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A Multi-Lingual Conversational AI Chatbot for Effective Educational Consultations: A Study of ACE-DS, University of Rwanda

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ABSTRACT

The demand for real-time consultation services from organizations is increasing, leading to prolonged waiting times, primarily due to limited opportunities for face-to-face interactions and language barriers. This study addresses this challenge by leveraging Artificial Intelligence (AI), Natural Language Processing (NLP), and linguistic technologies to develop a multilingual conversational AI Chabot for managing educational consultation services, using the African Center of Excellence in Data Science (ACE-DS), University of Rwanda, as a case study. Information and frequently asked questions (FAQs) about ACE-DS were used to train a Deep Learning Gated Recurrent Units (GRUs) algorithm to power the Chabot. Language detection and translation APIs were integrated to facilitate seamless multilingual conversations. The result of user survey conducted revealed that over 60% of respondents expressed high satisfaction with the Chabot's performance including grammar, efficiency, language preferences, and response quality. This study showcases the potential of AI particularly NLP in enhancing educational consultation services, providing a framework for efficient information acquisition.

Keywords: Artificial Intelligence (AI) in Education, Deep Learning, Multilingual Chatbot, Conversation AI, Natural Language Processing.

1. INTRODUCTION

The demand for real-time consultation services in various sectors is steadily increasing, especially outside traditional working hours, particularly in educational settings. In the educational sector, the general public, particularly students frequently request diverse types of educational information from their management. However, handling these consultations and requests presents numerous challenges

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for most institutions due to language barriers and shortage of personnel to manage the continuous influx of inquiries. Currently, Conversational AI Chatbots serve as an efficacious solution, having evolved into essential tools that empower organizations to deliver essential services to the public efficiently [6]. A conversational chatbot is essentially a piece of intelligent computer software that mimics human-to-human communication over the internet [2, 9, 15, 17]. A conversational agent chats with people in a particular industry or on a particular topic using sentences input in a single natural language [19]. Chatbots are usually integrated into messaging apps, mobile apps, or websites, and are made to converse with users in natural human language [12]. Artificial Intelligence (AI) chatbot deployment primarily aims to improve non-stop service delivery by organizations, ensuring that clients are attended to effectively, concurrently, without fatigue, day and night, thereby eliminating the problem of queueing [15]. Additionally, a study by [1] confirmed that by providing users with speedy services, chatbots have recently changed the dynamics of customer care services. Hence, Customers' queries or consultations can be addressed independently, efficiently, in real-time and without the need for human intervention [11].

According to [14], chatbots can be categorized into: Text-to-Text bot, Text-to-Speech bot, Speech to Text bot and Speech-to-Speech bot. Each of the categories of the chatbot type is denoted by the type of input data it receives and the type of output data it produces i.e. Text-to-Text bot receives input as text and produces textual output. The Text-to-Text is the most common used chatbot as in the case of this study. It can be implied that some of the reasons for its popularity and accessibility are because of the reasonable demands in terms of resources required for development, the readily available textual data required for training, convenience in terms of use.

A study by [17] utilized Chabot tools such as the IBM Watson Assistant, Tone Analyzer, and Language Translator to create a voice-activated multilingual Chabot that can adapt to users' moods, tones, and languages. Based on survey data from university students created with Google Forms, the chatbot was assessed using a use case designed to address users' concerns about test stress. According to the findings of evaluating the chatbot's efficacy in analyzing responses pertaining to exam stress, 76.5% of users reported that the chatbot accurately responded to their inquiries about how they were feeling about exams. The chatbot’s potential application areas extend beyond the academic setting, and could include government kiosks, student info centers, and mental health support systems [17].

