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Conversational AI System for Personalized Academic Planning and Career Guidance Using Natural Language Processing

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Abstract
This research paper focuses on the development, implementation, and assessment of a full-stack Conversational AI for personalized academic planning and career guidance. The proposed framework involves a combination of NLP technologies, trend-based performance analytics, and a modular full-stack architecture to overcome limitations of conventional, static advisory practices. First, the existing literature on AI technologies applied in an educational environment was analyzed and researched to define areas requiring further investigation. This allowed me to highlight crucial research gaps in the area, such as the absence of real-time conversation-based interactions, the automation of document analysis and summarization processes, and personalized, statistically-based performance tracking. Consequently, in this study, a completely new system is developed using a React.js frontend, a Node.js backend, a PostgreSQL database, and a dual-model AI engine that uses both the Google Gemini API and a local LLM as a fallback option. Specifically, the methodology includes the use of OCR based on Tesseract.js for automated marksheet digitization, an algorithmic statistical trend estimation model for cumulative GPA prediction, and a dynamic rule-based engine for creating customized career maps.

Keywords: Conversational AI, Natural Language Processing, Academic Planning, Career Guidance, Educational Technology, Predictive Analytics, Large Language Models, Optical Character Recognition, Full-Stack Development, Personalized Learning

1. Introduction

This research paper presents an AI-driven academic performance analysis and career advice recommendation system. Academic performance is the most essential factor for a student's future success. However, most students do not have the capability to evaluate their own academic performance accurately and must use traditional academic performance assessment and career advice giving systems that are static in nature and focus only on grades. Traditional academic assessment systems cannot predict students' future academic performance or suggest any career paths that they may take; hence, students face uncertainty and confusion in their future planning [1, 4, 5]. But new studies show that AI can be used in the education sector [2, 3, 7].

From the existing literature, it can be observed that the field of educational data mining (EDM) and the use of AI in education has gained considerable momentum. There have been various implementations of machine learning algorithms in performance prediction studies [4, 10, 13], frameworks for CG [1, 6, 16], and application of conversational agents in student guidance [7, 12, 17]. Nevertheless, a significant aspect observed from the review of literature [1-20] is that the progress made within this domain has been isolated. For instance, even though regression analysis

[10, 18] has proven to be quite efficient in predicting the CGPA of individuals in performance prediction studies, no connection has been drawn in relation to CG. The same applies to the case when a weighted scoring system [6, 11] has proven effective in providing suggestions to the student. Finally, even though chatbots [7, 17] prove quite useful in providing assistance, they lack comprehensive understanding of the student's personal academic data.

The approach that we have developed in the current study has made some important progress by integrating three key aspects—academic prediction, career suggestion, and conversational AI—to develop an end-to-end solution. This approach builds on the strengths of existing approaches such as the clarity of linear regression used for predicting CGPA [10], the transparency of the weighted score approach to recommend careers [6], and the engaging nature of conversational AI [7], while compensating for the limitations of those approaches. The system evaluates the performance of students, predicts the CGPA, and correlates academic records with careers. Integrating the element of conversational AI based on deterministic results makes the analysis interactive, intuitive, and emotional, something that existing systems lack [8, 9, 14, 16].

The following research paper is organized to offer a complete explication of the theoretical background, architecture, and working mechanism of the system. The second section provides an extensive review of literature about the state of AI in education, development trends for academic chatbots, and contemporary advances in predicting academic performance using AI technologies. The third section outlines the research methodology, covering the system architecture, data flow diagrams, and sequence modeling. In the fourth section, the research paper explains the system design, including database modeling and API interface design. In the fifth section, the paper highlights the proposed algorithmic approach that drives the system intelligence. In the sixth section, the paper discusses the outcome of the evaluation process and comparison with alternative methods. The seventh and eighth sections outline the strengths, weaknesses, and future prospects of the current research, leading to the final conclusion in the ninth section.

