CounselAI: Transforming Career Counseling with Gen AI for Personalized Multilingual Guidance

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***Abstract*—Career counseling is indispensable in helping people navigate the professional world and make well-informed decisions about their future; however, traditional methods often fail to address the fast-changing demands of today's job market. Many existing services lack the economic and linguistic accessibility needed to reach a diverse audience and often do not incorporate advanced, data-driven tools that improve the quality of guidance. In response to the need for more adaptable solutions, CounselAI harnesses the power of large language models to offer personalized career guidance that aligns with diverse user profiles, strengths, weaknesses and linguistic preferences. CounselAI's architecture features Llama 3.1 70B with the Serper API, which sources relevant blogs and articles from Google, enriching the user experience with improved responses and maintaining contextual coherence. CounselAI improves the conversational depth of the chatbot by employing a few-shot prompt, particularly in scenarios where zero-shot responses were insufficient or overly descriptive, such as in certain languages such as German. It guarantees accessibility in seven languages by utilizing Llama 3.1's powerful multilingual properties to provide meaningful recommendations. Through a rigorous manual validation process, responses are calibrated for accuracy and relevance, increasing the reliability of the chatbot as a virtual career coach. The results highlight the effectiveness of the chatbot in generating precise user-centric responses that allow users to navigate career decisions with confidence. CounselAI thus redefines career counseling by integrating Generative Artificial Intelligence into a comprehensive system that supports users in navigating career decisions with greater clarity at any point in their lives.**

***Index Terms*—Career Counseling, E-Learning, Generative AI, Large Language Models, Llama 3.1**

I. Introduction

Career counseling helps individuals understand, explore, and make well-informed decisions about their future [3]. Traditional methods rely on human counselors, but they face limitations in affordability, accessibility and scalability [1]. It struggles to meet the demands of a dynamic global job [4] market, leading to generic guidance that often overlooks an individual's unique strengths, weaknesses, and aspirations.

Existing AI-based [2] career counseling platforms have made significant strides in automating the process. However, these systems are limited in functionality, and flexibility. For instance, CareerBOT, cofunded by the European Union, focuses only on specific partner countries (Ireland, Austria, Greece, and Spain) and restricts user interactions [17] to pre-defined text options. This limitation prevents human-like conversations, reducing it's ability to address unique user queries. Inspired by the vision of democratizing career counseling and addressing these shortcomings, CounselAI integrates domain specificity [7] to reshape the way career guidance is delivered.

Using Llama 3.1 70B [18], CounselAI offers personalized, multilingual career counseling through a conversational AI agentic [6] system. It utilizes tools like Serper API to source blogs and articles, enriching user interactions with relevant context in real-time [9]. It uses few-shot prompting to generate better responses, particularly in scenarios like German [13]. CounselAI's dual functionality (Fig. 1) as a counselor (interaction based) and a coach (blogs) allows users to access tailored, data-driven insights catering to a global audience.

A. Major Contributions of Our Work:

- **Conversational Artificial Intelligence:** Enables human like dialogues instead of rigid predefined text options, significantly enhancing user engagement.
- **Global Accessibility:** Multilingual support across seven languages: English, Hindi, German, Spanish, Italian, Thai and Portuguese.
- **Dual Functionality:** Combines career counseling with blog-driven coaching for insights 24/7.
- **Personalization:** Leverages a large language model with real-time API to deliver tailored recommendation that adapts to individual's goals.

