# DESIGN AND IMPLEMENTATION OF CHAT-BOT FOR PROSPECTIVE STUDENTS: UNIVERSITY OF IBADAN ADMISSION UNIT

CSC 476 (Research Methods in Computer science) Project


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# ABSTRACT

The University of Ibadan's Admission Office plays a pivotal role in shaping the academic trajectory of aspiring students, necessitating a modernized approach to streamline the admission process. This research project aims to design and implement a specialized chatbot tailored for prospective students, aiming to provide quick, reliable, and accessible information regarding admission requirements, application deadlines, and other relevant details. The objectives encompass the development of a comprehensive chatbot capable of addressing frequently asked questions, enhancing accessibility for prospective students, alleviating staff workload through automation, and improving the overall efficiency of the admission process. Additionally, the project aims to evaluate the chatbot's impact on reducing staff workload and enhancing the admission experience for users.

To achieve these objectives, a qualitative research design employing purposive sampling is employed. The primary data collection methods involve in-depth interviews and open-ended survey questions. Prospective students and admission staff serve as key participants, offering unique insights into the desired functionality, features, and potential impact of the chatbot. Their diverse perspectives inform the user-centric design and development of the chatbot, ensuring alignment with the varied needs of stakeholders involved in the admission process. This meticulous approach seeks to elucidate stakeholders' expectations and preferences, guiding the creation of a user-oriented chatbot that optimizes the admission experience at the University of Ibadan. Additionally, the analysis of documents from the admission office will be utilized to train and build models for the chatbot to ensure accurate and informative responses based on official documentation. By leveraging technological advancements and qualitative research methodologies, this initiative endeavors to revolutionize the admission process, offering prompt, accurate, and round-the-clock assistance to prospective students.

# CHAPTER ONE
# PROPOSAL

## 1.1 Introduction

The intersection of academics and technology has created innovative potential in the rapidly changing world of higher education. With each passing year, universities worldwide find themselves increasingly entwined in a complex web of admissions, where prospective students, ambitious and inquisitive, seek to unlock the doors of knowledge and opportunity. In the heart of this educational crucible stands the venerable institution known as the University of Ibadan, a citadel of learning with a storied history and a profound commitment to excellence. A silent revolution is about to start in this esteemed university, one that promises to transform the very dynamics of student admissions. This revolution is being geared by the convergence of Computer Science, Natural Language Processing, and Artificial Intelligence.

For prospective students aspiring to embark on their academic journeys, the university admissions process serves as the inaugural step, a step that, though teeming with promise, is often laden with complexity and confusion. It is here that the need for innovation becomes acutely evident. As the University of Ibadan continues to attract a diverse group of ambitious individuals, each bearing a unique set of dreams and questions, the existing manual system finds itself ensnared in a web of inefficiency. Prospective students must navigate a confusing knot of admission procedures, deadlines, course options, and application status updates in their quest to open the door to knowledge.

The admissions staff, valiant stewards of knowledge and gatekeepers of the institution, labour tirelessly to respond to an ever-increasing deluge of inquiries. Yet, despite their dedication, the process often falters. The potential for human error, delays, and inconsistency in responses looms large. Prospective students, driven by dreams, are most times faced with frustrations that stem not from the rigour of academics but from the friction in the admissions process. This disconnect between the ambitious young people's goals and an established institution's practical issues begs for closure.

The stage is now set for a positive shift in operation. The research project "Design and Implementation of a Chat-Bot for Prospective Students: University of Ibadan Admission Unit" arises at the intersection of technological prowess and academic ambition. This project, firmly rooted in the field of Computer Science, carries the banner of Artificial Intelligence and Natural Language Processing. It aims to usher in a new era in which communication barriers dissolve and technology serves as a link between desire and accomplishment.

In the University of Ibadan, a silent revolution is underway, where the concept of a chat-bot, driven by the power of AI, emerges as the brain of transformation. A chat-bot set to provide answers, guidance, and clarity to the multitude of queries posed by prospective students, alleviating their uncertainty and paving the way for seamless interactions with the admission process. With the precision of algorithms and the elegance of language processing, this chat-bot stands to redefine the admissions experience, making it more intuitive, efficient, and responsive.

Successful completion of this project will usher in an era where the admissions process at the University of Ibadan transcends the confines of traditional paperwork, welcoming students into a world of clarity, efficiency, and personalized guidance. For the University, it represents a landmark in operational efficiency, allowing staff to refocus their energies on strategic initiatives. For the prospective students, it ushers the opportunity to embark on their academic journey with confidence, knowing that the gates to knowledge are not just open but accessible at their fingertips.

## 1.2 The Problem

The admissions process at a prestigious institution like the University of Ibadan is mostly complex. As the institution attracts a diverse pool of applicants, each with their unique set of queries and concerns, the existing manual system faces significant challenges. Prospective students, eager to embark on their academic journey, encounter difficulties navigating through the shadows of admission requirements, deadlines, course information, and application status updates. The admissions staff, burdened by the sheer volume of inquiries, are often unable to provide timely and accurate responses, leading to frustration and delays. The need for a solution that can effectively bridge the gap between the university's administrative unit and its aspiring students has become paramount.

### 1.2.1 Variables and Relationships

**1. Prospective Students**: These are the key stakeholders in the admissions process, seeking information and assistance on a range of admission-related inquiries, including eligibility criteria, application status, deadlines, and course offerings.

**2. Chat-Bot**: The heart of this research project, the chat-bot represents a sophisticated AI and NLP-driven system. Its primary role is to engage with prospective students, interpreting their queries, and delivering accurate and timely responses.

**3. University of Ibadan Admission Unit**: This administrative body plays a crucial role in overseeing the admissions process. Through the chat-bot, they can monitor its performance, provide guidance, and access invaluable insights into the types of inquiries and challenges faced by prospective students.

The relationships within this system are dynamic and interconnected:

a. Prospective students interacts with the chat-bot to seek information and guidance throughout the admissions journeys

b. The chat-bot, driven by advanced AI and NLP algorithms, serves as the primary interface, understanding and responding to prospective students' queries effectively

c. The University of Ibadan Admission Unit utilizes the chat-bot as an essential tool to streamline operations, gain insights, and offer guidance where needed.

## 1.3 Background

In this section of the proposal, we will delve into why the problem is important. We checked others who have worked on the similar problems and the methods that were used and the result of their research. It is also important to take a brief look at the University of Ibadan admission Office and how the why this research is important for them.

### 1.3.1 The University of Ibadan Admission Office

The University of Ibadan, situated within the Academic division, plays a pivotal role in shaping the academic future of aspiring students. Specifically, the Admission Office is entrusted with the crucial task of facilitating admissions for qualified candidates across the diverse academic programs offered by the university.

This intricate process adheres to a set of established rules and regulations that govern the admission procedure. Annually, the office orchestrates and oversees the entire admission process, commencing with the dissemination of information on the university's website, official bulletins, and prominent national newspapers. This initial phase serves to herald the beginning of the admission cycle. Applicants seeking admission are encouraged to upload their credentials online, which are subsequently gathered, sorted, and meticulously processed in alignment with the stipulated admission criteria. Following this thorough evaluation, the names of successful candidates who have successfully completed the Admission Post-UTME Tests are submitted to the Joint Admissions and Matriculation Board (JAMB) in Abuja for the requisite approval.

This detailed process underscores the complexity and importance of the admission unit's responsibilities within the broader context of the University of Ibadan.

### 1.3.2 Advancement in Technology

As the admission process is such a strenuous one, automation has been intrrodued in recent years to streamline operations in the University of Ibadan's Admission office. Advances in technology and rise of chatbots and AI have provided an opportunity to solve these challenges. According to a survey conducted by Intelligent, a prominent online education magazine catering to prospective college applicants, a significant shift towards AI adoption is apparent. Presently, half of educational admissions departments have already embraced AI, and an impressive 82% are poised to incorporate it into their operations by 2024. Moreover, a notable trend emerging from this adoption is that a substantial majority of educational institutions using AI entrust it with the final decision-making authority on applicants, emphasizing the growing confidence in AI's capabilities. (Intelligent, 2023).

However, it is essential to acknowledge that, as this transformative technology takes center stage, it has raised ethical concerns among admissions professionals. As per the same survey, two out of every three admissions professionals express concerns about the ethical implications of AI in the admissions process.

The primary driving force behind this shift towards automation in the case of the University of Ibadan is the pursuit of efficiency. Notably, the introduction of automation has led to a significant reduction in manual labour, especially in critical tasks such as scoring candidates' results to determine eligibility for the Post-UTME Tests. Additionally, the transition to online submission of credentials marks a substantial departure from the past when candidates were required to travel to Ibadan in person to submit their results by hand. These advancements have not only streamlined operations but have also markedly improved the overall efficiency and accessibility of the admission process. (University of Ibadan, n.d.).

Nevertheless, new challenges have surfaced as the volume of inquiries about admission at the University of Ibadan continues to grow. Traditionally, prospective students have been reliant on manual methods such as phone calls or emails to seek information regarding admission procedures, application deadlines, and requirements. Additionally, some students have resorted to asking their peers to gather information on their behalf. This traditional approach presents several limitations.

Firstly, it is marred by inconsistencies in information provision. Information relayed through these methods might vary from one source to another, leading to confusion among prospective students. Secondly, this manual approach is not accessible around the clock. In an era where students demand instant responses, the limited availability of these manual channels can hinder the admission process.

Moreover, the traditional methods are undeniably time-consuming. Students must allocate substantial time to make inquiries and await responses, which can be a significant inconvenience, particularly during critical admission periods.

Furthermore, the manual approach leaves ample room for incorrect information to be conveyed, leading to misguided decisions by students. These inaccuracies can have serious consequences for prospective students who may misinterpret the requirements or deadlines.

Perhaps most significantly, the delays inherent in the traditional methods can result in students losing interest or enthusiasm for pursuing their admission. In the fast-paced digital age, the wait for responses can be frustrating and disheartening, potentially deterring talented students from choosing the University of Ibadan.

It is at this juncture that the need for a chatbot tailored to prospective students becomes evident. A chatbot can bridge the gap by providing prompt, accurate, and consistent information, thereby addressing the various challenges associated with the traditional admission inquiry methods.

### 1.3.3 Why a Chatbot is needed

“Although conversing with a bot is not the same as speaking with a human, messaging a friend is the closest analogous experience. Since users are still getting used to bots, it is reasonable to take those interactions as samples of how a bot should behave”.

