Intelligent Admission Guidance for Higher Education: AI-Powered Chatbot

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ABSTRACT

Artificial Intelligence (AI) is a rapidly advancing field that enables machines to perform tasks requiring human intelligence. In today's fast-paced and competitive world, students often1 struggle to find accurate academic and career guidance. Many students face challenges when making decisions about their education, often due to limited access to career counsellors, a lack of awareness about available opportunities, and confusion about career paths. Traditional guidance methods can be time-consuming, generalized, and not always accessible to everyone.To address this, we developed a chatbot that helps students with the higher education admission process. Using Natural Language Processing (NLP) and machine learning, it provides quick and personalized support, making it easier for students to get the information they need.To measure its effectiveness, we conducted a usability study where students shared their feedback through a questionnaire and a decision matrix. The results were encouraging—the chatbot received an 87.3% usability score and a 96% accuracy score, showing that it simplifies the admission process and offers reliable academic guidance.

Keywords: AI, Chatbot, Higher Education, Natural Language Processing (NLP), Machine Learning, Academic Guidance.

1. INTRODUCTION

A chatbot is a computer program designed to simulate human conversation, either through text or speech. These intelligent systems assist users by answering questions, providing recommendations, and automating responses. They are widely used across industries such as customer service, healthcare, e-commerce, and education to improve accessibility, streamline processes, and reduce manual effort.Chatbots operate using artificial intelligence (AI), which enables machines to learn, solve problems, and make decisions. AI is generally categorized into three types: super AI, a theoretical concept that surpasses human intelligence; general AI, which mimics human cognitive abilities; and narrow AI, which is designed for specific tasks.A key part of AI is Machine Learning (ML), which helps chatbots improve over time by recognizing patterns and learning from data. ML techniques include supervised learning (trained on labeled data), unsupervised learning (finding patterns in unstructured data), and reinforcement learning (learning through trial and error). These methods help chatbots deliver more accurate and adaptive responses.Another essential technology behind chatbots is Natural Language Processing (NLP), which enables them to understand, interpret, and generate human language.

2. RELATED WORK

Abu Shawar and Atwell (2007) analyzed ALICE/AIML rule-based chatbots in education, identifying challenges in scalability and multilingual support. They highlighted the need for advanced AI and NLP models to overcome these limitations. This study utilized ALICE/AIML-based rule-based chatbots that rely on pattern matching to generate responses. While this technology allows for structured interactions, it lacks scalability and struggles with multilingual support. Additionally, it fails to adapt to dynamic conversations, making interactions feel repetitive and mechanical. [1]. Similarly, Molnár and Szűts (2018) explored chatbots' role in assisting students but noted their dependence on predefined responses, stressing the importance of AI integration for better contextual understanding. The research explored predefined rule-based chatbots integrated with basic AI to assist students. Although these chatbots provide quick and structured responses, they are heavily dependent on predefined scripts, limiting their ability to understand complex or contextual queries. The lack of true AI-driven learning also restricts their adaptability in handling diverse student needs. [2]. Tiwari et al. (2017) developed a chatbot for college-related queries but emphasized the necessity of real-time API and database updates to enhance adaptability. This study focused on an AI chatbot designed for handling college-related queries, with database integration for storing and retrieving information. However, the chatbot requires real-time API updates to ensure adaptability and relevance. Furthermore, it struggles with learning from past interactions and often fails to respond effectively to unexpected or unique queries. [3]. Gbenga et al. (2020) created an IBM Watson-powered university admissions chatbot, achieving 95.9% accuracy, and underscored the need for continuous dataset updates to maintain efficiency. The chatbot in this study was developed using IBM Watson AI and evaluated with Botium for performance testing. While it achieved a 95.9% accuracy rate in responding to university admission inquiries, it requires continuous dataset updates to maintain its effectiveness. The system also struggles with complex, non-standard queries, requiring human intervention in certain cases, and demands high maintenance [4]. Joseph et al. (2016) addressed the challenges of NLP in multilingual chatbots, advocating for deep learning models like BERT to improve language understanding. This research focused on NLP-based chatbots utilizing machine translation, tokenization, and sentiment analysis for improved language understanding. However, the technology requires significant computational power, making it less accessible for resource-limited environments. Additionally, these chatbots struggle with multilingual interactions and complex sentence structures, leading to misinterpretations in conversations. [5]. Smutny and Schreiberova (2020) examined Facebook Messenger chatbots and highlighted the importance of AI-driven adaptability for more dynamic interactions. The study examined AI-driven chatbots integrated with Facebook Messenger to support educational activities. While these chatbots enhance accessibility, they face challenges in handling open-ended questions and reasoning-based inquiries. Another key limitation is their restricted adaptability, as they require continuous AI integration to improve dynamic and personalized interactions. [6]. Aloqayli and Abdelhafez (2023) developed a chatbot with 91% accuracy for admissions but stressed the significance of automated updates for maintaining accuracy over time. This research focused on an AI-powered chatbot designed for university admissions, achieving a 91% accuracy rate in responding to student inquiries. However, the chatbot relies on frequent updates to maintain accuracy over time. Additionally, it struggles to handle unique or evolving admission-related queries, requiring manual intervention for certain responses. [7]. Adamopoulou and Moussiades (2020) recommended incorporating sentiment analysis and contextual AI to enhance chatbot precision The study proposed AI chatbots enhanced with sentiment analysis and contextual AI to improve response precision. Moreover, they demand high computational resources and require continuous improvements to balance automation with human-like interaction. [8]. Kingchang et al. (2024) introduced an educational chatbot with an 86.15% success rate in guiding students but pointed out the need for better scalability to support broader applications. This research introduced an AI-based chatbot leveraging machine learning to provide educational recommendations. While the chatbot demonstrated an 86.15% success rate in guiding students, it faces significant scalability issues. It also requires extensive training data to generate personalized recommendations, and its ability to adapt to diverse educational needs remains limited. [9].