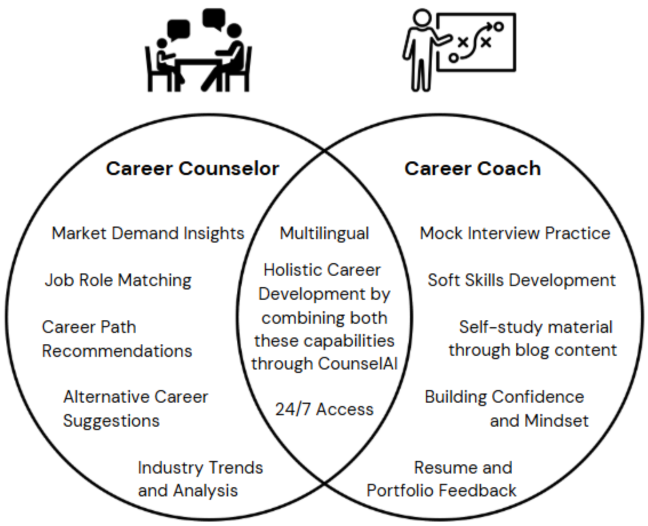

Fig. 1. CounselAI: The union of career counseling and coaching

II. Related Works

Career counseling serves as a guiding framework to help individuals achieve their professional goals by fostering skills, adaptability, and lifelong learning. [3] emphasizes that the increasing complexity of the workforce necessitates career guidance that prioritizes adaptability and continuous learning. [2] argue that the integration of AI technologies has created an imperative for individuals to develop skills such as digital literacy, critical thinking, and emotional intelligence to adapt to AI-driven transformations. [1] highlights the need for well-structured and reliable quality standards in career guidance to address diverse user needs effectively.

The incorporation of AI in career counseling has enabled personalization and multilingual support, making guidance more inclusive. [7] proposed a hybrid framework that combines large language models with Domain-Specific Generative Models (DGMs), offering flexibility and domain adaptability. [11] compared fine-tuning, prompt engineering, and Retrieval-Augmented Generation (RAG) as methods for enhancing chatbot performance. They concluded that fine-tuning achieves the highest accuracy (87.8%) by mitigating contextual inaccuracies, while RAG and prompt engineering complement each other by improving relevance and adaptability.

Despite these advancements, challenges such as hallucination and outdated knowledge persist in LLM applications for career counseling. [9] identified RAG as a solution for integrating external knowledge sources to improve accuracy and credibility in knowledge-intensive tasks. Similarly, [15] introduced hybrid RAG models combining parametric and non-parametric memory, achieving state-of-the-art performance in open-domain QA and fact verification. These developments underscore the potential of RAG architectures to provide reliable and context-aware career counseling.

Personalization and optimization remain key to advancing career counseling. [18] introduced "Tailored-LLaMA," a fine-tuning framework for pruned LLaMA models that leverages task-specific prompts and structural pruning to achieve efficient performance. Techniques such as Low-Rank Adaptation (LoRA) enable model compression while preserving performance, offering scalable solutions for domain-specific applications. Furthermore, [14] advocate for integrating ontology and knowledge graph techniques into RAG systems to reduce hallucination and enhance context awareness in domain-specific guidance.

The application of LLMs in education and natural language processing underscores their role in enabling adaptive and multilingual career counseling. [13] demonstrated how well-structured prompts enhance statistical validity in automated question generation (AQG) for English education. These findings highlight the potential for improving inclusivity and accessibility in career counseling, particularly for diverse linguistic and cultural user groups.

Finally, [6] provided a comprehensive overview of LLM-based agents, exploring their applications in reasoning, planning, and human-agent collaboration. The authors emphasized the ethical and social considerations essential for designing AI systems that align with societal values and user-centric goals, ensuring responsible adoption of AI in career counseling.

III. Data Preparation

In order to provide personalized and accurate career counseling, CounselAI relies on a well-structured dataset that feeds into its conversational model. The data preparation process is crucial to ensuring the chatbot delivers relevant career advice based on user inputs during the conversation.

A. Data Collection and Integration

Part of the dataset for CounselAI was sourced through web scraping by Selenium from *https://www.ncs.gov.in/*, a government website dedicated to job market data in India called the National Career Service portal [8]. This website offers comprehensive information about various careers, including detailed job descriptions, required skills, qualifications, and future job trends. By scraping this data, we compiled a list of target careers specific to the Indian job market. In addition, we further enriched the dataset by sourcing career-related information from reputable platforms. This included datasets from Kaggle [5] and Career Questions and Answers [21] through web scraping. These datasets contain valuable information: job titles and descriptions, required skills and qualifications, active employers, vacancies, and industry trends. This combined dataset ensures that the chatbot not only provides accurate and contextually relevant career guidance but also adapts to the latest requirements in the job market.

B. Preprocessing and Schema Design

The collected data was cleaned, processed, and structured into a usable format. This included basic NLP preprocessing techniques such as tokenization, stop-word removal, and lemmatization. To support classification and organization, light labeling was applied based on content-type keywords. To maintain the contextual flow needed for natural conversations, paragraph-level formatting was retained. However, a loose schema was imposed to support retrieval-based augmentation. This structure allows relevant content to be fetched and passed to the LLM during a session.