Szymon Rozga. Source: (Rajnerowicz, 2022)

Chatbots have become increasingly popular in the education sector due to their ability to provide students with immediate feedback, quick access to information, and personalized guidance and support. Since the COVID-19 pandemic, there has been a considerable shift in the way education is being delivered. Global e-learning is expanding at lightning speed and is expected to grow at a compound annual growth rate of 9.1% by 2026. The availability of distance learning and online courses means that people can learn alongside working and don't have to commute long distances or take a break from family life to learn new skills. This growth demands that educational institutions offering online learning provide excellent student support alongside it. Queries before, during, and after enrollments must be received efficiently and solved instantly. Chatbots for education deliver intelligent support and provide on-the-spot-solutions to alleviate doubts, provide additional information and strengthen the relationship between students and the institution. (Freshchat, n.d.)

A chatbot emerges as a versatile solution for prospective students seeking information about courses, scholarship opportunities, application deadlines, and other vital details offered by the University of Ibadan. It effortlessly handles diverse queries and efficiently directs users to the precise information they seek. One of the primary reasons for its necessity is the accessibility it provides—information can be accessed 24/7, an invaluable feature, particularly within the realm of education where prospective students may have inquiries at any hour.

Moreover, chatbots excel in managing a high volume of inquiries concurrently, significantly reducing the time prospective students spend awaiting responses. This efficiency not only expedites the admission process but also diminishes the risk of misinformation. Chatbots, being consistent in their responses, ensure that all users receive accurate, standardized information, eliminating confusion and ensuring a seamless experience for everyone interacting with them.

The introduction of chatbots into the admission process doesn't just benefit students; it also offers substantial advantages to the institution. By collecting data on user interactions and feedback, chatbots can provide valuable insights. This includes information on frequently asked questions, peak inquiry hours, and the geographical areas with the highest interaction rates. This data, in turn, can inform improvements in the Admission Office's processes and enhance the overall user experience.

Furthermore, embracing chatbot technology for the admission process positions the University of Ibadan as a beacon of innovation and a pioneer in enhancing the student experience. This, in itself, can serve as a compelling competitive advantage, attracting a greater number of prospective students who seek institutions committed to evolving with modern trends and prioritizing student satisfaction.

In addition to these benefits, there are many research studies that have been conducted on the use of chatbots in education. For instance, a study by Kapture CRM found that AI chatbots for education make learning more dynamic and lessen a student's uncertainty about various study areas by providing the answers they need (Singh, 2022). Another study by Comm100 found that chatbots in education can expand support hours, improve support to international students, and increase engagement – all while reducing costs of traditional support. (Rogerson, 2022).

## 1.4 Aim and Objectives

The aim of this project is to design and implement a chatbot for prospective students that will help streamline the admission process and provide students with quick and easy access to information they need about admission requirements, application deadlines, and other relevant information.

The objectives are as follows

1. To develop a chatbot that can answer frequently asked questions about admission requirements, application deadlines, and other relevant information.

2. To provide prospective students with quick and easy access to information they need about admission requirements, application deadlines, and other relevant information.

3. To reduce the workload on staff members by automating the process of answering frequently asked questions.

4. To improve the efficiency of the admission process by providing prospective students with a more efficient way to get the information they need

5. Evaluate the chatbot's impact on reducing the workload of admission staff and improving the efficiency of handling inquiries.

To measure user satisfaction with the chatbot and assess its effectiveness in enhancing the admission experience.

## 1.5 Methods

Designing and implementing a chat-bot for prospective students in the Admissions unit of a university, especially the University of Ibadan, requires careful consideration of various methods and approaches.

The proposed chatbot will be designed and implemented using the following methods:

1. **Requirements gathering**: The first step will be to gather requirements from the admission unit of the university. This will involve interviewing staff and students to understand what they need from a chatbot. We will conduct focus groups to gather insights from staff and students, and administer user surveys to obtain their input and preferences regarding the chatbot's functionalities and features.

2. **Chatbot design:** Once the requirements have been gathered, the chatbot will be designed. This will involve defining the chatbot's capabilities, its user interface, and its knowledge base. In addition, the design phase will encompass creating a personality and tone for the chatbot that aligns with the university's branding and values. We will outline the use cases and user stories, and visually represent the chatbot's functionality through flowcharts and wireframes.

3. **Chatbot development**: The chatbot will be developed using a chatbot development platform. This platform will provide the necessary tools and infrastructure for building and deploying the chatbot. We will outline the integration of a Natural Language Processing (NLP) library, and incorporation of a machine learning library to define the chatbot's capabilities, user interface, and knowledge base.

The organisation of educational activities for students to create chat bots emphasises the importance of teamwork, the use of templates and scripts, and the choice of project topics (Mamaeva, Gerasimova, Zaslavskaya & Shunina, 2022). These features can be applied in the context of designing a chat-bot for prospective students, as they facilitate collaboration and streamline the development process (Mamaeva et al., 2022).

4. **Chatbot testing**: The chatbot will be tested thoroughly before it is deployed, including unit testing, integration testing, and user acceptance testing. This process ensures a rigorous examination of the chatbot's functionality, accuracy, and performance before deployment, guaranteeing a seamless experience for prospective students.

5. **Chatbot deployment:** Once the chatbot has been tested and approved, it will be deployed to the university's website. By deployment, it means the chatbot will be hosted on the university's website using a chosen hosting provider. Additionally, it will be seamlessly integrated into the university's website, which is managed through a Content Management System (CMS) for efficient content updates and maintenance.

With these, the design and implementation of a chat-bot for prospective students in the University of Ibadan Admissions unit can benefit from a combination of educational activities, information retrieval and text summarization techniques, gamification elements, and machine learning approaches. By incorporating these methods, the chat-bot can effectively engage with prospective students, provide accurate and concise information, and offer personalized recommendations and assistance.

Throughout the development process, the chatbot will be evaluated using a variety of metrics, such as accuracy (the percentage of user queries that the chatbot can answer correctly), completeness (the percentage of user queries that the chatbot can answer in a comprehensive and informative way), and satisfaction (the level of satisfaction that users have with the chatbot).

The results of the evaluation will be used to improve the chatbot's design and implementation.

Several relevant references provide insights into different aspects of chat-bot design and implementation.

Guha (2021) presents a novel conversational interface chat-bot application with information retrieval and text summarization skills. This method can be valuable for designing a chat-bot that provides accurate and concise information to prospective students. By incorporating information retrieval and text summarization techniques, the chat-bot can efficiently retrieve relevant information and present it in a concise manner.

Additionally, Ong et al. (2021) discusses the coding of a Telegram Quiz Bot to aid learners in a specific subject area. This highlights the use of gamification and group competition to engage students. Incorporating similar elements of gamification and competition in the design of the chat-bot for prospective students can enhance their interaction and motivation to explore the university's offerings.

Furthermore, Patange, Bhadrashetty & Kodli (2022) focuses on the application of machine learning in developing a chat-bot for disease prediction and treatment recommendation. Although the specific context differs, the use of artificial intelligence and machine learning techniques can be relevant in designing a chat-bot for prospective students. These techniques can enable the chat-bot to provide personalized recommendations and assistance based on the students' preferences and needs.

## 1.6 Expected Result

The design and implementation of a chatbot for prospective students at the University of Ibadan Admission Unit offer a promising avenue for improving the admission process and enhancing prospective students' experiences. This innovative approach establishes a pedagogical model where students can address inquiries, seek information on admission procedures, and engage in reflective discussions, all facilitated by the chatbot's starting questions.

### 1.6.1 Enhanced Prospective Student Engagement

Prospective students extends beyond just providing information. It will encourage applicants to interact with each other, promoting discussions on shared experiences and concerns. By fostering a sense of belonging and community, this engagement can potentially lead to long-lasting relationships among applicants, benefiting their overall university experience and encouraging them to become active members of the University of Ibadan community.

### 1.6.2 Improved Staff Efficiency

The chatbot's ability to handle routine tasks will free up admission staff to provide more personalised support. This enhanced staff efficiency will not only lead to more effective and tailored assistance for applicants but also enable the staff to engage in more strategic and high-impact activities, such as targeted outreach to potential students or improving admission policies based on their interactions with the chatbot.

### 1.6.3 Streamlined Admission Process

The streamlined admission process will not only reduce the time needed for application completion and decision notification but will also lead to greater transparency in the process. Prospective students will have a clearer understanding of each stage of the admission process, reducing anxiety and improving the overall experience. Additionally, the improved efficiency will allow the university to attract a broader pool of applicants, including international candidates who may have tight timelines.

### 1.6.4 Data-Driven Decision Making

The data analysis performed by the chatbot will extend to providing insights into broader admission trends and patterns. University administrators can use this data for strategic decision-making, such as identifying the most effective recruitment strategies or understanding changing applicant preferences. This holistic approach to data-driven decision-making will enable the University of Ibadan to continuously adapt and stay competitive in the evolving landscape of higher education.

### 1.6.5 Enhanced Security and Privacy

The chatbot's commitment to data security and privacy compliance will extend to building trust and credibility for the university. Prospective students and their families will have confidence in the institution's commitment to safeguarding their personal information. This trust is essential in a time when data breaches and privacy concerns are prevalent, and it will positively impact the perception of the university as a whole.

# CHAPTER 2
# LITERATURE REVIEW

## 2.1 Introduction

Chatbots are intelligent conversational computer programs that mimic human conversation in its natural form (Jia, 2003; Sojasingarayar, 2020; Bala et al., 2017). A chatbot can process user input and produce an output (Ayanouz, Abdelhakim, & Benhmed, 2020). Usually, chatbots take natural language text as input, and the output should be the most relevant output to the user input sentence. Chatbots can also be defined as “online human-computer dialogue system(s) with natural language” (Cahn, 2017). Chatbots constitute therefore an automated dialogue system that can attend to thousands of potential users at once.

Chatbots are currently applied to a variety of different fields and applications, spanning from education to e-commerce, encompassing healthcare and entertainment. Therefore, chatbots can provide both support in different fields as well as entertainment to users (Okuda & Shoda, 2018). This is the case for chatbots such as Mitsuku and Jessie Humani, “small talk” oriented chatbots that could provide a sense of social connection (Brandtzaeg & Følstad, 2017). Chatbots appear, in fact, to be more engaging to the user than the static Frequently Asked Questions (FAQ) page of a website. At the same time, chatbots can simultaneously assist multiple users, thus resulting in more productivity and less expensive compared to human customer support services. In addition to support and assistance to customers, chatbots can be used for providing entertainment and companionship for the end user (Costa, 2018). Nonetheless, different levels of embodiment-the way chatbots are human-like (Go & Sundar, 2019)-and disclosure-how and when the nature of the chatbot is revealed to the user-seem to impact users’ engagement with and trust in chatbots (Luo, Tong, Fang, & Qu, 2019).