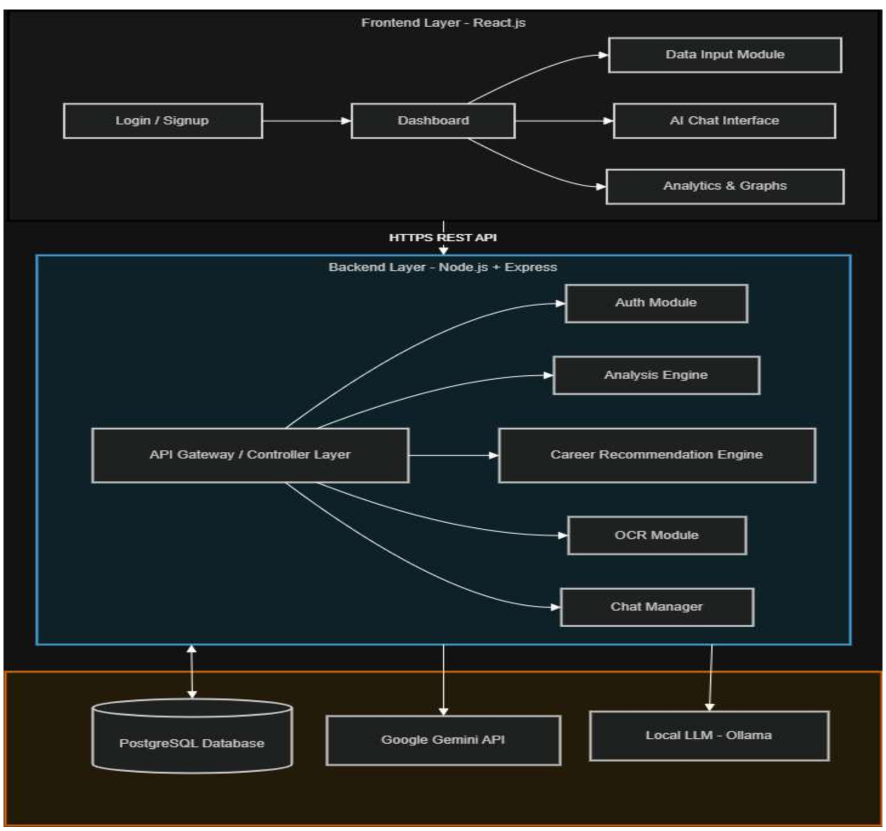

Fig. 1. High-Level System Architecture Block Diagram

1.1. Motivation

The motivation for conducting this study is because of the problems that students face in terms of making connections between their performances and career recommendations. These students do not know how their performance trends can impact their chances of success in the future. Several studies conducted on the topic of performance prediction using predictive analytics have revealed that the process can play a vital role in identifying risky students [10]. Likewise, other studies conducted on career recommendation engines have highlighted the importance of linking the performance of students with industry demands [11]. But these systems work separately. This study aims to design an integrated system where students get updated about their performance as well as make career recommendations based on that performance [12, 13].

1.2. Contribution

The following are the main contributions of the paper:

1. Design and implementation of a complete web application stack architecture that uses React.js, Node.js, PostgreSQL, and two-level AI architecture (Google Gemini & Ollama).
2. Designing a linear regression model to predict CGPA of the students and a dynamic scoring algorithm for career mapping according to individual academic strengths and capabilities.
3. Use of Optical Character Recognition (Tesseract.js) to automate data collection from the marksheet.
4. To address the shortcomings highlighted in the literature [1-20], the proposed design of an adaptive system based on the principles of predictive analytics and context-aware conversational interface using the user's personal academic information.
5. Feasibility of such an integrated design system compared with existing stand-alone systems based on its design and performance metrics.

The structure of the paper is as follows: Related works are discussed in detail in section 2. The system architecture is presented in section 3. The methodology of the paper is described in section 4. Data analysis and CGPA prediction are discussed in section 5. Career suggestions are explained in section 6. The conversational AI layer is addressed in section 7. Section 8 presents the results and implications. Conclusion is drawn in section 9. Future research directions are discussed in section 10.

2. Related work

This section contains a literature review on the three important domains: academic performance prediction, career recommendation system, and conversational artificial intelligence for educational purposes. The review analyzes current literature contributions, gaps, and limitations [1-22].