IV. Methodology and System Architecture

This section describes the research methodology behind the development of CounselAI, focusing on the integration of a large language [18] model, Llama 3.1, and the steps involved in building this multilingual, agentic [6] career counseling chatbot. It highlights the tools, frameworks, and architectural components, emphasizing their role in delivering a seamless user experience.

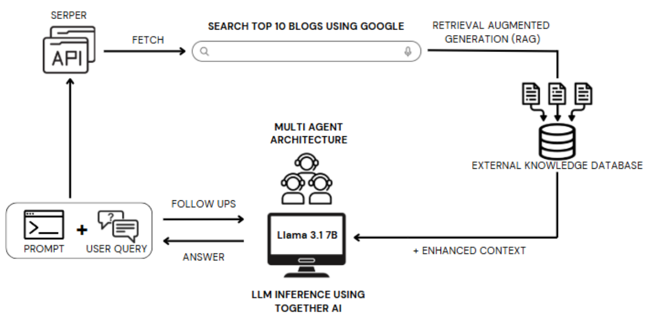

Fig. 2. Workflow diagram for CounselAI - LLM Career Coach.

A. Architectural Patterns and AI Frameworks

State-of-the-art patterns and frameworks are utilized to build a scalable and robust architecture for CounselAI.

1) Few-Shot Prompting: Few-shot prompting is employed to enhance the chatbot's contextual understanding [13] and generate nuanced responses. Unlike zero-shot prompting, which often results in generic outputs, few-shot prompting provides context, instructions, and examples to guide the LLM. This approach improves conversational depth, particularly in complex [12] scenarios, such as multilingual conversations where the nuances of languages like German require precise interpretation and responses.

2) Multilingual Support with LLM: The chatbot leverages the multilingual capabilities of Llama 3.1 70B to provide career counseling in seven languages: Hindi, English, German, Thai, Spanish, Italian, and Portuguese. By activating Llama's [19] capabilities, CounselAI ensures culturally relevant and linguistically accurate responses, making career counseling accessible to users from diverse backgrounds.

3) Retrieval-Augmented Generation (RAG): CounselAI incorporates Retrieval-Augmented Generation [15] to improve response relevance by combining information retrieval with generative AI in this knowledge intensive task. Using the Serper API (Fig. 2), real-time contextual information from blogs and articles is retrieved based on user queries. These details are integrated into the chatbot's input, enabling accurate, up-to-date [2], and enriched responses.

4) Prompt Engineering: Prompt engineering [19] plays a critical role in guiding the LLM to generate meaningful responses. Prompts are carefully crafted to provide the context and instructions for the chatbot to understand the user's intent.

- **Chain-of-Thought Prompts**: Encourages the model to break down complex reasoning into intermediate steps, leading to well-structured outputs. Our prompt: ”You are a professional career counselor and coach called CounselAI, who is an expert at guiding individuals based on their strengths, weaknesses, language, and current level, explaining topics and answering doubts. Given a topic and the information to answer, please educate the user about it according to the languageGroup chosen following the agent's orders. Start off by greeting the user and introducing yourself, giving them a short overview of the counseling process, and then ask them what they want to achieve in their career (in markdown numbers). Be interactive throughout the chat and ensure to ask questions that help you understand the user's profile better for the personality analysing agent.”
- **Scenario-Specific Prompts**: These prompts are tailored to handle situations where users do not directly ask counseling-related questions but instead may ask about unrelated topics, requiring redirection to career-specific guidance. This is achieved by utilizing few-shot learning, where a small set of carefully crafted examples is provided to the model. These examples demonstrate how to steer a conversation back to career-related topics, even when the user diverges. For instance, if a user asks for advice about personal hobbies or unrelated life events, the prompt guides the model to ”redirect the conversation back to career counseling, asking clarifying questions that guide the user towards their professional aspirations.”

This meticulous approach to prompt engineering significantly enhances the chatbot's ability to generate relevant responses, ensuring that the user stays focused on career counseling throughout their interactions.

5) Manual Validation Pipeline: To ensure the accuracy and reliability of chatbot responses, there is a basic manual validation and quality assurance process. This involves:

- **Continuous Monitoring and Satisfied User Feedback**: Helicone is used to track user interactions and collect basic feedback, primarily from users who indicate that the response was helpful. While this feedback is not yet used to directly fine-tune the model, it helps identify patterns in successful interactions and serves as an early signal for response quality.
- **Lightweight QA for Response Validity**: Additional spot-checks are periodically conducted to validate that generated responses remain coherent, relevant to the user query, and factually accurate within the scope of the underlying data.

