generative models create more unique opportunities. Users can interact with systems through multiple inputs, such as providing a product image and requesting variations. These systems use multimodal LLMs to process such requests by combining image encoders with text-based transformers. An example is Llava, which integrates text and image data for seamless interaction.

2.5.3 TECHNOLOGIES USED

The paper by Yashar et al discusses multiple practical applications that display how generative AI causes the transformation of recommendation systems, which can address challenges from conventional recommendation systems and expand their capabilities. A major instance given in the paper is the zero-shot and few-shot generative recommendation. In these cases, prompts are constructed using pre-trained large language models (LLMs), and these prompts represent user preferences, such as their recently liked items or search history. Also, these prompts help to generate tailored recommendations for new items. As an example, discussed in the paper, within some domains like movies or books, zero-shot models can suggest relevant options even when there is limited interaction data. Few-shot methods further enhance this process by including examples of input-output pairs in the prompts, giving the model more context and improving the quality of its predictions.

The use of virtual try-ons, made feasible by developments in diffusion models and multimodal big language models, is another significant application. With the help of these systems, users may see how goods like apparel or furniture might appear in their particular settings. For instance, a user might post a picture of their living room and ask for furniture suggestions that complement their current style. In a similar vein, customers may upload a photo of themselves to check how an outfit suggestion fits. These visualizations are made possible by tools like DALL-E and Stable Diffusion, which provide lifelike simulations that enhance consumer pleasure and lessen product returns, two important benefits for e-commerce platforms.

Another innovation is the idea of Retrieval-Augmented Generation (RAG). RAG offers contextually appropriate suggestions by fusing the advantages of generative models with retrieval methods. Using a user query or past interactions, the algorithm first generates a shortlist of possible objects. A generative model then improves this list by reordering the choices and creating justifications for the suggestions. This two-step procedure improves accuracy and guarantees that the recommendations closely match user preferences. RAG, for example, can be used to steer the discussion in conversational systems by retrieving pertinent product evaluations or previous user encounters, resulting in recommendations that are extremely contextually aware and tailored.

These uses highlight how generative AI may be used to develop recommendation systems that are more dynamic, interactive, and user-centered. These technologies mark a substantial advancement over conventional techniques by enabling features like realistic representations, adaptable dialogues, and precise contextual recommendations.

As discussed in the research paper by Elham Abdulwahab Anaam et al., fuzzy logic is a central component of the hybrid recommendation system. For user preferences and decision-making, this logic is helpful to handle uncertainties and imprecision. Even if only binary logic is available in conventional methods, fuzzy logic enables degrees of membership. This refers to the likelihood of a user being interested in a product on a scale rather than a simple binary option as yes/no. As an example, if a user is interested in a product category (e.g., smartphones), fuzzy logic can classify their interest as "medium" or "high" rather than just "interested" or "not interested." This nuanced understanding leads to more accurate recommendations.

To properly combine different recommendation systems and capitalize on their unique strengths, hybridization approaches are essential. A weighted strategy is one method that combines the scores of several algorithms to create a single suggestion list, guaranteeing a thorough and well-rounded outcome. There is another technique, which is called as switching approach, where this approach dynamically switches between various recommendation strategies according to the situation. For example, it might use content-based filtering for new users with little data and collaborative filtering for users with a large interaction history. Furthermore, feature augmentation is a potent strategy that incorporates layered insights into the recommendation process by using the output of one algorithm as an input for another. When combined, these tactics improve hybrid systems' robustness and adaptability.

Furthermore, Elham Abdulwahab Anaam et al. discuss another technique, which is the Analytic Hierarchy Process (AHP). This is a decision-making framework that evaluates various criteria to rank and prioritize items. This decomposes complex decisions into a hierarchy of criteria and alternatives. These are helpful for systematic comparisons. In recommendation, AHP evaluates the multiple features of products, preferences of users, and other important features that are useful to give the most relevant recommendations. This combines these criteria into a weighted scoring system, which ensures that recommendations align closely with user priorities. Providing transparency in decision-making can be considered as one advantage of AHP. This transparency helps to balance competing criteria, such as price, quality, and user ratings.

In another paper, Wenjie Wang et al. discuss the use of large language models for understanding and generating natural language. In this context, it enables users to provide explicit instructions or feedback through conversational interfaces. Here, mainly LLMs are used for instruction processing and user preference modeling, which leverage conversational data to build user profiles and refine recommendations.

Furthermore, this paper discusses diffusion models to create and edit multimodal content, including text, images, and videos. Applications discussed here are thumbnail generation and micro-video editing, and creation. As discussed in the paper, the Masked Conditional Video Diffusion Model is useful in fine-tuning for micro-video editing and creation. Also, stable diffusion is applied for image synthesis tasks. When discussing Contrastive Language-Image Pretraining is a powerful neural network that connects visual and textual data to compute representations for personalized content. The applications which are discussed in the paper are thumbnail selection, which is useful for selecting micro-video frames that align with user preferences based on historical data, and the other application, which is micro-video clipping, is useful for extracting personalized video segments to cater to user interests.

Additionally, Wenjie Wang et al. discuss pre-trained knowledge bases which have been used to enhance the quality and accuracy of generated content by incorporating factual knowledge. This knowledge base is used in generating trustworthy and relevant content for applications like news and music recommendations.

Further, Multimodal Interaction Frameworks are discussed because they enable user interaction through text, images, audio, and videos, ensuring a seamless and natural interface for content generation and recommendation. This paper discusses voice and visual interaction for enhanced user-system communication based on this framework.

CHAPTER 3

METHODOLOGY

For research purposes, proof of concept (POC) with a limited scope needs to be developed for the usage and elaboration of the functionalities recommendation system and chat agent. When explaining the methodology, the scope used for the POC is described.

3.1 DEVELOPMENT OF KNOWLEDGE BASE

When creating the knowledge base, few research papers related to Natural Language Processing (NLP) have been used.

1. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding" (2019) by Jacob Devlin et al.
   Summary: Introduces BERT, a model that significantly improved NLP tasks by pre-training deep bidirectional transformers.

2. "Attention Is All You Need" (2017) by Ashish Vaswani et al.
   Summary: Presents the Transformer architecture, which relies entirely on self-attention mechanisms, leading to more efficient training and superior performance in various NLP tasks.

3. "GPT-3: Language Models are Few-Shot Learners" (2020) by Tom B. Brown et al.
   Summary: Introduces GPT-3, a large-scale language model capable of performing tasks with minimal task-specific data, demonstrating the potential of scaling up language models.

4. "RoBERTa: A Robustly Optimized BERT Pretraining Approach" (2019) by Yinhan Liu et al.
   Summary: Builds upon BERT by optimizing the pre-training process, leading to improved performance across various NLP benchmarks.

5. "XLNet: Generalized Autoregressive Pretraining for Language Understanding" (2019) by Zhilin Yang et al.
   Summary: Proposes XLNet, which integrates the strengths of autoregressive and autoencoding models, achieving state-of-the-art results on several NLP tasks.

6. "T5: Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer" (2020) by Colin Raffel et al.

Summary: Introduces the T5 model, which frames all NLP tasks as text-to-text transformations, enabling a unified approach to various language tasks.

7. "ALBERT: A Lite BERT for Self-supervised Learning of Language Representations" (2019) by Zhenzhong Lan et al.
   Summary: Presents ALBERT, a lighter version of BERT that reduces memory consumption and increases training speed without compromising performance.

8. "ELECTRA: Pre-training Text Encoders as Discriminators Rather Than Generators" (2020) by Kevin Clark et al.
   Summary: Introduces ELECTRA, a pre-training method that trains models to distinguish real input tokens from fake ones generated by a small generator network, leading to efficient learning.

9. "BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension" (2020) by Mike Lewis et al.
   Summary: Proposes BART, a denoising autoencoder that combines bidirectional and autoregressive transformers, excelling in text generation and comprehension tasks.

10. "ERNIE: Enhanced Representation through Knowledge Integration" (2019) by Yu Sun et al.
    Summary: Introduces ERNIE, a model that incorporates knowledge graphs into pre-training, enhancing language understanding by integrating structured knowledge.

11. A Systematic Survey of Text Summarization: From Statistical Methods to Large Language Models" (2023) by Haopeng Zhang, Philip S. Yu, Jiawei Zhang
    Summary: Reviews the evolution of text summarization from statistical methods to deep learning and large language models (LLMs), covering key datasets, evaluation metrics, and emerging challenges in the field.

3.2 FINE-TUNING THE GPT-4 MODEL

3.2.1 FINE-TUNING PROCESS

3.2.1.1 Why is fine-tuning needed?

GPT-4.0 is considered a pre-trained model. Furthermore, unsupervised learning is used to train the model on a large dataset. During the fine-tuning process, supervised learning is used to train on a smaller but domain-related dataset. Fine-tuning helps to make models more domain-specific, personalized, and relevant. The fine-tuning process either makes modifications to the weights of the model or adds adapter layers.