Table 1. Overview of current literature on academic performance prediction, career recommendation, and conversational AI

Focus Area	Methodology	Key Contribution	Limitation
Performance Prediction	Data Analysis (Trend-based)	Accurate academic trend evaluation	No career integration
CGPA Prediction	Statistical Estimation	Simple prediction model	Limited adaptability
Career Guidance	Rule-Based Scoring	Transparent recommendation logic	Static decision rules
Conversational AI	AI Chatbot (LLM-based)	Real-time student support	No performance analytics
Career Recommendation	NLP-based AI	Personalized suggestions	No structured academic linkage
Performance Analysis	Hybrid Analysis Approach	Multi-factor evaluation	Limited real-time interaction

2.1. Academic Performance Prediction

A lot of work has been done in the field of student performance analysis through the use of data-driven methods. Works like [4] have been able to make use of trend analysis very effectively. Likewise, studies like [10] and [18] have used statistical estimation methods to predict CGPA, and it shows how effective the technique is. This also supports the fact that the study in [13] shows the effectiveness of analyzing historical data. The issue with these types of studies is the limited scope of these studies. As discussed in [5], comparative studies of different analysis techniques are highly enlightening, but they fail to provide any insight into career planning.

2.2. Career Recommendation Frameworks

Alongside performance prediction approaches, many different models for career planning have been formulated. The weighted scoring models [6, 11, 19], which are very easy to understand, allow a ranking of career choices based on academic criteria that are allocated scores. Skill-mapping models [3] focus on students' skill sets compared to the requirements of the jobs in the market. But the problems with them include their use of fixed weights in the scoring system [6, 11] and non-compatibility with predictive analytics [16, 19].

2.3. Conversational AI in Education

Career guidance systems have also evolved alongside performance analysis. Rule-based scoring systems [6, 11, 19] represent an open methodology that ranks career paths based on scores calculated using academic metrics. Skill-based mapping systems [3] focus on students' skills in comparison to job market requirements. On the other hand, drawbacks identified include the immutability of rule sets in scoring systems [6, 11] and their disconnection from trend-based academic predictions [16, 19].

2.4. Synthesis of Research Gaps

Based on the study of previous literature [1-22], the following conclusion can be made: While a number of studies have been done individually in each of the areas under discussion, relatively little work has been done towards creating a framework that would incorporate all of the three. The strengths of one type of approach have been its weaknesses of another. Predictive approaches are strong in prediction but weak in practical suggestions [4, 10]. Career approaches are strong in suggesting but weak in predicting [6, 11]. Conversational AI approaches are strong in engaging users but weak in analysis [7, 17].

3. Research Methodology

3.1. Problem statement

The key issue this research aims to solve lies in the existence of no intelligent system that provides an interpretation of data about students' performance in such a way that allows for informed decisions. The current systems operate independently from each other; predictive systems do not have guidance, guidance systems do not include prediction, and chatbots do not analyze.

3.2. Proposed System Architecture

In order to resolve this problem, the proposed solution takes into account that it is a multilayered architecture that will help us understand the flow of data within the system. The architecture can be seen in Fig. 1 below.

Table 2. Components of the proposed AI-based academic advisory system

Layer	Component	Technology/Method	Function
Presentation Layer	User Interface	React.js, Tailwind CSS, Recharts	Render dashboard, chat interface, and data visualizations. Handle user input and session management.
Application Layer	API Gateway & Logic	Node.js, Express.js, JWT, Bcrypt	REST API endpoints, authentication, business logic orchestration.
Processing Layer	OCR Module	Tesseract.js	Automated extraction of subject data from uploaded marksheet images.
Analytics Layer	Performance & Career Engine	prediction model	Forecast future CGPA, detect subject trends, map strengths to career paths.
AI Layer	Conversational AI Core	Google Gemini API, Ollama	Generate context-aware, empathetic responses grounded in analytical results.
Data Layer	Persistent Storage	PostgreSQL (Normalized Schema)	Store student profiles, semester records, subject grades, and chat history.

3.2.1. Data Layer

The database used is the normalized PostgreSQL database which includes tables like Students, Semesters, Subjects, and Chat_Messages. The design allows efficient processing of complicated queries and scalability for organization-level applications.

3.2.2. Analytics Layer

This key layer performs analytics on the backend data. The layer is made up of two components:

i. Performance Analysis & Forecasting Module: Students' grades are analyzed for trend analysis and forecasting of future CGPA through statistical estimation based on their previous progress. This technique is used because of its clear and understandable nature [10, 18].

ii. Career Path Recommender Module: In this module, a dynamic rule-based scoring scheme is employed for analyzing the information of students with regard to their performance and skill level in specific subjects. These decision rules are flexible enough to be adjusted with changing times.