Currently, feedback is not integrated into automated model updates. However, the structure allows for future use in refining prompts, retrieval behavior, or curating data for fine-tuning.

B. Tools and Frameworks

CounselAI integrates a wide array of tools and frameworks to create a seamless and efficient user experience. Llama 3.1 70B: The backbone of CounselAI, this large language model powers the chatbot's contextual and multilingual capabilities. Serper API: Enhances chatbot responses by sourcing real-time, external information such as blogs and articles from Google which can be used as coaching material. Helicone: Provides observability, enabling performance monitoring and optimization of LLM usage by incorporating user feedbacks based on history. Tailwind CSS and Next.js: Enables the development of an intuitive, responsive user interface for seamless user interactions. Manual Validation Tools: Supports human-in-the-loop workflows to refine and validate the generated outputs.

C. System Workflow

The system workflow for CounselAI involves these steps: User queries are processed and matched with pre-defined prompts or scenarios. Relevant data is fetched via the RAG mechanism, integrating real-time knowledge into the chatbot's response. The LLM agents collaboratively refine the output, ensuring accuracy and contextual alignment. Generated responses undergo a final validation step to maintain quality and coherence. Feedback from users is logged for continuous improvement using observability tools like Helicone.

Case Study: From Query to Career Guidance

Consider a user named **Ananya**, a recent graduate with a background in computer science. She asks *CounselAI*:

> *"What career suits someone with skills in Python and a strong interest in problem-solving?"*

The system processes her query as follows:

- **Profile Analysis Agent** interprets Ananya's query, identifies her skillset and interests, and matches it with her academic background.
- **Career Recommendation Agent** uses this profile to suggest relevant roles such as *Data Analyst*, *Software Developer*, or *AI Research Assistant*, based on current labor market trends.
- **Search Agent** enriches these suggestions with up-to-date information retrieved from blogs and job portals using the *Serper API*.
- **Goal-Setting Agent** assists Ananya in planning her next steps, which may include pursuing certifications in machine learning, building a project portfolio, or scheduling mock interviews.
- **Follow-up Agent** stores the session context for future reference, enabling personalized and continuous career guidance.

V. Results and Evaluation

The effectiveness of the CounselAI system is evaluated through a series of experiments comparing its performance against other AI chatbots in the career counseling domain. However, given that users' career journeys are long-term and evolving, not all standard metrics can be immediately measured. Instead, we focus on metrics that can provide valuable insights even in the early stages of user interaction, such as BertScore and MoverScore.

A. Experimental Setup

To assess the performance of CounselAI, we conducted a series of tests with both CounselAI and competing AI chatbots. The tests focused on common career-related queries, such as:

- "What career options align with my skill set?"
- "What certificates can help me transition to data science?"
- "How can I improve my CV for a software role?"

Public Dataset is available on the CounselAI Repository on HuggingFace. Questions and answers used from recommended interviewing sites used with permission. All systems were given the same set of input queries, and the responses were evaluated based on their accuracy and relevance.

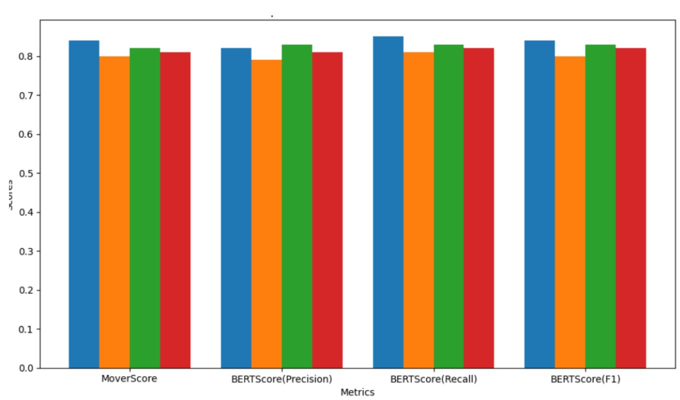

Fig. 3. Performance Comparison Between CounselAI and Other Chatbots

B. Metrics Used

We employed several key metrics to evaluate the performance of CounselAI: **BertScore**: The Bilingual Evaluation Understudy Score (BertScore) is used to evaluate the quality of AI-generated responses by comparing them to a reference set of ideal answers. This metric helps measure the semantic similarity and relevance of the responses. **MoverScore**: MoverScore evaluates the shift in semantic meaning between the AI-generated response and reference answers, providing insights into the relevance and comprehensiveness of the responses.

