Use of a ChatBot-Based Advising System for the Higher-Education System

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***Abstract*—The educational advising process most often consists of repeated queries related to institutional policies, academic progression, career pathways, and industry placements. In the higher education system, this procedure is usually initiated by various learners directing the same questions toward a limited number of advisors, which results in the advising process being reliant on the availability of the individuals and their hectic work schedules. Hence, this study introduces a feasible mechanism of a chatbot-based advising system to bridge this identified gap between learner requirements and resource availability by automating the prescriptive advising process beyond the traditionally available methods. Most existing systems provide a rule-based approach with limited pre-defined intent-response structures, resulting in several identified usability shortcomings. In response, this study utilizes an open-source Large Language Model (LLM) combined with a custom knowledge base to address critical aspects needed for a chatbot-based advising system, such as personalization, conversational memory, and ease of maintenance. The system is built around three major components: an admin panel for advisors, a conversational user interface (CUI) for learners, and an easy-to-maintain custom knowledge base. It uses the traditional form of information distributed to students through handbooks, guidelines, and course outlines to create a custom knowledge base which is then utilized to answer the user's queries through a semantic similarity algorithm. This work contributes (1) a prototype of a chatbot-based advising system for higher educational institutes in Sri Lanka, (2) the application of Large Language Models, vector databases, and semantic similarity in the design of the system, and (3) the results of evaluating the system's functionality and performance metrics through comprehensive test cases and a comparative analysis against the existing approaches. As identified, the proposed system showcased a response accuracy rate of 89% proving that this novel approach of a component-based architecture excels in performance when compared to similar approaches.**

Keywords*— *Educational Advising, ChatBot-based Advising System, Large Language Model (LLM), Vector database, Semantic Search

I. Introduction

The higher education sector mainly consists of two pillars driving the academic domain forward. These two pillars, namely: the instructors and the learners, interact regularly to ensure that the teaching-learning process thrives consistently. In this scholarly communication process, many repeated procedures occur that could benefit from information technology advancements. One such procedure is the academic advising process which consists of many underlying layers. A well-structured academic advising process provides timely guidance for learners regarding institutional policies, academic progression, career pathways, and industry placements[1]. Furthermore, a successful academic advising process caters to the overall learning environment by promoting supportive and personalized learning, providing continuous progress tracking and monitoring, assisting students in identifying their strengths and interests, and connecting them with various support services and resources.

However, the existing advising process in the majority of educational institutes across the world heavily relies on human resources that are limited in number [2] and constrained by their busy schedules. As a result of the growing demand for higher education, many higher education institutes (HEI) have grown to accommodate as many students as possible within their programs. The growth in the number of faculty members most often does not keep up with this surge in student enrollments, resulting in a discrepancy between the number of advisors available and the size of the student body. This problem of a disproportionate instructor-to-student ratio leads to negative consequences in the academic journey for both instructors and students. The limitations of resource availability, inability to provide dedicated and personalized support, and absence of timely guidance [3] are a few such consequences of this identified problem.

Furthermore, the obstacle of an imbalanced instructor-to-student ratio can be particularly highlighted in specific fields of study or programs that are popular among students. Programs with high demand, such as specific technology-related disciplines, health-related fields, and engineering disciplines, face more significant challenges in providing adequate advising support [4]. Consequently, it becomes imperative to explore solutions that can effectively resolve these challenges.

Thus, this study proposes a novel approach leveraging the power of Large Language Models (LLM) and vector search to create a chatbot-based advising system that can bridge the gap between the learner requirements and resource availability in the academic advising process. The proposed mechanism intends to outperform the traditionally available methods by automating the prescriptive advising process to provide instant and personalized support to students around the clock. This study aims to empower this chatbot-based advising system with usability features such as personalization, conversational memory, and ease of maintenance to streamline the academic advising process. Standardizing the advising process promotes self-help, where students can find answers to common queries independently while reducing the burden on the academic advisors for routine questions, effectively addressing the identified problem.

The rest of the paper will mainly consist of four sections. The related works section will provide an overview of the literature related to the academic advising journey in the higher education sector while shedding light upon the related research on automating the academic advising process through chatbots. The methods section will explain the research design and approach of this study, along with an in-depth look into the prototype development and evaluation of the proposed system. The results and discussion section will present an overview of the results of the system's evaluations, along with a discussion of its implications. The conclusion and future work section will summarize this study's purpose and propose possible approaches for future research work.

