Gen AI Career Guidance Chatbot

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***Abstract*—The process of career guidance has gained importance because students need help selecting their academic paths while the job market changes rapidly. The project introduces a career guidance chatbot which uses Generative AI to deliver personalized career recommendations through natural language processing. The system provides assistance to students through its accessible and reliable system which uses large language models and retrieval-based reasoning. Educational chatbots research indicates that AI systems enhance accessibility, reduce counselor responsibilities, and boost student participation. The current models available in the market show basic problems because they do not understand context correctly and they cannot provide personalized long-term guidance and they depend on fixed rule-based systems. Researchers who study the field encountered obstacles when they needed to manage intricate questions and used domain knowledge and tried to adapt their research to students from various academic backgrounds. The proposed system uses Lang Chain for its main functions while FAISS performs document retrieval based on vector data and Google Generative AI produces responses that take into account contextual information. The system used data processing and embedding creation and retrieval processes to deliver precise and tailored user recommendations. The chatbot delivers career information together with course recommendations and skill assessments all of which achieve precise results and better contextual understanding. Educational institutions can use its scalable design to manage their operational needs while serving numerous students.**

Index Terms*—Career Guidance Chatbot, Generative Artificial Intelligence, Machine Learning, Natural Language Processing.

I. INTRODUCTION

Artificial intelligence (AI) has brought about a complete revolution in the ways people interact with technological solutions which especially impacts the fields of education and professional development. The current employment market requires students to receive immediate job guidance which needs to be both accurate and personalized because their academic pathways have become more difficult to navigate. Traditional career counseling services need to be more accessible because they lack essential resources which makes it impossible to serve multiple students at once who require assistance from counselors. Educational institutions require intelligent systems which provide students with personalized assistance during their learning process in real-time situations [1] [2]. This project develops an AI-based career counseling chatbot system which replicates the functions of a certified career counselor.

The system generates context-specific answers by processing input information which includes the student's name and academic year and educational background information and career aspirations. The system gathers essential information to answer student questions while showing previous chat history and using a document-based knowledge base.
The chatbot functions as a 24/7 digital career planning tool which provides answers to multiple questions regarding internship recommendations and skill development pathways [3] [4]. The system uses retrieval-augmented generation (RAG) techniques to produce responses which reference verified content to improve both accuracy and relevance of its output [5].

The system demonstrates that AI technology can enhance academic career counseling services through three areas which include improved service quality and increased service capacity and extended service reach through its document search and chat memory and user management and question generation capabilities [6], [7]. The solution provides essential components which traditional counseling systems lack while creating opportunities for intelligent advisory systems that focus on students.

II. THEORETICAL FRAMEWORK

The Generative AI-based Career Advisor Chatbot functions based on two core components which are Natural Language Processing and Machine Learning. The system uses NLP to interpret user requests by determining their goals and producing relevant answers based on the situation. Basic NLP methods which include tokenization and semantic parsing and named-entity recognition and sentiment analysis form the essential framework that supports conversational comprehension. The chatbot system uses these components to accurately interpret user questions about their career goals and educational achievements and personal interests. The transformer-based architecture which includes GPT models enables understanding of extended text input and provides users with natural human-like assistance.

The The second layer of the framework is built upon Generative AI (Gen-AI) and Large Language Models (LLMs). The models utilize self-supervised training methods with extensive datasets to develop their capacity for understanding language structure and domain-specific information and their reasoning skills. Gen-AI enables career advising through its ability to generate real-time responses while creating custom recommendations and conducting scenario-based assessments. The system uses attention mechanisms and embeddings and probabilistic text generation as its theoretical basis to create personalized adaptive suggestions which reflect current industry developments and user expertise and career path changes. Recommendation System Architecture serves as a vital theoretical framework component which implements content-based filtering methods together with knowledge-based reasoning and rule-based mapping techniques. The engine uses user inputs that include skills and academic qualifications and interests and future goals to suggest appropriate job positions and certification programs and learning paths and skill development routes evaluation methods.

