

# Rag & Llm Based Tnea Student Assistant for Academic Guidance

Ms. K. Sabitha, B. Monish, M. Nithishkumar, S. Mohammed Al Ameen, S. Samvarthini  
Sri Shakthi Institute of Engineering and Technology, Coimbatore, Tamil Nadu, India

**Abstract-** The process of selecting an appropriate engineering course and college has become increasingly challenging due to the large volume of information and the complexity of admission procedures such as TNEA. Students often face difficulty in understanding cutoff trends, identifying suitable colleges, and making informed decisions because the available information is scattered and sometimes unreliable. To address this issue, this project proposes an intelligent academic assistance system that combines Retrieval-Augmented Generation (RAG) with Large Language Models (LLMs). The system is designed to provide accurate and user-friendly guidance by retrieving verified academic data and presenting it through an interactive conversational interface. The retrieval component ensures that information such as cutoff marks and college details is obtained from structured datasets, while the language model supports explanation-based queries related to courses and career paths. The system is implemented as a web-based application using modern technologies, enabling real-time interaction between the user and the system. By combining data retrieval techniques with intelligent response generation, the proposed solution improves accuracy, reduces misinformation, and enhances user experience. This approach simplifies the decision-making process and helps students choose suitable academic paths with confidence.

**Keywords-** Academic Guidance, TNEA, RAG, Large Language Model, Course Recommendation, Engineering Education.

## I. INTRODUCTION

In the present educational scenario, choosing an appropriate engineering course and college has become a complex task for students. The Tamil Nadu Engineering Admissions (TNEA) process requires students to analyze several factors such as cutoff marks, course availability, category-based eligibility, and geographical preferences. Since this information is distributed across multiple sources, students often find it difficult to access reliable and organized data. This leads to confusion and may result in poor academic decisions.

Traditional counseling methods provide some level of support, but they are limited by time constraints, accessibility, and lack of personalization. Not all students have equal access to expert guidance, and in many cases, the information provided may not be updated or tailored to individual needs. As a result, students tend to rely on unofficial sources, which increases the risk of misinformation.

To overcome these challenges, the proposed system introduces an intelligent academic assistant that uses advanced technologies to provide accurate and real-time guidance. The

system integrates Retrieval-Augmented Generation (RAG) with Large Language Models (LLMs) to handle different types of user queries. The retrieval component focuses on providing verified data such as cutoff marks and college information, while the language model supports explanatory queries related to courses and career opportunities.

The system is designed as a web-based platform that allows students to interact through a simple and user-friendly interface. It processes user queries, identifies their intent, and delivers relevant responses in a conversational format. By combining data accuracy with intelligent interaction, the system acts as a reliable digital advisor for engineering aspirants. Overall, the proposed solution aims to simplify the admission process, improve access to accurate information, and support students in making informed academic and career decisions. It represents a step towards the effective use of artificial intelligence in educational guidance systems.

## II. LITERATURE REVIEW

The advancement of artificial intelligence has significantly influenced the development of academic guidance systems.

Earlier approaches to career counseling mainly depended on manual interaction, where students received suggestions from teachers or counselors based on limited information. Although these methods provided basic support, they lacked scalability and consistency. With the growing number of engineering courses and institutions, especially in admission processes like TNEA, traditional methods are no longer sufficient to handle the complexity of decision-making.

Recent studies have highlighted the role of AI in improving fairness and efficiency in academic advisory systems. The use of intelligent tools in admission processes helps in analyzing large datasets and providing structured guidance to students [1]. Similarly, chatbot-based advisory systems have been introduced to offer continuous and real-time support, reducing the need for human intervention and making guidance more accessible [2].

The integration of digital platforms and open educational practices has also contributed to the improvement of academic support systems. These platforms allow students to access learning resources and guidance services from anywhere, enhancing flexibility and accessibility [3]. In addition, the emergence of large language models has enabled systems to understand user queries and generate meaningful responses, making interaction more natural and effective [4].

AI-powered career counseling systems have further improved the decision-making process by analyzing student interests, academic performance, and preferences. These systems provide personalized recommendations, helping students choose suitable academic paths with greater confidence [5].

Research on artificial intelligence in education also emphasizes its ability to transform learning environments by offering adaptive and intelligent support [6]. Foundational works in artificial intelligence have laid the groundwork for developing such intelligent systems [7], while intelligent tutoring systems have demonstrated the importance of personalized learning approaches [8].

