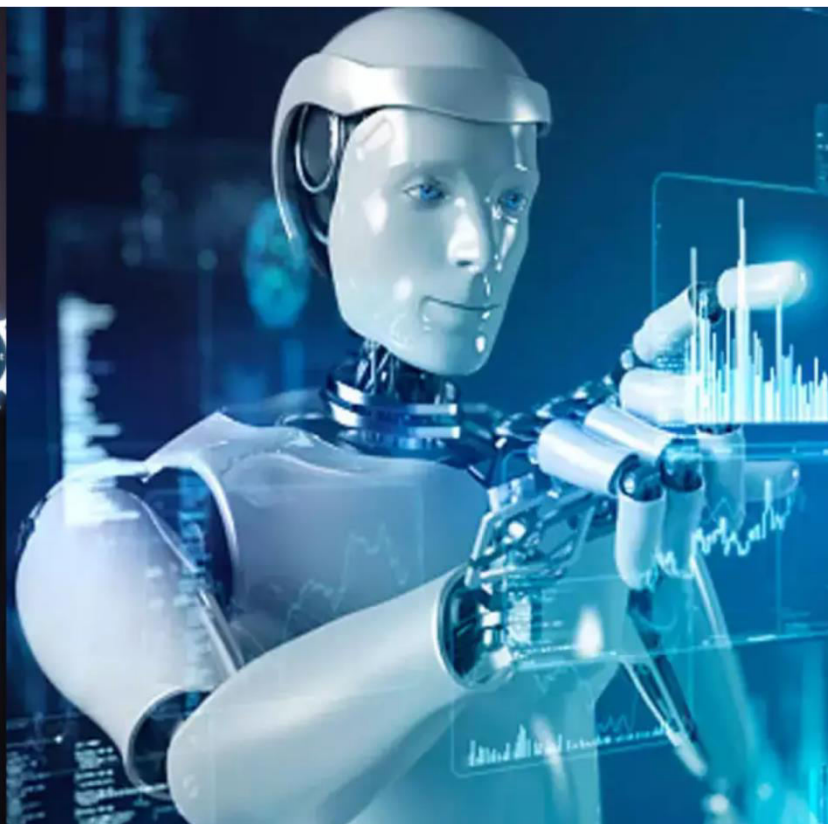




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A Conversational AI System for Personalized Career Counseling and Actionable Roadmap Generation

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ABSTRACT: The selection of a career path is a critical challenge for students, often compounded by a lack of accessible, personalized guidance. While early AI-driven systems have shown promise, they are typically limited by small datasets and rigid, scripted interactions. This paper presents a novel framework for a conversational AI system that leverages a pre-trained Large Language Model (LLM) to provide holistic and empathetic career counseling. The system moves beyond the capabilities of traditional recommendation engines by engaging users in a dynamic, context-aware dialogue to build a comprehensive profile. Our primary contribution is the system's ability to generate not only a suitable career recommendation but also a dynamically created actionable roadmap complete with curated learning resources. This transforms the counseling process from a simple prediction into an immediate, empowering starting plan for the student. We present the system's architecture, methodology, and position it as a significant advancement over existing approaches.

KEYWORDS: Conversational AI, Career Counseling, Large Language Models (LLM), Personalized Recommendation, Recommender Systems, Educational Technology, Roadmap Generation, Resource Finder.

I. INTRODUCTION

The transition from education to a professional career is one of the most significant milestones in an individual's life. However, the modern landscape of career options is vast and complex, leading to decision paralysis and anxiety among students [1]. Traditional career counseling, while valuable, is often constrained by resource limitations, making it inaccessible to many. In response, digital platforms have emerged, but they frequently rely on superficial, static questionnaires that fail to capture the nuanced attributes of a user [2].