In recent years, with the commoditization and the increase of computational power and the sharing of open source technologies and frameworks, chatbots programmes have become increasingly common. Recent developments in Artificial Intelligence and Natural Language Processing techniques have made chatbots easier to implement, more flexible in terms of application and maintainability, and increasingly capable to mimic human conversation. However, human-chatbot interaction is not perfect; some areas for improvements are contextual and emotional understanding and gender biases. Chatbots are, in fact, less able to understand conversational context and emotional linguistic cues compared to humans, which affects their ability to converse in a more entertaining and friendly manner

(Christensen, Johnsrud, Ruocco, & Ramampiaro, 2018; Fernandes, 2018). At the same time, chatbots tend to take on traditionally feminine roles which they perform with traditionally feminine features and often displaying stereotypical behaviour, revealing a gender bias in chatbots' implementation and application (Costa, 2018).

## 2.2 Chat-Bot Background

Although the quest for being able to create something that can understand and communicate with its creator has deep roots in human history, Alan Turing is thought to be the first person to have conceptualized the idea of a chatbot in 1950, when he proposed the question: "Can machines think?" Turing's description of the behaviour of an intelligent machine evokes the commonly understood concept of a chatbot (Turing, 1950). Chatbots have evolved with the progressive increase in computational capabilities and advances in Natural Language Processing tools and techniques. The first implementation of a chatbot, which relied heavily on linguistic rules and pattern matching techniques, was achieved in 1966 with the development of ELIZA. It could communicate with the user through keyword matching program. It searches for an appropriate transformation rule to reformulate the input and provide an output, i.e., an answer to the user. Eliza was a landmark system that stimulated further research in the field. Nonetheless, ELIZA's scope of knowledge was limited because it depended on minimal context identification and, generally, pattern matching rules are not flexible to be easily implemented in new domains (Weizenbaum, 1966; Shum, He, & Li, 2018; Zemˇcík, 2019).

A marked evolution in chatbot in the 1980s is the use of Artificial Intelligent. A.L.I.C.E. (Artificial Intelligent Internet Computer Entity) is based on the Artificial Intelligence Markup Language (AIML), which is an extension of XML. It was developed especially so that dialogue pattern knowledge could be added to A.L.I.C.E.'s software to expand its knowledge base. Data objects in AIML are composed of topics and categories. Categories are the basic unit of knowledge, which are comprised of a rule to match user inputs to chatbot's outputs. The user input is represented by rule patterns, while the chatbot's output is defined by rule template, A.L.I.C.E. knowledge base. The addition of new data objects in AIML represented a significant improvement on previous pattern matching systems since the knowledgebase was easily expandable.

Furthermore, ChatScript, the successor of AIML, was also the base technology behind other Loebner's prize-winning chatbots. The main idea behind this innovative technology was to match textual inputs from users to a topic, and each topic would have specific rule associated with it to generate an output. ChatScript ushered in a new era for chatbots' technology evolution. It started shifting the focus towards semantic analysis and understanding (Weizenbaum, 1966; Shum, He, & Li, 2018; Bradeško & Mladenić, 2012; Wilcox, 2014; AbuShawar & Atwell, 2015). The main limitation in relying on rules and pattern matching in chatbots is they are domain dependent, which makes them inflexible as they rely on manually written rules for specific domains. With the recent advances in machine learning techniques and Natural Language Processing tools combined with the availability of computational power, new frameworks and algorithms were created to implement "advanced" chatbots without relying on rules and pattern matching techniques and encouraged the commercial use of chatbots. The application of machine learning algorithms in chatbots has been investigated and new architectures of chatbots have emerged.

The application of chatbots has expanded with the emergence of Deep Learning algorithms. One of the new, and the most interesting applications, is the development of smart personal assistants (such as Amazon's Alexa, Apple's Siri, Google's Google Assistant, Microsoft's Cortana, and IBM's Watson). Personal assistants, chatbots or conversational agents that can usually communicate with the user through voice are usually integrated in smartphones, smartwatches, dedicated home speakers and monitors, and even cars. For example, when the user utters a wake word or phrase the device activates, and the smart personal assistant starts to listen. Through Natural Language Understanding the assistant can then understand commands and answer the user's requests, usually by providing pieces of information (e.g., "Alexa, what's the weather today in Los Angeles?" "In Los Angeles the weather is sunny and there are 75◦F"), or by completing tasks (e.g., "Ok Google, play my morning playlist on Spotify"). Nonetheless, the task of understanding human language has proven to be quite challenging because of tonal, regional, local, and even personal variations in human speech.

All smart personal assistants present the same core characteristics in terms of technologies used, user interface and functionalities. Some chatbots have, however, a more developed personality than others, and the most developed ones can also provide entertainment and not merely assistance with day-to-day tasks; these chatbots are referred to as social chatbots. An interesting example of a social chatbot is Microsoft's XiaoIce. XiaoIce is meant to be a long-term companion to the user, and in order to achieve high user engagement it has been designed to have a personality, an Intelligent Quotient (IQ) and an Emotional Quotient (EQ). Knowledge and memory modelling, image and natural language comprehension, reasoning, generation, and prediction are all examples of IQ capabilities. These are critical components of the development of dialogue abilities. They are required for social chatbots to meet users' specific needs and assist them. The most critical and sophisticated ability is Core Chat, which can engage in lengthy and open-domain conversations with users. Empathy and social skills are two critical components of EQ. The conversational engine of XiaoIce uses a dialogue manager to keep track of the state of the conversation and selects either the Core Chat (the open domain Generative component) or the dialogue skill in order to generate a response. Therefore, the model incorporates both Information-Retrieval and Generative capabilities (Dormehl, 2018; Spencer, 2018; Zhou, Gao, Li, & Shum, 2019).

## 2.3 Chat-Bots in Higher Education

In an era characterized by the pervasive influence of technology and the ever-evolving landscape of higher education, universities and colleges are at the forefront of innovation in their quest to provide prospective students with a seamless and informative admission experience. In this digital age, where information flows at the speed of light, institutions of higher learning are leveraging cutting-edge technologies to enhance the quality, efficiency, and accessibility of their admission processes. Among these technologies, chat-bots, driven by artificial intelligence (AI) and natural language processing (NLP), have emerged as a transformative tool, offering the potential to redefine the admission journey and elevate the prospective student's experience.

The deployment of chat-bots in higher education reflects a growing trend in the adoption of AI-driven technologies. These intelligent systems have found relevance across a spectrum of applications, from information dissemination to personalized student support. In particular, chat-bots are reshaping the admission experience by streamlining administrative tasks and ensuring prospective students have access to real-time, accurate information.

## 2.4 Implementation Approaches to Chat-Bots

In this section, we will give an overview of chatbots' implementation methods. We will distinguish between Rule-based chatbots, and Artificial Intelligence (AI) based chatbots. Within AI-based chatbots, we will further distinguish among Information-Retrieval chatbots and Generative Chatbots. We will also discuss drawbacks and limitations of each implementation approach, as well as recent improvements.

### 2.4.1 Rule-Based Chatbots

The very first attempts at chatbots' implementation were rule-based. Rule-based models are usually easier to design and to implement, but are limited in terms of capabilities, since they have difficulties answering complex queries. Rule-based chatbots answer users' queries by looking for patterns matches; hence, they are likely to produce inaccurate answers when they come across a sentence that does not contain any known pattern. Furthermore, manually encoding pattern matching rules can be difficult and time consuming. In addition, pattern matching rules are brittle, highly domain specific, and do not transfer well from one problem to the other.

### 2.4.2 Artificial Intelligence Chatbots

AI models, contrary to Rule-based models, are based on Machine Learning algorithms that allow them to learn from an existing database of human conversations. In order to do so, they need to be trained through Machine Learning algorithms that can train the model using a training dataset. Through the use of Machine Learning algorithms, there is no longer the need to manually define and code new pattern matching rules, which allows chatbots to be more flexible and no longer dependent on domain specific knowledge. As stated, AI models can be further categorised into Information Retrieval based models and Generative models.

**Information Retrieval Models**: Information Retrieval based models are designed so that given a dataset of textual information, the algorithm will be capable of retrieving the information needed based on the user's input. The algorithm used is usually a Shallow Learning algorithm. Nonetheless, there are also cases of Information Retrieval models that use Rule-based algorithms and Deep Learning ones. Information Retrieval based models include a pre-defined set of possible answers; the chatbot processes the user query and based on this input it picks one of the answers available in its set. The knowledge base for this kind of model is usually formed by a database of question-answer pairs. A chat index is constructed from this database, in order to list all the possible answers based on the message that prompted them. When the user provides the chatbot with an input, the chatbot treats that input as a query, and an Information Retrieval model akin to those used for web queries is used to match the user's input to similar ones in the chat index. The output returned to the user is thus the answer paired with the selected question among those present in the chat index (Shum, He, & Li, 2018). The main advantage of this model is that it ensures the quality of the responses since they are not automatically generated.

These models have seen a surge in popularity with the advent of the Web 2.0 and the increase in available textual information that could be retrieved on social media platforms, forums, and chats (Yan, Song, & Wu, 2016). One of the main downsides of this approach is that creating the necessary knowledge base can be costly, time-consuming, and tedious. Furthermore, if the great volume of data available provides for a greater training set and a wider knowledge base, it also implies it will be all the more challenging to match a user's input to the correct answer. A significant amount of time and resources must be deployed to train the system to select one of the correct answers available (Yan, Song, & Wu, 2016).

Finally, Information Retrieval systems, due to the fact that they do not generate answers but rather retrieve answers from a pre-defined set in their knowledge base, are arguably less suitable to be used as the underlying algorithm for conversational or chit-chat agents-the so-called social chatbots. Information Retrieval models are in fact less suitable to develop a personality, which is an important trait for this kind of chatbot (Shum, He, & Li, 2018). Nonetheless, some progress has been made in developing new Information Retrieval algorithms in recent time, and it is worth mentioning what Machine Learning algorithms are currently being used as underlying technology for this kind of model.

(Lu & Li, 2013) proposed a new model to represent local textual co-occurrence and map hierarchical information across domains for more semantically distant terms. This model was based on the idea that the higher the co-occurrence of two terms across domains, the more closely related the two terms are.