3. RESEARCH METHODLOGY

3.1 Chatbot Algorithm

The chatbot utilizes a hybrid AI model that integrates Naïve Bayes for intent classification and BERT for contextual understanding. Naïve Bayes is an efficient algorithm for text classification, allowing the chatbot to quickly identify user intents. Meanwhile, BERT enhances comprehension by analyzing text bidirectionally, capturing deeper context and meaning. This combination significantly improves the chatbot's accuracy, especially in multilingual interactions, ensuring more precise and natural responses.

3.2 Query Matching

BERT uses deep learning to understand user input more accurately than traditional keyword-based methods. Unlike simple pattern matching, BERT processes sentences in both directions, allowing it to grasp the full meaning of a query. This makes it especially effective in multilingual conversations, helping chatbots accurately identify and categorize user questions.

The chatbot follows a structured process to analyze and respond to queries effectively. First, it breaks down the input into smaller parts, such as words or subwords, through a process called tokenization, allowing for better analysis. Then, it examines how words relate to each other within the sentence using BERT, ensuring a deeper contextual understanding of the query. Once the context is clear, the chatbot classifies the intent behind the message, whether it's an admission inquiry or another type of request. Finally, based on the identified intent, it generates a relevant and helpful response, ensuring a smooth and meaningful interaction.

Example queries in English and Tamil:

- "How can I apply for admission?" → Intent: Admission Inquiry → Response: "You can apply through our online portal."

- "நான் சேரக் ்கக பற்றிய தகவலுக்கு எங்கு சேல்ல சவண்டும்?" → Intent: Admission Inquiry → Response: "நீங்கள் இகணயதளம் மூலம் விண்ணப்பிக்கலாம்."

3.3 Chatbot Evaluation

To evaluate the chatbot's performance, two key methods are used: the Chatbot Usability Questionnaire (CUQ) and the Confusion Matrix.The CUQ measures user satisfaction by gathering feedback through a structured survey. It assesses factors like response accuracy, relevance, and overall user engagement. The goal is to achieve an 87.15% satisfaction rate. After collecting responses, user testing and data analysis are conducted to identify areas for improvement.The Confusion Matrix helps determine the chatbot's accuracy by comparing its predicted responses with actual user inputs. This method involves preparing data, training the chatbot using Naïve Bayes and BERT, and evaluating its performance using accuracy, precision, recall, and F1-score. The target is to reach 96% accuracy, ensuring that the chatbot provides reliable and effective responses.

3.4 CUQ Calculation

The chatbot's effectiveness was assessed through a usability questionnaire and a decision matrix, which resulted in an 87.3% usability score and a 96% fidelity score. These results highlight the chatbot's accuracy and reliability in guiding students through the admissions process and addressing academic inquiries.

The CUQ score was determined using the following formula:

$$\mathrm{CUQ} = \left(\sum \frac{(\mathrm{Xi} - 1)}{\mathrm{N}}\right) \times 25 \tag{3.4}$$

where X_i represents the score for each question, and N is the total number of questions (16). The final score is normalized to 100 for usability comparison.This evaluation confirms the chatbot's effectiveness in handling multilingual admission queries in both English and Tamil, making the admission process more accessible and user-friendly for prospective students.