Finally, the theoretical framework incorporates AI Ethics, Transparency, and Responsible AI principles. These concepts ensure the chatbot operates safely, avoids bias, and provides fair career advice. Theoretical constructs such as ethical reasoning, explainable AI, data privacy norms, and fairness-aware algorithms guide system design. This prevents biased recommendations, enhances trust, and ensures compliance with professional and academic standards.

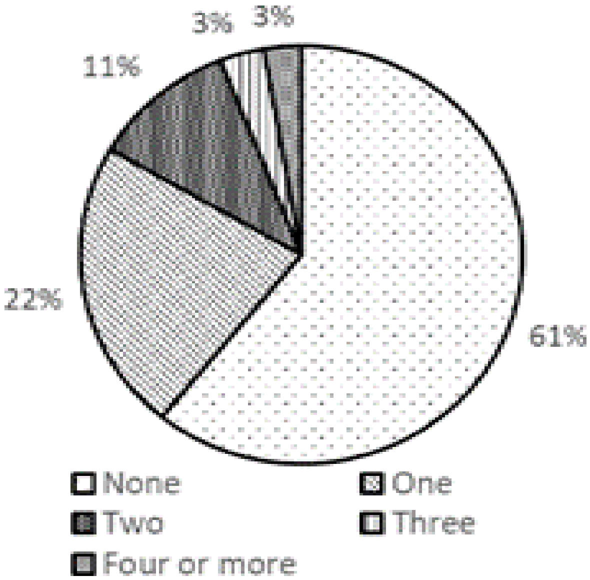
III. METHODS

A. Participants and Recruitment

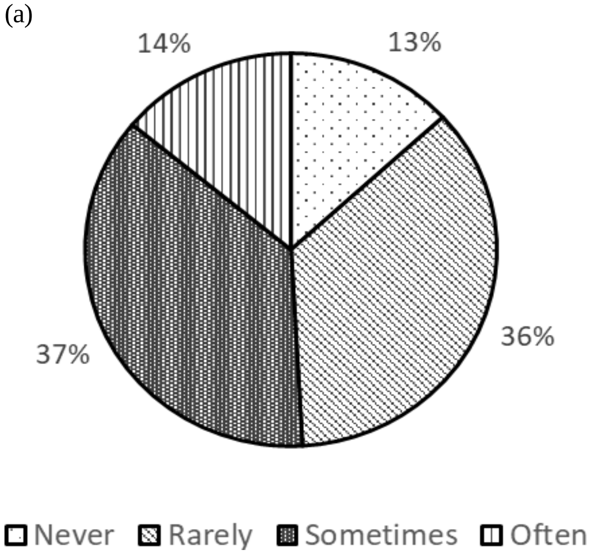
The quantitative phase of this research project exists as one element of a mixed-methods study that investigates adoption and usability and student engagement and career-related decision-making. The survey was distributed to academic coordinators, placement cell officers, and department heads across eight engineering and technology-focused universities. They were requested to forward the questionnaire to undergraduate and postgraduate engineering students across various disciplines. The specific engineering major was not considered essential to the study. The research team used digital gift vouchers to motivate students to complete the survey.

A total of n = 587 students participated in the study. Of these, 233 (40%) were male, 314 (53%) were domestic students, and 362 (62%) reported English as their primary language. Participants were also asked to specify their academic standing. Fifty-nine percent of respondents identified as early-stage students, including first- and second-year undergraduates and newly enrolled master's students. Meanwhile, 17% classified themselves as late-stage students, defined as those in their final year of undergraduate study, completing major projects, or nearing the completion of a postgraduate program.

Additionally, information regarding participants' career goals—such as interest in industry roles, higher studies, or research careers—was collected. The demographic section required participants to disclose their career-development resource usage and their academic advisor consultation frequency. According to Figure 1(a) and 1(b), 37% of students never used a Gen-AI career advising tool while 27% of students said they consulted faculty or placement officers about career-related questions either "rarely" or "never". The study results show a major difference in student participation because engineering students lack proper career guidance methods which include both standard advising and AI career assistance systems.



(a)



(b)

Figure 1: Participant characteristics. (a) Participant responses indicating how frequently they use the Gen-AI Career Advisor Chatbot. (b) Participant responses indicating how often they communicate with faculty or advisors regarding career-related guidance.