II. Related Work

The concept of automating the advising process and utilizing chatbot technologies in the educational domain has gained significant attention from scholars in recent years. Researchers have explored the need for automating the academic advising process while investigating various approaches to enhance the advising process. This section reviews the existing literature and studies related to the traditional academic advising process and its limitations, then delves into the current approaches of chatbot applications in the education domain globally and in the Sri Lankan context. Through an analysis of the strengths and weaknesses of both the traditional and existing chatbot-based approaches, this section lays the foundation for the proposed chatbot-based advising system to address the shortcomings of the existing methods and elevate the academic advising process.

A. Traditional Academic Advising Process

The traditional academic advising process across many countries in the world revolves around the availability of knowledgeable resources that can take up the task of providing relevant guidance to a large number of students. This resource-intensive task of academic advising includes providing learners with the necessary assistance in achieving their educational and career goals. The primary function of an academic advising process is to ensure that the students can navigate their higher education journeys with better performance and persistence [2]. In general, the academic advising process includes explaining major, career, and life goals, selecting courses, and clarifying institutional requirements [5].

The traditional academic advising process requires a lot of time and expertise. This approach is usually initiated by the student, who would reach out to an advisor in case of any grey areas in the academic progression process. The advisor would then have a direct conversation with the student – often a one-on-one session to clarify their doubts or concerns and provide the necessary guidance. This approach of the advisor needing to meet every student to clarify their doubts is an impossible task given the more significant number of students in an academic institute [5].

Thus, although the traditional academic advising process intends to enhance the student experience in higher educational institutions (HEI), this approach is highly limited in certain aspects [2], which will be discussed in the following section.

B. Challenges and Limitations in the Traditional Approach

It is unsurprising for any academic institute to have a massive number of students compared to the number of available faculty personnel. In the context of the traditional approach, where the availability of the advisor is a crucial factor [5] in furnishing a successful academic advising process, there arise many shortcomings and bottlenecks which need addressing. The studies[2] - [6] discuss a few such drawbacks, including the lack of academic advisors to cater to every single student and their needs, the lengthy waiting times to receive advice due to advisor's hectic schedules and other professional commitments, and the ethical barriers in reaching out to advisors after work hours. Furthermore, a significant drawback of the traditional academic advising process is its exhaustive nature [7], which requires the advisors to repetitively distribute the same set of instructions, guidance, and advice to individual students. Consequently, this hinders the timely resolution of any student query and delays academic progression.

To address these challenges, there is a crucial need for an improved academic advising system for the higher education sector, which should aim to improve the accessibility to the service, provide easy maintenance, and focus on streamlining the advising process. Since scholarly communication is a conversational process between two involved parties, one primary technological application for automating this process is using conversational agents: chatbots [7]. The following section sheds light on the existing chatbot-based approaches in education.

C. Existing Chatbot Applications: A Review

Chatbots are dialogue systems that can imitate human conversation. Over the years, the applications of chatbots have rapidly increased in various sectors, including customer service, healthcare, and education [8]. Chatbot-based systems can mainly be classified into two types: rule-based or AI-driven. Further classifications of chatbot-based systems can be based on the response generation method, such as retrieval-based or generative chatbots [9].

The study [7] presents a design of an automated *AdvisorBot* based on the bot framework, which follows a similar mechanism to a virtual support system model. However, this study only provides an implementation-ready specification and does not provide insight into the developed system or its evaluations. The study [8] introduces a bi-lingual conversational agent which uses a domain-specific corpus containing a set of common questions that advisors receive from students and the relevant responses as the knowledge base. Nevertheless, this study also uses an intent-response structure with a set of pre-identified English-Arabic intents and patterns, therefore, limiting the supported vocabulary. *UniBud* is another similar conversational agent developed in the study [10], which utilizes DialogFlow, a natural language understanding platform, to automate the academic advising process. Here, too the core of the approach is a pre-defined intent-response structure.