The Health sector is one of the essential areas where AI and NLP have been deployed as conversational tools, particularly in telemedicine. The deployment of conversational chatbot in health services is essential where consultation is imminent but physical contact between patients and clinicians is impeded by the presence of communicable diseases, necessitating virtual interaction. Telemedicine was particularly helpful during the COVID-19 pandemic, it enabling patients to utilize conversational AI-based applications for treatments, obtaining supportive care without physically visiting a hospital [3,17]. This shift towards Telehealth is expected to significantly change in-person care into remote patient consultations [3]. In a related study during the COVID19 pandemic, [20] built an AI chatbot capable of convincingly addressing open-ended questions about COVID-19 with a high degree of accuracy. In order to improve patients' quick access to healthcare information and to take advantage of the capabilities of AI to close the gap between access to healthcare providers, the work of [3] led to the development of a conversational Chabot system called "Aapka Chikitsak" on Google Cloud Platform (GCP) for telehealth provisioning in India. To provide timely care and high-quality treatment, these conversational applications have successfully lowered the obstacles to accessing healthcare-related services and facilities, and secured intelligent consultations remotely.

A study by [4] pointed out that using chatbots to inform patients about their health, medications, and other health-related issues could have significant ramifications in sectors like healthcare. Thus, chatbots are essential in situations where there are few opportunities for face-to-face interactions with medical professionals or there is a work overload as this can be done in an interactive way similar to the way patients and health professionals typically communicate in a typical interaction.

A study by [10] posits that the visceral communication and feelings which a client experience while receiving a service via the use of conversational agent is more important than the quality of the services provided and should, therefore, be prioritized. The study emphasizes that human satisfaction is essentially derived from the fulfilment of emotions. This viewpoint is in congruence with inferences derived from the work of [3] who outlined that one of the key lapses in the virtual medical AI assistant is the absence of empathy and a visceral connection between patients and the artificial agent. A crucial component of customer care systems is client satisfaction, and such systems must act courteously when responding to user requests, queries, and demands [6]. According to [7], one of the ways to resolve the problem of empathy is to accrue data from a highly interactive social networking platforms such as Twitter and Facebook, that constitutes all sorts of interactions, objective, sentimental, emotional, courteous and generic responses between users and or customer care agents.

In most contemporary AI-driven dialogue chatbot systems, the languages options are often limited, mostly in a range of 1 to 5 languages as a study by [21] affirmed that current dialogue systems, such as Amazon Alexa and Google Assistant, commonly interact with human users in a single language, which restricts the usage of these systems to conducting situated dialogues that require visual awareness or communicating with users proficient in different languages. While some chatbots also offer multilingual functionality, most chatbots are created with the English language in mind. Google Translate, for example, supports 103 languages, which is more than any other multilingual agent [13]. Hence, recent advances in AI have made provisions for multiple language implementation capabilities in Conversational AI chatbot systems which combine computational intelligence, linguistics, and computer science in their capabilities.

Another communication barrier between these systems and users is limited to written and oral forms, thereby excluding other users such as the deaf and dumb who essentially use sign language. The work of [21] addressed this issue by exploring the possibility of creating a system that interacts using visual, sign, oral, and written language. The proposed solution by [21] investigates ways to make it easier for an agent to link speech and vision to actions in a conversational setting. Additionally, to train task-oriented visual conversation systems, [21] suggested an alternate learning method that combines supervised learning with reinforcement learning algorithms to achieve a better balance between dialogue response quality and policy efficacy.

The literature evaluated thus far revealed that only little study was found on how a user's linguistic background affects their engagement with multilingual chatbots systems which can be inferred that there is no scientific evidence to support the notion that a user's level of fluency in a given language would influence how well they engage with a chatbot that uses that language. Additionally, in contemporary chatbot solutions, the range of languages available for interaction and consultation between the client and the system is typically in the range of 1 – 5 and also, it is often built based on dominant languages such as English, French, Spanish, Chinese, and German. Remote languages in Africa such as Kinyarwanda, Hausa, Igbo, Swahili, etc. are not available for communication.