Conversational agents play a crucial role in modern advisory systems by enabling interactive communication between users and the system. Studies have explored their applications and challenges, highlighting the need for accurate and context-aware responses [9]. Understanding user intent is another

important factor, as it helps in delivering relevant recommendations and improving system performance [10].

The development of large-scale language models has further enhanced the capabilities of AI systems. These models are capable of handling complex queries and generating high-quality responses with minimal training [11]. In educational contexts, AI-based chatbots have been successfully used to improve communication and learning outcomes [12]. The integration of language models with tutoring systems has also been explored to provide structured and effective learning experiences [13].

Data-driven approaches are widely used to analyze student performance and generate insights for improving educational systems [14]. Comparative studies have shown that AI-augmented advisory systems are more efficient and scalable than traditional counseling methods [15]. Furthermore, the integration of knowledge graphs with language models has been proposed to improve explainability and transparency in intelligent systems [16].

Recent advancements also include the development of multilingual systems to support students from diverse backgrounds [17]. At the same time, ethical considerations such as data privacy, fairness, and responsible use of AI have become important areas of research [18]. These studies highlight the need for reliable and transparent systems in educational guidance.

Overall, the literature indicates that combining artificial intelligence, data retrieval techniques, and conversational models can significantly improve the effectiveness of academic advisory systems. These advancements provide a strong foundation for the development of the proposed system, which aims to deliver accurate, reliable, and user-friendly guidance for engineering aspirants.

### III. PROBLEM STATEMENT

Students applying for engineering courses through the Tamil Nadu Engineering Admissions (TNEA) process often face significant challenges in selecting suitable colleges and academic programs. The decision-making process requires analyzing multiple factors such as cutoff marks, course availability, category-based eligibility, and location preferences. However, the required information is usually

scattered across different sources, making it difficult for students to access accurate and structured data.

Existing guidance methods, including manual counseling and basic online platforms, are limited in their ability to provide personalized and real-time support. Many systems rely on static data or outdated information, which can lead to confusion and incorrect decisions. In addition, current platforms often lack intelligent query handling and do not support interactive communication, reducing their effectiveness in assisting students.

There is a clear need for a reliable and intelligent academic guidance system that can provide accurate, up-to-date, and user-friendly information. Such a system should be capable of understanding user queries, retrieving verified data, and presenting it in a meaningful and interactive manner. Addressing this gap is essential to improve decision-making and reduce uncertainty among engineering aspirants.

### Objectives

The main objective of this project is to build a smart academic advisory system that helps students make better decisions during the engineering admission process by combining intelligent technologies with reliable data sources. The specific objectives of the project are:

- To develop a system that can analyze student input such as cutoff marks and preferences to provide suitable recommendations
- To create a centralized platform that brings together all essential TNEA-related information in one place
- To implement an intelligent query processing mechanism that can understand and respond to user questions effectively
- To design a system that distinguishes between factual queries and general guidance queries for better response accuracy
- To enhance user experience by providing clear, simple, and understandable explanations for complex academic information
- To reduce the time and effort required by students to search for colleges and course details
- To improve the reliability of academic guidance by using structured and verified datasets

- To support continuous interaction through a dynamic and adaptive user interface
- To build a flexible system that can be extended with advanced features such as analytics, personalization, and multilingual support

### Major Project Objectives

The main objective of this project is to develop an intelligent academic assistance system that supports students in making informed decisions during the engineering admission process. The system is designed to combine modern technologies with reliable data sources to provide accurate and efficient guidance.

### The specific objectives of the project are as follows:

- To design and develop a web-based academic advisor for TNEA students
- To provide accurate and verified information regarding cutoff marks, colleges, and courses
- To integrate Retrieval-Augmented Generation (RAG) for reliable data retrieval
- To incorporate Large Language Models (LLMs) for handling explanatory and conversational queries
- To enable users to interact with the system through a simple and user-friendly interface
- To improve decision-making by presenting clear and structured recommendations
- To reduce dependency on manual counseling and minimize misinformation
- To ensure scalability and adaptability for future enhancements

## IV. SYSTEM ARCHITECTURE

The proposed system follows a layered architecture designed to provide accurate, efficient, and interactive academic guidance for TNEA students. The architecture is divided into three main layers: the User Interface Layer, the Processing Layer, and the Data & AI Layer. Each layer performs a specific function and works together to deliver reliable results.