Accordingly, a high co-occurrence within a specific domain could inform the information retrieval process. This model was, thus, based on two steps: topic modelling for parallel text, and getting the hierarchy architecture. The first step aims at finding meaningful co-occurrence patterns of words. The second step aims at modelling the architecture of co-occurrences across topics. This architecture will be used to create the neural network that powers this machine learning algorithm. The interesting development made by this model lies therefore in its use of co-occurrences of words to define a context. The underlying aim of this research was to use contextual information to improve matching performances for Information Retrieval models (Lu & Li, 2013).

One interesting development, which aims at taking into consideration previous turn in the conversation, thus obtaining more contextual information in order to improve the quality and the correctness of the output is the one proposed by (Yan, Song, & Wu, 2016). In this model the Information Retrieval process is enhanced by a Deep Neural Network that ranks not only the question/answer pair matched with the last user's input, but also those question/answer pairs that match with reformulated versions of previous conversation turns. The ranking lists corresponding to different reformulations are then merged. In this way, contextual information can be leveraged from the user's previous queries, and these pieces of information can be used to retrieve a better answer within the knowledge base (Yan, Song, & Wu, 2016).

**Generative Models**: Generative based models, as the name suggests, generate new responses word by word, based on the input of the user. These models are thus able to create entirely new sentences to respond to users' queries; however, they need to be trained in order to learn sentence structure and syntax, and the outputs can somewhat lack in quality or consistency (Shang, Lu, & Li, 2015; Sordoni et al., 2015; Vinyals & Le, 2015).

Generative models are usually trained on a large dataset of natural phrases issued from a conversation. The model learns sentence structure, syntax, and vocabulary through the data that it has been fed. The overall aim is for the algorithm to be able to generate an appropriate, linguistically correct response based on the input sentence. This approach is usually based on a Deep Learning Algorithm composed of an Encoder-Decoder Neural Network model with Long-Short-Term-Memory mechanisms to counterbalance the vanishing gradient effect present in vanilla Recurrent Neural Networks (Vinyals & Le, 2015).

**Industry-Standard Algorithms**: Among AI models, Sequence to Sequence models have become the industry standard for chatbot modelling. They were first introduced to solve Machine Translation problems, but the underlying principles do in fact seem to perform well for Natural Language Generation as well. These models are composed of two Recurrent Neural Networks (RNN), an Encoder and a Decoder. The input sentence of the chatbot user becomes the input of the Encoder, which processes one word at a time in a specific hidden state of the RNN. The final state represents the intention of the sequence and is called the context vector. The Decoder takes the context vector as its input and generates another sequence (or sentence) one word at a time. The overall objective for this probabilistic model is to learn to generate the most probable answer given the conversational context, which in this case is constituted by the previous turn in the conversation, or the input sentence. In the learning phase, the answer, or output sentence, is given to the model so that it can learn through back propagation. For the interference phase, two different approaches can be used. The beam search approach provides several candidates as the input sentence and the output sentence is selected based on the highest probability. A greedier approach uses the predicted output token as an input to predict the next sentence in the conversation (Vinyals & Le, 2015).

This model does offer some interesting advantages. First, it does not involve domain-specific knowledge, but is rather an end-to-end solution that can be trained using different datasets, thus on different domains. Furthermore, although the model does not need domain-specific knowledge to provide valuable results, it can be adapted to work with other algorithms if further analysis on domain-specific knowledge is needed. It is thus a simple yet widely general and flexible model that can be used to solve different NLP tasks (Vinyals & Le, 2015). For these reasons, the Sequence-to-Sequence model seems to have become the industry standard choice for dialogue generation and many NLP tasks in recent years.

Nonetheless, it has a considerable limit: the entirety of the information contained in the input sentence must be encoded in a fixed length vector, the context vector, and thus, the longer the sentence, the more information gets lost in the process. That is why Sequence to Sequence models do not perform well when they must respond to longer sentences and tend to give vague answers. Furthermore, when generating an answer, these models tend to focus on a single response, which creates a lack of coherence in the turns of a conversation (Jurafsky & Martin, 2020; Strigér, 2017).

**Transformers:** One of the most interesting innovations in Deep Learning language models has been the introduction of Transformers, first presented by (Vaswani et al., 2017) in the paper “Attention is all you need”. Transformers are language models based solely on the Attention mechanism. Transformers are nowadays the model of choice for NLP challenges, replacing RNN models like long short-term memory (LSTM) by differentially weighing the relevance of each portion of the input data.

Furthermore, they provide training parallelization that permits training on larger datasets than was originally achievable. This led to the development of pre-trained systems such as BERT (Bidirectional Encoder Representations from transformers) (Devlin et al., 2019) and GPT (Generative Pre-trained Transformer), which were trained with huge language datasets, such as Wikipedia Corpus and Common Crawl, and may be fine-tuned for specific applications. Several different versions of the Transformer have since been presented, such as the Reformer (Kitaev, Kaiser, & Levskaya, 2020) and the Transformer XL (Dai et al., 2019). Each

version of the transformer has been developed to answer to specific challenges for the task at hand. Even though transformers were introduced to answer Machine Translation challenges, they
can be adapted and modified to perform dialogue modelling tasks.

In (Dai et al., 2019), the authors propose an updated version of the Transformer called TransformerXL. This model can go beyond the fixed-length context limitations of the Transformer, using sentence-level recurrence. Transformers show a potential of learning longer term dependency but are constrained by fixed length context in the setting of language modelling. The authors present a unique neural architecture named Transformer-XL that enables learning dependency beyond a given length without breaking temporal coherence. It comprises a segment level recurrence mechanism and a unique positional encoding technique. This solution aims at capturing longer-term dependency and resolving the context fragmentation issue. Even though this approach has not yet been applied to dialogue modelling, it be argued that once the appropriate and necessary modification implemented, it could prove useful in overcoming some of the issues current dialogue models present, namely context understanding.

In (Kitaev, Kaiser, & Levskaya, 2020), the authors introduce the Reformer, a more efficient version of the Transformer, that makes use of two techniques to improve the Transformer in terms of efficiency. Firstly, the authors substitute dot-product attention with one that employs locality-sensitive hashing, increasing its complexity from O(L2)toO(LlogL), where L is the length of the sequence. Secondly, they employ reversible residual layers instead of the standard residuals, which permits storing activation only once in the training process instead of N times, where N is the number of layers. As a result, the Reformer is significantly more memory-efficient and
substantially faster on longer sequences.

In (Adiwardana et al., 2020), the authors introduce Meena, a generative chatbot model that was trained end-to-end on 40 billion words extracted and filtered from public domain social media discussions. With Meena, the authors stretch the limits of the end-to-end approach in order to show that a big scale low-perplexity model can produce quality language outputs. The authors employ a seq2seq model (Bahdanau, Cho, & Bengio, 2016) with the Evolved Transformer (So, Liang, & Le, 2019) as the main architecture.

The four most important characteristics of the Evolved Transformer's architecture are the utilization of;

(i) Large depth-wise separable convolutions,

(ii) Gated Linear Units (Dauphin, Fan, Auli, & Grangier, 2017)

(iii) Branching structures and

(iv) Swish activations (Ramachandran, Zoph, & Le, 2017).

Both the Evolved Transformer's encoder and decoder independently generated a branched lower portion with wide convolutions. Also in both situations, the later portion is essentially identical to the Transformer (So, Liang, & Le, 2019). The model is trained on multi-turn dialogues where the input sentence is comprised of all turns of the context (up to 7) and the output sentence is the response. To quantify the quality of Meena and compare it with other chatbots, (Adiwardana et al., 2020), also propose an effective human evaluation metric. Sensibleness and Specificity Average (SSA) incorporates two basic qualities of a human-like chatbot: making sense and being specific in their response. The authors ask human judges to evaluate responses based on these two aspects.

## 2.5 Dataset used

This session summarizes the datasets that appears to be most frequently used to train deep learning chatbot models.

| Dataset | Content type | Phrases | Tokens | Sources |
|---|---|---|---|---|
| OpenSubtitles | Movie subtitles. Entire database of the OpenSubtitles.org repository | 441.5 M (2018 release) | 3.2 G (2018 release) | (Lison & Tiedemann, 2016) |
| Cornell | Raw movie scripts. Fictional conversations extracted from raw movie scripts | 304,713 | 48,177 | (Danescu-Niculescu-Mizil & Lee, 2011) |
| DailyDialog | Dialogues for English learners. Raw data crawled from various websites that provide content for English learners | 103,632 (13,118 dialogues with 7.9 turns each on average) | 17,812 | (Li et al., 2017) |

Table 2.1 Summary of chatbot dataset

## 2.6 Evaluation of the Chat-Bot

Evaluating dialogue systems, such as chatbots, is a complex task because conversations serve various purposes. The metrics for evaluating chatbots depend on their intended use. For instance, a personal assistant chatbot is assessed based on its effectiveness in completing user tasks and the efficiency of the interaction, while a companion chatbot is evaluated on its ability to maintain engaging conversations.

There are two primary approaches to chatbot evaluation: human evaluation and automated evaluation metrics. Human evaluation involves having participants interact with the chatbot and rate different aspects of the interaction using predefined evaluation criteria. These ratings help assess efficiency, effectiveness, and user satisfaction (Radziwill & Benton, 2017).

Human evaluation is a valuable method for assessing the quality of chatbot interactions, as it considers various aspects and can adapt to different chatbot functions. However, it has drawbacks, including cost, time consumption, scalability issues, and potential bias in ratings. Despite these challenges, human evaluation remains a comprehensive approach to evaluate conversations on multiple levels, with the evaluation framework tailored to the chatbot's specific goals and functions. For these reasons, human evaluation metrics are used in several pieces of literature analysed, such as (Christensen, S., Johnsrud, S., Ruocco, M., & Ramampiaro, H., 2018; Sordoni et al., 2015).

Automated evaluation metrics offer efficiency and cost-effectiveness in evaluating chatbots. However, there is a lack of industry standards for these metrics, and they may not fully assess the overall quality, efficiency, and effectiveness of conversations. Nevertheless, due to their ease of use, these metrics are commonly employed for chatbot evaluation. Standard evaluation metrics like BLEU, METEOR, and TER, which have been used in Machine Translation and Natural Language Processing tasks, are often applied to measure accuracy. Although these evaluation metrics are considered to be more suitable for Machine Translation problems, they can still provide valuable information regarding the Textual Entailment of the chatbot output (Saikh, T., Naskar, S.K., Ekbal, A., & Bandyopadhyay, S., 2018).

