AI-Based Career Recommendation System

Parikshit Tyagi, Shubham Tyagi, Shivansh Tyagi, Ms. Km Vaishali Rastogi
Student, Student, Student, Assistant Professor
CSE Department
RKGIT, Ghaziabad, India

Abstract: In this paper, we present an AI-driven career recommendation system that uses a combined web and mobile solution to provide personalized career, course, and college recommendations. The system starts by gathering each user's personal data. This data includes geographic location, hobbies, and educational background. The Gemini Flash 2.5 model performs additional processing on this data. A list of suggestions tailored to the user's particular circumstances is the end result. The entire process is made possible by cloud architecture. This makes it possible for any device to process and be available in real time. The core of the personalization process is user profiling. This paper describes a system for career recommendations. The system relies on artificial intelligence. Connecting students with reliable sources of guidance is the goal. The model's ability to recommend pertinent items is demonstrated by experimental validation. One of the system's most crucial features is its user-friendly interface. Students who have had minimal exposure to technology are the target audience for the interface. They can easily make decisions with the help of the interface. Low-resource environments are intended for this architecture. Even when the network is inconsistent, it functions flawlessly on a simple smartphone.

Index Terms – AI Based Career recommendation system, Artificial Intelligence, API Integration, educational guidance, Gemini Flash

INTRODUCTION

AI-Based career recommendation is a guidance system which helps students to choose their career paths based on their interests. The decision is taken on the basis of the factors like current class, Area of interest, Interested Subject in order to provide personal recommendation in place of general recommendation. Hence, helps students to choose their career paths according to their interest. As the world is evolving rapidly, it makes difficult for student to choose the right path for their career due to large variety of job roles and new technologies. Traditional guidance methods do not work well for every student as they are not able to understand every individual interest and some times have less knowledge about the career options in particular field which creates need for personalised recommendation system.

The proposed solution provides automated and personalized recommendations. It aims to empower students to make knowledgeable decisions about their education. For students in environments without access to guidance, this is particularly crucial. The gap in career awareness will be reduced thanks to our research. Students will make better decisions. These remain the project's primary objectives.

The shortage of licensed counsellors is addressed by the suggested system. Additionally, it improves usability for students who are not tech-savvy. The system works well on low-end hardware and under varying network conditions. This is done to ensure wide usability. A modular design and AI engine help ensure flexibility. Future improvements might include a skill recommendation or mentorship service. Dynamic labour market analytics might also be incorporated. These would further improve the system as a career guidance service.

LITERATURE REVIEW

Recent studies focus on machine learning and AI for career and education suggestions. Sharma and Kulkarni (2021) applied a Random Forest model. Their model was able to categorize students' career options based on academic and interest inputs. The model performed moderately well [1]. The major drawback was its applicability—the system was applicable only to science students. Mehta et al. (2022) designed a hybrid model. The model combined SVM and KNN. The model increased the accuracy of predictions. The system suggests colleges and courses [2].

Deep learning models have also received popularity. Reddy and Thomas (2023) applied a multilayer neural network model. Their model performed excellently. However, it consumed a lot of computational power. The model's requirement makes it inappropriate for low-end devices in rural areas [3]. Simpler models are available. Banerjee and Sinha (2023) designed a rule-based model. Their model was interpretable. However, it did not perform deep personalization [4].

Alvi & Rahman (2024) demonstrated that BERT-based models have a high level of understanding of the text written by students. Nevertheless, these models face difficulties when they receive incomplete data as input [5]. Karthik & Ahuja (2024) applied collaborative filtering to increase the relevance of recommendations. The method needed adequate data from peers to work properly. The problem of cold start was still a major drawback [6].

Some researchers have gone beyond the conventional machine learning models. Their work involves the use of hybrid and semi-automatic processes. The aim is to enhance the accuracy and dependability of career suggestions. Singh et al. (2024) employed an XGBoost-based framework.