### User Interface Layer

The User Interface Layer acts as the interaction point between the user and the system. It provides a chat-based interface through which students can enter their queries related to cutoff marks, colleges, and engineering courses. This layer is designed using web technologies to ensure ease of use and

accessibility across different devices. It captures user input and forwards it to the processing layer for further analysis.

**Processing Layer**

The Processing Layer is responsible for handling and analyzing user queries. It includes a query classification mechanism that determines the nature of the query. Based on the classification, the query is routed to the appropriate module. If the query is factual (such as cutoff marks or college details), it is directed to the RAG routing module.

- This layer ensures that each query is processed efficiently and sent to the correct component, improving the accuracy of responses.

**Data & AI Layer**

The Data & AI Layer is the core of the system, where data processing and intelligent response generation take place. It consists of two main modules:

**RAG Module**

The RAG module handles factual queries by retrieving relevant information from structured datasets. It uses a vector database that stores embeddings of TNEA data such as cutoff marks, college listings, and official information. By performing similarity-based search, it ensures that the retrieved data is accurate and relevant.

**LLM Module**

The LLM module is responsible for generating explanatory responses. It processes user queries related to academic guidance, career paths, and course descriptions. The module provides human-like explanations, making the system more interactive and user-friendly.

**Vector Database**

The vector database acts as a central storage system that holds processed academic data in the form of embeddings. It supports efficient retrieval of information based on similarity search, enabling quick and accurate responses.

**Working of the Architecture**

The system operates in a step-by-step manner. The user enters a query through the interface, which is then analyzed by the processing layer. The query is classified and routed to either the RAG or LLM module. The selected module processes the query using the vector database or language model and

generates a response. Finally, the result is displayed to the user through the interface.

**Advantages of the Architecture**

- Ensures accurate results by separating data retrieval and response generation
- Provides interactive and user-friendly communication
- Supports scalability and future enhancements
- Reduces misinformation by using verified datasets

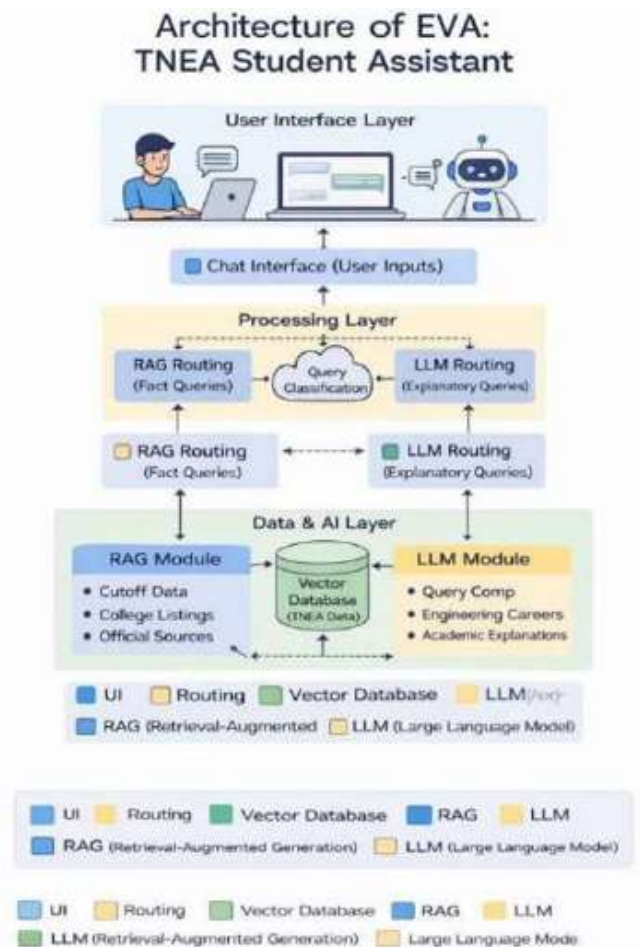


Fig 1: Architecture of EVA – TNEA Student Assistant

**V. METHODOLOGY**

**Overview**

The methodology of the EVA (Engineering Virtual Assistant) system follows a structured approach to provide accurate and user-friendly academic guidance. It combines data retrieval techniques with intelligent response generation to ensure both

reliability and clarity. The system is designed to process user queries step by step, analyze them, and generate meaningful outputs based on the type of request.

