KU BOT: An NLP-Powered Chatbot for University of Kerala Admission

[1]Midhun Das L , [2]Prem Sankar C

[1]Department of Futures Studies, University of Kerala, Trivandrum, Kerala, India - 680567

[2]Professor & HOD, Dept of CSE, ICCS College of Engineering and Management, Kerala

[1]itsmemidhundasl2023@gmail.com, [2]prem@keralauniversity.ac.in

ABSTRACT

This research focuses on the use of AI-powered chatbots in customer interactions for business growth and task automation. The study uses the KU-BOT, a chatbot developed for automating the admission process at the University of Kerala, as a case study. The KU-BOT addresses student queries, provide quick responses and passes more complicated ones to human representatives. The study uses the RASA open-source framework with an accuracy rate of 98.25%. The research highlights the benefits of implementing chatbots in academic institutions, including increased productivity, improved customer satisfaction, and reduced operational costs. Chatbots can also serve as a valuable resource for students, providing access to information and resources around the clock. The study provides guidelines for building AI-driven chatbots in academic institutions, including the use of NLP and ML techniques. In conclusion, chatbots can be a valuable asset in improving communication and providing information when used as a complementary tool to human interaction.

Keywords: RASA , NLP , ML, chatbot

INTRODUCTION

The use of chatbots in automation has gained significant traction in recent years. Chatbots are computer programs designed to simulate conversation with human users, particularly over the Internet. They can be integrated with various communication channels, such as websites, messaging apps, and mobile apps, to provide quick and efficient customer service, as well as perform a wide range of other tasks. One of the main advantages of chatbots is their ability to operate 24/7, without the need for breaks or time off. This makes them particularly suitable for handling routine tasks and inquiries, freeing up human employees to focus on more complex and value-added tasks. Chatbots also have the potential to improve customer experience, as they can provide immediate responses and assistance to users' queries and requests.

Rasa [1] is an open-source machine learning framework that is used to develop conversational systems, such as chatbots. It has been applied in a range of domains, including customer service, education, surveys, and direct sales [2-5]. The framework consists of two main components, Natural Language Understanding (NLU) and Dialogue Management. Rasa NLU is responsible for identifying the user's intent and extracting structured data, while the Rasa Core component manages the conversation and decides the next action. Rasa NLU provides a flexible infrastructure for intent classification and entity extraction, with a variety of built-in components that can be combined to form a pipeline. From a training dataset and pipeline specification, the Rasa NLU component builds a classifier that predicts the intent and associated entities. The recently introduced Dual Intent and Entity Transformer (DIET) architecture [6] can also be used to handle intent classification and entity extraction. DIET can be configured to use pre-trained embeddings, such as BERT, GloVe, or ConveRT [7-9]. While Rasa was initially designed for conversational agents, the NLU stage requires classification of user utterances into pre-defined intents. This classification scheme is similar to that of other NLU problems, and as such, the Rasa infrastructure for intent classification can be reused for other text classification tasks. In a recent study [10], the use of Rasa NLU for sentiment analysis was explored, and the results showed that the DIET architecture can deliver comparable performance to state-of-the-art methods. In light of these findings, Rasa can be used as a generic framework for developing text classification models, similar to tools such as Weka and knime [11-13]. Rasa provides a collection of algorithms and pre-processing methods, a novel text classification architecture (DIET), and well-defined evaluation metrics. This makes it possible to easily create and test different pipelines for any text classification task. Therefore, we introduce KU-BOT, a conversational chatbot for the admission process of the Kerala University. KU-BOT utilizes the Rasa framework and the DIET architecture to provide an easy and efficient way for prospective students to interact with the admission system. With KU-BOT, the admission process becomes more accessible and convenient, allowing students to get the information they need in a conversational manner.