The solution provided in this study targets the African Center of Excellence in Data Science (ACE-DS), University of Rwanda (UR) which is plagued with challenges where prospective students or international students, in particular, find it difficult to make consultations or obtain suitable information about studying at ACE-DS. The developed multilingual conversational AI system (Chatbot) is the ideal solution to adopt because it is essentially an automated AI system that utilizes a machine learning (ML), particularly deep learning algorithm, and language detection and translation technologies in its innovations. This enables the system to understand client queries/intents and attend to a large number of users simultaneously in a cross-language conversation, enhancing efficiency and client satisfaction. The system supports communication in up to 100 languages, allowing users to converse in languages they are comfortable and fluent in, including English, Swahili, Hausa, Igbo, Yoruba, Kinyarwanda amongst others.

2. METHODOLOGY

A combination of deep learning (GRUs) algorithm, natural language processing (NLP) techniques, alongside language detection and translation mechanisms using Lang Detect and Google Translator APIs, were employed to develop the multilingual AI chatbot in this study. The operation of the chatbot is divided into two distinct parts: The user query AI bot and the language detection and translation mechanisms. The software application was built using Python 3.9 on Flask Python Framework. The Gated Recurrent Units (GRUs) deep learning algorithm for the chatbot development was implemented on the PyTorch deep learning framework.

The research design used for this study is Action Research and in the context of this study, the key components as defined by [5] are outlined below as pertains to the implementation of the Multi-Lingual Conversational AI Chatbot.

Business Understanding

In this study, understanding the particular needs of ACE-DS at the University of Rwanda, as well as the difficulties it has with regard to information acquisition by the general public or visitors within the educational sector is crucial.

Data Understanding

The suitable type of data relevant to training the Chatbot ML model for this study can be categorized into the following:

a) ***Knowledge data*** – knowledge data are key domain-specific information that educates the general public on a subject matter or about organizational or industry services, it provides guidelines or instructions on solving a problem or certain information. Knowledge data typically comprises Frequently Asked Questions (FAQs) submitted by clients or employees in addressing issues, e.g. program information, scholarships, internships, study fees, registration processes, admission, accommodation, events, training facilities, campus clubs, sports and so on as it pertains to this study.
b) ***Conversational data*** – Conversational data are basically data that could be obtained from interactions between two or more parties, and can be obtained from a variety of sources, including real-life chat logs, phone calls conversations, customer service contacts, social media conversations, and even manually generated conversations, or publicly available datasets specifically designed for the purpose of chatbot training. This data is used to train and improve the chatbot's NLP capabilities, and importantly, allow the chatbot to understand user queries and predict appropriate responses.
c) ***Sentiment data*** – Sentiment data refers to information that captures the emotional tone expressed by users during interactions with artificial agents, e.g. with the chatbot system. It involves analyzing the sentiment of user inputs, to understand the user's mood, i.e. if they are positive, negative, or neutral at a moment. This data can help in assessing user satisfaction and understanding the effectiveness of the chatbot's responses. In this research, open-source

sentiment data from Kaggle was used together with other data to train a machine-learning model for the purpose of improving the chatbot's performance, identifying areas for enhancement, and ensuring better user and system engagement and satisfaction.

d) ***Annotated data*** – This data typically includes annotations where the data has been labelled manually or automatically for easy recognition by a program or machine learning algorithm. In this context, the data used in this study have been annotated into categories or topics such as establishment, admission, scholarships, programs, why study at ACE-DS and so on.

Data Collection Methods

The data used in this research consists of both primary and secondary data. The primary data includes FAQs and information about ACE-DS, University of Rwanda. The secondary data, on the other hand, comprises conversation and sentiment data from open source Chatbot dataset available on Kaggle.

Data Preparation

The phases in the data preparation are captured in the presentation in Figure 2.3 below. The dataset for the study was preprocessed using natural language preprocessing tool kits(nltk) Python package. These includes sentence tokenization; word lemmatization; and the creation of bag of words which are essential NLP data preprocessing techniques for the purpose of chatbot model training.

