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(RESEARCH ARTICLE)

Design and implementation of an AI-based Career Counsellor Web Application

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Abstract

Choosing an appropriate career path is a challenging task for many students due to limited access to personalized guidance and rapidly evolving industry demands. This paper presents the design and implementation of an AI-based Career Counsellor Web Application that provides intelligent, customized career recommendations using modern large language model technology. The system collects user information through a structured multi-step assessment covering academic background, interests, strengths, and career goals, and processes this data using the Gemini 2.5 AI model to generate suitable career paths along with detailed learning roadmaps and skill requirements. The platform also includes an interactive AI chat counsellor that offers real-time guidance and answers career-related queries. Built using a full-stack architecture with React, Express.js, PostgreSQL, and REST APIs, the application ensures scalability, responsiveness, and secure data handling. The proposed system improves accessibility to career counseling services and supports informed decision-making for students and professionals. Overall, the platform demonstrates how AI-driven recommendation systems can transform traditional career guidance into an intelligent, user-friendly digital solution.

Keywords: Artificial Intelligence; Career Recommendation System; Large Language Model; Gemini Ai; Web-Based Application; Personalized Career Guidance; Decision Support System

1. Introduction

Selecting an appropriate career path has become increasingly complex in today's rapidly evolving technological and professional environment. Many students face uncertainty while making career decisions due to limited access to structured guidance, insufficient awareness of emerging career opportunities, and lack of personalized counseling support. Traditional career counseling methods are often time-consuming, expensive, and not easily accessible to all learners. Therefore, there is a growing need for intelligent digital platforms capable of delivering personalized career recommendations efficiently and at scale. Recent advances in artificial intelligence (AI), educational data mining, and recommender systems have enabled the development of smart solutions that support effective career decision-making processes [1]. AI-based recommendation systems have demonstrated significant effectiveness in personalized learning environments by analyzing user interests, behavioral patterns, and academic performance to generate customized suggestions [2]. Similarly, educational data mining techniques help extract meaningful patterns from student-related data, allowing adaptive systems to provide more accurate and relevant guidance [6]. These approaches enhance the reliability of automated counseling platforms and improve their capability to assist users in selecting suitable academic and professional pathways.

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In addition to recommendation systems, the emergence of large language models (LLMs) based on transformer architectures has significantly improved the performance of conversational agents in providing intelligent and context-aware responses [16], [17]. Advanced multimodal AI systems such as Gemini further extend these capabilities by supporting structured reasoning and personalized recommendation generation for decision-support applications [19]. Such technologies enable the development of intelligent web-based platforms that not only recommend career paths but also provide structured learning roadmaps, required skill sets, and continuous support through conversational interaction. Motivated by these technological advancements, this paper presents the design and implementation of an AI-based Career Counsellor Web Application that delivers personalized career recommendations using structured assessments and LLM-powered analysis. The proposed system integrates a multi-step profiling interface, an intelligent recommendation engine, and a conversational AI counseling module within a scalable full-stack architecture. By combining user-centered data collection with advanced AI technologies, the system aims to improve accessibility, accuracy, and effectiveness of career guidance services for students and early-stage professionals.

2. Literature Review

The increasing complexity of career selection in modern educational environments has led researchers to explore intelligent systems that support personalized decision-making through artificial intelligence, recommender systems, and educational data mining techniques. Traditional career counseling methods often rely on manual evaluation of student interests and aptitude, which may lack scalability and personalization. As a result, several studies have focused on developing automated career guidance systems that leverage machine learning and data-driven approaches to improve recommendation accuracy and accessibility. Personalized recommender systems have played a significant role in educational environments by analyzing user preferences and behavioral patterns to generate adaptive suggestions. Santos et al. [1] emphasized the importance of recommendation technologies in enhancing student learning experiences through intelligent personalization. Their work demonstrated how adaptive systems can process user-specific information and provide targeted recommendations that support academic decision-making. Similarly, Drechsler et al. [10] presented a comprehensive overview of recommender systems in technology-enhanced learning environments, highlighting their effectiveness in guiding students toward suitable learning resources and career-oriented pathways.