It should be noted that this distribution may be due to the sampling population of current graduate students at research-focused institutions. The total number of participants represented by Figure 1 does not total the number of participants in the study because participants were requested to simply indicate the likelihood they would pursue a career in any given sector, and therefore a single participant could indicate a high likelihood of pursuing careers in all the sectors. The decision to open this question is representative of the open-ended career planning paths that many students embark upon, if they are open to certain career paths more than others, but may hesitate to reject opportunities in other sectors. The distribution of frequencies also reflects the current job climate for engineering graduate students, which offers fewer faculty opportunities and more industry and research positions.

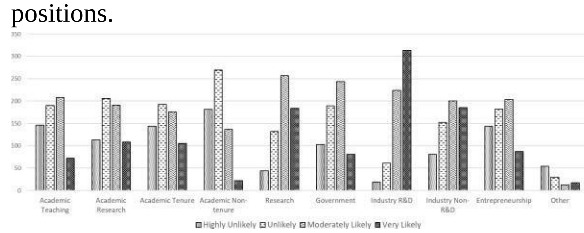


Figure 2: This bar chart displays participants perceived likelihood of various outcomes for the "Project Gen AI Career Advisor Chatbot," categorized from "Highly Unlikely" to "Very Likely."

Table 1: Likelihood of Career Choices Across Different Domains

Career Path	Highly Unlikely	Unlikely	Moderately Likely	Very Likely
Academic Teaching	150	190	210	70
Academic Research	110	205	190	105
Academic Tenure	145	190	175	105
Academic Non-tenure	180	270	135	25
Research	45	130	255	185
Government	100	190	240	80
Industry R&D	20	60	252	310
Industry Non-R&D	80	150	200	185
Entrepreneurship	145	180	200	90
Other	55	30	10	20

The table demonstrates that **Industry R&D** serves as the primary career choice because it received the highest number of "Very Likely" answers while only a few individuals selected negative responses. The general research field establishes strong backing through its extensive distribution between the "Moderately Likely" and "Very Likably" categories. People prefer academic careers which include non-tenure positions less than they prefer other career options because they select "Highly Unlikely" and "Unlikely" responses in greater numbers. People now prefer careers that combine industry work with research activities instead of following academic paths that involve traditional educational methods.

Survey Description

The comprehensive survey was designed to correlate graduate students' self-reported career trajectory likelihood with their approaches, concepts, and self-efficacy related to writing and research. The instrument package consisted of four validated surveys which include the Inventory of Graduate Writing Processes and Graduate Concepts of Academic Writing to measure a writer's affective relationship with the writing process and beliefs about writing and a Writing Self-Efficacy Survey which quantifies confidence in completing academic writing tasks and a Research Self-Efficacy Survey which gauges belief in the ability to complete complex research tasks. The researchers calculated individual construct scores through data cleaning procedures which involved averaging within-construct item responses and they used Pearson correlations to determine the statistical relationship between writing and research psychological disposition and academic career and industry R&D career and entrepreneurship career paths.

1. Writing Self-Efficacy Survey [43]

The system uses a standard Likert scale which contains five or six response options that range from "Not at all confident" to "Completely confident" to measure how participants assess their ability to complete academic writing tasks. The survey items are constructed to measure confidence across various aspects of writing which include composing clear and coherent arguments organizing and structuring long-form documents like theses or manuscripts and generating ideas while overcoming writer's block. The research team calculated overall confidence by averaging individual item responses which resulted in a composite self-efficacy score that showed participants' confidence in their academic writing abilities.

2. Research Self-Efficacy Survey [44]

This The self-assessment tool uses a ten-point scale to evaluate how participants believe they will perform the research process's demanding tasks. The instrument measures confidence across core research skills essential for graduate-level work and beyond, which include the ability to develop viable research questions and hypotheses and to design and conduct experiments or studies and to analyze and interpret both quantitative and qualitative data and to troubleshoot technical and methodological issues and to communicate research findings effectively to different audiences.