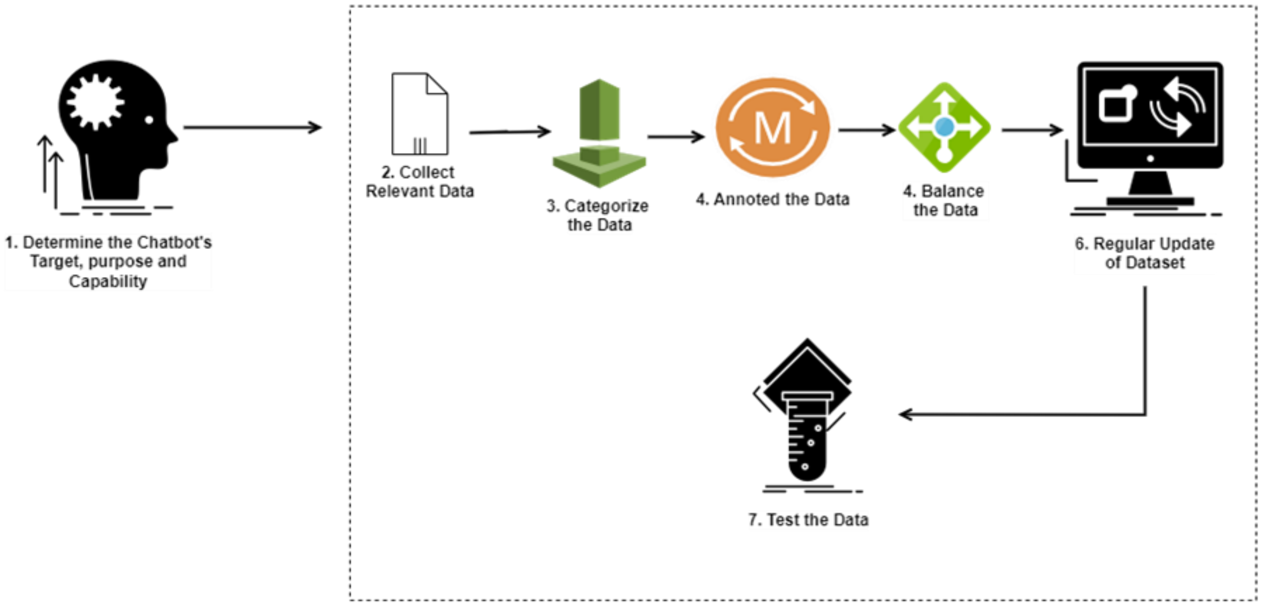

Figure 2.3: Data Preparation Diagram

Modeling

The Model configuration makes use of Gated Recurrent Units (GRUs), an advanced kind of RNN architecture that has LSTMs features and in addition, has information flow controlling gating techniques that makes them computationally more efficient than LSTMs and still capture the long-term dependencies in LSTMs architecture. The following were taken into consideration in training the GRU Recurrent Neural Network model for this study:

i. Problem Definition
ii. Data Preprocessing
iii. Network Architecture
iv. Activation Function (Rectified Linear Unit-ReLU)

v. Training Algorithm
vi. Training Process:
vii. Optimization and Fine-Tuning

The model was configured, trained, and fine-tuned on a local personal computer (PC). The model achieved optimal accuracy after 1500 epochs, with a batch size of 8, and a learning rate of 0.00134. The model achieved a training accuracy of 98%, and weighted average precision, recall and f1-score of 98%, 98%, 98% respectively.