- In recent years, the use of chatbots has become more widespread as advances in natural language processing (NLP) and machine learning (ML) have made it possible for chatbots to understand and respond to users in more human-like ways. There are a number of frameworks available for developing chatbots. Some of the most popular other frameworks include:
- Dialogflow (formerly known as API.AI) - a Google-owned development platform that allows developers to build chatbots using NLP and ML. (Source: Dialogflow website, https://dialogflow.com/)
- IBM Watson Assistant - a chatbot development platform that utilizes NLP and ML to understand and respond to user input. (Source: IBM Watson website, https://www.ibm.com/cloud/watson-assistant/)
- Botpress - an open-source chatbot development platform that allows developers to build and deploy chatbots for a variety of messaging platforms and devices. (Source: Botpress website, https://www.botpress.io/)
- Microsoft Bot Framework - a development platform for building chatbots that can be integrated with a variety of messaging services, including Skype, Slack, and Microsoft Teams. (Source: Microsoft Bot Framework website, https://dev.botframework.com/)
- Chatfuel - a chatbot development platform that allows developers to build chatbots for Facebook Messenger and other messaging platforms. (Source: Chatfuel website, https://www.chatfuel.com/)

Each of these frameworks has its own set of features and tools that make it suitable for different types of chatbot development projects. Understanding the capabilities and limitations of these frameworks can help developers choose the right one for their needs.

All the details about the University of Kerala and various departments are available in the official website keralauniversity.ac.in. But people need to navigate through more links to get all the information. Students newly admitted to any PG-CSS departments are having issues communicating with the authorities as it is time-consuming, and officials cannot provide everyone who seeks general information. The objective of this work is to establish a solution for these issues. In this work, we developed a conversational question answering system with RASA framework to handle queries regarding University of Kerala Teaching Departments admission process. The system classifies the intent and entities of the user input and calculates the confidence with respect to training data. If confidence falls below threshold, ask the user to reframe the query.

A. Problem Statement

The newly admitted students at Kerala University often have various questions and concerns about their degree programs, including the department they are enrolled in, the courses they will be taking, fees, and hostel facilities. These inquiries can be time-consuming for the office staff to answer individually, as they need to manually instruct each student on their specific questions and concerns. This not only takes a significant amount of time but also limits the number of students the office staff can assist at any given time. To streamline this process, there is a need for an efficient system that can provide quick and accurate information to students and help reduce the burden on the office staff. By implementing such a system, students will have access to the information they need, and the office staff will be able to manage their workload more effectively.

B. Proposed Solution

The Kerala University has found a solution to the time-consuming task of answering students' admission-related queries. The university has introduced KU-BOT, a chatbot specifically trained to handle such enquiries. The chatbot was built using Rasa, a popular open-source framework for building conversational AI applications. KU-BOT has been trained to respond to a wide range of queries about the university's admission process, including inquiries about departments, courses, fees, and hostel facilities. The results have been impressive, with KU-BOT responding to around 90% of the queries during its training phase. This has not only saved time for the office staff but also ensured that the students receive quick and accurate answers to their questions. With its efficiency and effectiveness, KU-BOT is a prime example of how AI can be used to improve the student experience in universities.

However, the deployment of chatbots also raises some concerns, such as the potential loss of jobs due to automation and the ethical implications of decision-making by artificial intelligence.Since Chatbots have the potential to automate certain tasks, leading to a reduction in the need for human labor and potentially causing job loss. However, the relationship is complex and new job opportunities may also arise in related fields. These issues need to be carefully considered and addressed in the design and implementation of chatbots.