The F-score, alternatively referred to as the F1-score, is a statistic that indicates how accurate a model is on a given dataset. It is used to assess binary classification systems that categorize example evaluation s as either ‘positive’ or ‘negative’. The F-score is a measure of the model’s precision and recall; it is defined as the harmonic mean of the model’s precision and recall. The equation is presented in 1. The F-score is frequently used to assess information retrieval systems such as search engines, as well as numerous types of machine learning models, most notably in natural language processing. The F-score can be adjusted to prioritize precision above recall, or vice versa. The F0.5- and F2-scores, as well as the normal F1-score, are often used adjusted F-scores. The standard F1-score is calculated as the harmonic mean of the precision and recall. The F-score of a perfect model is 1 (Wood, T.). This evaluation metrics has been applied in a few research papers to evaluate chatbots performances, such as in (Xu, J., Ju, D., Li, M., Boureau, Y.L., Weston, J., Dinan, E., 2020; Cuayáhuitl, H., Lee, D., Ryu, S., Cho, Y., Choi, S., Indurthi, S., Yu, S., Choi, H., Hwang, I., Kim, J., 2019).

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

## 2.7 Related Works

Previous literature survey work on different aspects of chatbots have focused on the design and implementation, chatbot history and background, evaluation methods and the application of chatbots in specific domain

(Abdul-Kader & Woods, 2015) compare design techniques drawn from some selected papers. The authors focus especially on Loebner’s winning chatbots, and compare models used to develop those chatbots to the models presented in the selected papers. (Ketakee & Champaneria, 2017) discuss areas where chatbots fall short and explore research areas that need attention.

The survey conducted by (Rahman, A.M., Mamun, A.A., & Islam, A., 2017) focused on cloud-based chatbot technology, chatbot programming and present and future programming issues in chatbots. The authors conclude that stability, scalability and flexibility are the most important issues for consideration in chatbot development. (Cahn, 2017) conducts a study of the literature on the design, architecture, and algorithms used in chatbots. (Bernardini, A.A., Sônego, A.A., & Pozzebon, E., 2018) conducted a systematic literature review and quantitative study related to chatbot. They concluded by expressing concerns regarding the amount of published material and emphasized the importance of interdisciplinarity. (Nuruzzaman & Hussain, 2018) compare the functionality and technical requirements of the eleven most common chatbot application systems.

The study conducted by (Adamopoulou & Moussiades, 2020) involved two analysis of the literature that discuss the history, technology and applications of chatbots. While tracing the historical progression from the generative idea to the present day, the authors highlighted potential shortcomings at each point. Following the presentation of a comprehensive categorization scheme, the authors discussed critical implementation technologies. Finally, they discussed the general architecture of modern chatbots and the primary platforms for their creation. The authors concluded that further research is needed on existing chatbots platforms and ethical issues related to chatbots. The study by (Singh, R., Paste, M., Shinde, N., Patel, H., & Mishra, N., 2018) aimed at resolving the critical issue of identifying suitable deep learning techniques. They offered an overview of numerous commonly used deep learning systems models for learning. Additionally, they provided overviews of the entire design process, tips for implementation, and links to several tutorials, analysis summaries and community-developed open-source deep learning pipelines and pre-trained models.

# CHAPTER 3
# METHODOLOGY

## 3.1 Introduction

### 3.1.1 Research Problem

The research problem is concerned with the need to address the complex admissions process at the University of Ibadan, which is compounded by a diverse pool of applicants with unique queries and concerns. The existing manual system struggles to handle the volume of inquiries from prospective students, resulting in frustration and delays. The research aims to investigate and develop a solution to effectively bridge the communication gap between the university's administrative unit, prospective students, and a chat-bot system, driven by advanced AI and NLP algorithms, to provide timely and accurate responses and streamline the admissions process.

### 3.1.2 Objectives

The objectives of this research are as follows:

- To understand the complexities of the admissions process at the University of Ibadan, including the challenges faced by both prospective students and the admissions staff.
- To develop a sophisticated AI-driven chat-bot capable of effectively engaging with prospective students, interpreting their admission-related queries, and providing timely and accurate responses.
- To facilitate a dynamic and interconnected system where prospective students interact with the chat-bot for information and guidance throughout their admissions journey, improving their experience.
- To enable the University of Ibadan Admission Unit to use the chat-bot as a valuable tool for monitoring and optimizing the admissions process, gaining insights into the types of inquiries and challenges faced by prospective students.
- To ultimately, bridge the gap between the university's administrative unit and aspiring students, streamlining the admissions process, reducing frustration, and delays, and enhancing the overall experience for both students and the institution.

### 3.1.3 The Significance of the Methodology

The University of Ibadan has a complex admissions process, and the existing manual system faces significant challenges. The methodology aims to address this complexity and streamline the process.

The institution attracts a diverse pool of applicants with unique queries and concerns. The methodology, through the use of a chat-bot, can effectively cater to the specific needs of each prospective student.

The manual system's inability to provide timely and accurate responses leads to frustration and delays for prospective students. The chat-bot's role in delivering accurate and timely responses is crucial in mitigating these issues.

The methodology seeks to bridge the gap between the university's administrative unit and its aspiring students. The chat-bot acts as a communication link, ensuring that information flows smoothly and efficiently.

The relationships within this system are dynamic and interconnected, with prospective students, the chat-bot, and the University of Ibadan Admission Unit all playing essential roles. The methodology aims to optimize these relationships to enhance the admissions process and improve the overall experience for prospective students.

### 3.1.4 Overview of the Methodology Structure

**Stakeholders Involved**

The methodology structure for this project involves three key stakeholders:

1. **Prospective students:** These are the main users of the chat-bot, who will interact with it to get information and assistance with their admissions-related inquiries.
2. **Chat-bot:** This is the central component of the system, powered by advanced AI and NLP algorithms. It will interpret the queries of prospective students and provide accurate and timely responses.
3. **University of Ibadan Admission Unit:** This administrative body will oversee the chatbot's performance, provide guidance, and analyze the data it generates to gain insights into the types of inquiries and challenges faced by prospective students.

**Relationship Between the Stakeholders Involved**

- Prospective students interact with the chat-bot to seek information and guidance throughout their admissions journeys.
- QThe chat-bot, powered by AI and NLP algorithms, serves as the primary interface, understanding and responding to prospective students' queries effectively.
- The University of Ibadan Admission Unit utilizes the chat-bot as an essential tool to streamline operations, gain insights, and offer guidance where needed.

**Steps Involved in the Methodology**

1. **Requirement gathering**: This will involve gathering requirements from the University of Ibadan Admission Unit and prospective students to understand their needs and expectations for the chat-bot.

   As this research uses Agile methodology, the first thing to do is plan and this involves gathering requirements. As a supervised learning method, Multinomial Naïve Bayes needs a training data set to classify incoming questions from prospective students. It can be achieved by asking student admission staff what kind of questions (intents) prospective students usually ask when they want to get information about new student admission.

2. **Data Preprocessing**: This step involved understanding the needs of students, identifying the chatbot's features and functionalities, and defining the chatbot's scope.

3. **Chatbot Design and Implementation:** The chat-bot was developed (designed and implemented) using artificial intelligence (AI) and Natural Language Processing (NLP) techniques.

4. **Chatbot Deployment:** The chat-bot was deployed on a platform that allows prospective students to access it easily, such as the University website or the admissions portal.

5. **Chatbot Evaluation**: The chat-bot was evaluated to measure its effectiveness in meeting the needs of prospective students and the University of Ibadan Admission Unit.

## 3.2 Research Design

For this research, we used the mixed-methods design approach. This type of design combines quantitative and qualitative methods to provide a more comprehensive understanding of the phenomenon being studied.

**Quantitative methods** were used to measure the impact of the chatbot on the workload of admission staff and the efficiency of handling inquiries. By collecting and analyzing quantitative data, we will achieve the following objectives:

1. Measure the Reduction in Workload: We quantified the reduction in the number of inquiries that admission staff need to handle by comparing the volume of inquiries before and after the chatbot's implementation. This data provides concrete evidence of the chatbot's ability to alleviate the staff's workload.
2. Analyze Response Time Efficiency: Quantitative data were gathered to assess the average time it takes for the chatbot to respond to inquiries as opposed to human admission staff. By comparing response times, we realized that the chatbot contributes to faster and more efficient inquiry handling.
3. Assess Staff Satisfaction: By conducting structured surveys with admission staff, we were able to determine how satisfied they were with the chatbot and its impact on their daily responsibilities.
4. Monitor Chatbot Usage Metrics: Tracking metrics such as the number of chatbot interactions, common inquiry topics, and user engagement rates can provide quantitative insights into the chatbot's utilization. This data can help us understand which areas of inquiry the chatbot excels in and where improvements may be needed.

Qualitative methods are not left out as well. This method would be used to gather feedback from prospective students about their experience using the chatbot. For example, we could conduct interviews or focus groups to learn more about what students liked or disliked about the chatbot, and how it could be improved. This information would be used to identify the key features and functionalities that the chatbot should provide.

We could also analyze social media posts and online reviews to get a sense of how students are talking about the chatbot, and also conduct usability testing with prospective students to assess the chatbot's ease of use, accuracy, and helpfulness. This feedback can be used to refine the chatbot's design and functionality.

## 3.3 System Requirements

The role of the system is to provide a chatbot that will be able to answer questions related to the admission procedure. It will provide a web interface for the users to interact with the system and an administration interface. A user is anyone who would like to visit the website and engage in a conversation. As well as talking the user should be able to submit a log of whether he is satisfied with an answer and produce a link. Other than communicating, the user should be able to rank the system. The rank of the system should be a five star ranking system where one is poor and 5 is excellent. A user should also be able to write a review using the feedback form. The administrator of the system shall be able to log in using a user name and a password. The responsibility of the administrator will be to maintain the system by adding questions and answers to the database and by updating current information sets when necessary. Furthermore he should be able to view the user ranking, feedback messages and logs. The system shall provide its users with spell checking suggestions on screen, when they make such errors. Moreover the parsing of sentences will avoid sending to the system words that do not form a sentence.

There are several security issues which need to be taken into consideration when designing the system. These include personal and sensitive information. The data should not be accessed without authorisation and authentication. Disclosure or leak of data should be protected against various types of attacks and be encrypted and password protected.

### 3.3.1 Functional Requirements

1. **Chatting**

a. The system should allow users to chat.

b. The system shall inform the user if an answer is not available.

c. The system shall inform the user about spelling mistakes.

d. The system shall inform the user about the validity of the sentence.

**2**. **Searching**

a. The system should allow users to search for information about admissions.

b. The system should allow users to search for information about tuition fees.

c. The system should allow users to search for information about accommodation.