C. Key Observations

From the results, we observe the following: BERTScore and MoverScore provide objective measures of semantic quality, and initial tests will rely on these automated metrics. Effective career counseling often requires ongoing interactions, and

TABLE I
PERFORMANCE COMPARISON OF CHATBOTS

Model	MoverScore	Precision	Recall	F1 Score
CounselAI	0.84	0.82	0.85	0.84
Gemini Flash	0.80	0.79	0.81	0.80
GPT4-mini	0.82	0.83	0.83	0.83
Llama-3.1 70B	0.81	0.81	0.82	0.82

long-term evaluations are essential to fully assess the system's impact on users' career journeys.

D. Advantages of the Multi-Agent System

The superior performance of CounselAI can be attributed to the multi-agent architecture and its shared knowledge base. The distinct agents in CounselAI—each specializing in a specific area such as profile analysis, market trends, or resume optimization allow the system to provide more nuanced career advice. This multi-layered approach enables the AI to offer tailored solutions that address the complexity of career counseling, which a single-agent system may struggle to handle. The shared knowledge base also ensures that each agent has access to the latest information, whether it is emerging job market trends, new certifications, or evolving industry standards. This continuous flow of information allows CounselAI to maintain up-to-date and contextually relevant guidance, which is essential for effective career counseling.

E. Summary

The results indicate that CounselAI significantly outperforms traditional AI chatbots in the career counseling domain. By leveraging a multi-agent architecture and a shared knowledge base, CounselAI provides more accurate, relevant, and comprehensive advice, leading to higher task completion rates, user engagement, and satisfaction.

VI. USER INTERFACE

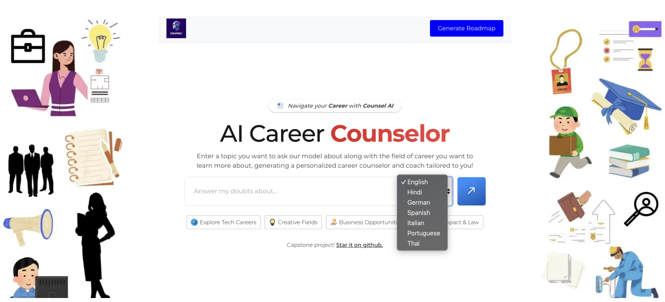

Fig. 4. CounselAI Landing Page

CounselAI's interface is designed to be intuitive and inclusive, supporting interaction in seven languages. On the landing page (Fig. 4), users are greeted with a clean layout that prompts them to enter a career-related topic or optionally select from predefined career fields (e.g., Tech Careers, Creative Fields, Business Opportunities). A language selection menu is prominently displayed, allowing users to choose from seven supported languages: Hindi, English, German, Thai, Spanish, Italian, and Portuguese.

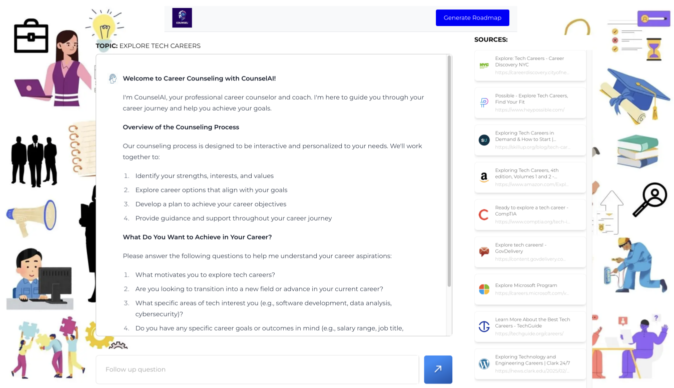

Fig. 5. CounselAI Chat and Blogs Interface

After submitting their query, users are taken to the chat interface (Fig. 5), where the AI counselor begins the session. Responses are displayed alongside a panel of curated, real-time blog and article links. These are sourced using the RAG + Serper mechanism and serve as supplementary reading or coaching material, enhancing the session's depth.