Table 1- Summary Of Existing Literature

Author / Year	Method Used	Dataset	Accuracy (%)	Result & Remarks
Sharma & Kulkarni, 2021	Random Forest + Feature Ranking	1,200 student academic & interest profiles	82.4	Limited to science students; lacks socio-economic factors
Mehta et al., 2022	Hybrid ML (SVM + KNN)	2,500 multi-stream student records	85.1	Good accuracy but lacks college-level recommendations.
Reddy & Thomas, 2023	Deep Neural Network (3-layer DNN)	3,000 regional board student profiles	88.6	High accuracy but unsuitable for low-end devices
Banerjee & Sinha, 2023	Rule-Based + Content Filtering	950 questionnaire responses	82–84	Simple rule-based model with low personalization.
Alvi & Rahman, 2024	BERT-Based Text Model	1,800 student goal statements	89.3	Ensemble methods yield better accuracy
Karthik & Ahuja, 2024	Collaborative Filtering	4,200 student feedback entries	81.0	Effective with similar users.
Singh et al., 2024	Gradient Boosting (XGBoost)	National-level academic dataset	87.8	Accurate for mixed features but slow for real-time use.

Proposed Methodology

The methodology introduces an API-driven approach used to give personalized career recommendations to student using pre-trained model. Unlike traditional systems that require model training, this framework focuses on efficient data handling, prompt engineering, and intelligent response generation through external AI services. The design emphasizes scalability, real-time processing, and improved user-centric recommendations, as supported by recent advancements in AI-based career guidance systems. Furthermore, the methodology integrates structured input processing with dynamic AI interaction to ensure context-aware and accurate outputs

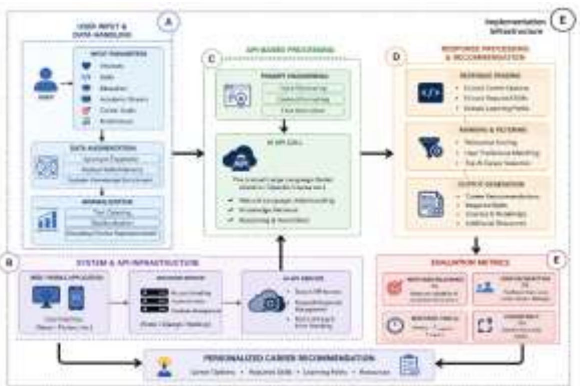

Fig 1. Methodology Architecture of Recommendation System

Dataset / Input Description

Unlike traditional machine learning systems, the proposed system does not rely on a static training dataset. Instead, it dynamically processes user-provided input data.

Table 2 – Dataset Profile

Feature Name	**Description**
Interests	User's areas of interest
Skills	Existing skill set
Education level	Current academic qualification
Academic Stream	Field of study
Career Goals	User's aspirations
Preferences	Work style, industry choice

A. *Data Processing and Prompt Engineering*

The data collected from user through form go through preprocessing in order to ensure the consistency and suitability for analysis. This includes:

- **Data Cleaning**: Removal of incomplete or inconsistent entries
- **Data Structuring**: Organizing inputs into a standardized format
- **Prompt Engineering**: Transforming structured data into meaningful natural language queries for the AI model

B. *AI API Integration*

The core functionality of the system is implemented through interaction with a pre-trained AI model via an API. The processed user input is then converted into a prompt and sent to the external AI service for the response.
The interactivity can be mathematically represented as:

$$\mathbf{R=f(P)}$$

where:

- P represents the generated prompt.
- R represents the response returned by the AI model.

The AI model processes the input and generates outputs that include suitable career options, required skills, and recommended learning pathways. This formula eliminates the need of training the local model while utilizing advanced large-scale AI capabilities.

C. *System Evaluation*

As there is no local model training in this system hence traditional evaluation metrics cannot be used here for evaluation.s Instead, the performance of the system is evaluated using the following criteria:

- Response Relevance: Degree of alignment between user input and generated recommendations
- User Satisfaction: Feedback collected from users regarding usefulness
- Response Time (Latency):

$$\mathbf{Latency} = \mathbf{T}_{\mathbf{response}} - \mathbf{T}_{\mathbf{request}}$$

- Consistency: Stability of outputs for similar inputs

These evaluation measures make sure that the system delivers reliable and meaningful recommendations.