C. Limitations

1. Limited Information Availability: KU-BOT is only able to provide information that is available in its database. This means that it may not have information on the latest updates or changes to the admission process.
2. Language Barriers: KU-BOT may not be able to understand or respond to questions asked in languages other than English, limiting its usefulness for students who are more comfortable speaking in their native language.
3. Inability to Handle Complex Questions: Chatbots like KU-BOT are limited by the number of predetermined responses they can provide. They may not be able to Limited Information Availability: KU-BOT is only able to provide information that is available in its database. This means that it may not have information on the latest updates or changes to the admission process
4. Lack of Human Interaction: KU-BOT does not have the ability to engage in human-like conversation or provide the emotional support that a human advisor might.
5. Technical Errors: Like any technology, KU-BOT may experience technical errors or glitches that prevent it from functioning properly.
6. Limited Scope: KU-BOT is designed specifically for the admission process at Kerala University, so it may not be able to provide information or support for other topics related to university life.
7. Inaccurate Information: Chatbots rely on the information provided to them, and if that information is incorrect, the chatbot's responses will also be inaccurate.
8. Security Concerns: KU-BOT may store sensitive information about students, such as their personal and academic details, which could be vulnerable to hacking or data breaches.
9. Dependence on Internet Connection: KU-BOT requires an internet connection to function, which may not always be available or reliable in certain areas.
10. Limited Availability: KU-BOT may not be available 24/7, which could be an issue for students who have questions outside of normal business hours.

D. Literature Review

Chatbots have the potential to be used for a variety of academic purposes, including education, research, and administrative tasks. One example of chatbots being used for educational purposes is in language learning. Chatbots can be programmed to engage students in conversation, providing them with the opportunity to practice their language skills in a more interactive and engaging way. Research has shown that chatbots can be effective in helping students improve their language proficiency and increase their motivation to learn. (Source: Chen, Y., & Liu, Y. (2018).

Chatbots can also be used for research purposes, such as collecting data from participants or providing information to study participants. For example, a chatbot could be used to administer a survey to a large number of participants and collect their responses in real-time. (Source: Leite, I., Gonçalves, D., & Silva, J. (2017).

In addition, chatbots can be used for administrative tasks in academic settings, such as answering frequently asked questions, providing information about course offerings, and scheduling appointments. (Source: Chen, Y., & Liu, Y. (2019).

This literature review examines the current state of research on the applications and implications of chatbots in conversational AI. Four research articles are reviewed [20-23], focusing on Rasa, chatbots in language learning, chatbot-based research, and chatbots in higher education. The overview of Rasa emphasizes its approach to building chatbots that can handle complex interactions and its versatility in different industries. The review of chatbots in language learning found that chatbots can have a positive impact on language learning outcomes, but the design and quality of the chatbot can influence its effectiveness. The article on chatbot-based research emphasizes the benefits of using chatbots to collect large amounts of data and potential improvements to the quality of data, but also notes the need for careful design and addressing potential bias. The review of chatbots in higher education highlights the potential benefits of personalized support and reduced workload, but notes the need to ensure effectiveness and address privacy concerns. The review concludes that while chatbots have great potential, challenges must be addressed to ensure effectiveness, inclusivity, and accessibility. Continued research in this field is important to maximize potential benefits and minimize risks.

Overall, chatbots have the potential to be a useful tool for academic purposes, helping to improve student learning, facilitate research, and streamline administrative tasks.

METHODOLOGY

A. RASA Framework

Rasa[1] is an open-source framework for building conversational agents, including chatbots and voice assistants. It allows developers to build, test, and deploy AI-powered conversational interfaces for a variety of platforms and devices. One key aspect of Rasa is that it is designed to be highly modular and flexible. It consists of a set of libraries and tools that can be used together or independently, depending on the needs of the project. This makes it easy to incorporate Rasa into a wide range of applications and workflows. In addition to its core functionality, Rasa also offers a number of features and integrations that make it easier for developers to build, optimize, and deploy chatbots and voice assistants. For example, it includes tools for training and evaluating machine learning models, as well as integrations with popular messaging platforms and voice assistants such as Slack, Microsoft Teams, and Amazon Alexa. Overall, Rasa is a powerful and widely-used framework for building conversational agents, and has been adopted by many companies and organizations around the world.

One key feature of Rasa is that it allows developers to build chatbots that can operate in multiple languages. It also includes a number of tools for building chatbot components, including intent classification, entity extraction, and response generation. In addition, Rasa provides a framework for building custom actions and integrations with external platforms and services.