Deployment Architecture

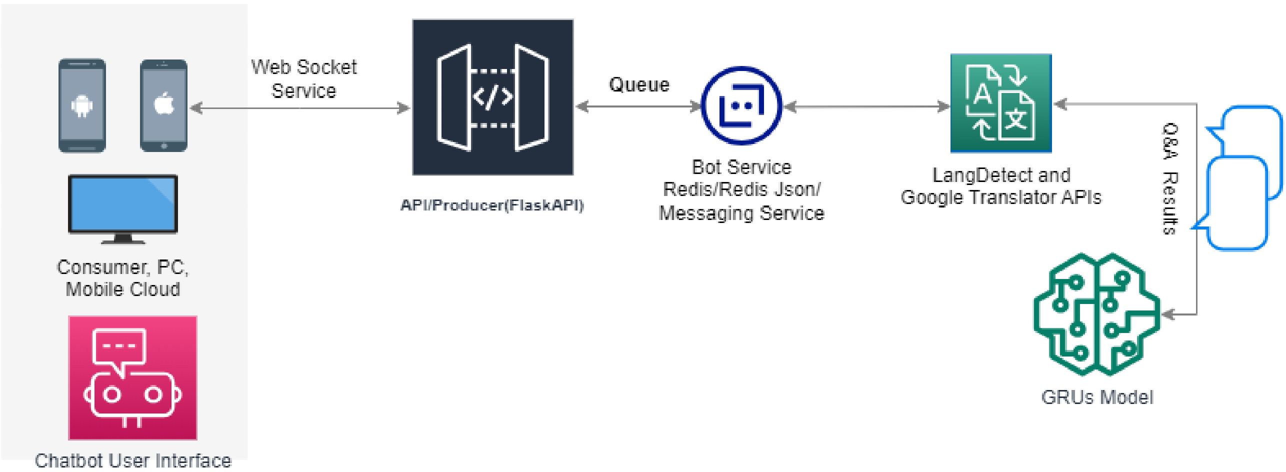

Figure 2.4: The Deployment Architecture of the Multi-lingual AI Chatbot Solution

The diagram in Figure 2.4 above illustrates the deployment architecture of the chatbot system. From the presentation Language detection and Translation APIs (LangDetect and Google translator) were utilized to detect user's queries' s language and target language, and translate the queries and pieces of information processed into target languages, thereby facilitating the multilingual conversation process.

3. RESULT DISCUSSIONS AND EVALUATION

The characteristic and outcome of the user interface (UI) of the chatbot application when launched is presented in Figure 3.1 below.

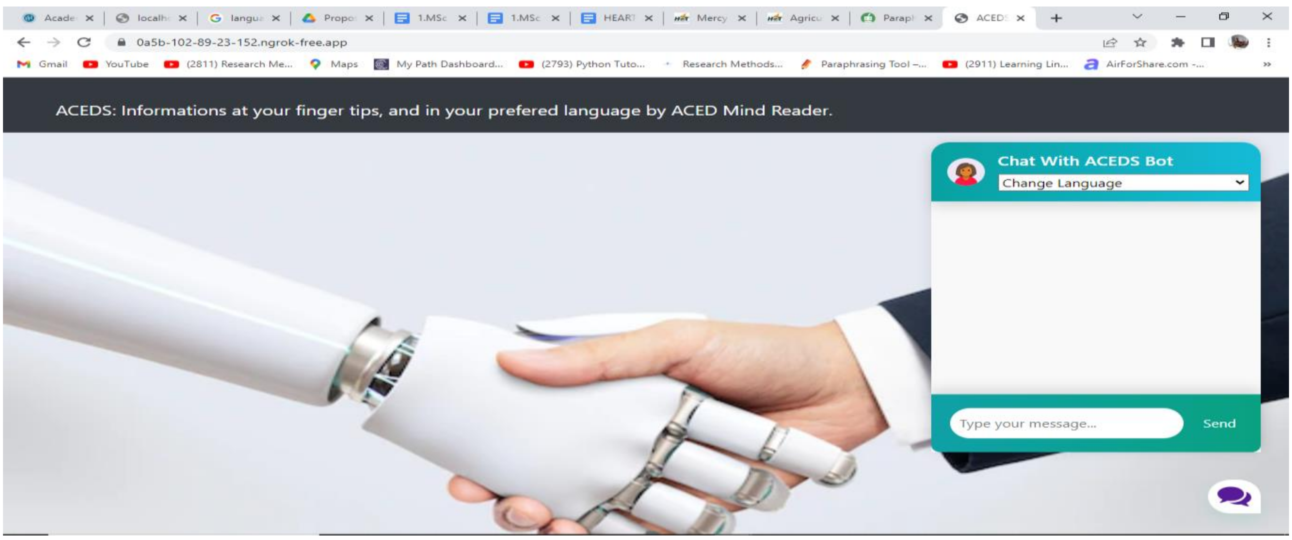

Figure 3.1: Chatbot User Interface (GUI).