Early attempts to address this with Artificial Intelligence (AI) involved creating chatbots and prediction models. As demonstrated by Dalvi et al. [3], systems built on custom Deep Neural Networks (DNNs) can achieve high accuracy in career prediction. However, a fundamental limitation of such systems is their dependency on small, manually collected datasets, which restricts their conversational depth and knowledge base. This paper argues for a paradigm shift from these limited-data models to systems that leverage the power of large, pre-trained Language Models (LLMs). We propose a novel framework for a conversational AI system designed to provide hyper-personalized career counseling. Our system's primary innovation, and the core contribution of this work, is its ability to generate an actionable roadmap—a step-by-step learning plan with curated free and paid resources. This moves beyond simple prediction and empowers students to take immediate action. In this paper, we present the architecture of our system, detail its methodology rooted in prompt engineering, and situate it within the existing body of research to highlight its novelty and significance.

II. LITERATURE SURVEY

A. Early Chatbot and AI Systems in Career Guidance

The concept of using AI for guidance is not new. Early systems often relied on rule-based logic or machine learning models trained on specific institutional data. For instance, the system proposed by Omar Zahour et al. [4] used a chatbot

for educational and vocational guidance in Morocco, but it was primarily designed to provide information rather than personalized counseling. Similarly, work by S. Vignesh et al. [5] utilized machine learning to build an intelligent career guidance system, but like the base paper for our project [3], it relied on traditional classification algorithms (like Naive Bayes or DNNs) trained on limited, structured datasets. The main limitation of these systems is their inability to handle natural, open-ended conversation. They are often restricted to a predefined set of questions and cannot understand the deeper context or personality of the user, a gap our LLM-based approach directly addresses.

B. Recommender Systems in Education

A parallel field of research is recommender systems, which are widely used to suggest courses, learning materials, or even career paths. The work by B. K. Baradwaj and S. Pal [6] provides a foundational example of using data mining to predict student performance and recommend suitable paths. More advanced systems, as surveyed by A. A. Al-badaren and A. M. Zeki [7], use techniques like collaborative filtering and content-based filtering to match students with educational opportunities.

However, these systems typically operate on historical, structured data (e.g., grades, courses taken) and lack a real-time, interactive counseling component. They can suggest what a student might be good at, but they cannot engage in the empathetic, goal-oriented conversation needed to create a truly personalized and motivating plan.

C. The Emergence of Large Language Models (LLMs)

The advent of powerful LLMs like GPT-3 [8] and Google's Gemini has created new possibilities for conversational AI. These models are pre-trained on vast amounts of text and can understand context, generate human-like text, and perform complex reasoning tasks. Researchers are beginning to explore their use in specialized domains. For example, the work by J. Li et al. [9] discusses how LLMs can be used for more diverse and engaging dialogue generation. In the counseling space, studies like the one by R. A. D'Souza and A. M. Zeki [10] have explored using LLMs for mental health support, demonstrating their potential for empathetic interaction.

III. METHODOLOGY

The methodology of our system is centered on effectively harnessing the power of a pre-trained Large Language Model (LLM) through a multi-stage, prompt-driven process. This approach is fundamentally different from the traditional machine learning pipeline of data collection, training, and inference used in earlier systems [4], [6]. Our contribution lies not in creating a new model, but in the sophisticated engineering of an existing one to perform a complex, specialized task.