**3**. **Logs:** The system should maintain a log of the current question and answer if the user is not satisfied.

**4. Feedback:** The user should be able to leave feedback, which consists of a text message and a rating.

**5. Administrative system**

a. Information management: The administrator should be able to to add, update and delete questions, answers and keywords.

b. Log management: The administrator should be able to view and delete logs.

c. Feedback management: The administrator should be able to view and delete feedback.

### 3.3.2 Non-Functional Requirements

**1. User Interface**

a. The system shall maintain an easy to use interface across all functionality and for all users

b. The clients' user interface should be compatible with all commonly used browsers, such as Internet explorer, Firefox, Google chrome and Safari.

**2. Scalability:** The system shall be able to scale based on the number of users using the system.

**3. Security**

a. The administrative system should be protected from unauthorized access.

b. The database should be protected from attacks and unauthorized access.

c. The interface should be protected from attacks. d. All passwords should be stored as a secure hash of the administrator password.

**4. Third party interactions**

*a.* The system should be able to interact with the Google spelling server, which handles the spelling.

b. The system should be able to interact with the Google search server, which is used for the customized search on the admissions website.

**5. Portability**

a. The system should run on a variety of operating systems that support the Java language.

b. The system should run on a variety of hardware.

**6. Maintainability**

a. The system should be easy to maintain.

b. There should be a clear separation of HTML and Java interface code.

c. There should be a clear separation between the interface and the business logic code.

d. There should be a clear separation between the data access objects that map the database

and the business logic code.

**7. Exception handling:** Exceptions should be reported effectively to the user if they occur.

**8. Ethics:** The system shall not store or process any information about its users.

### 3.3.3 Use case model

The use case diagram describes the functionality of the system as designed from the requirements and can be found below.

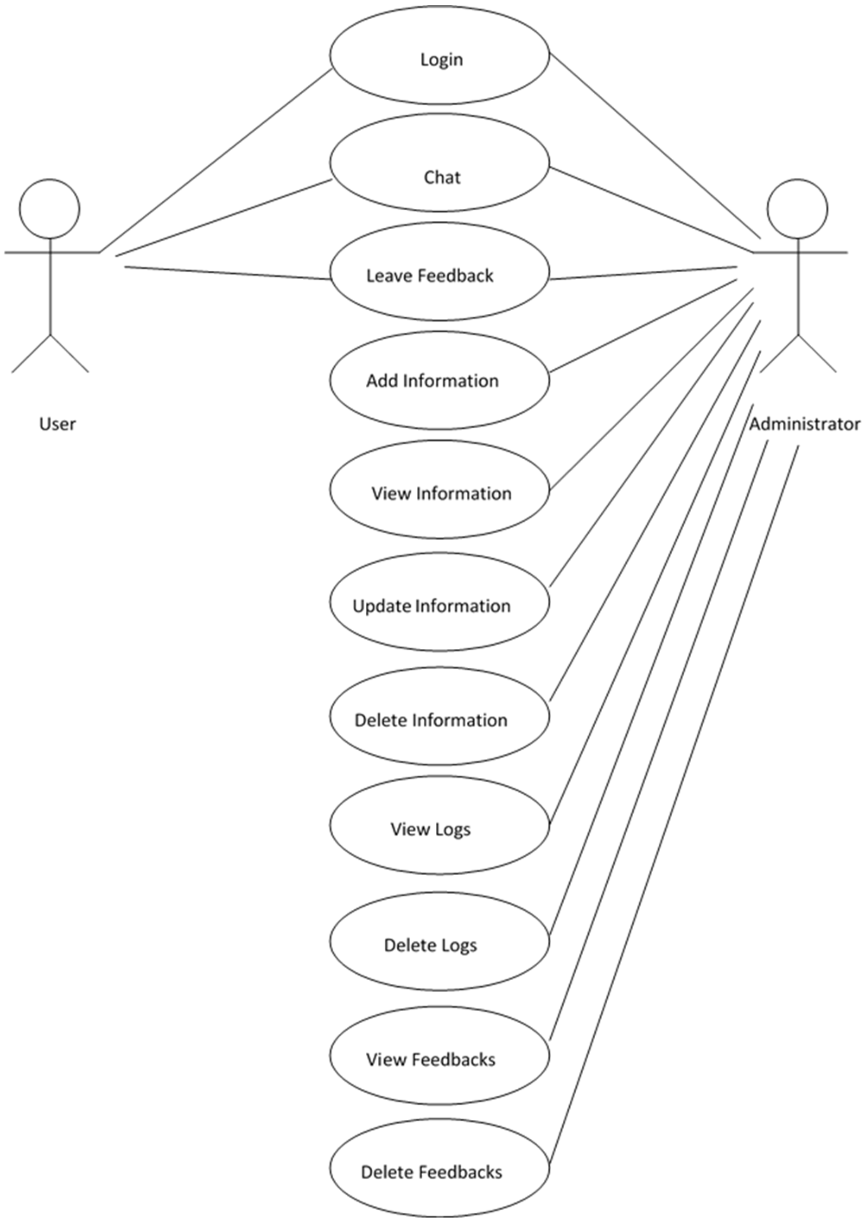


**Figure 3.3.1** Use case diagram

### 3.3.4 Actor Documentation

| Actor | Description |
|---|---|
| User | Someone who makes use of the system to make conversation. |
| Administrator | The administration of the system. Allowed to carry out administrative tasks. |

**Table 3.31** Actor documentation

## 3.4 Data Collection

The principal data sources for this research are the prospective students and admission staff who will provide their unique perspectives on the expected performance of the chatbot. The research approach to purposive sampling ensures that the selected participants represent a diversity of roles and experiences within the admission process, allowing for a comprehensive understanding of the varying expectations.

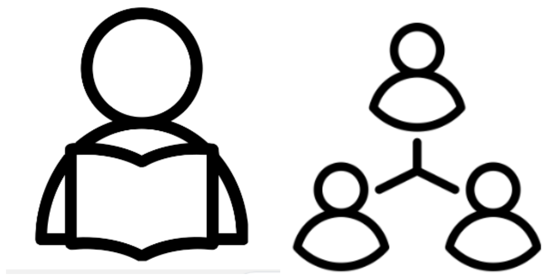

**Figure 3.4.1** Prospective Students and Admission Office Staffs

This research design, rooted in qualitative methods, is meticulously crafted to gather the critical early-stage insights and requirements that will steer the design and development of the prospective chatbot. It harmonizes seamlessly with the research objective, as it aspires to capture and document the preliminary expectations and preferences of prospective students and admission staff, thereby paving the way for the design and implementation of a user-centric chatbot in the forthcoming phases of the project.

### 3.4.1 Data Collection

Here we will look at the methods, techniques and instruments we will use to collect data from prospective students and from other sources. We will implore the use of surveys,in-depth interviews with prospective students and analysis of some current documents to gather our data.

The data collection phase is a critical component of this research, designed to capture the initial expectations and preferences of prospective students and admission staff regarding the development and implementation of a chatbot at the University of Ibadan's Admission Unit. The selection of data collection methods aligns closely with the research objectives, aiming to provide an in-depth understanding of user requirements that will inform the chatbot's design.

### 3.4.2 Survey and Interview

Two primary data collection methods will be employed: in-depth interviews and open-ended survey questions. The rationale for choosing these methods is rooted in their effectiveness in collecting narrative and nuanced data. In-depth interviews allow for extensive exploration of participants' expectations, preferences, and perspectives, while open-ended survey questions facilitate free expression and insight-rich responses. The combination of these methods is tailored to the research's qualitative nature at this early planning stage.

Participants, in this context, are prospective students and admission staff who will provide unique insights into the desired functionality, features, and potential impact of the forthcoming chatbot. The decision to engage these participants is driven by their direct involvement in the admission process and their valuable perspectives, which will ultimately shape the chatbot's development. A purposive sampling approach will be used to ensure the representation of various user groups. This method of selection enables the inclusion of participants with diverse roles, experiences, and expectations, providing a comprehensive understanding of the early-stage requirements.

### 3.4.3 Some Survey Questions

1. How likely are you to use a chatbot for admission inquiries at the University of Ibadan? (1 = Very Unlikely, 5 = Very Likely)

2. What specific features or information would you expect a chatbot to provide to assist with the admission process?

3. In what areas of the admission process do you think a chatbot could be most beneficial?

4. Please rate the importance of a chatbot in improving the admission process at the University of Ibadan on a scale from 1 to 5. (1 = Not Important, 5 = Very Important)

5. How frequently do you anticipate using a chatbot for admission-related queries?

    a. Daily
    b. Weekly
    c. Monthly
    d. Rarely
    e. Never

6. What concerns or reservations do you have about using a chatbot for admission inquiries?

7. What would be your preferred method for interacting with a chatbot (e.g., text-based, voice, or both)?

8. Are there any specific admission-related tasks or questions you believe a chatbot could handle more effectively than traditional methods?

9. How do you envision a chatbot improving your overall experience with the admission process?

10. Do you have any additional comments or suggestions related to the development of a chatbot for admission inquiries at the University of Ibadan?

**Part 2: Respondent are the admission unit staffs**

1. Can you describe your role and experience in the university admission process at the University of Ibadan?

2. What are your expectations for a chatbot that will assist with the admission process at the University of Ibadan?

3. In your opinion, what features or capabilities should a chatbot have to be most effective in assisting prospective students?

4. How do you anticipate a chatbot will influence your daily responsibilities and tasks related to the admission process?

5. Are there specific challenges or pain points in the current admission process that you believe a chatbot could address?

6. How do you envision prospective students interacting with the chatbot? What communication channels do you think they would prefer?

7. What ethical considerations or concerns do you have about the use of a chatbot in the admission process?

8. Can you provide examples of successful chatbot implementations in similar contexts, and what lessons can be learned from them?

9. What, in your opinion, are the key success factors for the successful development and implementation of a chatbot in the admission process?

10. How do you foresee the chatbot impacting the overall user experience for prospective students and admission staff?

### 3.4.4 Thematic Mapping

The data collection phase, carefully designed with a qualitative approach, focuses on gathering the preliminary expectations and preferences that will shape the forthcoming chatbot's design and development. It is a cohesive strategy in consonance with the research objectives, aiming to provide the intricate insights needed to create a chatbot that accurately reflects user needs and enhances the admission process at the University of Ibadan.

The thematic mapping process involved a systematic review of the transcripts and survey responses to identify recurring themes and sub-themes. This process was guided by the principles of grounded theory, allowing themes to emerge organically from the data itself.