### Data Collection and Preparation

The system uses structured datasets that include information such as cutoff marks, college details, and course availability. These datasets are collected from reliable and verified sources to ensure accuracy. Before using the data, it is cleaned and organized by removing unnecessary or incomplete entries. This process helps in improving the efficiency and performance of the system.

### Query Processing and Classification

When a user enters a query, the system first processes the input to understand its meaning. Important details such as cutoff marks, location, and course preferences are identified. The query is then classified into two categories:

**Factual Queries:** Related to cutoff marks, college lists, and admission data

**Explanatory Queries:** Related to career guidance, course details, and general information

This classification helps in directing the query to the appropriate module.

### Retrieval Process (RAG Module)

For factual queries, the system uses the Retrieval-Augmented Generation (RAG) approach. The query is converted into a vector format and compared with stored data in the vector database. Based on similarity, the most relevant information is retrieved. This ensures that the output is based on verified and accurate data rather than generated assumptions.

### Response Generation (LLM Module)

For explanatory queries, the system uses a Large Language Model (LLM) to generate responses. The model interprets the user's query and produces a clear and meaningful explanation in natural language. This helps students understand complex concepts in a simple and interactive way.

### Integration of Modules

The RAG and LLM modules work together to provide a complete solution. While the RAG module ensures accuracy by retrieving real data, the LLM module enhances user interaction

by generating explanations. This integration improves both the reliability and usability of the system.

### Output and User Interaction

The final response is displayed through a chat-based interface. Users receive either direct data responses (such as college lists) or explanatory responses (such as career guidance). The system ensures quick response time and easy understanding, making it suitable for real-time academic support.

## VI. DESIGN AND IMPLEMENTATION

### System Design

The design of the EVA (Engineering Virtual Assistant) focuses on creating a simple, efficient, and user-friendly system that integrates both web technologies and artificial intelligence. The system follows a layered structure where each component is responsible for a specific function. This separation makes the system easy to understand, maintain, and expand in the future. The overall design includes three main parts: the user interface, the backend processing system, and the data handling components. These parts work together to ensure smooth communication between the user and the system while maintaining accuracy in responses.

### User Interface Design

The user interface is developed using HTML, CSS, and JavaScript. It provides a clean and interactive chat-based environment where users can easily enter their queries. The design focuses on simplicity so that students can use the system without any technical knowledge. Features of the interface include chat input for user queries, display of system responses, and easy navigation and readability. The interface ensures that users can quickly access information and interact with the system in a natural way.

### Backend Implementation

The backend of the system is developed using Python and the Flask framework. Flask is used to handle user requests, process inputs, and connect different components of the system. It acts as a bridge between the frontend interface and the AI modules. The backend performs functions such as receiving user queries, processing and classifying input, routing queries to appropriate modules, and sending responses back to the interface. This ensures smooth and efficient communication within the system.

### Data Handling and Storage

The system uses structured datasets that include cutoff marks, college details, and course information. These datasets are stored in a format that allows easy access and processing. A vector database is used to store the data in embedding form, enabling the system to perform similarity-based searches quickly and efficiently. This improves both speed and accuracy when retrieving information.

### Implementation of RAG Module

The RAG (Retrieval-Augmented Generation) module is implemented to handle factual queries. When a user asks for specific information such as cutoff marks or college lists, the system retrieves relevant data from the database using similarity search. This approach ensures that the information is accurate, the response is based on real data, and the system avoids generating incorrect results.

### Implementation of LLM Module

The LLM (Large Language Model) module is used to generate explanatory responses. It helps in answering questions related to career guidance, course details, and academic planning. The model processes the user query and generates responses in natural language, making it easy for students to understand. This improves user interaction and enhances the overall experience.

### System Integration

All components of the system are integrated to work together seamlessly. The frontend collects user input, the backend processes the query, and the appropriate module generates the response. The integration ensures fast response time, accurate information delivery, and smooth user interaction.

### Testing and Validation

The system is tested to ensure proper functionality and accuracy. Different types of queries are used to verify whether the system provides correct and relevant responses. Testing includes checking query classification, verifying data retrieval accuracy, and ensuring proper response generation. The system performs efficiently and provides reliable guidance to users.