Since the GPT-4 model follows decoder-only transformers, the adjustment of assigning attention weights and updating the hidden states based on new task-specific data is focused on during the fine-tuning process.

3.2.1.2 Dataset for fine-tuning

The dataset that has been used for fine-tuning was developed using the questionnaire collected from the post-graduate students. This contained the following columns.

- Subject-specific area
- Reference materials
- The main areas covered in the reference materials

3.2.1.3 Comparison between different fine-tuning approaches

For the fulfillment of the purpose of fine-tuning, it is essential to choose the correct fine-tuning approach. There are a few major fine-tuning approaches that have been listed below.

TABLE 3.1: COMPARISON OF DIFFERENT FINE-TUNING APPROACHES

Fine-tuning method	Computation cost	Best use case
Full fine-tuning	High	Domain adaptation, highly specialized tasks
LoRA (Adapter-based Fine-Tuning)	Moderate	Efficient tuning for recommendation & support

RAG (Retrieval-Augmented Generation)	Low	Combining LLM with external knowledge
Few-Shot Learning	Very low	Quick adaptation without proper fine-tuning

3.2.2 FINE-TUNING RAG WITH LORA

3.2.2.1 How does RAG help with fine-tuning?

When using the RAG method, it combines the retrieval from vector search with generation from the GPT-4.0 model.

TABLE 3.2: PERFORMANCES OF RAG FINE-TUNING

Challenge	How RAG fine-tuning helps
Outdated knowledge	Instead of keeping static weights, it retrieves the latest facts.
Hallucination	This reduces false information by extracting information from real-world data sources.
Expensive model updates	It updates the retrieval database, which refrains from retraining from scratch.

3.2.2.2 How can LoRA be incorporated with RAG?

When incorporating Low-Rank Adaptation (LoRA) along with RAG, it makes fine-tuning much more efficient for the following reasons.

- It dynamically updates only the FAISS vector retrieval components, without requiring full model training.
- It adapts model responses together with the newly retrieved knowledge, but it does not require excessive computational cost.

3.2.2.3 Usage of LoRA in fine-tuning

After the fine-tuning using LoRA along with RAG, a performance comparison is done to assess the improvement.

TABLE 3.3: PERFORMANCE COMPARISON OF DIFFERENT METRICS

Metric	Original model (no fine-tuning)	RAG only	LoRA + RAG
VRAM usage	16GB	40GB+	20GB
Training time (5K samples)	No training	24h+	4h
Cloud GPU cost	$0	$200	$50
Response accuracy	~60% (generic)	76% (task-adapted)	85% (task adapted & optimized)

3.3 DEVELOPMENT OF RECOMMENDATION SYSTEM

Both collaborative filtering and content-based filtering are integrated with this recommendation system for students to experience the suggestions of personalized learning materials. User-centric recommendations are received for students due to this methodology because it analyzes both past interactions and document content.

3.3.1 CORE FEATURES AND FUNCTIONALITIES

3.3.1.1 System Architecture

When developing the recommendation system, FAISS is used for similarity-based retrieval, and the SVD algorithm is used for collaborative filtering. Furthermore, Streamlit is used for the development of user interfaces. Also, Azure Blob storage is used to store PDF documents. Singular Value Decomposition (SVD) is a mathematical technique that includes matrix factorization and is widely used in linear algebra. When it comes to practical applications, it is widely applied in machine learning, especially in recommendation systems. This algorithm predicts the missing ratings by identifying hidden patterns in user-item interactions. To identify these patterns and to capture user preferences and item features in a lower-dimensional space, it breaks down these matrices into three smaller matrices.

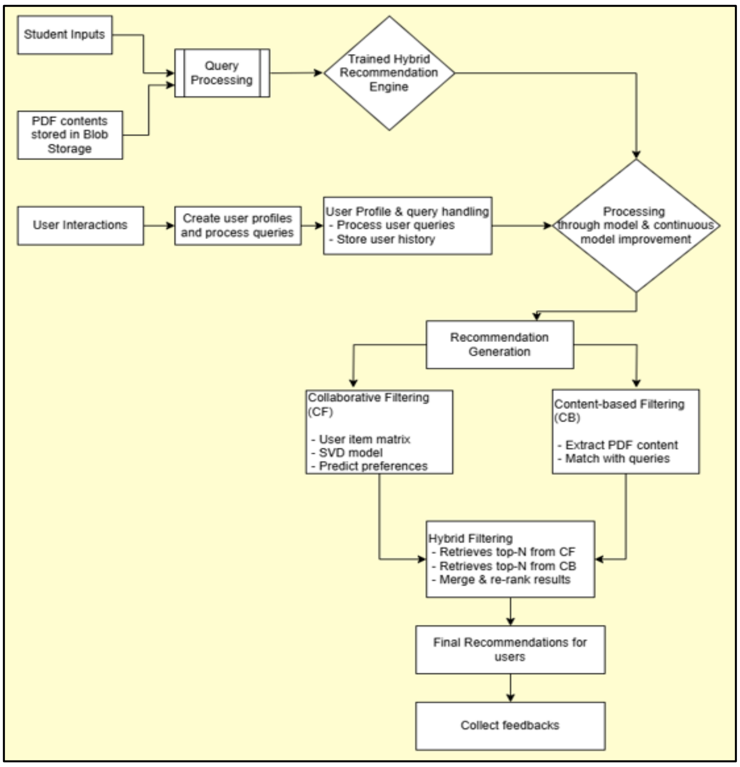


Fig.3.1: Architecture of the recommendation system

3.2.1.2 Document Storage and Preprocessing

Azure Blob Storage is selected for document storage purposes. Azure Blob Storage is known as secure and scalable object storage, and it is optimized for high availability. Library: PyPDF2 is used to process the uploaded documents. This library facilitates extracting both structured and unstructured text data from PDF files that have multiple pages. Subparts of the processing pipeline are mentioned below:

i. Text Chunking:

Content that has been extracted from PDF files should be processed into semantically meaningful chunks to ensure that every chunk segment represents a coherent unit of information. This facilitates well-informed analysis, and this leads to the improvement of the precision of document search tasks. These chunks are developed based on the logical basis of text breaking, such as sections or paragraphs, and this allows for better context retention during retrieval.

ii. Metadata Augmentation:

Relevant metadata is appended for each text chunk to enhance traceability and context preparation when retrieving query results. Details like page numbers, section headers, file names, paragraph headers, and timestamps of document uploads are included in metadata. This metadata acts as additional information aids to aid in verifying the relevance of search results, and metadata provides clarity on the source of each retrieved segment.

iii. Content Indexing:

After the chunks are processed, they need to be indexed into dense vector representations. For this process, Facebook AI Similarity Search, which is known as FAISS, is used. The embeddings are optimized for semantic similarity, and this makes the retrieval more accurate and rapid. OpenAI Embeddings are integrated into the indexing workflow to encode texts. This ensures the capturing of subtle meanings in the search results.

3.3.1.3 Functionalities of the recommendation system

i. User profiles and query handling

The recommendation model is trained and fine-tuned using the data collected by a sample of students. Postgraduate students of the Department of Computer Science Engineering were selected to collect this data, and a questionnaire was shared with them. Apart from the initial training set, the model is consistently grabbing information by storing the user history, such as their courses, recommended materials, and how they rate the recommendations through the feedback mechanism, and these data also help the model to consistently improve and refine its performance over time. This ensures that future recommendations of the system are evolving and well aligned with the preferences and behaviors of students.

ii. Implementation of collaborative filtering

The SVD model facilitates collaborative filtering for the recommendation system. This model predicts user preferences and provides recommendations based on past interactions. Here, the student IDs, PDF IDs, and interaction scores (user ratings) are used to develop a user-item interaction matrix. Behavioral patterns of users are analyzed through the SVD model, and it predicts recommending the most suitable materials to students based on the ratings for unseen PDFs.

For this context, Stochastic Gradient Descent (SGD) based SVD models are being used. This approach helps to update the latent factors of users and items iteratively. One complete pass is represented over all the training data through each epoch, and it allows the model to adjust its parameters in a way that minimizes the error. Factorized matrices are gradually improved when there are more epochs to train the model, and this causes reduced errors as well.

The below chart shows how the root mean squared error (RMSE) varies based on the number of epochs.

TABLE 3.4: ACCURACY VARIATION WITH THE NUMBER OF EPOCHS

Epochs	RMSE
5	1.2
10	1.0
15	0.9
20	0.85
25	0.845
28	0.841

Since there is no significant improvement in RMSE after 20 epochs, and RMSE is stabilized, 20 epochs are considered for the model.

iii. Content-Based Filtering (CB) Implementation

PDFs related to the system are stored in Azure Blob Storage, and their textual content is extracted through content-based filtering. After the extraction, the content is matched along with the student information, user history, and keywords of queries. The system identifies and retrieves PDFs that are well-aligned with the needs of students by leveraging text similarity metrics.

iv. Hybrid Filtering & Recommendation Generation

Recommendations are enhanced by using the hybrid filtering approach, which is a combination of collaborative filtering and content-based filtering. Depending on the behavioral patterns and interactions of the students, the system first retrieves the top N recommendations of collaborative filtering. Parallelly, it retrieves top N recommendations of content-based filtering after the analysis of document text for contextual relevance. Hybrid filtering ensures that the most relevant recommendations for students are made after both collaborative and content-based results are merged and re-ranked.