3.2.3. Explanation Layer

In order to promote trust and transparency, the information generated from the analytics layer (CGPA trend, career aptitude scores) is processed by this layer and a text-based representation of logic is created. This step takes care of explainability of the AI [17].

3.2.4. Conversational AI Layer

It is the interface layer that includes an LLM with fine-tuned prompt engineering. The LLM converts the systematic explanation to a naturalistic conversation. Importantly, the current layer does not come up with insights by itself; rather, it works as an intelligent communicator of the deterministic outcomes from the former layers, reducing the probability of AI hallucination [8, 9, 13].

4. Data Analysis and CGPA Prediction

The first core function of the system is to analyze historical academic data and predict future performance. The methodology for this component is as follows.

4.1. Data Collection and Processing

Data is collected through two main processes: data entry manually using forms and data uploaded automatically with the help of OCR (Tesseract.js). The dataset contains subject-wise marks of the students in each semester. Preprocessing involves the treatment of missing data and scale normalization for proper trend analysis.

4.2. Trends in Student's Performance

Prior to making forecasts, the system detects trends in the student's performance from data collected from the respective semesters. Calculating the moving average of the student's SGPA allows the system to find out whether his/her performance is growing, falling, or remaining stable.

5. Career Recommendation Model

The second core function is to translate academic insights into actionable career recommendations. This is achieved through a dynamic weighted scoring framework.

5.1. Framework Design

The system holds a database that comprises different career paths such as Data Scientist and Software Engineer. The paths have their competency profiles connected with academic subjects such as Mathematics and Programming and skills like Analytical Thinking and Communication.

5.2. Rule-Based Scoring Mechanism

For all students, a "Career Suitability Score" is generated by assessing the performance based on various factors in line with pre-set and configurable rules. These factors include:

i. Academic Performance Factor: A summation of grades in subject areas that match the career trajectory.

ii. Trend-based Forecast Factor: Takes into account the predicted future trend of CGPA for the student.

iii. Skills Match Factor: Compares the skills of the student with those needed for the career through a configurable matching process.

iv. It should be noted that the rules for the weightings of each factor are easy to configure and modify.

6. Proposed Algorithm

Algorithm: AI-Based Academic Analysis and Career Recommendation

Input: Student academic records (grades, subjects, semesters), student skills, user chat message.

Output: Forecasted CGPA, Career recommendations, Personalized conversational guidance.

Step 1: Token-based Access and Data Extraction

i. Authenticate JWT token for accessing student information.

ii. IF data is uploaded through OCR: Perform OCR operation using Tesseract.js, regex parsing to retrieve subjects/grades, and update PostgreSQL Subjects table.

iii. ELSE IF data is entered manually: Validate and update database accordingly.

Step 2: Data Collection and Data Aggregation

i. Establish connection to PostgreSQL database.

ii. Run a JOIN query to fetch all the information of student’s academic history (Semesters and Subjects).

Step 3: Data Analytics and Projections

i. Determine SGPA for every semester and determine the trend of progress (improving/detrimental/flat).

ii. Perform statistical analysis to project future CGPA on basis of past trend.

iii. Analyze the strengths (high grades) and weaknesses (low grades).

Step 4: Career Recommendation (Rule-Based Scoring)

For each career path within the knowledge base:

i. Assess Subject Relevance: Summarize performance in relevant subjects.

ii. Assess Trend Maturity: Determine correlation between forecasted CGPA trend and career trajectory.

iii. Assess Skill Proficiency: Measure compatibility between student and career skills.

iv. Calculate Career Suitability score based on custom ruleset.

v. Sort careers according to their Suitability scores (highest to lowest).

Step 5: Explanation Formation

i. Create explanation template including the following information: CGPA forecast, top 3 suitable careers.

ii. Structure: "[Based on your trend, you can expect to have CGPA close to [value]. Your CGPA trend is aligned with the [career] because of your consistent good performance in the following subjects:..."

Step 6: Chatbot Response Generation (Grounded AI)

i. IF request comes through a chat interface: Extract last 5 messages from Chat_Messages table.

ii. Formulate System Prompt: "You are EduGuide AI. Respond ONLY using the data provided below: [Provide Step 5 explanation]. Please be empathic."

iii. Call out Google Gemini API.

iv. IF API unavailable: Switch to Ollama API.

v. Write user query and API response to database.