3.5 Confusion Matrix

The Confusion Matrix assesses the chatbot's accuracy by comparing actual user queries with the chatbot's predicted classifications. It includes four key components:

- True Positive (TP): Correctly classified as positive.
- True Negative (TN): Correctly classified as negative.
- False Positive (FP): Incorrectly classified as positive.
- False Negative (FN): Incorrectly classified as negative.

The chatbot's performance was assessed using Precision, Recall, Accuracy, and F-Score, calculated as follows:

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \times 100\% \tag{3.5.1}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \times 100\% \tag{3.5.2}$$

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \times 100\% \tag{3.5.3}$$

$$\mathrm{F} - \mathrm{Score} = 2 \times \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{3.5.4}$$

The chatbot achieved an accuracy of 96%, showcasing its reliability in correctly classifying user queries. This result is consistent with the findings of Gbenga et al. (2020), whose IBM Watson-based chatbot achieved 95.9% accuracy in query classification. These results reinforce the effectiveness of AI-driven models in providing accurate and efficient support for university admissions.

4. IMPLEMENTATION

4.1 Data Collection and Preprocessing

The chatbot's dataset is built from admission-related queries, sourced from university FAQs, student inquiries, and academic handbooks to ensure comprehensive coverage and To improve accuracy and performance, the data undergoes several preprocessing steps, including Data Cleaning, Tokenization & Lemmatization, Intent Classification, Data Augmentation.

4.2 Chatbot Design

The chatbot was designed with several key components to ensure a smooth and intelligent user experience. It features a web-based and mobile-friendly user interface (UI), making it accessible across different devices. At its core, the NLP engine, powered by spaCy and BERT, enables advanced language processing for accurate understanding. To interpret user queries effectively, a deep learning-based intent recognition module maps questions to relevant categories. The chatbot then generates responses either through AI-driven processing or predefined templates, ensuring quick and meaningful replies. Additionally, a real-time database management system stores user interactions, allowing the chatbot to learn and improve over time. To keep information upto-date, the system is integrated with university portals and scholarship databases, providing users with live updates on admissions, courses, and financial aid opportunities.

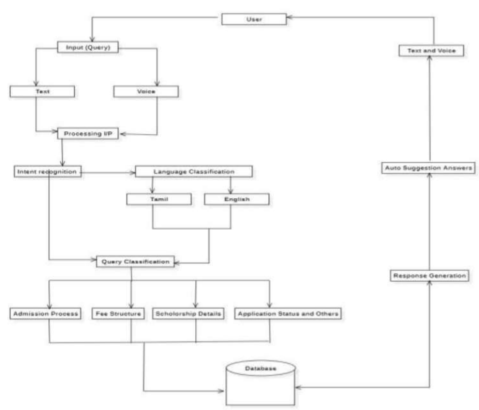

Figure 4.2. Chatbot system workflow

4.3 Chatbot Evaluation Metrics

The chatbot was assessed using:

1. Chatbot Usability Questionnaire (CUQ): A survey measuring user satisfaction and system efficiency.

    o CUQ Score: 87.3%

2. Confusion Matrix: Evaluates classification accuracy based on:

    o True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN) o Accuracy: 96%

3. Decision Matrix Analysis: Determines the reliability of chatbot responses.

5. PERFORMANCE EVALUATION

The chatbot demonstrated high accuracy and usability, making interactions smooth and efficient. It received a CUQ score of 87.3%, reflecting strong user satisfaction, while its fidelity score of 96% confirmed the reliability of its responses. Additionally, it effectively processed real-time queries related to admissions, scholarships, and eligibility, seamlessly handling conversations in both English and Tamil. These results highlight the chatbot's ability to simplify the university admission process, reduce administrative workload, and improve accessibility through its multilingual support, making it a valuable tool for students and institutions alike.

6. CONCLUSION

This study introduced an AI-powered chatbot to assist students with university admissions and scholarships by providing quick, accurate responses. Using machine learning and NLP, it ensures smooth interactions and improves over time. Supporting both English and Tamil, it makes information more accessible.Evaluated with the Chatbot Usability Questionnaire (CUQ) and a decision matrix, it scored 87.3% for usability and 96% for accuracy, proving its reliability. A confusion matrix analysis showed minimal errors, reducing university staff workload. Compared to other chatbots, this model stands out for its accuracy, ease of use, and adaptability, making the admission process simpler and more efficient for students.

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