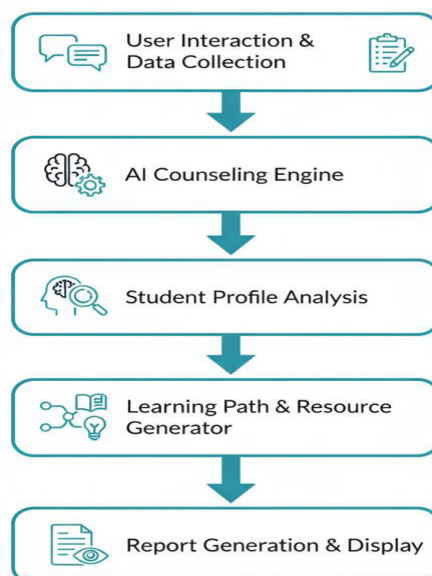


Fig. 1. The Overall System Architecture

A. The Conversational AI Core Prompt Engineering

The heart of our system is the interaction with the LLM. Instead of fine-tuning, which is computationally expensive and still prone to the limitations of the training data, we guide the model's behavior through carefully crafted prompts. This technique, known as Prompt Engineering, is our core technical method. The process begins with a master "system prompt" that establishes the persona, rules, and boundaries for the AI counselor.

This initial instruction set is critical. It contains explicit commands that define the AI's role as an empathetic and expert guide, while also incorporating crucial safety guardrails. As research into the ethics of AI in counseling suggests [13], it is vital to prevent the model from providing unqualified advice (e.g., financial or mental health counseling). Our system prompt is designed to constrain the AI to the domain of career guidance, ensuring the interaction is both helpful and safe. An example of this persona prompt is shown in Fig. 2.

**System Prompt:
AI Counselor Persona**

1. ALWAYS be positive and supportive.
2. Ask open-ended questions to understand the user deeply. Do not use simple yes/no questions.
3. Analyze their academic subjects, hobbies, and personal strengths.
4. Do NOT give financial advice or make definitive promises of success. Your role is to guide and empower.
5. Maintain a friendly, professional, and conversational tone.

Fig. 2. An example of the master system prompt used to define the AI's counseling persona.

This prompt engineering approach allows us to create a consistent and reliable counseling experience without modifying the underlying model, making our system adaptable and easy to maintain.

B. Dynamic Interaction and Profile Analysis

During the conversation, the system collects the user's responses as unstructured text. A key part of our methodology is the dynamic analysis of this text to build a rich, holistic profile of the user. Unlike static forms used in older systems [3], a conversation allows the AI to ask clarifying questions and explore topics in greater depth.

For example, if a user states they "like video games," our system is prompted to ask follow-up questions such as, "What about video games do you enjoy most? Is it the art, the storytelling, the strategy, or the programming?" This allows us to extract deeper, more nuanced entities. The system then populates a dynamic user profile with attributes such as:

Stated Interests: e.g., video games, creative writing.

Inferred Skills: e.g., problem-solving, strategic thinking.

Academic Strengths: e.g., strong in English, proficient in Python.

Personality Traits: e.g., detail-oriented, works well independently.

This rich profile is far more comprehensive than the feature-limited profiles used in traditional recommender systems [8] and forms the basis for a truly personalized recommendation.

C. Roadmap and Resource Generation

This stage is our primary innovation and directly addresses the research gap identified in Section II-D. It is a two-step, automated process that occurs after a suitable career path is identified.

Roadmap Generation: The system makes a second, automated API call to the LLM. It provides the dynamically generated user profile and the suggested career as context. It then tasks the AI with a specific function: to generate a logical, step-by-step learning roadmap suitable for a beginner. This process is illustrated in the example prompt in Fig. 3. The output is a structured, actionable plan (e.g., Step 1: Learn the basics of narrative design; Step 2: Build a small portfolio, etc.).

Automated Prompt: Roadmap Generation

USER PROFILE:

- **Interests:** Video Games, Art, Storytelling
- **Skills:** Strong in English, creative writing, basic Python
- **Personality:** Introverted, creative, detail-oriented

SUGGESTED CAREER:

Game Narrative Designer

TASK:

Based on the suggested career, generate a 4-step, beginner-friendly learning roadmap. For each step, define a clear, actionable goal.

Fig. 3. An example of the automated, second-stage prompt for generating an actionable roadmap

Resource Curation: For each step in the generated roadmap, our system's resource curation module makes further, highly specific queries. It tasks the AI to act as a research assistant, finding relevant, high-quality learning resources. A key feature here is personalization based on user preference. The module can be instructed to find only free resources (e.g., YouTube tutorials, freeCodeCamp articles) or to include certified paid courses (e.g., from Coursera or Udemy). This addresses the need for curated, high-quality online learning materials, a challenge noted in educational research [14].