The constant comparative method was applied to refine these themes as new data were analyzed. Themes emerged through a rigorous coding process. Segments of text were labeled with codes representing specific themes and sub-themes. As these codes were applied to the data, overarching themes became evident, and relationships between themes were identified. Below are some of the text segments from the interview and the codes applied to them.

1. Interview Transcript from a Prospective Student

**Text Segment**

"*I really wish the chatbot could provide information about the admission requirements and criteria, like the specific grades needed for each program*."

**Code**

"Admission Requirements Information"

2. Open-Ended Survey Response from an Admission Staff

**Text Segment**

"*We often receive inquiries from students about the admission deadlines. It would be helpful if the chatbot could automatically provide this information.*"

**Code**

"Automated Admission Deadlines"

3. Interview Transcript from a Prospective Student

**Text Segment**

*"I find it frustrating when I have to search through the website to find basic admission details. The chatbot should be easy to navigate and user-friendly.*"

**Code**

"User-Friendly Interface"

4. Open-Ended Survey Response from an Admission Staff

**Text Segment**

*"Students often ask us the same questions repeatedly, especially during the admission season. If the chatbot could handle these common queries, it would save us a lot of time."*

**Code**

"Handling Common Queries"

5. Interview Transcript from a Prospective Student

**Text Segment**

*"I appreciate it when I get immediate responses to my questions. It's frustrating to wait for hours or days to get a reply.*"

**Code**

"Immediate Responses"

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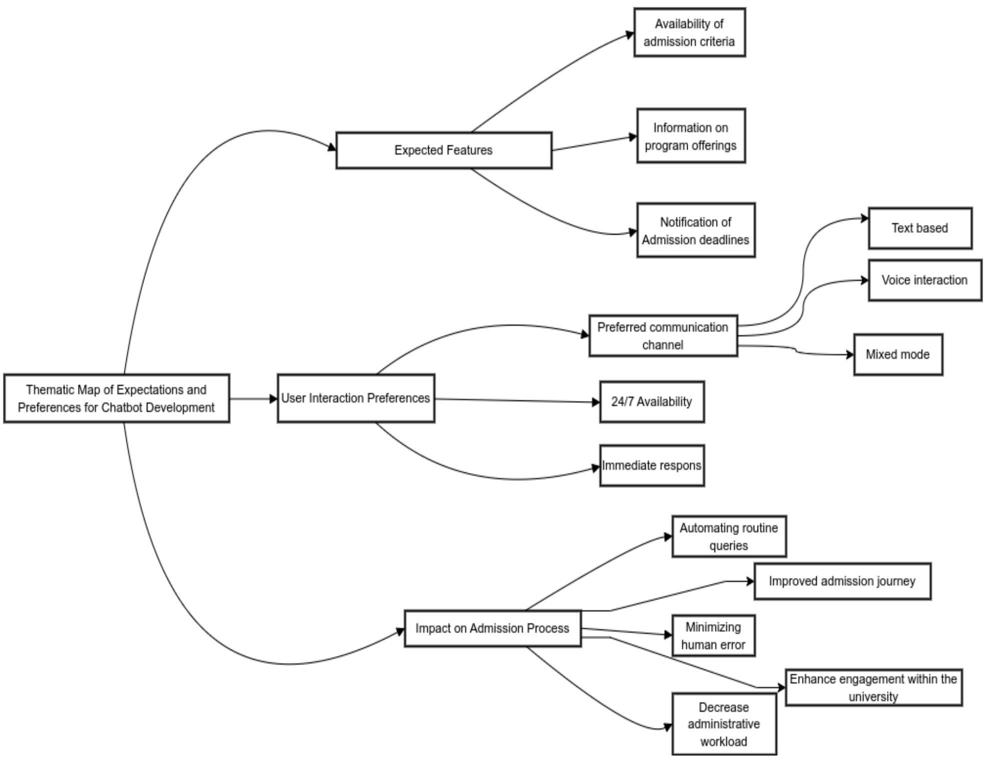


**Figure 3.4.2** The initial thematic map from the qualitative analysis of interview and survey data from prospective students and admission officers

The thematic maps were created to visually represent the identified themes, sub-themes, and their relationships. These maps serve as a visual roadmap for readers, enabling a clear understanding of the structural organization of the data analysis.

### 3.4.5 Queries and Response Gathering

In this research, 1.330 questions are gathered and distributed into 17 intents during the requirements gathering phase as shown in Table 3.4.1. Each intent has three answers where one of the three will be randomly given to every incoming question from the website visitors.

**Table 3.4.1**: Likely user queries and Chatbot responses

| Likely User Queries | One of the Chatbot’s responses |
|---|---|
| What are the admission requirements for University of Ibadan? | To be admitted to University of Ibadan, you must meet the following requirements: [List of admission requirements] |
| What are the tuition fees for University of Ibadan? | The tuition fees for University of Ibadan vary depending on the program and your residency status. For more information, please visit our website or contact the admissions office. |
| What are the different courses offered at University of Ibadan? | University of Ibadan offers a wide range of courses, including: [List of courses] |
| What is the application deadline for University of Ibadan? | The application deadline for University of Ibadan is [date]. However, it is recommended that you apply early to ensure that your application is considered. |
| How do I apply to the University of Ibadan? | To apply to the University of Ibadan, please visit our website and complete the online application form. You will also need to submit transcripts, letters of recommendation, and a personal statement. |
| What is the financial aid process for University of Ibadan? | For information on the financial aid process at University of Ibadan, please visit our website or contact the financial aid office. |
| Can you tell me more about the [Department Name] department at University of Ibadan? | The [Department Name] department at University of Ibadan is a leading department in the field of [field of study]. The department offers a variety of undergraduate and graduate programs in [field of study]. To learn more about the department, please visit their website. |
| What are the different scholarships and bursaries available to students at University of Ibadan? | There are a variety of scholarships and bursaries available to students at University of Ibadan. For more information, please visit our website or contact the financial aid office. |
| What is the campus life like at University of | The campus life at University of Ibadan is |

| | |
|---|---|
| Ibadan? | vibrant and diverse. There is something for everyone to enjoy, including student clubs and organizations, intramural sports, and social events. |
| What are the different housing options available to students at University of Ibadan? | There are a variety of housing options available to students at University of Ibadan, including residence halls (for freshmen and final-year students), private hostels, and students may sort themselves out for off-campus housing. For more information, please visit our website or contact ITeMS. |
| What are the different student clubs and organizations at University of Ibadan? | There are over 100 student clubs and organizations at University of Ibadan. To find a club or organization that interests you, please visit our website or contact the student life office. |
| How do I get involved in extracurricular activities at University of Ibadan? | To get involved in extracurricular activities at University of Ibadan, you can attend club or organization meetings, sign up for intramural sports, or volunteer for student government. |

### 3.4.6 Data Collection Tools

Data collection tools, such as interview recording software and online survey platforms, have been chosen to streamline the process and enhance efficiency. These tools are well-suited to capture both audio and written responses, ensuring the thorough documentation of participant perspectives. The use of technology is in alignment with the practical approach of the research, as it enables organized data collection and storage.

We will use Google forms as our online survey platform as it is more accessible and easy to use. Microsoft Excel will be used as our data management software for organizing and analyzing survey responses and interview data


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**Figure 3.4.3** Data Collection Tools

## 3.5 Data Preprocessing

Cleaning and preprocessing of the data collected for the chatbot for prospective students is essential to ensure that the chatbot can provide accurate and helpful responses to prospective students.

After all relevant data has been gathered from all the relevant data sources, such as admission requirements, FAQs, application forms, and any historical chat or email interactions with prospective students, the next phase involves the inspection of data which is to examine the data to understand its structure and format. Identify the types of information available and any potential data quality issues.

Furthermore, we will be conducting data cleaning which involves the removing or correcting of any inaccuracies, inconsistencies, or errors in the data. Common cleaning tasks include:

- Removing duplicate records.
- Standardizing data formats (e.g., date formats, names, addresses).
- Handling missing data (imputing or removing).
- Correcting typos and spelling errors.
- Eliminating irrelevant or redundant information.

Next is Text Preprocessing, which is preparing the text data by applying natural language processing (NLP) techniques including:

- Tokenization: Split text into individual words or tokens.
- Lowercasing: Convert all text to lowercase to ensure case-insensitivity.
- Stopword Removal: Remove common words (e.g., "and," "the," "is") that don't contribute much to the content.
- Lemmatization or Stemming: Reduce words to their root form to normalize variations (e.g., "running" becomes "run").
- Entity Recognition: Identify and categorize entities like names, dates, and places.

After the text preprocessing stage is completed, we will then proceed to the Data Structuring phase which involves organizing the data into a format suitable for chatbot training and retrieval, such as question-answer pairs or intents with associated responses.

If it is necessary, the Feature Engineering phase follows which is to create additional features or attributes that can enhance the chatbot's understanding and performance. This may involve sentiment analysis, topic modeling, or other NLP techniques.

Intent Labeling stage comes next which is to assign intents or categories to user queries or statements in the data. For example, common intentions might include "Admission Requirements," "Application Process," "Financial Aid," and so on.

Following the intent labeling phase is the response generation stage which is majorly the preparation of well-structured, informative responses to user intents. These responses may come from the data used or would be generated by the chatbot based on predefined templates or dynamic information retrieval. Data splitting then comes next which is the splitting of the data into training, validation, and test sets. The major importance of splitting the data is for training and evaluating the chatbot's performance.

### 3.5.1 Model Training

After the data splitting has been successfully done, training of the model is the next stage which includes a whole lot of techniques.

A combination of Natural Language Processing (NLP), Machine Learning and Deep Learning techniques is used. Below is the breakdown of how each of the techniques is applied for specific stages or phases of the chatbots.

**Natural Language Processing (NLP)**

NLP is a fundamental component for understanding and processing user inputs. It includes techniques like tokenization, stemming, lemmatization, and entity recognition, which are crucial for making sense of the text. NLP libraries and tools like NLTK and spaCy, can be used for these tasks.

**Machine Learning (ML)**

Machine Learning would be used to identify user intents and extract information from user queries. The Machine Learning algorithms and approach for chatbots that would be used is the Text Classification; which includes algorithms like Naive Bayes and Support Vector Machines (SVM)

**Deep Learning**

We will be specifically using deep learning for generating responses and understanding user context. More specifically, the deep learning model that we will be making use of is the Transformers model (BERT). These models have achieved state-of-the-art results in various NLP tasks and are particularly useful for generating context-aware responses and understanding user intent.