VII. LIMITATIONS

While CounselAI delivers promising results in career guidance, it also operates within certain known limitations. First, the platform's reliance on real-time external sources requires frequent updates to ensure information accuracy and relevance. A curation schedule exists to maintain freshness in domain-specific knowledge. Second, user privacy remains a critical concern. CounselAI addresses this by anonymizing all conversations and storing no personally identifiable information (PII). All interactions are logged solely for model improvement purposes in compliance with ethical AI and data protection standards. Third, despite offering diverse and personalized advice, CounselAI is not a substitute for certified legal, medical, or psychological counseling. Disclaimers are prominently included within the chat interface to communicate this boundary, and responses in such domains are intentionally limited or redirected to appropriate resources.

VIII. CONCLUSION

To summarize, CounselAI revolutionizes career counseling by addressing critical challenges through the integration of state-of-the-art AI technologies. Leveraging Generative AI, Retrieval-Augmented Generation, and LLM agents, CounselAI fosters a dynamic interaction between users and the platform, redefining how career guidance is delivered in today's world.

The platform's hybrid approach, where AI operates as an assistant rather than a sole decision-maker, ensures that human judgment remains pivotal to all processes. This thoughtful design mitigates the risks of biases inherent in automated systems while maintaining transparency and fairness. For instance, CounselAI's real-time career counseling capabilities, offer nuanced and actionable insights tailored to individual user profiles. However, critical elements like manual validation ensure the reliability and accuracy of the chatbot's outputs, bridging the gap between technological efficiency and human oversight.

By supporting seven languages and offering modular features such as personality analysis, career recommendations, and roadmap generation, CounselAI ensures inclusivity and scalability, making career counseling accessible to users from diverse linguistic and cultural backgrounds. Its dual functionality as a counselor (chat-based interaction) and coach (content-driven guidance) enhances the depth and breadth of career advice, empowering users to navigate their professional journeys with clarity and confidence.

Initial outcomes highlight CounselAI's effectiveness in transforming user experiences by offering precise, practical recommendations that align with both individual aspirations and market demands. As the employment landscape continues to evolve, such a platform will be pivotal in fostering adaptive, data-driven environments that cater to diverse career needs.

Ongoing refinements, including feedback loops and ethical AI practices, will further enhance the platform's usability and relevance, solidifying its position as a groundbreaking solution for career counseling. CounselAI exemplifies the future of personalized, multilingual, and accessible career guidance, empowering individuals to achieve their professional aspirations while embracing inclusivity and innovation.

IX. Future Work

CounselAI aims to become a key resource in the career counseling space by focusing on several areas. First, it plans to develop an in-house domain specific LLM tailored for career counseling, which will reduce reliance on third-party models, eliminating a single point of failure. Expanding multilingual capabilities to include more regional languages and dialects will ensure the platform is accessible to underserved communities. It intends to introduce a humanistic voice mode, allowing users to interact with an anonymous, non-judgmental AI, making career counseling more approachable. The platform will also explore emotion recognition and sentiment analysis to provide more empathetic responses.

As the number of users increase and data coverage expands, CounselAI will focus on optimizing it's infrastructure for scalability. To ensure robust performance with more concurrent users, hardware acceleration techniques will be leveraged, such as using GPUs or TPUs for faster processing. Model pruning methods like LoRA (Low-Rank Adaptation) will be explored to reduce the size of the models for faster deployment without compromising the quality of responses. The platform will also enhance its system architecture to handle increasing loads while maintaining low latency and high reliability. These efforts will make sure CounselAI provides timely and personalized career advice to a growing global audience.

References

[1] Plant, Peter. ”Quality in career guidance: Issues and methods.” International Journal for Educational and Vocational Guidance 4 (2004): 141-157.

[2] Bankins, Sarah, Stefan Jooss, Simon Lloyd D. Restubog, Mauricio Marrone, Anna Carmella Ocampo, and Mindy Shoss. ”Navigating career stages in the age of artificial intelligence: A systematic interdisciplinary review and agenda for future research.” Journal of Vocational Behavior (2024): 104011.

[3] Watts, A. G. ”Career guidance policy: An international review.” The Career Development Quarterly 54, no. 1 (2005): 66-76.