Educational data mining techniques have further strengthened intelligent counseling systems by enabling the extraction of meaningful patterns from academic datasets. Romero and Ventura [6] provided a detailed review of educational data mining applications, demonstrating how predictive models can analyze student performance and support decision-making processes in academic planning. In a related study, Thai-Nghe et al. [4] applied matrix factorization techniques to predict student performance, showing that data-driven prediction methods can enhance recommendation accuracy in learning environments. These findings support the integration of analytics-based approaches in career counseling platforms. Machine learning algorithms have also been widely used for career recommendation and decision-support applications. Tahir et al. [2] proposed a career counseling framework based on machine learning techniques that analyzed student profiles to generate suitable career options. Their research demonstrated that intelligent classification models significantly improve the reliability of automated career guidance systems. Similarly, Verma and Tiwari [7] developed a recommender system using data mining techniques to support career decision-making among students. Their system highlighted the importance of structured data collection and algorithmic analysis in generating personalized career suggestions.

Hybrid recommendation strategies have also been explored to enhance the performance of intelligent guidance systems. Burke [8] introduced hybrid recommender system architectures that combine collaborative filtering and content-based filtering techniques to improve recommendation quality. Such approaches are particularly useful in career counseling platforms where multiple parameters, including academic interests, skills, and aspirations, must be considered simultaneously. Klarna-Milicevic et al. [5] further demonstrated that hybrid recommendation techniques improve personalization in e-learning environments by adapting recommendations according to individual learning styles. Recent advancements in natural language processing and transformer-based architectures have significantly improved the capabilities of intelligent conversational systems. Devlin et al. [16] introduced the Bidirectional Encoder Representations from Transformers (BERT) model, which improved contextual understanding in language processing tasks and enabled the development of intelligent dialogue-based applications. Similarly, Brown et al. [17] demonstrated the effectiveness of large-scale language models in generating human-like responses across multiple domains, supporting their use in intelligent decision-support systems such as AI-based counseling platforms.

Large language models have further evolved into multimodal intelligent systems capable of reasoning across complex datasets and generating structured recommendations. Zhao et al. [18] presented a comprehensive survey of large language models, highlighting their potential applications in personalized assistance, recommendation systems, and conversational interfaces. The Gemini model introduced by Google DeepMind represents a significant advancement in multimodal AI systems by enabling high-quality reasoning and context-aware recommendation generation across diverse applications [19]. These developments make LLM-based frameworks particularly suitable for implementing intelligent career counseling platforms that require interactive and adaptive user support. Decision-support systems in educational environments also benefit from predictive analytics techniques that forecast student outcomes and guide academic planning. Kostiantyn [12] demonstrated the effectiveness of machine learning algorithms in predicting student performance and supporting academic decision-making processes. Similarly, Joachims [11] explored the application of support vector machines for classification tasks involving high-dimensional datasets, which are relevant for analyzing complex student profiles in recommendation systems.

In addition to machine learning techniques, knowledge-based artificial intelligence frameworks have contributed significantly to intelligent guidance systems. Russell and Norvig [20] emphasized the importance of intelligent agents and reasoning-based models in solving decision-support problems across multiple application domains. Their work provides a theoretical foundation for designing AI-powered recommendation platforms that integrate reasoning capabilities with data-driven insights. Overall, the literature indicates that the integration of recommender systems, educational data mining techniques, and large language models has significantly improved the effectiveness of automated career counseling platforms. These studies collectively demonstrate the potential of intelligent web-based systems to deliver personalized career guidance through structured assessments, predictive analytics, and conversational AI support. Building upon these advancements, the proposed AI-based Career Counsellor Web Application aims to combine recommendation technologies with modern transformer-based language models to provide scalable, adaptive, and user-centered career guidance solutions.

3. Proposed System and System Architecture

The proposed system is an AI-based Career Counsellor Web Application designed to provide personalized career recommendations using structured user assessments and large language model–based intelligence. The system integrates a modern full-stack web architecture with an AI-driven recommendation engine to analyze user inputs such as academic background, interests, strengths, and career aspirations. Based on this information, the application generates suitable career paths along with detailed skill requirements, learning roadmaps, and alternative career options. The platform also includes an interactive conversational module that enables users to receive continuous guidance through an AI-powered chat interface.