The researchers calculated study scores by averaging responses through multiple sub-constructs, which allowed them to show how participants perceived their research competence in relation to their interest in research-intensive career paths such as Industry R&D and Academic Research.

B. Analysis Methods

The researchers conducted initial survey data processing to delete all respondents who failed to finish the complete survey except for demographic information. The research team examined each survey according to the original purposes which the authors had established in their initial published work. The MATLAB script performed two functions by first reverse coding specific survey items then creating distinct category groups for survey responses which enabled researchers to calculate construct scores through within-construct item average scores for each participant. The script analyzed data to identify which writing concepts and methods each participant used as their main and secondary writing concepts and methods. The researchers used Pearson correlations to examine the statistical connections between participants' writing approach scores and their self-reported career development chances while they conducted their statistical analysis with SPSS software which generated correlation tables.

The survey data underwent rigorous preparation, beginning with a cleaning phase where incomplete responses (excluding demographic information) were removed. Following this, the analysis adhered to the original validated methods for each of the four instruments. A MATLAB script was custom-employed to handle the scoring: it performed necessary reverse-coding of items and categorized the survey responses by construct. This sorting allowed for the averaging of item responses within each construct to yield a single, composite score for every participant, representing their standing on factors like "Procrastination" or "Research Self-Efficacy."

This quantitative processing enabled the core statistical goal of the study. Using the scores derived from the writing and self-efficacy constructs, correlation tables were generated to statistically examine the relationships between these psychological measures and a participant's

The study gathered data about participant career paths which included Academic Teaching and Industry R&D and Entrepreneurship. The researchers utilized SPSS software to execute all correlation tables and their accompanying statistical tests because this software provided accurate and dependable methods to measure the confirmed correlations between the studied variables.

The survey data first underwent a rigorous cleaning process to remove incomplete responses because a custom MATLAB script was used to handle the intricate scoring. The script performed necessary reverse-coding of items and categorized responses by construct. The script enables researchers to calculate composite scores through averaging which scientists use to measure participants' writing processes and self-efficacy. The core statistical analysis required rigorous processing work which created correlation tables through Pearson correlations that the SPSS statistical software executed to measure the statistical connections between participants' psychological construct scores and their self-reported career path interests. Researchers used MATLAB and SPSS to measure the relationship between construct scores and career interest. The analysis aimed to identify patterns and correlations between participants' scores on writing processes, self-efficacy, and their likelihood of pursuing specific career trajectories.

IV. RESULTS AND DISCUSSION

The result page of the Career Guidance Chatbot presents an interactive platform which enables students to create their academic and professional plans with ease. The left side of the page contains the Student Profile section which enables users to input their required information including their name, college name, degree, year of study and career goals. The chatbot uses additional options which include internship experience and placement status to create customized advice based on the user's educational achievements and current academic status. Students can obtain personalized guidance that matches their objectives by completing the form and clicking the "Get Personalized Advice" button. The chatbot presents itself as a Career Guidance Chatbot at the page center to provide users with customized career advice and answers to their career questions. The interface encourages students to fill in their details to unlock personalized, context-aware responses. The layout displays a clean design which creates an attractive visual experience. The black and white and green color combination creates a design that allows users to read content in a professional manner. The design enables users to move through the interface while concentrating on the main purpose of the chatbot.

The chatbot provides Suggested Follow-up Questions such as “What are the top 3 soft skills needed for my career goal?”, “Can you suggest a 6-month study plan for this goal?”, and “What are common interview questions for a role in my field?”. The recommendations help users to discover appropriate subjects while they obtain organized guidance which helps them to upgrade their professional abilities and educational background and job market preparedness. The page has an organized appearance which helps students to advance their career goals through valuable AI-based interactions that lead them to specific outcomes.

The result page displayed in the image shows the Career Guidance Chatbot actively responding to a student named Sanika, who has entered her academic details and career goal of becoming a Full Stack Developer in a good company. The Student Profile panel displays essential information about the student which includes their name and college name which is SIT and their B.E degree and their current study year which is 4 and their particular career goals. The chatbot uses this information to create customized recommendations which will suit the user's present academic level and their career goals. The form provides checkboxes which allow students to indicate their internship and placement status which helps to create advice that better matches their specific circumstances.