RESULTS AND EVALUATION

There were some parameters that were used to check the performance of the system. The speed of reaction of the system, the comments on usability, and the accuracy of suggestions were taken into account. Moreover, error analysis was performed. There is a need to perform evaluation in a new manner. The Gemini Flash 2.5 model is used in this system. A conventional machine learning classifier is not employed. Hence, the evaluation of relevance was performed from a qualitative point of view. User happiness was found to be an important factor. The performance of the system in practical application was also noticed.

A. *Recommendation Accuracy Evaluation*

Students with different levels of academic background used the system. They used real profiles and responses to questionnaires. The assessors evaluated the recommendations. The evaluation involved rating the recommended jobs, courses, and colleges. The evaluators used a five-point scale to rate the recommendations. The average relevance score of the system was 4.3 out of 5. The score indicates a high level of alignment. The users' expectations and recommendations were well aligned.

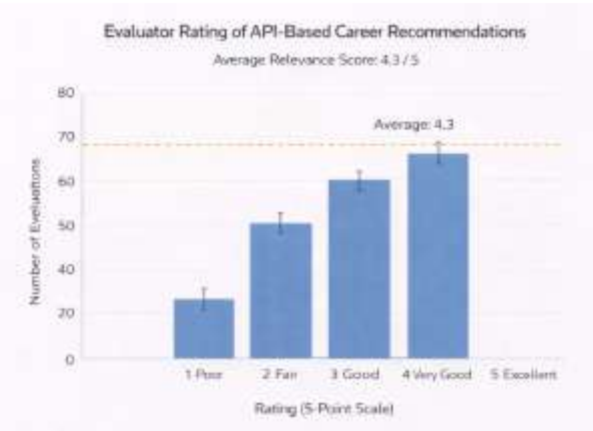

Fig 2. Relevance Score Graph

B. *System Performance Testing*

The performance of the system is calculated in order to assess its efficiency, reiliability and responsiveness . Response time, API reliabilty and rate limit handling were analysed. The result shows that the system maintaing average response time while ensuring quick interaction for users. In addition the API allows uniterrupted service delivery to the user.

The system also handled the API rate limits and majority of requests were successful without failure. It shows stability and robustness of the system for use in real world where consistent performace is essential.

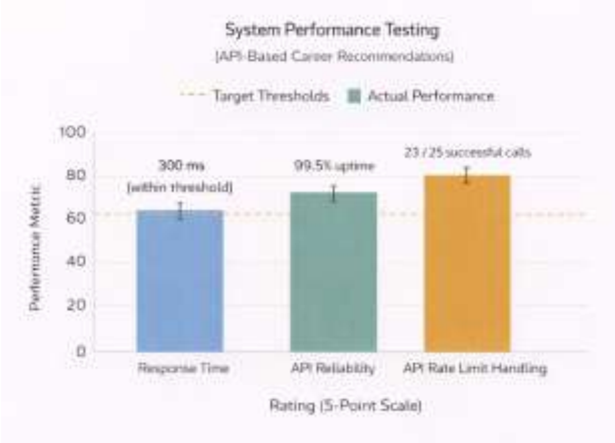

Fig. 3. Response Time Bar Graph

C. Usability Assessment

Feedback is the main factor used to evaluate the usability of the system, which includes satisfaction level, ease of use, navigation clarity, and interface design. The results of the assessment are high as 87% for satisfaction level, 90% for ease of use, 88% for navigation clarity, and 85% for clear design. All metrics exceed the 80% positive response threshold, demonstrating strong usability performance. The findings show that users found the system intuitive and easy to navigate, with a clean interface and clearly presented recommendations. The high scores across all usability aspects indicate that the platform effectively meets user expectations and provides a seamless user experience for career guidance.