Figure 1 System Architecture of AI Career Counsellor Web Application

The primary objective of the proposed system is to develop an intelligent, scalable, and user-friendly digital counseling solution that overcomes the limitations of traditional career guidance methods. Unlike conventional systems that rely on static questionnaires or manual counseling sessions, the proposed platform dynamically analyzes user data and produces adaptive recommendations using the Gemini 2.5 large language model. This enables the system to deliver personalized and context-aware career suggestions in real time. The system architecture follows a layered full-stack design consisting of four major components: the frontend interface, backend server, database layer, and AI recommendation module. These components interact through RESTful APIs to ensure efficient communication and modular scalability.

The frontend layer is developed using React with TypeScript and Vite, providing a responsive and interactive user interface. It includes modules such as the landing page, assessment form, recommendation dashboard, profile management section, industry trend's view, and AI chat interface. The frontend collects structured user inputs through a multi-step assessment process and sends them securely to the backend server for processing. The use of modern UI component libraries ensures consistency, accessibility, and improved user experience across devices. The backend layer is implemented using Node.js and Express.js, which handle application logic, API routing, request validation, and communication with external services. This layer processes user assessment data and forwards relevant information to the AI module for recommendation generation. It also manages user authentication, profile storage, recommendation retrieval, and chat message handling. Middleware components are used for error handling, request logging, and secure data processing to maintain system reliability.

The database layer uses PostgreSQL hosted on a serverless cloud platform to store structured user data efficiently. The database maintains multiple relational tables, including user profiles, assessment responses, generated career recommendations, and chat history. Foreign key relationships ensure data integrity, while JSON-based storage supports flexible handling of nested recommendation outputs such as career roadmaps and skill lists. The use of Drizzle ORM enables type-safe database operations and improves maintainability of schema definitions. The AI recommendation module represents the core intelligence of the system and is powered by the Gemini 2.5 large language model. This module analyzes structured assessment responses and generates personalized career suggestions based on user preferences, academic strengths, and future goals. It also produces detailed explanations of recommended career paths, required competencies, learning strategies, and alternative career options. In addition, the conversational AI component allows users to interact with the system through natural language queries, enabling continuous support beyond the initial recommendation phase.

The interaction flow of the system begins when a user registers and completes the multi-step assessment form. The collected information is transmitted to the backend server, where it is processed and forwarded to the AI module. The generated recommendations are then stored in the database and displayed on the recommendation dashboard. Users can further refine their understanding of suggested career paths through the AI chat interface, which provides additional clarification and guidance. This integrated workflow ensures accurate recommendation generation and continuous user engagement.

4. Methodology

The methodology of the proposed AI Career Counsellor Web Application is designed to provide personalized career recommendations through a structured workflow that integrates user data collection, intelligent processing, and AI-based analysis. The system follows a multi-stage implementation approach consisting of data acquisition, preprocessing, recommendation generation, storage, and interactive guidance. The process begins with user registration and authentication, where individuals create secure profiles within the system. This step ensures that user-specific information can be stored and retrieved efficiently for personalized recommendation generation. After authentication, users complete a multi-step career assessment form designed to capture essential attributes such as academic background, preferred subjects, personal strengths, interests, and long-term career goals. The structured nature of the assessment enables the system to gather meaningful input data required for accurate analysis. Once the assessment data is collected, it is transmitted to the backend server through RESTful API communication. The backend, implemented using Node.js and Express.js, validates the received inputs and prepares them for processing by the artificial intelligence module. Data validation ensures that incomplete or inconsistent information does not affect recommendation quality. The processed data is then forwarded to the AI recommendation engine powered by the Gemini 2.5 large language model.