In the chat area, Sanika asked an exact practical question about which she should study first between Data Structures and Algorithms (DSA) and complete development. The chatbot delivers a professional yet supportive and analytical response. The solution presents an organized answer which acknowledges her final-year student status and her goal of securing a job. The bot recommends that she should first dedicate time to mastering DSA skills because most reputable companies use this skill for their initial selection process. The recommendation also includes that she should dedicate specific periods to web development work and project deployment activities.

This The output demonstrates the chatbot's capability to function as a personal career mentor because it combines data-based analysis with information about each individual student. The system provides users with guidance while explaining its reasoning process which enables users to understand how to reach their specific objectives. The page design presents a readable layout together with visible advice boxes and an easy-to-use input system which creates an effective and enjoyable guidance process for students who are preparing for placements.

IV. LIMITATIONS, CONCLUSIONS, AND FUTURE WORK

The Generative AI Career Advisor Chatbot delivers instant data-driven career guidance to students which proves that AI technology can improve accessibility and operational efficiency for career counseling services. The system functions under several restrictions because its performance depends on the complete knowledge base and its present content quality while it produces standard answers which it cannot improve to meet current employment market needs and it does not support multiple languages. The chatbot operates successfully through its combination of AI models and retrieval techniques and its custom knowledge base which it uses to provide precise user recommendations. The knowledge base should be expanded to incorporate real-time labor market information while users should be able to communicate in different languages through personalized dialogue systems which should include emotional intelligence features that enhance user interaction. The system needs to establish connections with educational platforms which will enable automated course and internship suggestion processes.

The Generative AI Career Advisor Chatbot provides valuable career guidance, but it has certain limitations that need to be addressed. The system depends on its knowledge base because its performance needs complete and accurate data to make successful recommendations which will fail if the available information is insufficient. The chatbot handles basic inquiries successfully yet it produces responses which lack specific context when dealing with complicated or unclear questions.

The chatbot cannot update its responses according to current job market changes and new job opportunities. The system cannot handle real-time labor market information, which will result in inaccurate guidance for users. The chatbot supports only one language, which makes it difficult for non-native speakers to use, and it does not provide advanced emotional intelligence capabilities, which limits its ability to create personalized user experiences.

Despite The project shows considerable educational potential through its AI-powered tools for educational purposes and career guidance. The chatbot provides immediate personalized career advice through its combination of large language models and retrieval-based reasoning and its custom knowledge base.

The system enables students to make better choices while decreasing the job demands on career counselors and enhancing access to career advisory services.

Future improvements can concentrate on two main tasks which require expanding the knowledge base while maintaining continuous updates to include upcoming career trends and industry standards and academic programs. The system would benefit from real-time labor market analytics which should be combined with AI-based solutions to deliver better recommendation results.

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REFERENCES

[1] Sharma and M. Lee, "Machine Learning Applications in Decision Systems," *IEEE Trans. Syst., Man, Cybern.: Syst.*, vol. 52, no. 7, pp. 4567–4579, Jul. 2022.

[2] R. Gupta and S. Mehta, "Conversational AI in Education: A Review," IEEE Access, vol. 10, pp. 98245–98256, 2022.

[3] T. Nguyen and L. Kumar, "Personalized AI for Student Career Support," IEEE Access, vol. 11, pp. 20445–20460, 2023.

[4] N. A. Khan and M. Roy, "AI in Academic Counseling: Design and Evaluation," in Proc. IEEE Conf. EdTech Innovations, 2022, pp. 88–94.

[5] P. Yadav and K. Sundaram, "Career Guidance Automation Using Chatbots," in Proc. Int. Conf. Smart Learning for Community Development, 2021, pp. 127–132.

[6] S. Wang, J. Li, Y. Chen, and R. Zhao, "Retrieval-Augmented Generation for Intelligent Assistants," IEEE Trans. Artif. Intell., vol. 5, no. 3, pp. 456–470, 2023.

[7] H. Zhou, Y. Jin, and D. Zhang, "Enhancing Chatbots with Context-Aware Document Retrieval," IEEE Trans. Knowl. Data Eng., vol. 36, no. 5, pp. 901–912, 2023.