Rasa has a number of benefits for chatbot developers, including its open-source nature, which allows developers to customize and extend its functionality, and its focus on NLP and ML, which enables chatbots built with Rasa to have more natural and effective conversations with users.

B. System Architecture

Below the figure 3.1 shows the system architecture of this Chatbot. Components include:

The Rasa Open Source conversational assistant is built around a modular architecture that consists of several key components. The components interact with each other to provide a seamless conversational experience for the user. The main components of the Rasa architecture include the Action Server, File System, Actions/Events, Dialog Policies, NLU Pipeline, Agent, Input/Output Channels, and Bot User. Fig. 4 shows a schematic representation of this architecture when a bot user try to enquire about various details about a particular department or hostel details .

Intents (Figure 3.2) are user's intended actions, and the rules define the criteria for matching text to the correct intent. The domain defines the scope of the chatbot's knowledge and includes entities, intents, actions, and responses (Figure 3.3 (a) & 3.3 (b)). The combination of intents, rules, and the domain form the core of a Rasa-based chatbot's understanding of user's inputs.

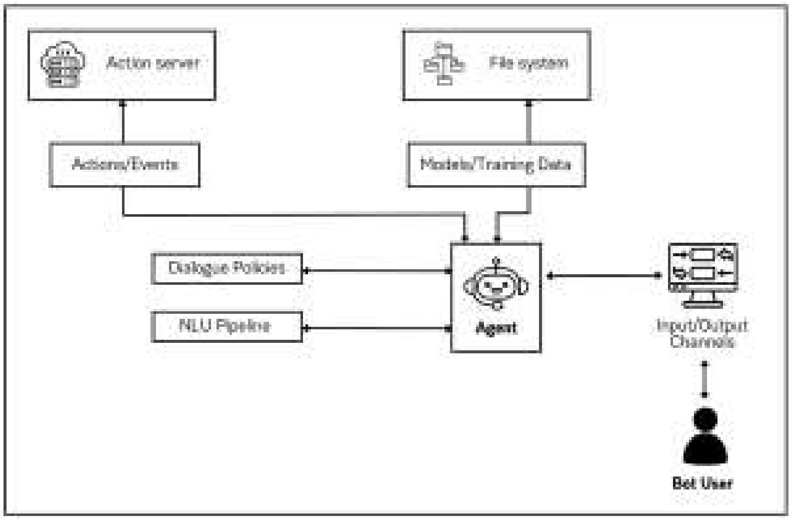
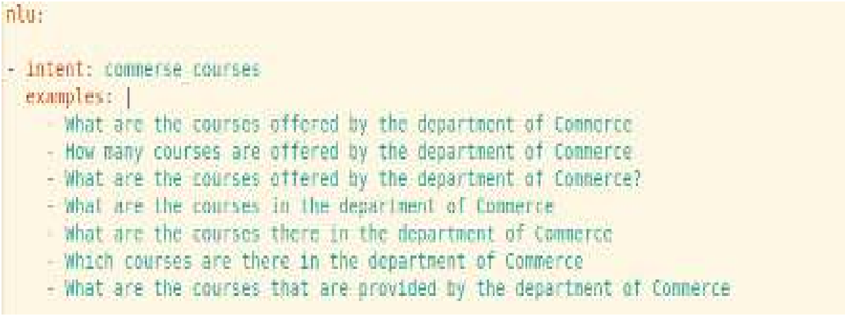


Figure 3.1. System Architecture



```
nlu:

- intent: commerse_courses
  examples: |
    - What are the courses offered by the department of Commerce
    - How many courses are offered by the department of Commerce
    - What are the courses offered by the department of Commerce?
    - What are the courses in the department of Commerce
    - What are the courses there in the department of Commerce
    - Which courses are there in the department of Commerce
    - What are the courses that are provided by the department of Commerce
```