After incorporating hybrid filtering, a comparison is made to check the performance of each approach, which is shown below.

TABLE 3.5: VARIATION OF ACCURATE METRICS WITH DIFFERENT RECOMMENDATION APPROACHES

Metric	Collaborative filtering only	Content-based filtering only	Hybrid approach
RMSE	0.85	-	0.86
Precision	72%	65%	81%
Recall	68%	60%	79%

3.4 DEVELOPMENT OF SUPPORT ASSISTANT

The Support Assistant is a sophisticated application engineered to optimize document analysis workflows and automate question-answering evaluations. By leveraging state-of-the-art technologies, including AI-driven natural language processing and advanced data storage systems, the platform facilitates seamless management of educational or professional materials. Built using Streamlit for interactive front-end interfaces, Azure OpenAI for NLP, and LangChain for embedding-based search capabilities, it represents a convergence of advanced tools to deliver high precision and usability.

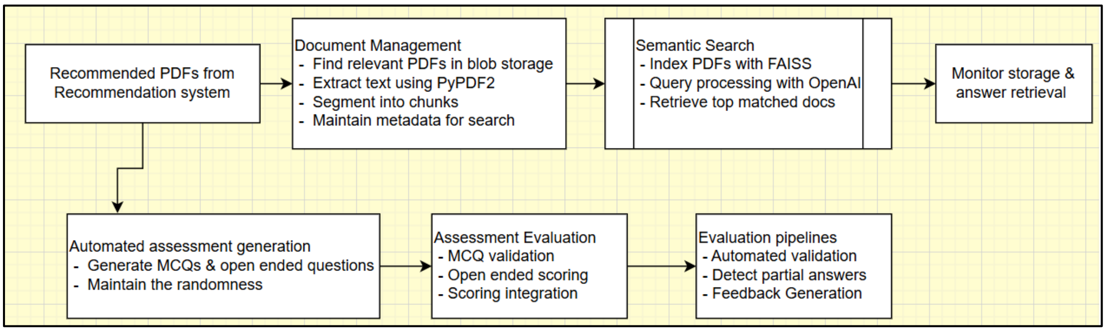


Fig.3.2: Architecture of chat assistant and evaluation

3.4.1 CORE FEATURES AND FUNCTIONALITIES

3.4.1.1 Document Management

When developing this application, the document management system is developed using Azure Blob Storage, because it provides a robust framework to store and manage

PDF files securely. Using the PyPDF2 library facilitates parsing the documents to extract textual content and also segments the documents into meaningful chunks, which enables efficient downstream processing. This technique helps process unstructured data to index and analyze.

3.4.1.2 Automated Assessment Generation

Since it is needed to create assessments to check how well students have understood the content included in the documents that are recommended, it is needed to automate the generation of both open-ended and multiple-choice questions (MCQs) based on the PDF documents. If more than one document is recommended, then the student has the capability to choose a document for the assessment.

For this purpose, it incorporates structured JSON schemas to ensure uniformity in question formats. Further, it raises questions in a way that they are aligns with the automated evaluation pipelines. Multiple-choice questions consist of one correct and three distractor options, while open-ended questions are designed to encourage critical thinking and comprehension.

One of the key features of the support assistant is the facilitation of a natural language querying system. This enables users to raise questions in the document repository. This functionality is powered by FAISS (Facebook AI Similarity Search), and it helps to index document content as vector embeddings to support similarity-based retrieval. When converting textual data into dense vector representations, OpenAI Embeddings performs a major task to transform textual data into dense vector representations. This process ensures semantic search functionality. The application delivers highly relevant query results, complete with metadata, enhancing its utility for both educational and professional scenarios.

3.4.1.3 User Interface

An open-source Python framework, which is Streamlit, is used to develop the user interface. This framework facilitates a responsive user interface along with intuitive navigation. PDF evaluation and support assistant are the two primary functionalities. The PDF evaluation is used for automated assessments, and the support assistant is used for natural language querying. A sidebar menu facilitates toggling between these two primary functionalities. There are some interactive components, such as dropdowns, text inputs, and buttons, that enhance user engagement, while the chat-like interface streamlines query interactions.

3.4.2 TECHNICAL ARCHITECTURE

Modular architecture and industry-standard tools are used by the support assistant. This helps the system to keep a high performance. Further, it ensures the reliability and extensibility. There are some specific challenges that are combined with natural language querying, document management, and automated assessments.

3.4.2.1 Frontend Architecture

A Python-based framework is used for the frontend development, which is Streamlit. That can be used as a data-centric application. This facilitates building interactive and real-time web applications with minimum effort. There are various widgets such as buttons, sliders, and dropdowns. These widgets help to increase user interaction. Further, this facilitates the chat interface through conversational agents. These conversational agents provide an exclusive user experience when generating queries and assessing the workflow. REST APIs help the frontend to interact with the backend, and this process ensures consistent data exchanges and low latency.

3.4.2.2 Backend Framework

Python is the main coding language which is used to design the backend. Furthermore, as the framework for NLP and reasoning facility, LangChain is used, because it makes the orchestration of embedding-based querying workflows simple, which helps with the multi-turn conversations and context-aware operations. APIs, which are implemented by the backend, are used to handle query processing, preparing assessment logics, and document retrieval. Also, asynchronous processing ensures scalability, enabling concurrent handling of multiple user sessions without performance degradation.

3.4.2.3 Semantic Search and Retrieval

Facebook AI Similarity Search (FAISS) is used as a search and retrieval system. This is to ensure the execution of vector similarity-based searches. Furthermore, to ensure the semantic interpretation of content and queries, documents are embedded into dense vector representations. For this process, model embedding features of Azure OpenAI have been used.

Below explained is the workflow of retrieval.

i. Vector Indexing:

Flat and hierarchical indices are constructed using FAISS to store document embeddings, which are optimized for high-dimensional spaces. There are some techniques where these indices are utilized, like search techniques such as approximate nearest neighbor (ANN) and clustering algorithms. These techniques help to get the retrieval from larger-scale datasets in sub-millisecond retrieval times by ensuring scalability and efficiency.

ii. Query Embedding:

OpenAI Embeddings which is a transformer-based model that is used to process the user inputs and generate dense vector representations. Semantic texts and contextual relationships within the input text are captured by these embeddings. This ensures a high alignment with the indexed content. Even if the wordings are different, consistent and accurate answers were retrieved due to the embedding process.

iii. Ranking and Filtering:

There is a multi-step relevance ranking process for the retrieved chunks to be processed. For this ranking process, cosine similarity calculation is used, and priority is given to the highest-scoring chunks. Also, some additional filters are there, based on source, date, or section, to accelerate the custom filtering.

3.4.2.4 Assessment Generation and Evaluation

When it comes to question generation and evaluation, Azure OpenAI models are incorporated into the assessment module. Standardized formats for both open-ended questions and multiple-choice questions are designed from JSON schema-based templates.

Below are the functionalities for the assessment evaluation:

i. MCQ Validation:

There is a validation process to check whether a predefined correct answer for each multiple-choice question is being mapped. A schema-driven approach is used for this. User responses are compared with the correct answers using a rule-based algorithm, and this ensures that scoring is accurate and consists of zero ambiguity. This approach works even when there are large datasets since it uses batch processing of responses.

ii. Open-Ended Scoring:

GPT models of Azure OpenAI evaluate the responses for open-ended questions by using advanced natural language understanding capabilities. Scoring algorithms are designed to process user submissions, analyze the logical flow and structure of the answer, check whether the answer is relevant to the intent of the question, and finally, whether the response is elaborated comprehensively. Feedback is important for these GPT models to identify key strengths, improve areas in the response, and present users the actionable insights to enhance their understanding.

iii. Scoring Integration:

Both MCQ results and evaluations of open-ended questions are combined into a single analytics dashboard. The necessity of a statistical aggregation method is useful for calculating the overall scores and performances. Furthermore, an analytics framework can be used for real-time visualization, which makes the result interpretation easier, and progress can also be tracked.