[8] Y. Liu, X. Zhang, T. Chen, and M. Wu, "Knowledge-Grounded Dialogue Systems: A Survey," IEEE Trans. Neural Netw. Learn. Syst., vol. 34, no. 11, pp. 14567–14583, 2023.

[9] M. Prasad and S. Kapoor, "Design of Interactive Educational Chatbots for Scalable Student Support," IEEE Access, vol. 11, pp. 125678–125690, 2023.

[10] A. K. Verma and R. Singh, "AI-Based Counseling for Higher Education: A Systematic Approach," IEEE Trans. Educ., vol. 67, no. 9, pp. 822–833, 2023.

[11] J. Allen, L. Perez, and C. Davis, "Human-Centered AI in Education," IEEE Trans. Learn. Technol.

[12] K. Brown and J. Smith, "Developing AI-Powered Chatbots Using Large Language Models," IEEE Access, vol. 12, pp. 115233–115247, 2024.

[13] M. Abedi, I. Alshybani, M. R. B. Shahadat, and M. S. Murillo, "Beyond Traditional Teaching: The Potential of Large Language Models and Chatbots in Graduate Engineering Education," IEEE Trans. Educ., vol. 68, no. 3, pp. 321–333, 2024.

[14] P. Panagiotidis, "LLM-Based Chatbots in Language Learning," IEEE Trans. Educ. Technol. Learn., vol. 18, no. 2, pp. 155–164, 2024.

[15] B. Debnath and A. Agarwal, "A Framework to Implement AI-Integrated Chatbot in Educational Institutes," in Proc. IEEE Int. Conf. Educational Technology (ICET), 2023, pp. 201–209.

[16] N. Labadze, I. Grigolia, and N. Machaidze, "Role of AI Chatbots in Education: Systematic Literature Review," IEEE Access, vol. 12, pp. 128945–128962, 2024.

[17] D. Roy, A. Banerjee, and P. Saha, "AI-Driven Student Support Systems Using Transformer Models," IEEE Access, vol. 11, pp. 189345–189360, 2023.

[18] L. Martinez and F. Rosenfeld, "Adaptive Recommendation Engines for Academic Decision Support," IEEE Trans. Syst., Man, Cybern.: Syst., vol. 54, no. 1, pp. 112–125, Jan. 2024.

[19] M. K. Singh and R. Thomas, "Chatbot-Based Virtual Assistants for Higher Education," in Proc. IEEE Int. Conf. Adv. Comput., 2022, pp. 556–562.

[20] A. Das and V. Rao, "Evaluation of Large

Language Models for Student Query Resolution," IEEE Trans. Artif. Intell., vol. 4, no. 4, pp. 789–801, 2023.
[21] B. Krishnan and P. Menon, "Semantic Search Approaches Using Embedding Models for Knowledge Retrieval," IEEE Access, vol. 12, pp. 100345–100357, 2024.
[22] S. Choudhury and Y. Lin, "Deep Learning for Personalized Learning Assistants," IEEE Trans. Educ., vol. 67, no. 7, pp. 950–961, 2023.
[23] F. Ahmed and L. Wong, "FAISS-Based Vector Retrieval for Scalable AI Applications," in Proc. IEEE Int. Conf. Big Data, 2023, pp. 412–419.
[24] G. Watson and C. Hill, "Student Engagement Through AI-Powered Interactive Systems," IEEE Trans. Learn. Technol., vol. 18, no. 1, pp. 55–66, 2024.
[25] R. Mishra and A. Kulkarni, "Improving Chatbot Reliability Using Hybrid Retrieval and Generation Models," IEEE Access, vol. 12, pp. 110245–110260, 2024.
[26] H. Park and M. Young, "Evaluating the Effectiveness of Educational Chatbots in Career Counseling," in Proc. IEEE EDUCON, 2023, pp. 233–240.
[27] P. Banerjee and S. Reddy, "User-Centric Design Principles for AI Chatbot Interfaces," IEEE Trans. Hum. -Mach. Syst., vol. 54, no. 3, pp. 402–414, 2024.