To sum up, the automation of the academic advising process through conversational agents: chatbots, is rising across various countries. However, little to no research has been done on the same in the Sri Lankan education domain. One closely related study [8] introduces a student information chatbot developed using DialogFlow, which can only support very few pre-defined questions and answers. Nevertheless, as per the researcher's understanding, no other study has directly addressed the possibility of creating a chatbot-based system to assist the academic advising process in the Sri Lankan education domain.

D. *Challenges and Limitations in Existing Chatbot Applications*

The existing works related to chatbot-based advising systems lack the ability to easily expand the developed system to match the growing and dynamic domain of academic advising due to the approach of pre-defined intent-response structures [11]. Further, they also lack certain usability features such as personalization, conversational memory, and ease of maintenance [12]. A highly detailed systematic review [1] on using chatbots in education clearly emphasizes the unexplored areas of the literature in this context, including exploring the potential of chatbots for mentoring students. The study highlights that most of the existing works focus on the functionality of the system rather than its ability to assist in improving the teaching-learning process.

Considering the challenges mentioned above in the existing chatbot-based advising systems and the lack of any such advising system in the Sri Lankan higher educational domain, this study aims to develop a chatbot-based advising system to answer queries on course completion progression and career placements. The proposed system will support the English language as the institution of the study conducts its courses mainly in English. Furthermore, the system will leverage the advanced Natural Language Understanding (NLU) capabilities of a Large Language Model (LLM) along with other technologies such as vector database and semantic search. Thus, this study is novel in its context of technology usage for an academic advising system.

III. Methodology

The main objective of this study is to provide a feasible solution to the identified problem of low advisor-to-student ratio in the higher education sector by using a chatbot-based advising system to automate the prescriptive advising process. The study also addresses the usability shortcomings of the existing chatbot-based academic advising systems by incorporating personalization, conversational memory, and ease of maintenance into the proposed system. The proposed system in this study uses Large Language Models (LLM) as the underlying technology, along with vector databases and semantic search algorithms, to generalize Natural Language Processing (NLP) and yield significant accuracy with less cost [13].

A. *Research Design*

To ensure that this study is feasible to conduct within the allocated timeframe, the scope of it is narrowed down to designing and developing only a prototype of the proposed system. The research design was structured with an emphasis on the functional and performance aspects of the proposed system. The study highlights the design of the proposed system along with the development and evaluation of a working prototype of the same. The design approach guided this study in establishing valid simulations of real-world user interactions to test and evaluate the developed prototype.

The research process began with the architecture design of the proposed system. A component-based software engineering approach with tool integration was used as the ground concept in this architecture design so that the time spent on developing each component from scratch could be eliminated, resulting in an efficient system being developed within a limited period. Figure 1 depicts a high-level design of the proposed system, which uses a set of external components to assist the system in processing the user input and deriving the expected outputs. Furthermore, the operational language for the proposed system was selected to be English, as the institute of study uses English as its primary language of course delivery. Therefore, all tools and components selected for the prototype development of the system were to complement this decision.

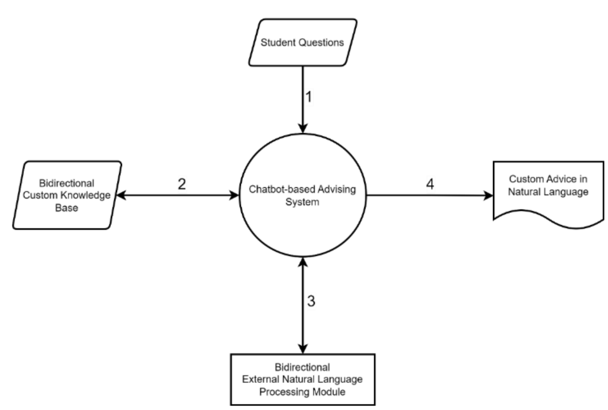

Fig. 1. High-level Abstract View of the Proposed System

The next step in the process was requirement identification to identify some general questions related to internship programs, academic progression and institutional policies that the students in the higher education sector have for their advisors. The data gathering was essential in order to properly curate the test cases used to evaluate the developed prototype of the system. The data gathering took place via keen observations of the researcher within an actual Sri Lankan state university establishment – Faculty of Computing and Technology, University of Kelaniya, Sri Lanka – and through authoritative public sources such as the faculty website, Learning Management System (LMS), handbooks, and guidelines as well as published papers, journal articles, and case studies. Along with the findings of the observations, this study mainly utilizes secondary data used in similar studies to develop the proposed solution, as such data have already been proven to be correct and reliable. Therefore, it is more efficient and productive than collecting primary data to complete the study within the time and resource constraints.