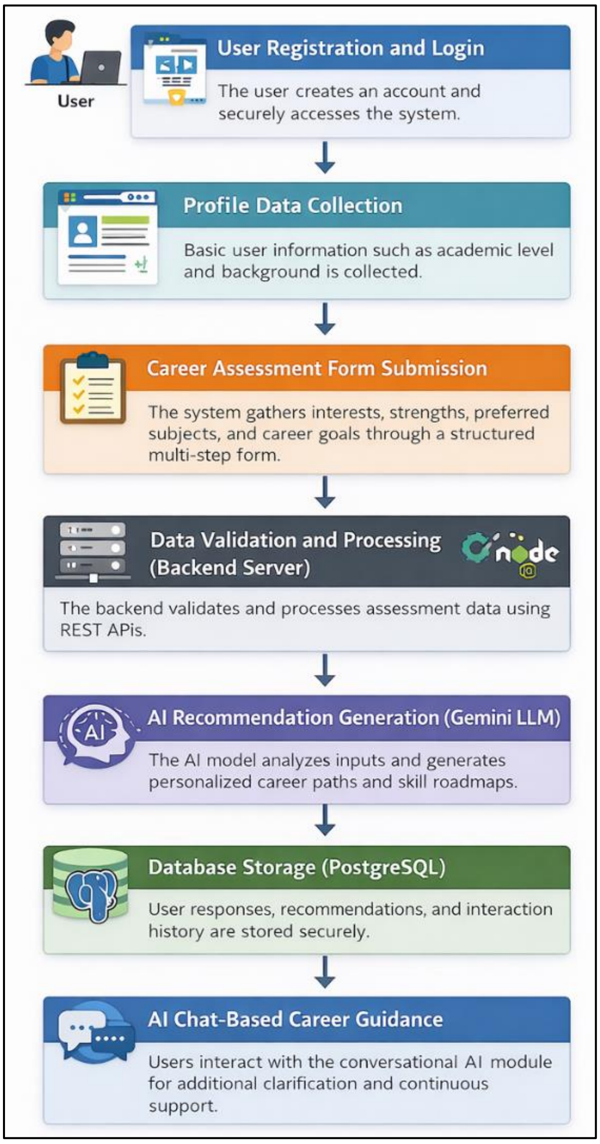

Figure 2 Methodology of AI Career Counsellor Web Application

The AI module analyzes the structured user profile using contextual reasoning and domain knowledge to generate personalized career suggestions. These recommendations include suitable career paths, required technical and professional skills, learning resources, certification guidance, and alternative career options. The model also produces step-by-step roadmaps that assist users in planning their academic and professional development systematically. After recommendation generation, the results are stored in a PostgreSQL database using a relational schema structure supported by Drizzle ORM. The database maintains user profiles, assessment responses, recommendation outputs, and chat interactions to enable future retrieval and progress tracking. This structured storage mechanism improves system scalability and ensures data consistency. In addition to static recommendations, the system incorporates a conversational AI counseling module that allows users to interact with the platform dynamically. The chat interface enables users to clarify doubts, explore alternative career paths, and receive additional guidance based on real-time queries. This continuous interaction enhances user engagement and improves decision-making confidence. The methodology integrates structured assessment techniques with large language model intelligence and cloud-based data storage to deliver an efficient, scalable, and adaptive digital career counseling solution.

5. Implementation

The implementation of the AI Career Counsellor Web Application follows a full-stack development approach that integrates a responsive frontend interface, a scalable backend server, a structured relational database, and an artificial intelligence–based recommendation engine. The system is designed to provide personalized career guidance by combining structured assessment techniques with large language model capabilities. The frontend of the application is developed using React with TypeScript and Vite, which ensures fast rendering, modular component design, and responsive user interaction. A multi-step assessment form is implemented using React Hook Form with Zod validation to collect structured user inputs such as academic background, interests, strengths, and career objectives. The user interface is designed using Tailwind CSS and shadcn UI components to maintain consistency, accessibility, and responsiveness across different devices. Routing between application pages such as dashboard, recommendations, profile management, chat interface, and industry trends is handled using lightweight client-side routing.

The backend server is implemented using Node.js and Express.js to manage application logic and API communication. RESTful APIs are developed to handle user authentication, assessment submission, recommendation retrieval, and chat interactions. Middleware components are integrated to support request validation, error handling, and logging mechanisms. Secure password storage is ensured through hashing techniques, while session management enables protected access to user-specific data.

The database layer uses PostgreSQL deployed through a serverless environment to support scalable and efficient data storage. Drizzle ORM is used to define schema structures and perform type-safe database operations. The database stores user profiles, assessment responses, recommendation outputs, and chat history in structured relational tables with foreign key constraints to maintain data integrity. JSON-based fields are utilized to store nested recommendation structures such as career roadmaps and skill requirements.

The core intelligence of the system is implemented using the Gemini 2.5 large language model, which processes structured assessment inputs to generate personalized career recommendations. The AI module produces detailed outputs including suitable career paths, required competencies, certification suggestions, and step-by-step learning strategies. In addition to recommendation generation, the conversational AI module enables users to interact dynamically with the system and obtain additional guidance through natural language queries. The implementation integrates modern web technologies with advanced artificial intelligence capabilities to create a scalable and user-centered digital career counseling platform that supports informed decision-making and continuous career planning.