## VII. RESULT AND DISCUSSION

### Overview of Results

The EVA (Engineering Virtual Assistant) system was implemented successfully and tested with different types of

user queries related to TNEA admissions. The system was able to provide both factual information and explanatory guidance effectively. The results show that the integration of Retrieval-Augmented Generation (RAG) and Large Language Models (LLMs) improves both accuracy and user interaction.

### Result Analysis

The system produced accurate results when handling factual queries such as cutoff marks, college listings, and course availability. The RAG module retrieved relevant data from the dataset based on similarity search, ensuring that the output was reliable and based on verified information. For explanatory queries, the LLM module generated clear and understandable responses. It helped users gain better insights into engineering domains, career opportunities, and academic planning. The responses were presented in a simple and conversational manner, making it easier for students to understand.

### System Performance

The performance of the system was evaluated based on response time, accuracy, and user experience. The system responded quickly to user queries, making it suitable for real-time usage. The combination of structured data retrieval and intelligent response generation ensured high accuracy. Key observations include fast response time for both query types, accurate retrieval of cutoff and college data, clear and meaningful explanations for user queries, and smooth interaction through the chat interface.

### Discussion

The results demonstrate that combining RAG and LLM techniques provides a balanced solution for academic advisory systems. The RAG module ensures that all critical information is retrieved from verified sources, reducing the risk of incorrect data. At the same time, the LLM module enhances the system by providing explanations in a user-friendly manner. Compared to traditional systems, EVA offers a more interactive and reliable experience. It not only provides data but also helps users understand the information, which is important for decision-making. The modular design of the system also allows easy expansion and integration of additional features in the future.

### Limitations

Despite its effectiveness, the system has some limitations. It depends on the availability and accuracy of the dataset used, and any outdated data may affect the quality of results.

Additionally, the system currently handles only predefined types of queries and may require further improvement to manage more complex scenarios.

### Summary

Overall, the EVA system performs efficiently and meets its objective of providing accurate and interactive academic guidance. The results confirm that the integration of retrieval and generation techniques enhances both system reliability and user experience.

## VIII. CONCLUSION

The EVA (Engineering Virtual Assistant) system offers a meaningful and efficient solution to the challenges faced by students during the TNEA admission process. With the increasing complexity of engineering admissions and the availability of scattered information, students often struggle to make informed decisions. EVA addresses this problem by providing a centralized and intelligent platform that combines accurate data retrieval with user-friendly interaction.

By integrating Retrieval-Augmented Generation (RAG) and Large Language Models (LLMs), the system ensures that users receive both reliable information and clear explanations. The RAG module retrieves verified data such as cutoff marks, college availability, and course details, thereby minimizing the chances of misinformation. At the same time, the LLM module enhances the system by generating natural language responses, making complex information easy to understand for students.

One of the key strengths of the system is its ability to provide real-time interaction through a chat-based interface. This makes the system more engaging and accessible compared to traditional static platforms. Students can ask questions, explore different options, and gain insights into engineering domains in a simple and interactive manner. The system also reduces the dependency on manual counseling by offering consistent and unbiased guidance.

The modular design of EVA ensures flexibility and scalability, allowing future improvements and integration of advanced features. The combination of structured data handling, intelligent query processing, and conversational interaction makes the system both efficient and reliable. Performance evaluation shows that the system delivers accurate results with

fast response time, making it suitable for real-time academic support.

In conclusion, EVA demonstrates the potential of combining modern AI technologies with educational guidance systems. It not only improves access to accurate information but also enhances the overall decision-making experience for students. By transforming complex admission data into meaningful insights, the system helps students make confident and well-informed choices about their academic future. strong foundation for the development of next-generation intelligent advisory systems that are more personalized, adaptive, and widely accessible.

### FUTURE WORK

The EVA system can be further enhanced by integrating real-time TNEA data sources, allowing the system to provide up-to-date information on cutoff marks, college availability, and admission trends. This would improve the accuracy and relevance of the guidance provided to students. In addition, a personalized recommendation module can be developed using advanced machine learning techniques to suggest colleges and courses based on individual student profiles, including marks, interests, category, and preferred location.

Future improvements can also include the addition of multi-language support, especially regional languages such as Tamil, to make the system accessible to a wider range of users. Developing a mobile application would further enhance usability by allowing students to access the system anytime and anywhere. The integration of an AI-powered chatbot with memory capabilities can enable more interactive and context-aware conversations, improving user experience over multiple queries.