As a result, the researcher identified approximately hundred (100) frequently asked and repeated questions by the students. Adopting the style of work done in [14], the identified questions were divided into a set of applicable categories under the main scope of prescriptive advising to promote ease of evaluation.

B. Prototype Development

After the completion of the architecture design and requirements identification, the next step was the prototype development of the proposed system. The proposed solution consists of two main modules at the outset: an admin dashboard and a chatbot interface visible to the end users. Here, the end-users are the two parties involved in the academic advising process: the advisor and the student. Therefore, the admin dashboard in the proposed solution is targeted for the use of the academic advisors, whereas the chatbot interface is targeted for the use of the students. The high-level user journeys within the solution for these two types of end-users are as follows:

Advisor:

1. Logs into the admin dashboard.
2. Selects the relevant level of study from the given dropdown (Level 1, Level 2, Level 3, Level 4)
3. Selects the relevant academic year from the given dropdown (2017, 2018, 2019, 2020)
4. Uploads a few documents which contain guidelines, instructions, and answers for repeated student questions.
5. Clicks on the 'Process' button to create the custom knowledge base from the content given in documents.

Student:

1. Navigates to the chatbot interface in the system.
2. Enters the name and selects the level of study and academic year.
3. Keys in a preferred question in natural language.
4. Receives the applicable answer from the chatbot as a concise natural language output.

To facilitate these two user journeys, a significant amount of processing occurs within the core component of the proposed solution, which is the chatbot-based advising system itself. The diagram below depicts the proposed solution's in-depth operational flow and each component's contribution to the successful execution of the intended processes and outcomes.

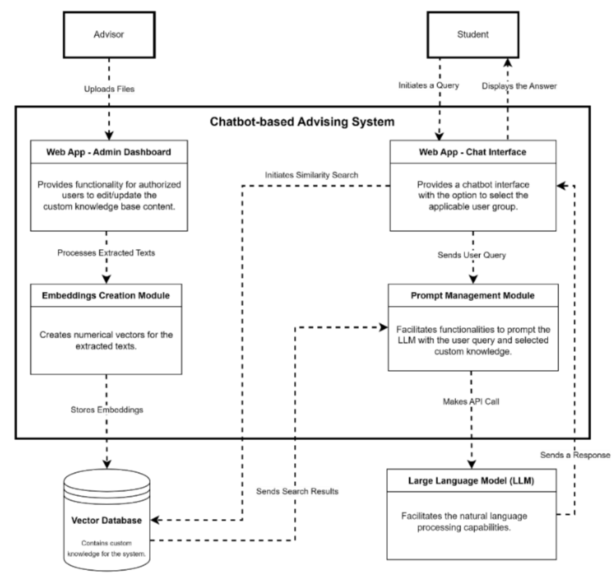

Fig. 1. Component Diagram Providing In-depth Overview of the System

In terms of the technology stack utilized to develop the solution, Python was used as the base programming language since it is proven to be the most used and widely accepted language for Machine Learning (ML) and Artificial Intelligence (AI) based applications. Therefore, the rest of the technologies, frameworks, and libraries used in the system were chosen to complement the core Python program, enabling seamless integration across all the necessary modules and components. The following steps provide detailed explanations of the actions and decisions involved in the coding process of the prototyped system.

1) Web App User Interface (UI) Design: Streamlit library was used to develop the UI for the proposed system, as it provides a vast range of pre-built ReactJS components which are reusable and mobile responsive, resulting in minimal effort in UI development.

2) Content Extraction and Embedding Creation: PyPDF2 library was used to extract the textual content of the PDF documents, as it provides more control over extracting and manipulating the content of the PDFs. The extracted texts were then pre-processed using a series of steps, including creating text chunks, generating embeddings, and storing the embeddings in a vector database. An open-source sentence transformer model – all-MiniLM-L6-v2 – from the HuggingFaceHub Instruct Embeddings collection and LangChain framework was used to create the text chunks and generate the embeddings from the extracted content. The mentioned transformer model was selected as it is not only open source but is also placed on top within the leading sentence-transformer models for general-purpose usage in the HuggingFaceHub leaderboard. Furthermore, the LangChain framework was selected as it provides a vast range of capabilities in terms of conversation handling and language model integration.