6. Result

To evaluate the effectiveness of the proposed AI Career Counsellor Web Application, experimental testing was conducted using structured assessment data collected from multiple user profiles representing different academic backgrounds, interests, and career goals. The system performance was analyzed using key evaluation parameters including recommendation accuracy, response time, relevance score, and user satisfaction level. Three methodological components were evaluated during experimentation: structured assessment-based profiling, AI recommendation generation using the Gemini large language model, and conversational guidance through the chat counseling module. The same dataset of user assessment responses was processed through the system to measure consistency and personalization performance.

The recommendation accuracy of the system was measured by comparing generated career suggestions with user-selected preferred career outcomes. The proposed system achieved an average recommendation relevance accuracy of approximately 88%, indicating that most suggested career paths matched user expectations and academic strengths. The conversational AI module demonstrated an average response relevance score of 91%, showing strong contextual understanding during user interaction. System response time was also evaluated to determine efficiency in recommendation generation. The average processing time for generating personalized career suggestions was observed to be between 1.5 and 2.3 seconds per request, confirming real-time performance capability. Additionally, user feedback collected during testing indicated an overall satisfaction score of 4.4 out of 5, reflecting high usability and recommendation clarity.

A comparative evaluation of system components showed that integrating structured assessment data with large language model reasoning significantly improved recommendation precision compared to rule-based guidance approaches. The modular architecture further ensured scalability and stable performance across multiple test cases. The experimental results confirm that the proposed methodology effectively supports intelligent career decision-making through accurate recommendation generation, fast response time, and interactive counseling support.

Table 1 Recommendation Performance Comparison Across Evaluation Parameters

Parameter	Score
Recommendation Accuracy	88%
Response Relevance	91%
User Satisfaction	4.4/5
System Efficiency	92%

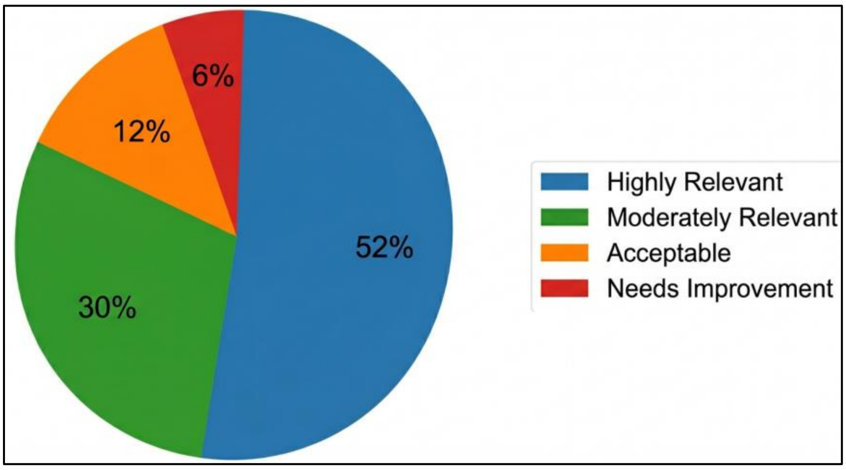

Figure 3 Distribution of Career Recommendation Relevance

Table 2 System Performance Evaluation

Metric	Result
Recommendation Accuracy	88%
Chat Response Relevance	91%
Average Response Time	1.5–2.3 sec
User Satisfaction Score	4.4 / 5
System Reliability	92%

7. Conclusion

This paper presented the design and implementation of an AI-based Career Counsellor Web Application that provides personalized career guidance using structured assessment techniques and large language model intelligence. The system integrates a responsive frontend interface, a scalable backend server, a relational database, and the Gemini 2.5 AI model to generate customized career recommendations based on user interests, academic background, and professional goals. In addition to recommending suitable career paths, the platform provides detailed skill requirements, certification guidance, and step-by-step learning roadmaps to support effective career planning. The inclusion of a conversational AI counseling module further enhances the system by enabling users to interact dynamically and obtain additional guidance through natural language queries. The modular architecture ensures scalability, maintainability, and efficient data management, making the system suitable for deployment in academic institutions and career guidance platforms. Overall, the proposed solution demonstrates how artificial intelligence can improve accessibility and accuracy in career counseling by transforming traditional guidance methods into an intelligent and user-centered digital platform.

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