3.4.2.5 Evaluation Pipeline

In the process of evaluation, there are multiple stages in validation mechanisms as mentioned below.

i. Automated Validation:

This refers to a hybrid approach of rule-based algorithms and AI-based models to evaluate responses. This ensures that accurate evaluation is based on predefined criteria. Syntactical correctness and the logical consistency of the responses need to be verified using rule-based mechanisms. These AI-based models facilitate to increase in the understanding of nuanced responses, and this ensures that response evaluation is more accurate, scalable, and robust.

ii. Contextual Insights:

Transformer-based models are available to analyze the responses to open-ended questions, as they facilitate considering the context included in the materials. Context embeddings are incorporated in the evaluation pipelines, and they facilitate checking the alignment of responses with the expected answers by detecting subtle errors and comparing the differences between partial and complete responses.

iii. Feedback Generation:

Feedback generation is one key area here, and for this process, large language models of Azure OpenAI are used, and they provide comprehensive and constructive feedback. These models first identify the strong areas of responses and highlight the areas for improvement, along with the relevant suggestions to enhance the quality and relevance of the answer. Since customized feedback is generated for each input or response, students receive actionable insights and constructive feedback to improve their learning.

3.5 KEY DESIGN DECISIONS

3.5.1 SYSTEM ARCHITECTURE

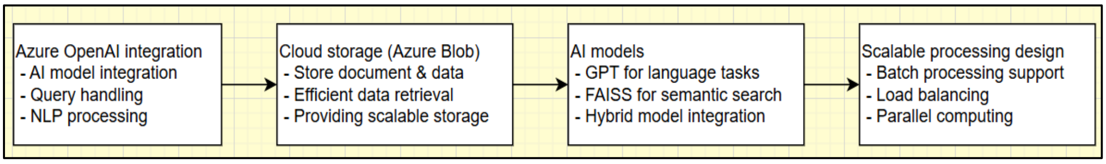


Fig. 3.3: Technical architecture

The below section highlights the reasoning behind choosing specific techniques mentioned in the system architecture, along with their usage and advantages for the final product.

3.5.1.1 Data Storage and Management: Azure Blob Storage

The reason for selecting Azure Blob Storage is based on its special enterprise-grade features to handle unstructured data. It facilitates storing and managing data along with its strong security controls, such as encryption and access controls. Furthermore, it is globally available, and it facilitates the integration with data-intensive applications due to the Azure ecosystem. Additionally, its development has become simple because of Python SDKs, and it provides smooth interaction with other components. It is noted that Azure Blob Storage consists of tiered storage, which facilitates cost optimization, because of this feature, this is relevant for both frequently and infrequently accessed data.

TABLE 3.6: TECHNICAL HIGHLIGHTS OF DATA STORAGE AND MANAGEMENT

Functionality	Rationale
Encryption	Security standards like GDPR and HIPAA are embedded into Azure Blob Storage. This supports AES-256 encryption at rest and TLS encryption in transit.
Access Control	Azure Blob Storage facilitates Shared Access Signatures (SAS) and RBAC along with Azure Active Directory. This provides access controls for users and services.

Global Availability	This storage consists of Read-Access GRS (RA-GRS) and Geo-Redundant Storage (GRS). This provides the readiness for disaster recovery and also ensures high availability.
Tiered Storage	In blob storage, there are three tiers: hot, cool, and archive. This facilitates efficient active workloads and archival purposes by optimizing the cost based on data access frequency.
Python Integration	Azure Blob Storage uses Python SDKs, and this provides programmatic access to manage blob data, such as reading and writing data through integrated Python-based pipelines.
Scalability	These storage systems have the capabilities to handle a large amount of data. It allows for the successful execution of an enterprise-level solution.

3.5.1.2 High-Performance Semantic Search: FAISS and OpenAI Embeddings

The combination of FAISS and OpenAI Embeddings facilitates handling the larger datasets in a very fast and efficient manner, and it also supports semantic similarity search. The technique used in OpenAI Embeddings encodes the semantic meaning of the text, and in parallel, nearest neighbor search is used in FAISS. Having both techniques together helps the system handle complex queries efficiently, and it also provides contextually accurate results for both larger and smaller inputs.

Furthermore, it should be noted that MongoDB can also be used to store PDF files and for vectorization, as it allows for semantic search. However, after careful consideration of the features, functionalities, and performances of FAISS against MongoDB, it was decided to continue with FAISS, and some facts that were considered are mentioned below.

TABLE 3.7: COMPARISON CHART OF DOCUMENT STORAGE

Metric	*FAISS (vector-based)*	*MongoDB*
Query latency	Faster	Moderate (depends on vector indexing)
Scalability	Efficient for larger-scale data	Scales well with distributed storage
Indexing speed	Faster	Moderate

Flexibility	Lower – requires periodic embedding updates	Support real-time vector updates

When it comes to this system, speed and efficiency are more important than real-time updates on a document base; it is decided to move forward with FAISS and Azure blob storage.

A retrieval time comparison is also mentioned below based on the average values of 10 iterations each.

TABLE 3.8: DOCUMENT PROCESSING TIME WITH EACH STORAGE METHOD

Document processing method	*Average Retrieval Time*
PyPDF2 + Azure blob storage	120ms
PyPDF2 + MongoDB	145ms

Table 3.9: RETRIEVAL TIME IN DIFFERENT SEMANTIC SEARCH METHODS

Semantic search method	*Average Retrieval Time*
FAISS + Azure OpenAI	6 ms
MongoDB Atlas search	34 ms

TABLE 3.10: TECHNICAL HIGHLIGHTS OF SEMANTIC SEARCH METHODS

Functionality	Rationale
FAISS for Vector Indexing	FAISS uses the technique of Approximate Nearest Neighbor (ANN) algorithms for searching. This makes searches in high-dimensional vector spaces speed, and it causes to reduction in query time when compared with brute-force methods
OpenAI Embeddings	This type of embedding converts textual data into dense numerical vectors. This causes the easy and advanced query interpretation of both contextual and semantic data.

Scalability	To handle larger datasets, FAISS facilitates GPU acceleration and sharding for distributed indexing.
Hybrid Search Capabilities	The hybrid mechanism helps to combine semantic similarity along with metadata-based filtering. This is useful when it comes to precision in the retrieval process.
Real-Time Querying	This facilitates the response time of the similarity search being around sub-seconds. This feature makes systems useful when they require real-time or near-real-time performance.
Customizability	This feature makes the systems adapt fast to specific use cases because of options like fine-tuning embedding dimensions, distance metrics, and search algorithms.

3.5.1.3 Interactive Visualization: Streamlit

Streamlit was chosen to bridge the gap between data insights and user interaction by providing a lightweight, Python-based framework for building interactive applications. It eliminates the need for extensive front-end development, allowing rapid prototyping of dashboards and data-driven apps. The ability to seamlessly integrate with Python libraries makes it a natural choice for data scientists and engineers.

Table 3.11: TECHNICAL HIGHLIGHTS OF INTERACTIVE VISUALIZATION

Functionality	Rationale
Declarative Programming Model	Enables developers to create user interfaces with just a few lines of Python, abstracting complex UI logic
Dynamic Widgets	Offers interactive components such as sliders, text inputs, and dropdowns that update application outputs in real time
Data Visualization Integration	Compatible with Matplotlib, Plotly, Seaborn, and Vega-Lite for creating rich, interactive charts and graphs

Real-Time Data Processing	Automatically recalculates and updates outputs as users interact with input elements, providing instant feedback.
Scalability & Deployment	Applications can be deployed using Streamlit Cloud or containerized for deployment on platforms like Kubernetes, ensuring scalability and flexibility.
Extensibility	Supports custom components, enabling integration with third-party APIs or libraries for advanced functionality

3.5.1.4 Selection of AI models

This selection was mainly based on the comparison of test results.

Table 3.12: QUESTION GENERATION TIME WITH EACH AI MODEL

Model	MCQs generation time (ms)	Open-ended questions generation time (ms)
GPT-4	300	440
GPT-3.5	400	600
GPT-4o	380	560
Claude-2	340	500
LLaMA 2 13B	320	480

Based on the question generation time, it is decided to use GPT-4, even if it is a bit expensive than other GPT models. Apart from the question generation time, the reasons below are also considered when deciding to use GPT-4.

i. Coherence is better in GPT-4 than in other models, and repetition is much lower. This causes human-like responses which are more structured and naturally sounding.
ii. GPT-4 is more efficient in reasoning abilities and complex problem solving.
iii. Since the GPT series has a larger context window, it allows us to manage longer documents. But LLaMA and Claude models have a lower context window.

3.5.1.5 Language Model Workflow Management: LangChain

LangChain simplifies the orchestration of workflows involving large language models (LLMs) by providing a modular and extensible framework. It abstracts the complexities of chaining LLM interactions, enabling efficient handling of tasks like query answering, summarization, and knowledge base retrieval. This modularity makes it easier to adapt workflows to evolving requirements and scale as the system grows.

Table 3.13: TECHNICAL HIGHLIGHTS OF LANGUAGE MODEL WORKFLOW MANAGEMENT

Functionality	Rationale
Pipeline Abstraction	Allow developers to define workflows for preprocessing inputs, managing LLM interactions, and post-processing results.
Scalability	Supports asynchronous execution and batching, optimizing performance for high-throughput applications
Vector Database Integration	Integrates seamlessly with vector stores (e.g., FAISS, Pinecone) for efficient retrieval-augmented generation (RAG) workflows
Custom Logic Support	Provides hooks for injecting custom logic at various stages of the workflow, ensuring flexibility
Error Handling and Logging	Includes robust mechanisms for managing model failures, timeouts, and retries, ensuring system reliability
Advanced Applications	Facilitate complex use cases, such as multi-turn conversations, contextual query handling, and hybrid AI workflows.