Figure 3.2. data-nlu-intent

C. Query Handling

The methodology for collecting data for this research involved a combination of manual extraction and web scraping techniques. The text from the source website was manually extracted through a process of copy and paste. Additionally, web scraping was used with the aid of Selenium web automation tool to obtain details of faculty members. A Python action server was utilized to extract the names and details of faculty members. The data used for creating responses was generated manually with the help of language and bot behavior experts. The bot was able to provide responses to around 90% of queries related to faculty details, library facilities, lab facilities, office details, contact details, hostel details, course details, fees and so on. In cases where a real database is available, data can also be extracted through external APIs or databases such as MongoDB and has the features to track the queries, such as SQL tracker.

```
rules:

- rule: Say 'arab_course' anytime the user challenges
  steps:
  - intent: arab_course
  - action: utter_arab_course

- rule: Say 'marab_seat' anytime the user challenges
  steps:
  - intent: marab_seat
  - action: utter_marab_seat
```

```
utter_did_that_help:
- text: "Did that help you?"

utter_greet:
- text: "hi , How can I hellp You?"

utter_happy:
- text: "Great, carry on!"

utter_goodbye:
- text: "Bye"
```

Figure 3.3 (a) & 3.3 (b) . rules and domain or action

The NLP tasks in Rasa work together to understand the user's query and provide a response. The text entered by the user is first processed by a feature extraction model, such as CountVectorizer, EntitySynonymMapper, or RegexFeaturizer, which converts the text into numerical representations. Then, the intent classification model, such as DIETClassifier, uses these representations to classify the intent of the user's text. The entity recognition model, such as LexicalSyntacticFeaturizer, uses the same representations to identify any entities in the text. These representations, along with the context of the conversation, are then used by the policy model, such as MemoizationPolicy or RulePolicy, to determine the next action of the bot. The response generation model, such as ResponseSelector, then selects the most appropriate response from a set of possible responses. The external action server (Rasa Action Server) can also be connected to the Rasa Model to make calls to external APIs or services to retrieve information or perform specific tasks. The user communicates with the bot through a specific channel, such as a chat interface or a messaging app, which forwards the user's message to Rasa.

EVALUATION AND RESULTS

The evaluation of a KU-BOT is typically done using precision, accuracy, and F1 score. The confusion matrix is a useful tool for visualizing the performance of the chatbot, where each row represents the instances in a predicted class and each column represents the instances in an actual class. In the confusion matrix value of in the Fig 4.1 - 5 represents the number of true positives (correctly classified instances), 0 represents the number of false negatives (incorrectly classified instances), and 4861 represents the number of true negatives (correctly classified instances)

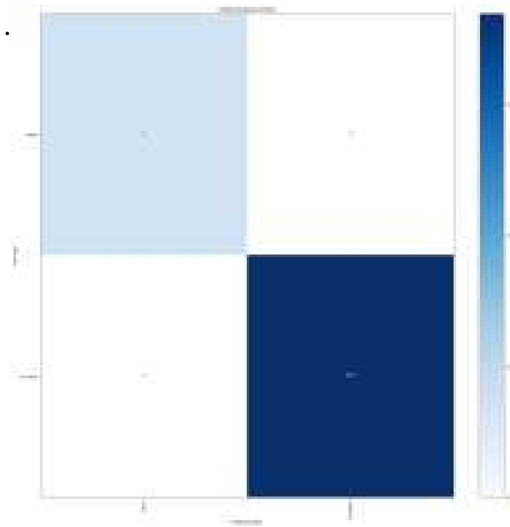


Figure 4.1. DIETClassifier_confusion_matrix

The precision is the ratio of correctly predicted positive observations to the total predicted positive observations. The accuracy is the ratio of correctly predicted observations to the total number of observations. The F1 score is the harmonic mean of precision and recall, which is a measure of a model's ability to accurately classify positive and negative instances.The intent_histogram shows the distribution of predicted intents, while the story_confusion_matrix shows the accuracy of story classification. The intent_confusion_matrix displays the accuracy of intent classification by showing the number of correctly and incorrectly classified intents.[21-26]