3) Vector Store Creation: ChromaDB was used as the choice of vector store for the proposed system as it provides the ability to store the embeddings locally in a persistent database at no monetary cost in comparison to other available options [15], such as Pinecone, which is a cloud-based paid vector store platform, and FAISS which is a free but temporary memory base. Furthermore, the reason for not leveraging any standard relational or no-SQL database was to smoothen the semantic similarity search function of the system that entirely depends on vector search techniques [16]. Therefore, using a database structure specialized for this purpose was a self-evident choice.

4) Prompt Management Module: The pre-defined prompt templates within the Retriever module of the LangChain framework were further fine-tuned to match the domain and the context of the proposed system. The final prompt generated through this module plays a vital role in ensuring the accuracy and relevance of the system output. Therefore, the fine-tuning of the default template was needed to carry the user question along with the semantically matched chunk of the custom knowledge selected from the vector store.

5) Natural Language Processing (NLP) Module: The final step of the coding process was to generate the output of the system in natural language. This is where an external Large Language Model (LLM) – google/flan-t5-XXL was used. This enabled the system to detach from focusing on pure NLP tasks such as text classification, named entity recognition (NER), part-of-speech (POS) tagging, information extraction, and text generation. The chosen LLM handled all these tasks since it is pre-trained for these tasks on a massive dataset from Google Inc. Hence, trying to facilitate the mentioned tasks within this system itself would not have been fruitful considering the limited time, cost, and resources as well as the solution scope of this study. Thus, the system passes the prompt generated using the prompt management module to this top-ranked LLM, which then generates a text-based output to match the question and context given in the prompt. The generated text is returned as the output of the chatbot to the student.

C. *Evaluation procedure*

Once the development phase was completed, the next step was to evaluate the system to assess its performance in addressing the targeted problem. The evaluations were conducted to test the system's qualitative performance metrics, such as response accuracy, personalization, ease of maintenance, and conversational memory retention, compared to similar existing solutions which use various other approaches and technologies. A range of test cases was carefully designed to assess multiple functionalities of the chatbot-based advising system, including its ability to provide accurate responses, understand user queries and handle different conversational contexts. The evaluation procedure consisted of the following steps:

- Test Case Preparation: A comprehensive test plan was prepared to include all the possible test cases identified concerning the system's priority use case: academic advising with custom knowledge. The test cases were prepared to assess the system’s functional aspects catering to multiple question categories including long/short questions, incomplete questions, unexpected questions, follow-up questions and incorrectly typed questions.

- Test Case Execution: Each test was executed one by one while providing an applicable input query and recording the generated outputs to assess the system's functional as well as performance metrics which included response accuracy, personalization, memory retention and ease of maintenance aspects.

- Response Evaluation: The data gathered from each test case execution was systematically organized in a spreadsheet to ensure smooth evaluation and analysis. The data included the user queries, actual chatbot responses, the number of text chunks considered for each query, and the number of correct or acceptable responses for each test case. The collected data were then statistically analyzed to extract meaningful insights. In this step, percentages were calculated for the chatbot's tested functional scenarios and the overall system's targeted performance metrics.

IV. RESULTS AND DISCUSSION

In this study, we used a component-based software engineering approach to develop a chatbot-based advising system that leverages Large Language Models (LLMs) for Natural Language Understanding and Vector Search Techniques for querying a custom knowledge base created out of available data in the form of PDF documents. These PDF documents mainly consisted of the standard guidelines, instructions, and policies the students must comply with to achieve proper course completion and successful career placements. The underlying premise was to gain a deeper understanding of how these advanced technologies can assist in enhancing the efficiency of academic advising services while addressing the identified problem of an imbalanced instructor-to-student ratio.

This study evaluated the functionality of a prototyped chatbot through a series of meticulously designed test cases, which simulated real-world user interactions. These test cases covered the chatbot's capability to handle various question types and conversational aspects.