3.5.1.6 Data Validation and Integrity: JSON Schema Validation

JSON Schema was adopted to standardize data structures across the system, ensuring consistency, quality, and reliability. By defining a schema for JSON payloads, the system can enforce rules for required fields, data types, and formats, reducing the likelihood of errors during data processing or integration with external systems.

Table 3.14: TECHNICAL HIGHLIGHTS OF DATA VALIDATION

Functionality	Rationale
Schema Definitions	Provides a clear definition of the structure, types, and constraints of JSON payloads, ensuring predictable data formats.
Automation in CI/CD Pipelines	Validates data against schemas as part of CI/CD workflows, catching issues early in the development cycle
Version Control	Supports versioned schemas, enabling backward compatibility as data structures evolve over time
Error Feedback	Offers detailed error messages when validation fails, simplifying debugging and ensuring faster issue resolution
Cross-System Consistency	Ensuring that all systems interact with the data (e.g., APIs, databases) conform to the same structure, reducing integration issues.
Library Support	Integrates with JSON schema libraries in Python (jsonschema, pydantic), providing robust validation mechanisms

CHAPTER 4

IMPLEMENTATION AND RESULTS

4.1 KNOWLEDGE BASE

As mentioned in the methodology, Azure Blob Storage is used to store the PDF files in the knowledge base. A container is created inside the storage, and all the relevant resources are uploaded to the container as shown below:

Name	Modified	Access tier	Archive status	Blob type	Size
1043-2503-1-PB (1).pdf	2/12/2025, 4:53:24 PM	Hot (Inferred)		Block blob	3.6 MiB
1043-2503-1-PB.pdf	2/12/2025, 4:53:24 PM	Hot (Inferred)		Block blob	3.6 MiB
2304.03516v2.pdf	2/12/2025, 4:53:20 PM	Hot (Inferred)		Block blob	2.32 Mi
2305.09773v1.pdf	2/12/2025, 4:53:22 PM	Hot (Inferred)		Block blob	2.4 MiB
2305.14842v1.pdf	2/12/2025, 4:53:10 PM	Hot (Inferred)		Block blob	892.61 k
2404.00579v2.pdf	2/12/2025, 4:53:17 PM	Hot (Inferred)		Block blob	819.64 k
Open NLP Research Questions.pdf	2/12/2025, 12:51:27 ...	Hot (Inferred)		Block blob	2.13 Mi
Text Summarization From Statistical.pdf	2/12/2025, 12:51:23 ...	Hot (Inferred)		Block blob	1.31 Mi

Fig. 4.1: Screenshot of the sample PDF files stored in the container in Azure Blob Storage

As the knowledge base, most of the journals and research papers are developed based on Natural Language Processing (NLP), have been used.

4.2 DATA COLLECTION

4.2.1 QUESTIONNAIRE DESIGN

The first step of developing a recommendation system is to collect data from the target audience for the Proof of Concept (POC), which is the postgraduate students in the Department of Computer Science Engineering. This data collection helps the recommendation system understand the target group to get the relevant learning materials recommended more efficiently. Among the collected data, some information, like preferences for learning materials of students, frequently using journals, and reasons for referring to these external materials, is included.

A questionnaire was designed to collect this information and distributed as a Google form among the postgraduate students of 4 batches from 2022 onwards. This questionnaire consists of three sections to collect basic information about students, along with the grades, details on reference materials used for NLP courses by these students, and also their suggestions for the recommendation system. The link to the questionnaire and a few screenshots of Google Forms are attached below.

(link to questionnaire: https://forms.gle/3vesjASfo1egngUu5)

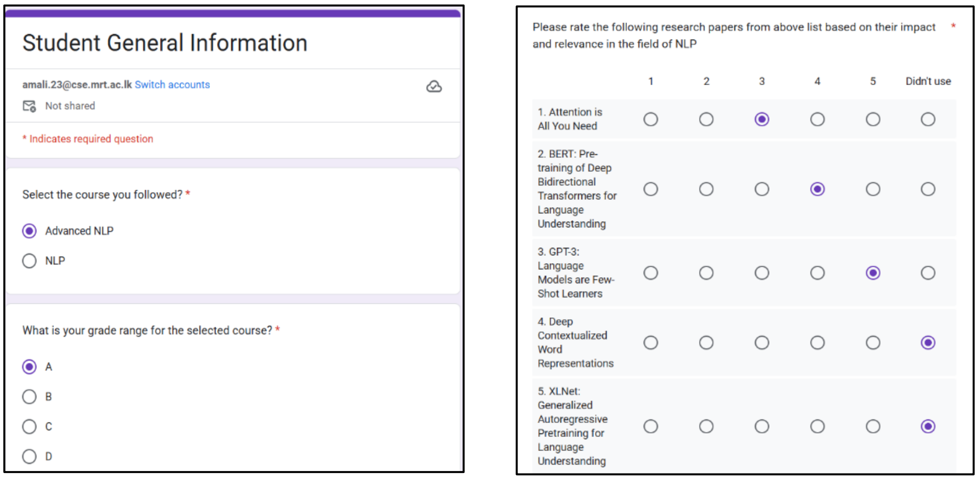


Fig.4.2: Snapshots of the questionnaire

After several analyses were conducted based on the collected data, the main takeaway that was drawn is the correlation between the reference of external learning materials with the grades of students. It turned out in the way that most of the students who are referring to these materials are getting good grades in the module. However, it should be noted that approximately 40% of the students are not referring to external materials. When deep diving for the reasons of not referring to learning materials, that is mainly because of the inconvenience of finding and exploring these materials. Furthermore, they stated that they are willing to refer to extra learning materials if they are easy to find and can explore the content more conveniently.

From these data collections, students' grades and reference materials. And difficulties when referring to these materials. And they are interested in such a system.

4.2.2 INSIGHTS THROUGH DATA COLLECTION

Below are the main insights that can be taken from the data collection from the selected student group.

i. Variation of respondent rate

For this survey, 212 respondents have taken part, and these respondents are from 22, 23, and 24 batches in the Department of Computer Science Engineering. The below chart shows that the variation and the highest contribution are from 23 batch.

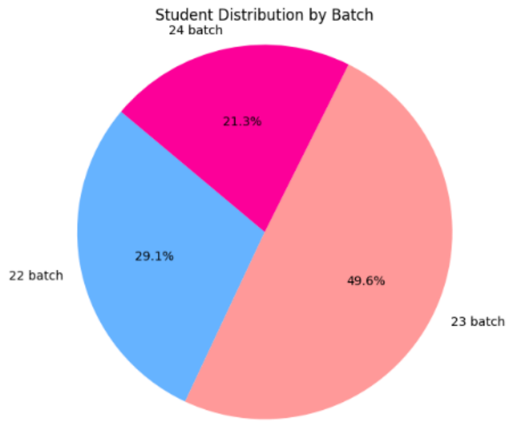


Fig 4.3: Pie Chart of respondent rate variation

ii. Variation of referring to supporting materials

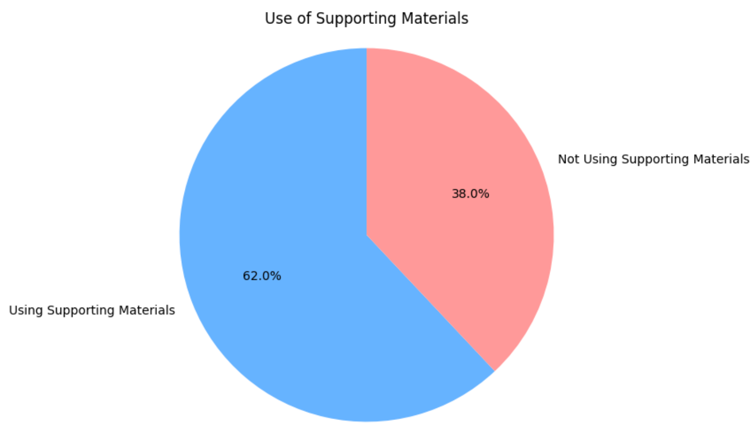


Fig 4.4: Pie chart of supporting materials reference variation

The above pie chart of supporting materials reference depicts that the majority of the respondents are referring to supporting materials for their studies, which shows that students are also aware of the importance of referring to supporting materials.

iii. Relationship between referring to supporting materials and GPA

From this survey, what can be understood is as same as students are aware of the importance of referring to supporting materials, and GPA also supports the same point. Below box plots below show that the median GPA is higher for the students who are referring to supporting materials rather than students who don't.