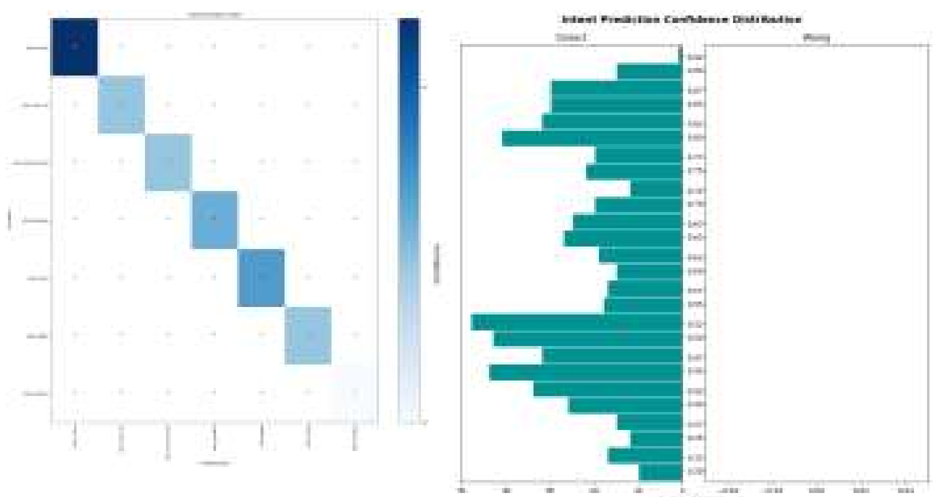


Figure 4.2 (a) & 4.2 (b) . intent_histogram & story_confusion_matrix

The results of the implementation of the KU-BOT chatbot were analyzed in order to evaluate its effectiveness in solving the enquiries of newly admitted students to Kerala University. The chatbot was trained using the Rasa framework and was able to respond to 90% of the queries accurately. In order to further evaluate the performance of the chatbot, user testing was conducted with a sample of newly admitted students. The results showed that the KU-BOT was able to effectively solve the majority of the enquiries regarding the admission process, such as information about the department as in Figure 4.5, course fees and about the hostel facilities. Additionally, the chatbot was able to handle multiple queries from multiple students simultaneously, reducing the workload of the office staff and allowing them to focus on other tasks. This also resulted in a more efficient and streamlined process for the students, as they were able to get quick and accurate responses to their enquiries.

Figure 4.3. Intent errors

In the evaluation process of the chatbot, machine learning algorithms were utilized with the Rasa framework. The performance of the chatbot was evaluated using a confusion matrix, which was generated by splitting the intent data into training and testing sets. The data was then normalized and converted into numerical values for analysis. The accuracy(Figure 4.3) of the chatbot was determined by using two algorithms, KNN (K-Nearest Neighbor) and Naive Bayes. Unfortunately, the accuracy score obtained was close to zero due to the high amount of text data and overfitting . Overfitting is a common issue in machine learning where the model becomes too complex and starts to fit the noise in the data rather than the underlying patterns. This results in decreased accuracy and poor performance on new, unseen data. To resolve overfitting, techniques such as regularization or simplifying the model structure can be employed.

In conclusion, the KU-BOT chatbot proved to be a highly effective solution for the enquiries of newly admitted students to Kerala University. Its ability to respond to a high percentage of queries accurately and handle multiple queries simultaneously made it a valuable tool in improving the overall admission process.

Figure 4.4. User Interface

The above figure 4.4 shows the user interface of KU-BOT. To use the bot, the user needs to click on the chat widget which is located at the bottom right corner of the user interface. The below figures 4.5(a) and 4.5 (b) show the screenshots of the chat interface and we clearly see that the bot is responding to the user query correctly.