The Chatbot UI is shown in *Figure 3.1* above, the interface has a caret drop-down button that allows users to select their preferred consultation language from the list of languages available. By default, the chatbot responds to all multi-lingual queries in English. That is, the system has the capability to automatically detect the client's language of conversation and responses are provided to the user in English language. This unit's functionality allows flexibility to switch to other languages such as Kirundi, Kinyarwanda, Hausa, French, Luganda, and so on.

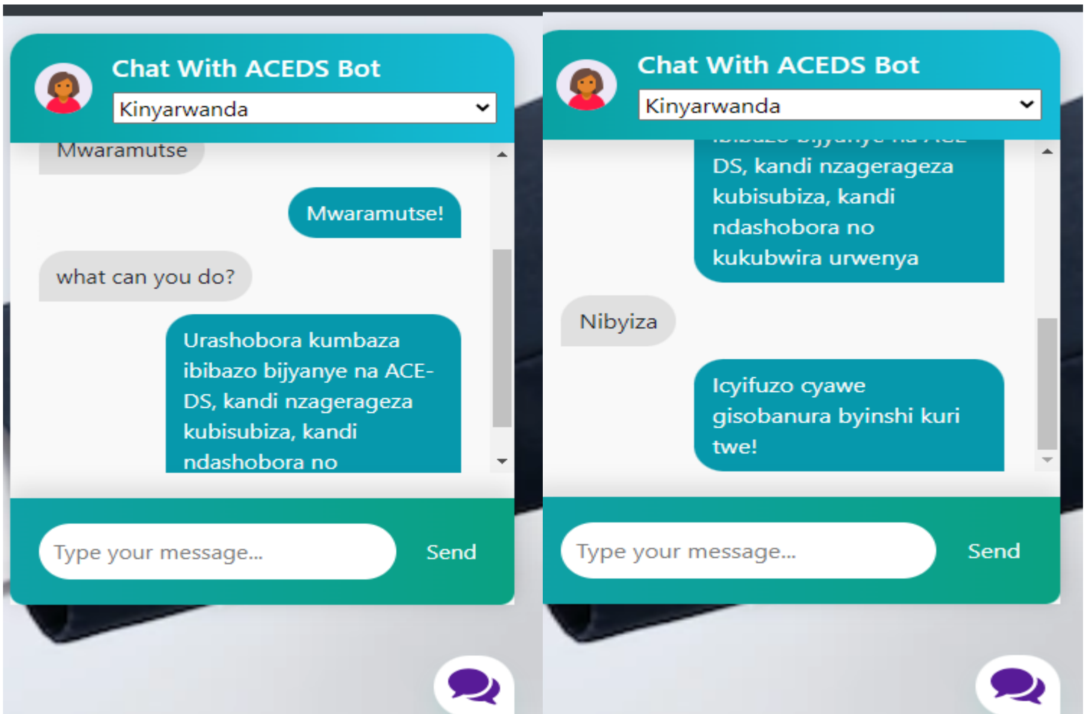

Figure 3.2: Multi-lingual Conversation with the chatbot system

Figure 3.2 above is an illustration of the multi-lingual conversation. From the dialogue between client and system, the user's target language is switched to Kinyarwanda. In this scenario, the user has the leverage to engage the system with conversations in Kinyarwanda or any other languages available on the APIs, that is, the Google translator API and receive responses in Kinyarwanda as a target language selected efficiently.