[4] Wang, Zhuang, Guoxi Liang, and Huiling Chen. ”Tool for predicting college student career decisions: an enhanced support vector machine framework.” Applied Sciences 12, no. 9 (2022): 4776.

[5] Ankur Sharma, Satyamsetti Vinay, Debarati Bhattacharjee, Mohamed Muhsin et al. (2022). Understanding Career Aspirations of GenZ [Data set]. Kaggle. https://doi.org/10.34740/KAGGLE/DS/2751150

[6] Xi, Zhiheng, Wenxiang Chen, Xin Guo, Wei He, Yiwen Ding, Boyang Hong, Ming Zhang et al. ”The rise and potential of large language model based agents: A survey.” arXiv preprint arXiv:2309.07864 (2023).

[7] Zhou, Xiaomao, Yujiao Hu, Qingmin Jia, and Renchao Xie. ”Cross-Domain Integration for General Sensor Data Synthesis: Leveraging LLMs and Domain-Specific Generative Models in Collaborative Environments.” IEEE Sensors Journal (2024).

[8] National Career Service. 2024. Home page. Retrieved August 1, 2024 from https://labour.gov.in/national-career-service.

[9] Gao, Yunfan, Yun Xiong, Xinyu Gao, Kangxiang Jia, Jinliu Pan, Yuxi Bi, Yi Dai, Jiawei Sun, and Haofen Wang. ”Retrieval-augmented generation for large language models: A survey.” arXiv preprint arXiv:2312.10997 (2023).

[10] Raghavan, Priyanka. ”Ipek Ozkaya on Generative AI for Software Architecture.” IEEE Software 41, no. 6 (2024): 141-144.

[11] Chaubey, Harshit Kumar, Gaurav Tripathi, and Rajnish Ranjan. ”Comparative analysis of RAG, fine-tuning, and prompt engineering in chatbot development.” In 2024 International Conference on Future Technologies for Smart Society (ICFTSS), pp. 169-172. IEEE, 2024.

[12] Duijst, Daniëlle. ”Can we improve the user experience of chatbots with personalisation.” Master's thesis. University of Amsterdam (2017).

[13] Lee, Unggi, Haewon Jung, Younghoon Jeon, Younghoon Sohn, Wonhee Hwang, Jewoong Moon, and Hyeoncheol Kim. ”Few-shot is enough: exploring ChatGPT prompt engineering method for automatic question generation in english education.” Education and Information Technologies 29, no. 9 (2024): 11483-11515.

[14] DeBellis, Michael, Nivedita Duttab, Jacob Ginoc, and Aadarsh Balajid. ”Integrating Ontologies and Large Language Models to Implement Retrieval Augmented Generation (RAG).” Applied Ontology 1 (2024): 1-5.

[15] Lewis, Patrick, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler et al. ”Retrieval-augmented generation for knowledge-intensive nlp tasks.” Advances in Neural Information Processing Systems 33 (2020): 9459-9474.

[16] Khan, Ayman Asad, Md Toufique Hasan, Kai Kristian Kemell, Jussi Rasku, and Pekka Abrahamsson. ”Developing Retrieval Augmented Generation (RAG) based LLM Systems from PDFs: An Experience Report.” arXiv preprint arXiv:2410.15944 (2024).

[17] Adamopoulou, Eleni, and Lefteris Moussiades. ”Chatbots: History, technology, and applications.” Machine Learning with applications 2 (2020): 100006.

[18] Aftab, Danyal, and Steven Davy. ”Tailored-LLaMA: Optimizing Few-Shot Learning in Pruned LLaMA Models with Task-Specific Prompts.” In ECAI 2024, pp. 3844-3850. IOS Press, 2024.

[19] Wang, Li, Xi Chen, XiangWen Deng, Hao Wen, MingKe You, WeiZhi Liu, Qi Li, and Jian Li. ”Prompt engineering in consistency and reliability with the evidence-based guideline for LLMs.” npj Digital Medicine 7, no. 1 (2024): 41.

[20] Gmyrek, Paweł, Christoph Lutz, and Gemma Newlands. ”A technological construction of society: Comparing GPT-4 and human respondents for occupational evaluation in the UK.” British Journal of Industrial Relations (2024).

[21] The Interview Portal. 2024. Career Questions page. Retrieved August 6, 2024 from https://theinterviewportal.com/career-questions/.