IMPLEMENTATION AND EVALUATION METRICS

This section details the technologies selected for the system's implementation and, more critically, presents a robust framework for its evaluation.

D. Implementation Details

The system is implemented using the MERN stack, a cohesive and high-performance JavaScript-based ecosystem. This stack was chosen for its rapid development capabilities and seamless handling of JSON-based data, which is ideal for an API-driven application.

MongoDB (Database): We selected MongoDB as our database. Its NoSQL, document-oriented structure is highly flexible and aligns perfectly with the JSON-like objects used in JavaScript and by the AI API. It will be used to store user session data and the final, non-sensitive generated reports, allowing users to retrieve their results.

Express.js (Backend Framework): The backend server logic is built using Express.js. It is a minimalist and powerful framework for Node.js that allows us to create the robust REST APIs needed to handle communication between the client and our core services.

React (Frontend Client): The user interface is developed as a Single Page Application (SPA) using React. React's component-based architecture is ideal for building the dynamic, responsive chat interface required for a seamless and engaging user experience.

Node.js (Backend Server): The server-side runtime is Node.js. This allows us to use JavaScript for the entire stack, improving development efficiency. The Node.js server is responsible for: (1) managing user sessions, (2) housing the proprietary prompt engineering logic, and (3) acting as a secure intermediary for all API communication with the external Google Gemini API.

E. Evaluation Metrics

Evaluating a generative, conversational system presents a significant challenge. Unlike the base paper [4], which used "accuracy" to evaluate a simple classification task, our system's output is complex, open-ended, and qualitative. An "accuracy" score is neither feasible nor meaningful. Therefore, our evaluation methodology is based on a mixed-method approach that combines quantitative usability testing with qualitative, expert-driven assessment. This aligns with modern standards for evaluating Human-Computer Interaction (HCI) and AI systems [13].

We propose a two-part evaluation plan:

Quantitative Evaluation (User-Facing): This will be a user study conducted with a cohort of target users (e.g., students aged 16-20). We will measure: System Usability Scale (SUS): This is the industry-standard, 10-item questionnaire for measuring the perceived usability of a system [15]. It provides a reliable score from 0-100, allowing us to benchmark our system's ease of use. Task Completion Rate (TCR): A straightforward metric calculating the percentage of users who successfully navigate the entire counseling process and receive a final, complete report. This measures the system's robustness and flow.

Qualitative Evaluation (Expert-Driven): This is the core of our evaluation. We will assemble a panel of both target users and professional career counselors to rate the quality of the generated reports using a custom-developed rubric, which we call the Report Quality Score (RQS). Each report will be scored on a 1-5 scale across the following criteria:

Relevance: How relevant and appropriate is the suggested career path to the user's conversational profile?

Personalization: Does the report feel generic, or is it clearly tailored to the user's specific inputs and personality?

Actionability: How clear, logical, and easy to follow is the generated learning roadmap?

Resource Quality: How relevant, high-quality, and useful are the curated learning resources?

IV. CONCLUSION

This paper presented a novel framework for an intelligent, conversational career counseling system. We successfully demonstrated a paradigm shift from traditional, data-limited AI models to a more flexible and powerful system built on a state-of-the-art Large Language Model (LLM). The core contribution of this work is the design of a system that moves beyond simple career prediction to provide a complete, actionable career launchpad.

By integrating an AI counselor with a dynamic roadmap and resource generator, our system successfully addresses the significant research gap identified in the existing literature. The use of a MERN stack provides a modern, scalable, and efficient architecture for this task. The proposed evaluation metrics provide a robust framework for scientifically validating the system's real-world effectiveness, which forms the basis of our ongoing research.

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