Model Evaluation Through Real-Time Testing

The real-time testing of the app (Multi-lingual Chatbot system) was done with aims to assess its performance using real time consultation queries in line with it purpose. The real-time evaluation testing metric employed confidence level metric from Scikit-learn machine learning package to measure the certainty and uncertainty of the model in its predictions of users' queries/consultations. Sampled results of the evaluation of the chatbot performance in its queries prediction are presented in Table 3.3 below:

Table 3.3: Real-Time Chatbot Test/Evaluation

Input messages or Query	Intent or tag	Intent Prediction	Confidence Level (0-1)

hello dear	greeting	Greeting	1
what can you do?	Tasks	Tasks	0.999957
Does ACEDS have state of the art facilities for learning?	facilities	facilities	0.999747
How much is ACEDS fees?	Fees	Fees	**1**
How can i apply for admission at ACEDS?	admission	admission	1
What master's programs does offers	Master or	programs	0.999387 ACEDS
What are the necessary academic requirements for enrolling in the Masters program?	master	master	1
information about masters programs	master	master	0.999966
Tell me about ACEDS?	About	About	0.999742

Table 3.3 above presents a sampled real-time testing report of the chatbot system, the report shows that the system can effectively make accurate predictions confidently based on its knowledge scope. Hence, it can be concluded that the solution demonstrates excellent real-time predictions of user engagement with above 95% confidence level when presented with queries related to the trained information in its knowledge scope. However, in the cases where the model encounters a query outside its knowledge scope or topics, a fallback prompt is utilized as a response to the user, prompting the user to be more specific about what they want to know from ACE-DS.

3.5 User Satisfaction Survey Evaluation of the Chatbot Solution

User evaluation testing was conducted with a survey using google form to obtain feedbacks from Postgraduate students and management staff of ACE-DS regarding their experience testing the chatbot solution. This survey is centered on how efficient is the system in the areas of ACE-DS information provisioning. Table 3.4 below detailed the survey's feedback obtained from Fourteen (14) respondents (ACE-DS Staff and Postgraduate Students) expressing their experience testing the solution;

Table 3.4: **User Satisfaction Survey Evaluation of the Chatbot Solution**

Questions	Response 1	Response 2	Response 3	Response 4	Response 5
How do you rate the Vocabulary, mechanical accuracy, sentence construction and soundness of expression of the responses provided by the Chatbot?	(0-30%) =0% users	(31-50%) =7.1% users	(51-80%) =50% users	(81-100%) =42.9% users	
Does the system converse efficiently using your preferred language (e.g English, French, Kinyarwanda etc)?	Yes=71.4%	No=0%	Partially=28.6 %		
How satisfied are you generally with the answers provided by the cha bot in terms of efficiency and accuracy?	(0-30%) =7.1% users	(31-50%) =14.3% users	(51-80%) =57.1% users	(81-100%) =21.4% users	

In which of the following categories did the chatbot perform poorly in terms of the correctness and usefulness of the answers provided?	Academic-related questions =21.4% users	Accommodation related questions =21.4% users	Admission enquiry =21.4% users	History about the institution =21.4% users	Socializing and Extracurricular =7.3% users
Did the chatbot answer your questions promptly and correctly?	Yes=64.3%	Partially =28.6%	No=7.1%		
Which features are most valuable to you?	The promptness of response provided=35.7%	The accuracy of responses provided =35.7%	The interactivity, choice of design and display of output =28.6%		
Did the chatbot software contribute to a more efficient and time-saving inquiry session for you?	Yes=92.9%	No=7.1%			
How well did the chatbot software adapt to your individual needs and learning style within the educational context?	Perfectly =35.7%	Average =57.1%	Poorly =7.1%		
Overall, how likely are you to recommend this chatbot software to other students or educators in an educational setting?	Certainly =28.6%	Highly =71.4%	Unlikely =0.0%		

The survey summary in Table 3.4 above indicated that 71.4% of users are satisfied with the efficient use of their preferred language in making consultations. The chatbot performed poorly in terms of responding to queries that are historical and descriptions about the institution which was not part of the training dataset. Queries related to academics and accommodation had the best ratings from users. Regarding the promptness of responses provided by the chatbot, 64.3% of survey respondents are satisfied. In terms of time-saving sessions and ease of information acquisition, the feedback indicates 92.9% user's satisfaction. Concerning the features of the chatbot that users find most valuable, the survey indicated that responses provided by the chatbot is the most valuable as opposed to design and interactivity features.