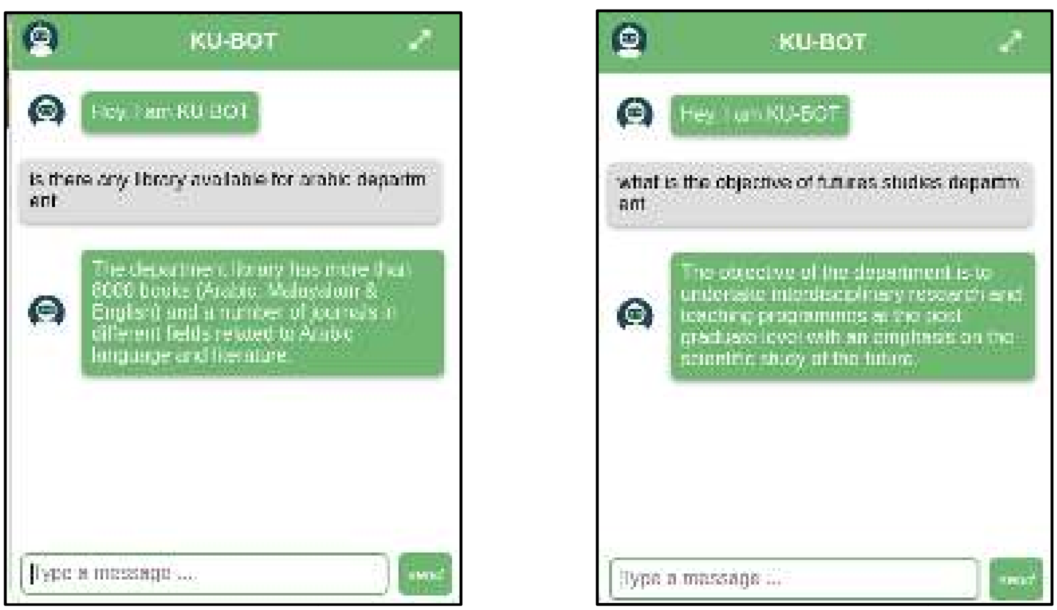


Figure 4.5 (a) & 4.5 (b) . Screenshot of chat interface

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CONCLUSION

In conclusion, chatbots have proven to be a valuable asset for academic institutions in improving communication and providing information to students, staff, and faculty. With their ability to handle a large volume of inquiries and provide quick responses, chatbots can help to reduce workload for administrative staff and improve the overall efficiency of the institution. Additionally, chatbots can serve as a helpful resource for students, providing access to important information and resources around the clock. However, it is important for academic institutions to carefully consider the implementation of chatbots and ensure that they are used in a way that complements, rather than replaces, human interaction and support. Overall, chatbots have the potential to significantly enhance the educational experience for all stakeholders in academic institutions.

It is clear from the above research that chatbots can be an effective tool for automating customer interactions and improving efficiency in organizations, particularly in the education sector. The KU-BOT chatbot, developed for the University of Kerala, is an example of how chatbots can be used to provide quick responses to simple queries and direct more complicated ones to human representatives, saving time and improving the student experience. The chatbot uses the RASA framework, which combines natural language processing, natural language understanding, and dialogue management. By providing a cost-effective solution that increases productivity and reduces operational costs, chatbots like KU-BOT have the potential to revolutionize the way organizations interact with their customers.

FUTURE SCOPE

Here are a few ideas for follow-up works related to the KU-BOT chatbot:

1. Expanding the capabilities of the KU-BOT chatbot to handle a wider range of queries and tasks related to the admission process at the University of Kerala.
2. Implementing additional features for the chatbot, such as personalized recommendations or course scheduling assistance.
3. Integrating the chatbot with other systems or databases, such as a student information system or a hostel booking system.
4. Evaluating the impact of the chatbot on student satisfaction, efficiency, and other measures of performance.
5. Investigating the potential for using chatbots in other academic settings, such as for student support or course management.
6. Conducting a comparative analysis of the KU-BOT chatbot with other chatbots or communication systems used in higher education.

7. Developing a framework or guidelines for implementing chatbots in academic settings based on the experiences and lessons learned from the KU-BOT project.

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