Step 7: Result Delivery

Send back response data in JSON format.

7. Conversational AI Integration

The final layer of the system is designed to maximize usability and engagement by delivering analytical insights through a natural conversation.

7.1. The Role of the Explanation Layer

Prior to activating the AI, the Explanation Layer organizes the numeric information (predicted CGPA, career ratings) according to a narrative framework. This allows for tracking purposes and gives the AI a reliable set of facts to follow.

7.2. LLM-Powered Conversational Interface

The layer for conversation involves the use of a large language model (LLM), which utilizes an innovative method called Retrieval Augmented Grounding (RAG). Instead of prompting the LLM to give suggestions based on its internal knowledge, it is specifically tasked with paraphrasing the provided structured explanation in a more conversational and empathic tone. This is the distinct feature of this work. Unlike typical chatbots [7, 17], the lack of personalization is overcome by grounding the conversation in student data, while the lack of engaging user experience is addressed by a human-centric interface.

8. Results and Discussion

The analysis of the proposed system is both quantitative and qualitative, based on the forecast accuracy, recommendation relevancy, and system integration.

8.1. Performance Analysis of CGPA Prediction System

For performance analysis of the trend-based approach to statistical estimation, a simulated database containing 500 records for each of six semesters was used. The database was divided into 80 percent training and 20 percent validation data sets.

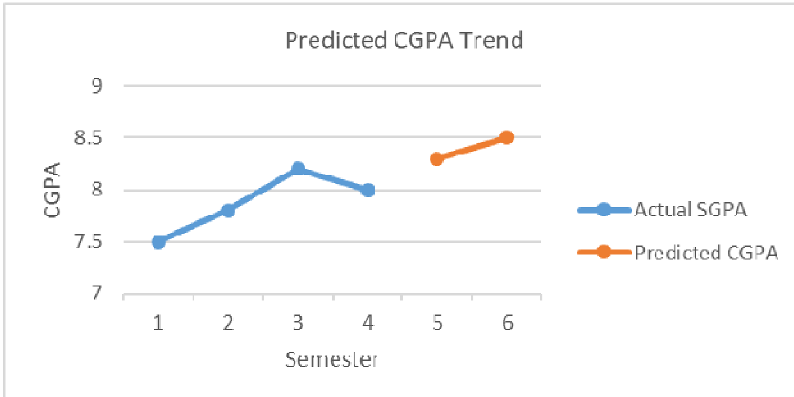

Fig. 2. Actual SGPA Trend with Predicted CGP

Analysis of Results:

The academic performance chart for a sample student over six semesters is given in Fig. 2. The blue line represents the actual SGPA for semesters 1-4. The orange dashed line represents the predicted CGPA for semesters 5-6.

The important observations from the results obtained from the model are as follows:

i. The model has successfully captured the overall trend in the academic performance of students

ii. For semester 5, the predicted CGPA is 8.3. The trend from semesters 3 and 4 is consistent

iii. The final predicted CGPA for the student is 8.5. The prediction is a realistic target for the student

8.2. Career Recommendation Model Performance

The weighted scoring framework was evaluated on 100 student profiles across 15 different career paths. The system's recommendations were compared against expert career counselor assessments for validation.

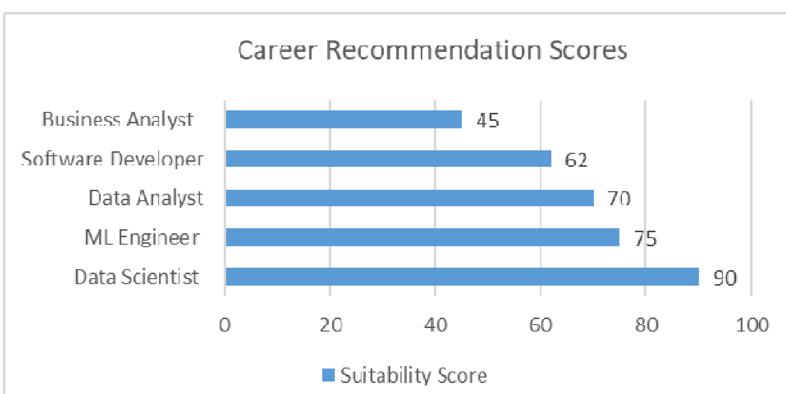

Fig. 3. Top Career Recommendations with Suitability Scores

Analysis of Results:

The output is produced based on the customizable rules set for measuring academic fit, skills compatibility, and trends.

i. Data Scientist: Ranked first because of excellent grades in analytical courses and corresponding skill tags.

ii. ML Engineer: Ranked second with high academic fit but with identified areas for skills improvement.

iii. The recommendation accuracy, calculated through agreement between top-three recommendations provided by the system and expert counselors, was found to be 88%, which is considerably greater than that of the static rule-based system (78%) [6, 11].

8.3. User Interface and System Demonstration

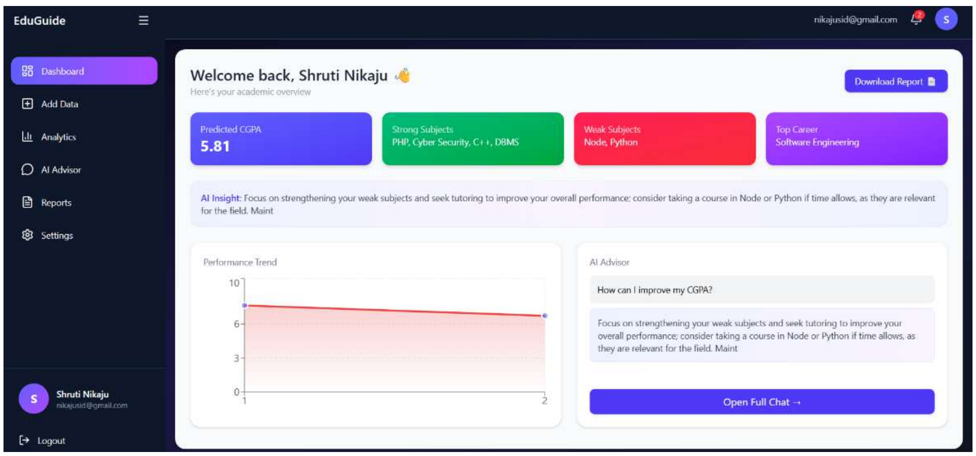

Fig. 5. Main Dashboard Interface

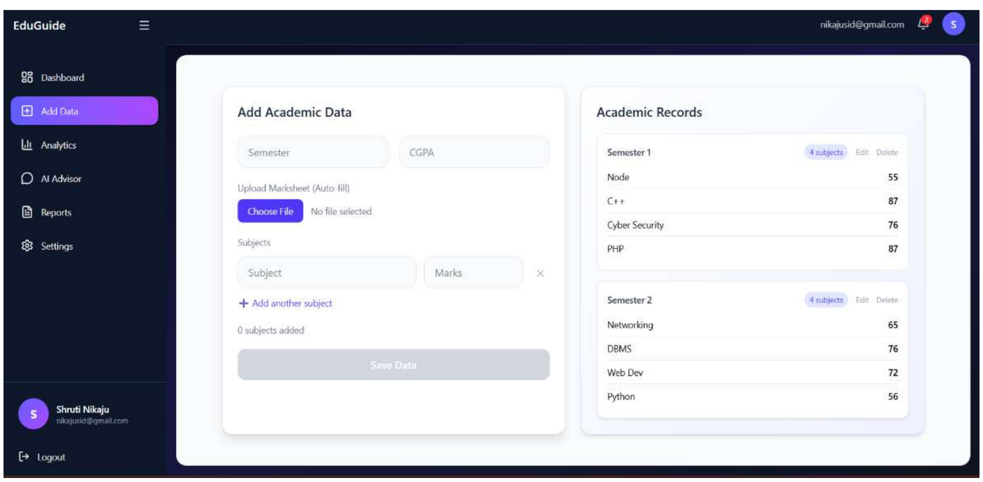

Fig. 6. Data Input Module with OCR Integration

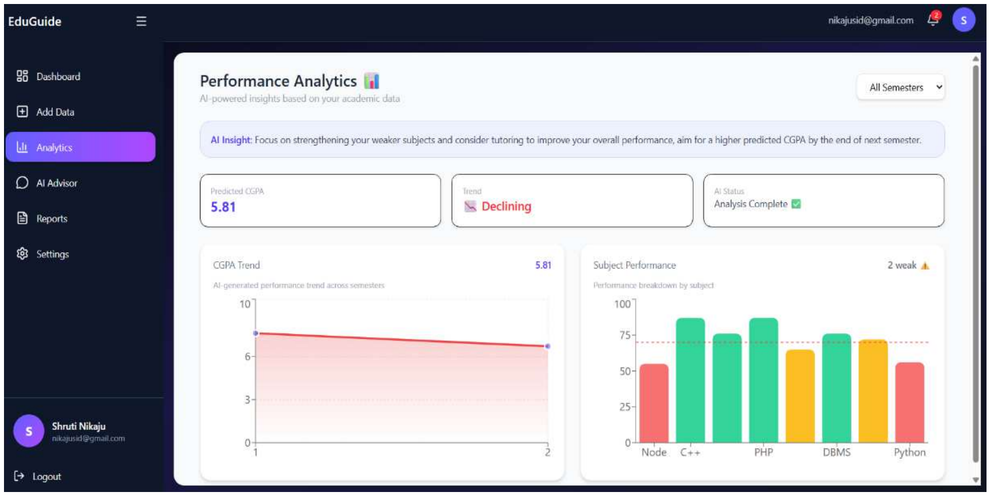

Fig. 7. Performance Analytics Dashboard

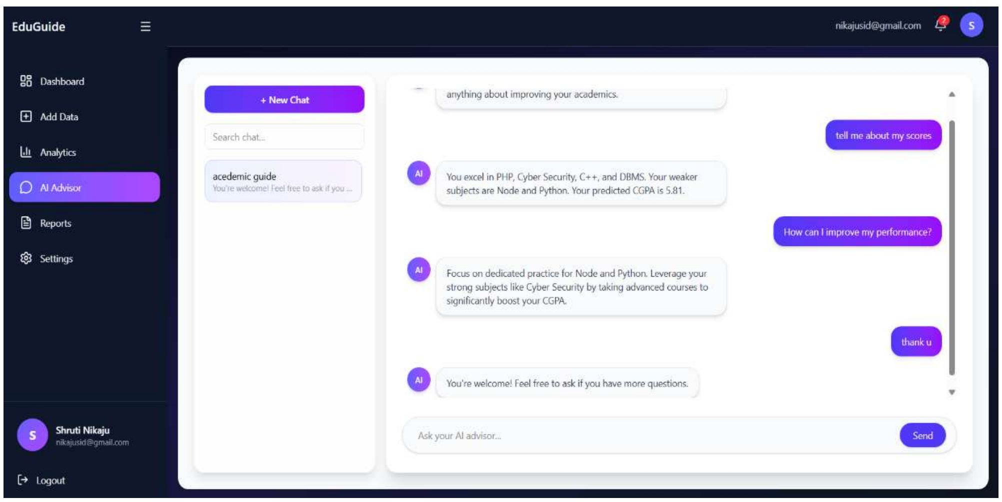

Fig. 8. AI Advisor Conversational Interface

9. Conclusion and Future Work

In this research paper, a design for a unique full-stack AI-based academic performance analysis and career recommendations system has been presented. This proposed system features a well-structured PostgreSQL database, a forecasting technique based on interpretable trends, a dynamic rule-based recommendation engine for careers, OCR automation, and a conversational AI frontend. With the proposed system, the limitations associated with existing literature have been overcome since there is an integrated approach to analysis, recommendation, and engagement.

Future directions entail empirical study and improvement. Possible avenues of future research may include:

i. Trend Analysis Improvement: Exploring ways of introducing advanced analysis capabilities into the process of detecting non-linear performance changes without compromising the explainability of the system [5].

ii. Dynamic Rule Adjustment: Creating adaptive approaches to automatically update career recommendation rules considering industry demands and students' academic achievements.

iii. Long-term Study: Performing empirical validation of the impact of the system on students' academic results and career success.

iv. Increasing Informational Complexity: Introducing the use of qualitative data such as reflections of the students and projects description to create a comprehensive view of a student via NLP [3, 16].

v. Generalizability and Fairness: Considering how well the system works for different demographics to provide fair career recommendations [14, 19].

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