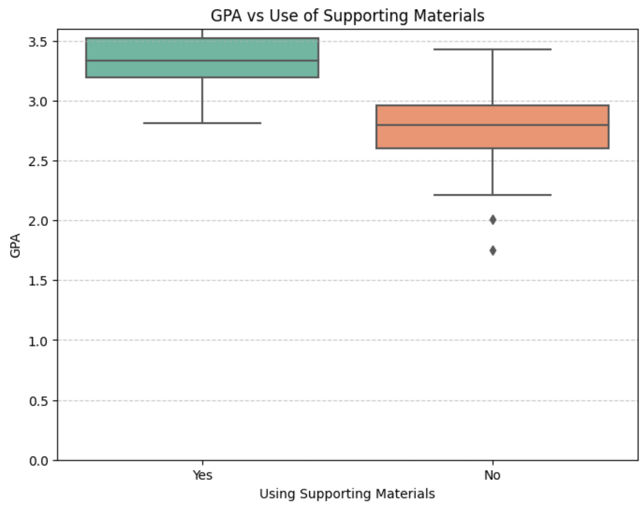


Fig.4.5: Box plots of GPA vs use of supporting materials

iv. Variation of modules supported by materials

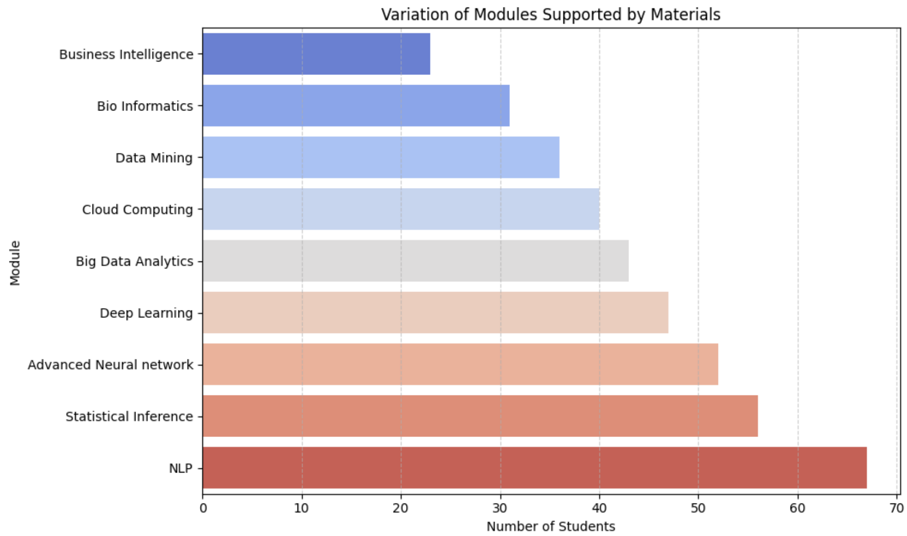


Fig.4.6: Bar chart of variation of modules supported by materials

The above bar chart depicts students not using supporting materials for all the modules. The bar chart shows that students need a lot of supporting materials for the NLP module.

Based on these results, it is decided to use NLP-related materials for the development of POC, which helps students to get some benefits even from the POC level development, and this is a good support for system evaluation also, because students have good knowledge of available supporting materials for NLP.

v. Variation of reasons for not using reference materials

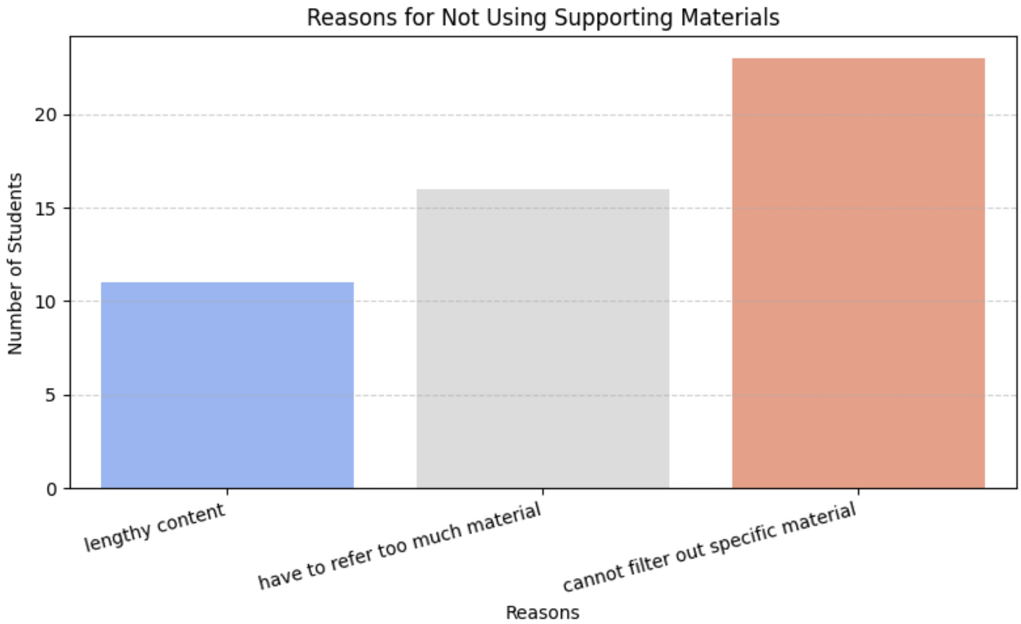


Fig.4.7: Bar chart of different reasons for not using reference materials

As per the bar chart, the main reasons for not using references are content is too lengthy, and hence, it is difficult to filter out the specific materials. Also, students must refer to lots of materials to find out the specific facts or details they want, which results in a longer time.

4.3 FUNCTIONALITIES OF THE SECTIONS

4.3.1 RECOMMENDATION SYSTEM

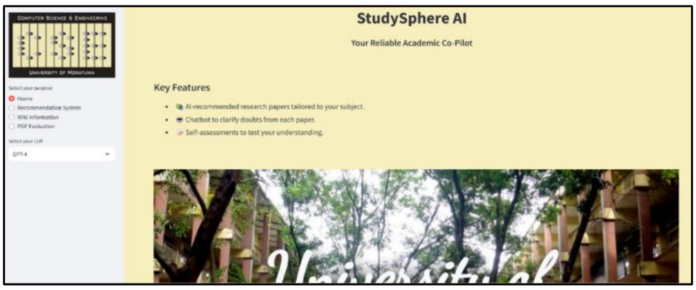


Fig.4.8: Interface of Home page

As an answer to the prevailing issue, which affects approximately half of the postgraduate students, this recommendation system can be used.

After the 'Home Page', it is directed to the recommendation system.

In the sidebar of the recommendation system, it can be directed to the recommendation system. Further, relevant LLM models can also be chosen among GPT-3.5, GPT-4 and the Embedding model. The initial interface of the recommendation system is shown below. It allows users to enter their name and select the courses.

At this point, the student has to insert his name and his course, and this information is getting saved along with his search history in the recommendation system, and chat history by using the chat assistant.