Another important enhancement is the inclusion of advanced analytics and visualization features. These can provide students with insights such as cutoff trends, admission probability, and comparison between colleges. A dedicated college comparison module can help users evaluate institutions based on factors like placements, infrastructure, and academic performance.

Furthermore, the system can be expanded to include career path prediction and skill recommendation features, guiding students not only in choosing courses but also in planning their future careers. Integration with external APIs and official educational

portals can ensure continuous data updates and improved system reliability.

Finally, future research can focus on improving the scalability and adaptability of the system by incorporating more advanced AI models and fine-tuned domain-specific language models. This will enable EVA to handle more complex queries, provide deeper insights, and evolve into a comprehensive intelligent academic advisory platform.

## REFERENCES

1. J. M. Smith and J. Williamson, "Equity implications of using AI tools in the college admissions process," *Proc. AAAI Conf. Artificial Intelligence*, vol. 38, no. 24, pp. 22230–22238, 2024.
2. M. M. Thotli, B. H. Alruqaishi, and A. Soosaimainadam, "Robo academic advisor: Chatbots and artificial intelligence replace human interaction," *Contemporary Education Technology*, vol. 16, no. 1, Art. no. ep485, 2024.
3. F. Nascimbeni, D. Burgos, L. M. Campbell, and A. Tabacco, "Institutional mapping of open educational practices beyond use of Open Educational Resources," *Distance Education*, vol. 39, no. 4, pp. 511–527, 2018.
4. M. R. Waters, S. Aneja, and J. C. Hong, "Unlocking the power of ChatGPT, artificial intelligence, and large language models: Practical suggestions for radiation oncologists," *Practical Radiation Oncology*, vol. 13, no. 6, pp. e484–e490, 2023.
5. M. Ghose, I. Kamble, A. Mahardwaja, A. Kumari, and V. Raikar, "Envisioning tomorrow: AI powered career counseling," *Proc. Int. Conf. Innovations Industrial Applications*, pp. 377–383, 2023.
6. L. Chen, P. Chen, and Z. Lin, "Artificial intelligence in education: A review," *IEEE Access*, vol. 8, pp. 75264–75278, 2020.
7. S. J. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*. London, U.K.: Pearson, 2016.
8. B. P. Woolf, *Building Intelligent Interactive Tutors: Student-Centered Strategies for Revolutionizing E-Learning*. San Mateo, CA, USA: Morgan Kaufmann, 2010.
9. A. Alemahe, S. Singh, B. Kocbali, and M. Prasad, "An overview of conversational agent applications, challenges and future directions," *Proc. Int. Conf. Web Information Systems Technology*, pp. 388–396, 2021.
10. S. Farshidi et al., "Understanding user intent modeling for conversational recommender systems: A systematic literature review," *User Modeling and User-Adapted Interaction*, vol. 34, pp. 1–64, 2024.
11. T. Brown et al., "Language models are few-shot learners," *Proc. Advances in Neural Information Processing Systems*, pp. 1877–1901, 2020.
12. D. U. Jiming and B. Kim Daniel, "A systematic review of AI-powered chatbots in ESL speaking practice," *Computers and Education: Artificial Intelligence*, vol. 6, Art. no. 100230, 2024.
13. P. Chowdhury, V. Sankalan Zouhar, and M. Sachan, "Autotutor meets large language models," *Proc. ACM Conf. Learning at Scale*, pp. 5–15, 2024.
14. K. Ahmad et al., "Data-driven artificial intelligence in education: A comprehensive review," *IEEE Trans. Learning Technologies*, vol. 17, pp. 12–31, 2024.
15. K. Lekan and Z. Pardos, "AI-augmented advising: A comparative study of GPT-4 advisor-based recommendations," *Journal of Learning Analytics*, vol. 12, pp. 1–9, 2025.
16. C. Park, H. Lee, S. Lee, and O. Jeong, "Synergistic joint model of knowledge graph and LLM," *Mathematics*, vol. 13, no. 6, Art. no. 949, 2025.
17. B. Ayesha, U. Thayasim, and U. Thayasivam, "Multilingual student performance prediction using Llama 3," *Proc. IEEE Int. Conf. Big Data*, pp. 5936–5945, 2024.
18. J. Huallpa Jinchua, "Exploring the ethical considerations of using ChatGPT in university education," *Periodicals of Natural Sciences*, vol. 11, no. 4, pp. 105–115, 2023.