- Response Accuracy: The system showcased high accuracy in generating responses to user queries in all test cases. That is, the chatbot performed significantly well in answering a spectrum of question types, resulting in an astonishing overall success rate of 89% for the simulated conversations.

- Personalization: The system showed a personalization rate of 85.29% based on the year and level of study selected by the student before entering the query. That is, the system generated the response by retrieving the custom knowledge applicable to the selected year and level of study and not the entire knowledge base. However, there is room for further improvements in this aspect, where the system could be connected to a user profile to understand the student's GPA, preferred course modules, level of English knowledge and tailor the output based on those identified demographics.

- Ease of Maintenance: The system's maintenance of the custom knowledge base was found to be highly efficient, with an average processing time of 157.83 seconds to handle a substantial volume of documents and generate the custom knowledge base. The system performed well in retrieving information from a vast knowledge base created with more than ten PDF documents of guidelines, handbooks, and instruction manuals, each containing around twenty to thirty-odd pages. Even when new documents were added to the knowledge base, it was able to properly handle the vector search and provide accurate, up-to-date information.

- Conversational Memory: The results showcased a conversational memory retention rate of 82.61% proving that the system was able to understand the context of the question with relevance to the previous queries of the user and provide relevant, coherent answers. However, the memory was only limited to one session of the user's conversation. Thus, this area can be further improved by implementing a mechanism to retain the past conversations of the user beyond a session time.

V. CONCLUSION

This study discusses designing, developing and evaluating a chatbot-based advising system for the higher education sector, focusing on a defined scope of prescriptive advising. Although the literature evidently shows a few automated academic advising systems using conversational agents, there were a few noticeable drawbacks, such as a lack of personalization, high maintenance, and lack of conversational memory. And so, to address these shortcomings, this study proposed, developed, and evaluated a chatbot-based academic advising system that uses a component-based software engineering approach with multiple pre-built components to fulfil each key aspect of the overall system. The driving concept of the system was a custom knowledge base connected to an open-source Large Language Model to generate accurate advice in the natural language: English. The prototype system was developed as a web application, and the results showed promising outcomes, rendering the system a highly dependable and efficient tool for higher educational institutes (HEIs).

This study holds significant implications for the field of education and advising systems, as no other automated academic advising system utilized Large Language Models, vector databases and semantic similarity techniques for improved efficiency. Therefore, the prototype development of the system serves as a valuable contribution that showcases the practical application of integrating pre-built and pre-trained components for higher accuracy of natural language understanding in Artificial Intelligence (AI) and Machine Learning (ML) applications. Furthermore, the proposed system was superior in processing highly complex queries compared to similar AI-based chatbots developed using various other approaches and standard rule-based chatbots with limited intent-response structures. This indeed emphasizes this approach's potential in future related research work.

VI. FUTURE WORK

While the study has achieved its objectives, it is essential to acknowledge certain limitations which open doors for future work to expand on the approach proposed in this study.

- Conducting user-centric evaluation to gain insights into user expectations and experiences when interacting with the academic advising system.

- Integrating with other institutional systems, such as the learning management system and student information system, to allow further personalized advice for the students.

- Refining the implementation approach from a web-based app to a mobile app or social media integrated platform to enhance system accessibility.

Along with these recommendations for future research endeavours, the targeted research field can further advance the development and implementation of the component-driven chatbot-based advising system leading to improved user experience and streamlined academic advising process across higher educational institutes.

ACKNOWLEDGMENTS

The authors would like to express sincere gratitude to several individuals whose support was instrumental in the completion of this research.

Dr. Gamini Wijayarathna and Dr. Laalitha Liyanage: Senior Lecturers in charge of related course modules within the Software Systems Pathway at the Faculty of Computing and Technology, University of Kelaniya, provided invaluable suggestions, guidance, and constant support throughout the research completion journey. Their understanding, patience, and motivation are deeply appreciated for navigating the highs and lows of this endeavor.

Undergraduates at Faculty of Computing and Technology, University of Kelaniya: Initial requirements gathering was facilitated by a majority of supportive undergraduates, whose collaboration helped direct the research path.

Workplace Colleagues: Heartiest gratitude is extended to all colleagues at the authors' workplace for their understanding and continuous encouragement throughout the research journey.

The author is grateful for the contributions of all individuals mentioned above. Their support was essential in bringing this research to completion.

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