4. CONCLUSION

The research successfully demonstrated that the multi-lingual AI chatbot solution efficiently and accurately provide users with essential educational information, overcoming the challenges associated with direct inquiries with ACE-DS management staff. A key contribution demonstrated by the study is the ability of the developed chatbot to converse in 1 to over 50 languages with users, despite being trained on English Language curated datasets rather than using the conventional approach where datasets must be curated in all languages used. This is a great improvement in terms of efficiency because the model is not trained to learn hundreds of languages which is time-consuming but rather, queries and responses are analyzed in English, and then language detector and translator APIs are used to handle the cross-language translation. This is a novel approach to resolving AI multi-lingual conversational challenges that require interpretations in many languages.

The AI chatbot achieved a high performance as the real-time testing consistently yielded a confidence level of accurate predictions above 95%. The chatbot performed satisfactorily as the user satisfaction survey indicated that over 60% of the correspondents are satisfied with the chatbot's performance in correctness of grammar usage, efficient use of preferred language, prompt and correct responses provisioning, and time-saving in information acquisitions. The overall performance of the model indicates that it successfully achieved the aim and objectives of the study. However, it is important to note the model's prediction scope has limitation due to the insufficient training data used for the model training. According to [8], limited training data can lead to model under fitting or overfitting. It is important to acknowledge that there are areas that need further improvement, which include the implementation of the attention mechanism or the transformer model, incorporation of reinforcement learning, and or the use of transfer learning algorithms which have the potential for better performance and generalization. Additionally, the model needs to be trained with a larger quality dataset to achieve an advanced sophistication expected to cover a wider educational consultation scope.

Future research should focus on implementing technologies that facilitate efficient documentation of all data exchanged during client-system interactions for analysis and software improvement. This involves integrating a structured and efficient database system for storing user data and conversations. Additionally, implementing reinforcement learning technique that could facilitate continuous learning leveraging user interaction records for self-retraining to improve its information provisioning capacity and prediction accuracy over time. Additionally, another area of research for multilingual conversational AI systems is data privacy and security issues because these systems may interact with users who speak different languages and come from different countries, hence, safeguarding user data may create particular difficulties that call for more research. There is a large research deficit in this area despite the growing popularity of multilingual conversational AI systems. Future research in this area may focus on standardization, linguistic diversity, cultural and regional aspects, as well as data privacy and security issues which are indispensable in addressing these problems. These will make Multilingual AI systems to be more effective and have a greater potential impact on businesses and the larger customer base.

AUTHOR CONTRIBUTIONS: K.R.G designed the study, data collection, report writing and software development. K.N critical review and supervision of the study. K.R.G, K.N and L.E finalized the assessment, review and drafted the manuscript. All authors have read and agreed to publish this version of the manuscript.

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ETHICAL DECLARATIONS:

This study, strictly adhered to the ethical guidelines and regulations of the University of Rwanda. The study was approved by the African Center of Excellence in Data Science (ACE-DS), University of Rwanda.

INSTITUTIONAL REVIEW BOARD STATEMENT: Not applicable.

DECLARATIONS:

- We declare that there is no conflict of interest.
- **Consent for publication:** We would want to certify that this paper has not been published or accepted for publication elsewhere, or is undergoing editorial review for publication elsewhere. We would also like to confirm that my supervisors and my university are aware of this submission.
- **Availability of data and materials**: The dataset and the materials used in this study are available from the corresponding author upon request.

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