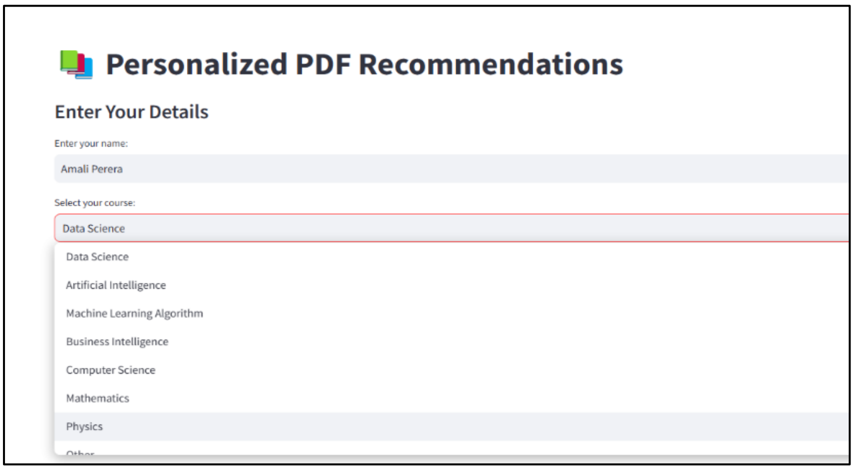


Fig.4.9: Initial interface of the recommendation system

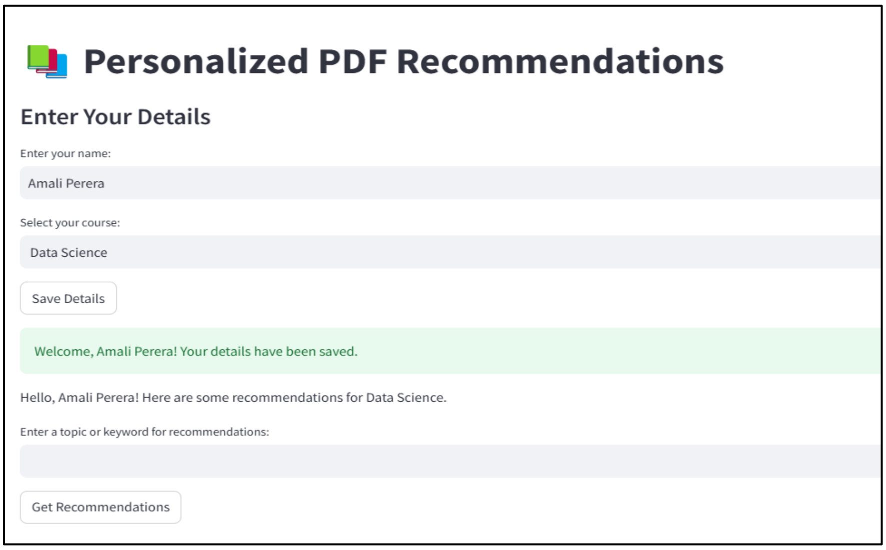
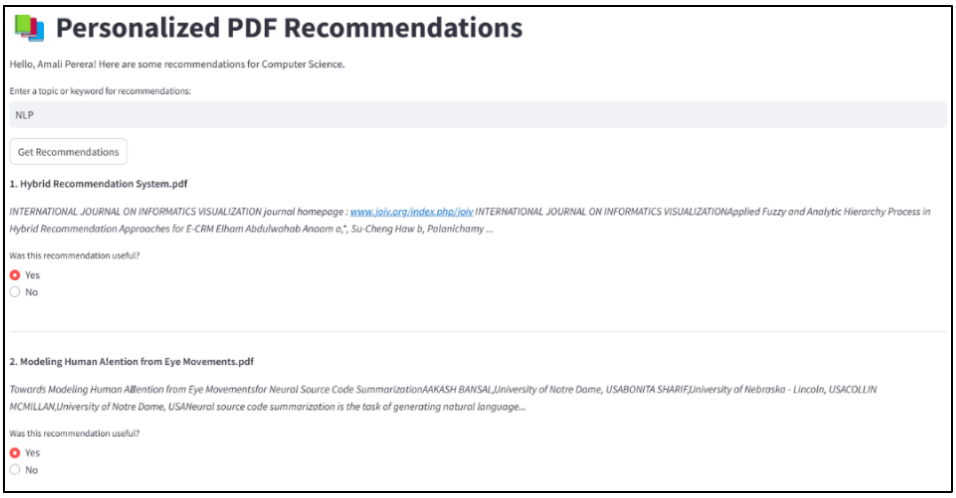


Fig.4.10: Second interface of the recommendation system

As shown in Figure 4.10, after the information is entered, the system gives the interface to enter a keyword or topic for which the user needs to have recommendations.

Based on the keywords that users enter, it recommends research papers as below.

Fig.4.11: Interface where recommendations are given



4.3.2 SUPPORT ASSISTANT

Support Assistant is specifically designed to explore the content of materials that are recommended by the recommendation system. The support assistant enables students to ask questions for further clarification of previously recommended journals or research papers. This facilitates students to deepen their understanding of the learning materials by continuing to ask questions from the tool. The Support Assistant provides not just the answer to the question, but it gives a vast explanation based on the background and the content of the relevant material.

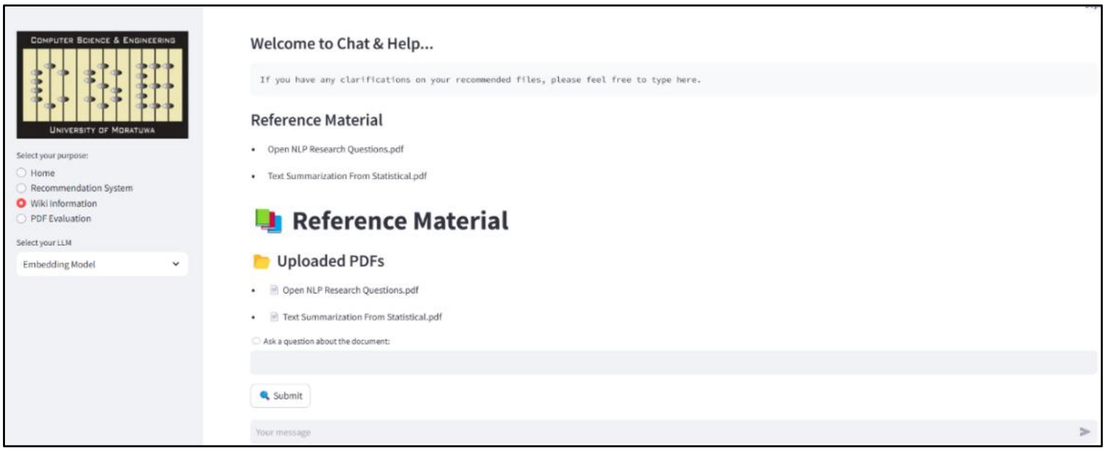


Fig.4.12: Initial interface of the Support Assistant

As shown in Figure 4.12, it shows the recommended materials and space to type their inquiries and submit them to get the answer which is shown in Figure 4.13.

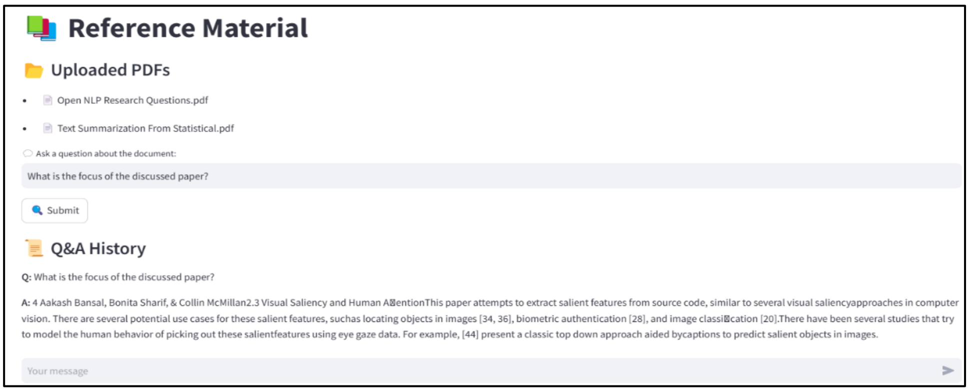


Fig.4 .13: Interface of the support assistant when asking questions & retrieving answers

4.3.3 SELF-EVALUATION

The evaluation section consists of 10 MCQ questions and 2 open-ended questions it enabling users to select the materials they need to be evaluated. These MCQ and open-ended questions are generated by the system itself without any human interference.

Fig.4.14: Interface of MCQ questions

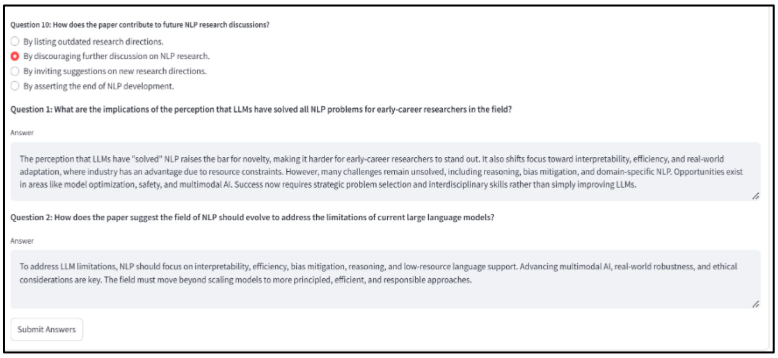


Fig.4.15: Interface of open-ended questions

As shown in Figure 4.15, students need to submit their answers after they finish answering. After the submission, the system evaluates our answers based on the recommended materials and finally retrieves the results and correct answers. Furthermore, for open-ended questions, it does not just answer, but it also provides clear clarification.

Fig.4.16: Interface of answer evaluation

4.4 RESULTS

4.4.1 RESULTS AND COMPARISON

After the recommendation system was developed, there is a necessity to identify the most appropriate large language model for the context. To properly test this, 15 postgraduate students were selected from the initial sample, and a test version was given to interact with the system, get relevant recommendations, and finally, to rate the recommendations they received.

Below is how the evaluation was conducted.

Student groups:

- Group 01 - MSc in Computer Science (23 batch) – 4 students
- Group 02 - MSc in DS & AI (23 batch) – 8 students
- Group 03 - MSc in DS & AI (24 batch) – 2 students
- Group 04 - MSc in DS & AI (25 batch) – 1 student

This student group was asked to get recommendations 5 times by integrating each of these models into query processing and formation of recommendations among GPT-3.5, GPT-4 and GPT-4-o. The table below consists of the results of their vote on whether the recommendation is relevant. This table well depicts that GPT-4 is satisfying user requirements, even if its pricing tier is a bit higher than the other models.