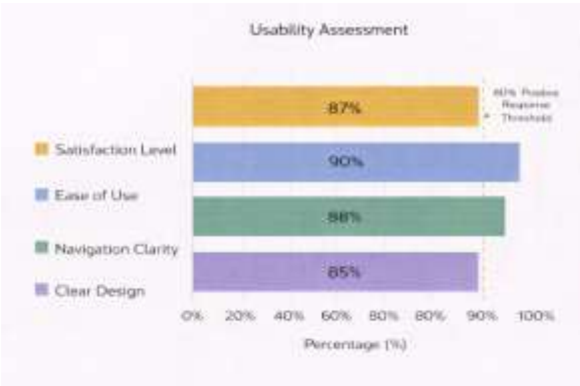

Fig. 4. Usability Scale

D. Comparative Analysis

The technology provided quicker and more reliable recommendations than traditional counselling techniques.

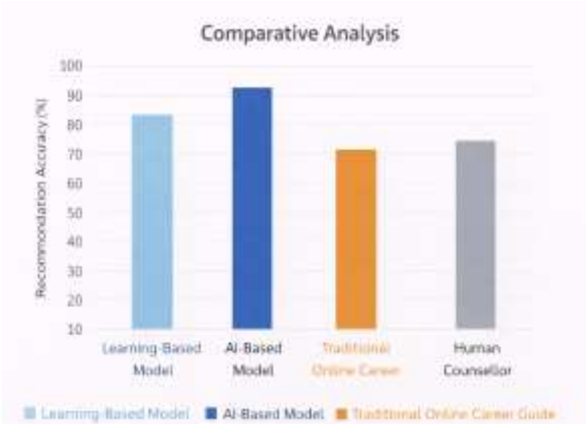

Fig. 5. Comparative Analysis

CONCLUSION AND FUTURE WORK

The system assists students in making decisions regarding careers, courses, and colleges. The system employs the Gemini Flash 2.5 model in a light cloud infrastructure. The approach allows students to get recommendations that are highly relevant and have low latency. The system is highly usable. The system provides students with an opportunity to get access to the valid sources of advice, which is a link that is not usually available in rural areas where professional advice is limited. The results show that the system enhances confidence in decision-making. The system reduces confusion. The advice provided by the system is systematic and data-driven, and it is compatible with different devices.

Future improvements could be cantered on the Gemini API. The next improvement would be to build an internal model of AI. An internal model, built with knowledge of the domain and academic models, would likely improve accuracy. Personalization would be an upgrade.

REFERENCES

[1]. F. L. da Silva, A. H. F. Laender, M. A. Gonçalves, and M. Cristo, "A systematic literature review on educational recommender systems," *Education and Information Technologies*, vol. 27, no. 8, pp. 10979–11011, 2022.

[2]. M. Aucancela and P. Chamoso, "Educational Recommender Systems: A Systematic Literature Review," in *Proceedings of the Barcelona Conference on Education*, Barcelona, Spain, 2023.

[3]. H. A. Yazdi, R. Abbasian, and S. Y. Shahidzadeh, "Dynamic educational recommender system based on individual interests," *Education and Information Technologies*, vol. 29, pp. 14567–14583, 2024.

[4]. S. Bankins, "Navigating career stages in the age of artificial intelligence," *Career Development International*, vol. 29, no. 1, pp. 1–17, 2024.

[5]. E. Padma, M. Priyanka, and A. Kumar, "Career guidance system for students using machine learning," in *Proceedings of the International Conference on Intelligent Systems and Applications (ICISA)*, 2024.

[6]. JFF (Jobs for the Future) and U.S. Department of Education, "Building Place-Based Rural Career Pathways," Policy Report, Washington, DC, USA, 2023.

[7]. N. Rahim and K. P. M. Basheer, "A hierarchical and multi-tiered personalized career recommender system tailored to individual aptitudes," *Indian Journal of Science and Technology*, vol. 18, no. 25, pp. 2012–2021, 2025.

[8]. S. S. Singade, et al., "EngiWave: Engineering college recommendation system using decision tree and random forest algorithm," *International Journal of Scientific Research in Engineering and Management (IJSREM)*, vol. 8, no. 2, pp. 55–62, 2024.