TABLE 4.1: STUDENTS' RATING BASED ON THE USED AI MODEL

Student group	*GPT-3.5*	*GPT-4*	*GPT-4.o*
Group 01	0.4	0.6	0.4
Group 02	0.2	0.8	0.4
Group 03	0.2	0.6	0.6
Group 04	0.4	0.6	0.6

4.4.2 SUPPORT ASSISTANT- RESULTS COMPARISON

After implementing the Support Assistant, the same group of students was assigned to rate answers from Chat Assistant, based on its relevancy. The maximum they can select is 5 stars, which is 5 points. This comparison was done using three different versions of the GPT model series.

TABLE 4.2: STUDENTS' FEEDBACK FOR DIFFERENT GPT MODELS WHEN USING CHAT ASSISTANT

Student group	*GPT-3.5*	*GPT-4*	*GPT-4.o*
Group 01	0.2	0.8	0.2
Group 02	0.2	0.4	0.4
Group 03	0.2	0.8	0.6
Group 04	0.4	0.6	0.6

4.4.3 SELF ASSESSMENT- RESULTS COMPARISON

Further, the same set of students was asked to use the self-evaluation assessment, which contains both MCQ and open-ended questions. These students were facilitated to rate the MCQ and open-ended question generation based on its relevancy to the content, because these questions are auto-generated through the GPT-4 model as per the instructions given in prompt engineering. Also, they rated the accuracy of the answers and feedback that were given from open-ended questions. The table below shows how students rated each of the segments based on different GPT models, after generating and answering 5 times.

TABLE 4.3: STUDENTS' FEEDBACK FOR DIFFERENT GPT MODELS FOR RELEVANCY OF QUESTION GENERATION

Student group	*GPT-3.5*	*GPT-4*	*GPT-4.o*
Group 01	0.4	0.6	0.6
Group 02	0.2	0.8	0.4
Group 03	0.2	0.8	0.8
Group 04	0.2	0.6	0.6

TABLE 4.4: STUDENTS' FEEDBACK FOR DIFFERENT GPT MODELS FOR OPEN-ENDED QUESTIONS – FEEDBACK GENERATION

Student group	*GPT-3.5*	*GPT-4*	*GPT-4.o*
Group 01	0.4	0.6	0.6
Group 02	0.2	0.8	0.4
Group 03	0.2	0.8	0.8
Group 04	0.2	0.6	0.6

The above 2 tables show that higher user ratings are given when they are using the GPT-4 model. This shows that GPT-4 can provide a convenient user experience, which is the basic requirement of the system.

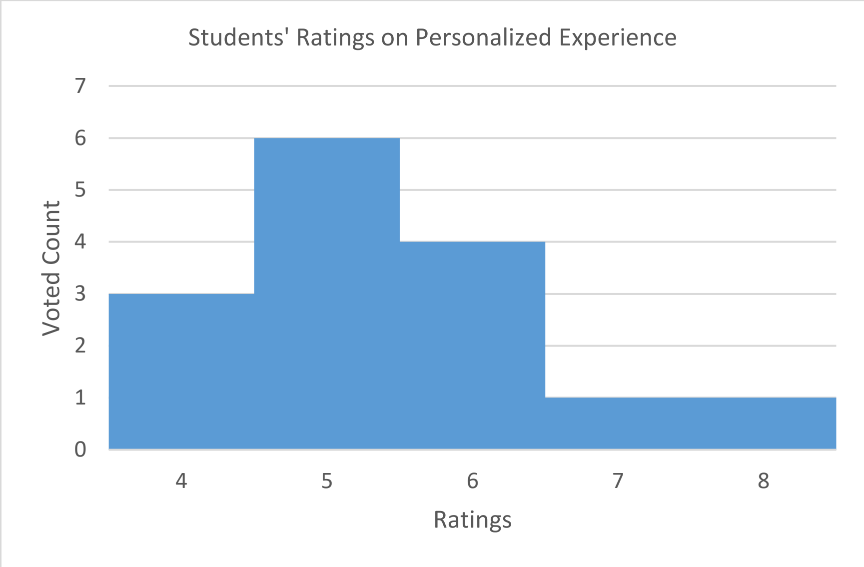


Fig.4.17: Histogram of ratings on personalized experiences

Based on the overall performance of the recommendation system along with the support assistant was rated by the above-selected group of students. According to the ratings, it can be concluded that users are receiving their expected personalized experience to some extent. The above graph shows the variation of how students have been rated on a scale from 1 to 10, with an average score of 5.4.

CHAPTER 5

DISCUSSION, CONCLUSION AND POSSIBLE FUTURE WORK

5.1 DISCUSSION

This study addresses several questions that students are currently dealing with. Developed personalized recommender system demonstrates a larger potential towards the improvement of the education field in the country, especially when it comes to higher education. This study discusses the limitations of traditional learning materials and the advantages of having AI-driven recommendation approaches. Furthermore, the study itself evaluates the pros and cons of various AI-driven methodologies and selects the best option, which is optimal in terms of performance, cost, and execution time to provide a more tailored and effective academic experience for students.

5.1.1 KEY FINDINGS

1. Improvement of Personalization:
   This learning support assistant provides personalized recommendations for students by observing the historical behavior of students who have referred to similar subjects. This also gives an option to customize easily for a certain group of students by recording their actual profiles and tracking past search and recommendation history.
   Furthermore, the average rating of 5.4 for the personalization indicator suggests that postgraduate students are generally satisfied with the personalized experiences provided by the system. This positive feedback reflects approval of the proof of concept (POC) and indicates that the effectiveness of personalization is likely to improve over time as more students engage with the system. As shown in Figure 4.12, 80% of the students rated the user experience as 5 or above.

2. Enhancing interactivity and learning efficiency:
   Facilitating students to get clarifications on recommended materials through the chat assistant helps to improve the interactivity and the engagement of students with the learning materials. The chart assistant instantly replies to questions that are based on the recommended materials, and the system was trained in a way that facilitates the content summarization of either the whole material or specific parts. As per Table 3.8, retrieval time is as small as 6ms, and the chat assistant received an average of 65% ratings from the test group of students.

It also allows students to answer some MCQ and open-ended questions related to recommended materials and provides real-time feedback as well. As Table 4.3 shows, this section has user ratings of an average of 70%.

3. Performance of LLM Models:
   Techniques used to develop a recommendation system and chat assistant are performed well in a way that offers precise and context-based answers with minimal hallucinations, where the sample that the recommendation system has been tested on gave good ratings as per Tables 4.1 and 4.2. The recommendation system and chat assistant show an average rating of 65% for both.

5.1.1 COMPARISONS WITH EXISTING RESEARCH

The foundation and background of the findings of the study align with the previous studies, which are based on personalized recommendation systems and extension with AI integration for better performance of the results in the educational sector.

However, this study extends the previous studies by the integration of a full package of recommendation systems, which is not merely suggesting learning materials, but goes beyond by facilitating end users to get assistance and clarifications on those recommended materials with interactive learning by the support of a chat assistant. Furthermore, it also provides a comprehensive set of questions which cover the recommended materials; both MCQs and open-ended questions, along with the evaluations and feedback mechanism, which gives students a chance to evaluate their understanding, and also to receive feedback.

As sections 4.2 and 4.3 demonstrated the functionalities, a full package of AI-integrated learning assistants is suggested by the study. While its current implementation is limited to a few postgraduate modules, the system holds the potential to be scaled and adapted to other modules across various academic levels, provided the relevant learning materials are available.

5.2 CONCLUSION

The study has successfully demonstrated the development of comprehensive AI-integrated educational recommender systems along with interactive learning environment where the end-user can have relevant recommendations as per the requirement, then chat assistance for any explanations related to the suggested materials, and he can also assess the understanding on the suggested materials by following the assessment and receiving feedback. This is highly contributing to the improvement of learning efficiency, and most importantly, to having a personalized way of learning.

The integration of advanced features into the recommendation tool leverages the latest Large Language Model (LLM) technologies, enabling it to deliver precise answers with low latency.

By leveraging generative AI models, the system enhances personalized learning experiences by offering relevant, high-quality educational content and real-time academic support. The results indicate that such systems can mitigate common learning challenges such as information overload, irrelevant content discovery, and lack of engagement in digital learning environments.

5.3 POSSIBLE FUTURE WORKS

Even if the study lays a strong foundation for a personalized recommendation system along with a chat assistant and student self-evaluation platform, it should be noted that this is a POC developed for a smaller scope. But in due course, it carries out great potential to enhance its scope and functionality. Below are the listed future works for the study:

- Cross-Domain Recommendations: Expand the recommender system not only for postgraduate students, but also for undergraduate students, high-school students, and also for industry-level as well.
- Scalability: Can further improve the efficiency of the models used and also increase the computational power to support the large-scale implementation across platforms.
- Integration with Learning Management Systems (LMS): Integrate refined recommendation systems to LMS platforms like Moodle for the wider use of students throughout all academic institutions.

By attending to these future works, this recommendation system can be widely used in academia; not only for postgraduate students, but at any level, as well as in industry as an AI-driven personalized recommendation system.

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