Machine learning models can be sufficient for basic intent recognition and information extraction, while deep learning models, especially transformer-based models, excel in more complex NLP tasks and can generate more context-aware and human-like responses. However, they often require more data and computational resources.

The approach we would be making use of is the hybrid one, where NLP is used for data preprocessing, machine learning models handle intent classification and entity recognition, and deep learning models come into play for generating responses and understanding user context. The specific algorithms and tools are selected based on their ease of scalability and ease of maintenance.

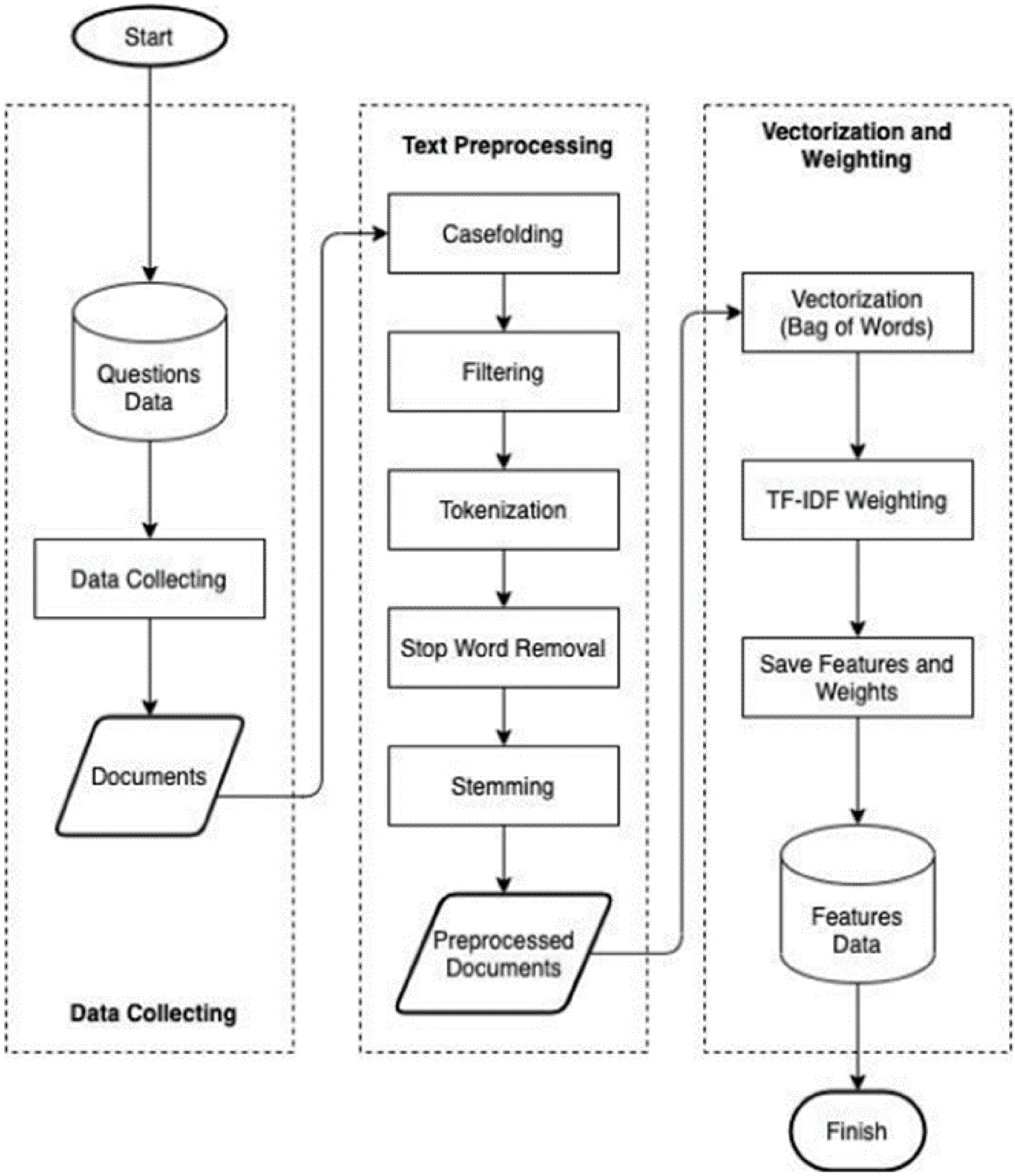



**Figure 3.5.1** Model Training process flow

# 3.6 Chatbot Architecture

The design of an effective chatbot for admissions targeting prospective students involves a critical decision regarding the chatbot's architecture. This section outlines the rationale behind the chosen chatbot architecture, describes the key components, and provides a justification for its selection based on the research objectives.

## 3.6.1 Chatbot Architecture Choice

For the specific task of assisting prospective students in the admissions process, a **retrieval-based chatbot architecture** has been chosen. This architecture is characterized by its ability to provide predefined responses based on a structured dataset of questions and answers. It aligns with our research objectives due to its suitability for handling the unique requirements of admission procedures. The retrieval-based chatbot architecture consists of several key components:

**Natural Language Processing (NLP)**

NLP techniques are employed to preprocess and interpret user queries. This component is essential for the chatbot to understand the diverse range of questions and user intents typically encountered during the admissions process.

**Intent Recognition**

Machine learning models are utilized for intent recognition, enabling the chatbot to categorize user queries into specific intent categories, such as "Admission Requirements," "Financial Aid," and "Application Deadlines."

**Response Retrieval**

The core of the retrieval-based architecture involves retrieving relevant responses from a predefined knowledge base. This knowledge base comprises a structured repository of questions and corresponding answers, including detailed information on admission requirements, application procedures, academic programs, and more.

**Context Management**

To maintain context throughout a conversation, the chatbot manages the history of the interaction, allowing it to refer back to previous user queries and responses. This contextual understanding is crucial for providing coherent and personalized information.

### 3.6.2 Justification for Retrieval-Based Architecture

The selection of a retrieval-based chatbot architecture is rooted in the alignment with our research objectives:

**Accuracy**: Accuracy is a paramount consideration in admission-related queries. Retrieval-based models ensure precision by providing answers directly from a predefined knowledge base, reducing the likelihood of erroneous or misleading information.

**Control and Compliance**: The admission process often involves adherence to specific regulations and standards. Retrieval-based chatbots offer a high level of control over responses, ensuring that accurate and approved information is consistently conveyed to prospective students, meeting compliance requirements.

**Efficiency**: Efficiency in handling user inquiries is of utmost importance, especially in scenarios where the chatbot must address a large volume of admission-related queries. Retrieval-based architectures excel in this aspect, as they can quickly retrieve relevant responses from a structured knowledge base.

The retrieval-based chatbot architecture, encompassing NLP, intent recognition, response retrieval, and context management, has been thoughtfully selected for our research objectives, which emphasize accuracy, control, and efficiency in providing reliable and precise information to prospective students. This architecture serves as the foundation for the chatbot implementation, aiming to enhance the admissions process and provide a user-friendly and informative experience for prospective students.

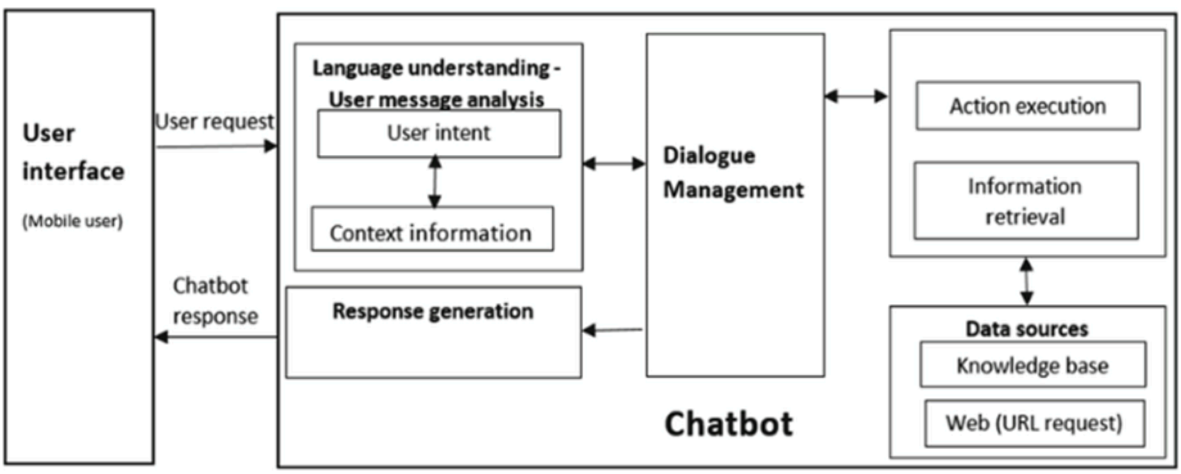



**Figure 3.6.1** Chatbot Architecture

## 3.7 Chatbot Development

This section outlines the methodology employed in the development of a chatbot dedicated to facilitating the admission process for prospective students. It discusses the tools, technologies, and platforms used, as well as the iterative development process that includes testing and refinements.

### 3.7.1 Tools and Technologies

The development of an admission chatbot necessitates the selection of tools and technologies that are conducive to achieving the research objectives. The following tools and technologies were employed in the development process:

**Programming Languages**

Python, a versatile and widely adopted programming language, was chosen as the primary language for chatbot development. Python is well-suited for natural language processing (NLP) tasks, making it an ideal choice for chatbot implementation.

**NLP Frameworks**

The development process leveraged popular NLP frameworks, including spaCy and NLTK, for tasks such as text tokenization, entity recognition, and intent classification. These frameworks provided essential capabilities for processing and understanding natural language.

**Chatbot Framework**

For building and deploying the chatbot, the Rasa framework was employed. Rasa offers a comprehensive solution for chatbot development, encompassing natural language understanding, dialogue management, and conversation flow design.

**Web Framework**

To provide a user-friendly interface for prospective students, a Flask web application was developed. Flask, a micro web framework for Python, was used to create a simple and responsive chatbot interface that integrates with the Rasa chatbot backend.

**Cloud Services**

The chatbot system was deployed on a cloud platform, specifically Amazon Web Services (AWS), to ensure scalability, reliability, and availability. AWS provides the infrastructure required to handle varying loads and maintain a responsive user experience.

### 3.7.2 Iterative Development and Testing

The chatbot development process followed an iterative approach that included multiple stages of testing and refinements:

**Data Collection and Annotation**

A significant amount of data, including admission-related questions and responses, was collected and annotated. This dataset served as the training and validation data for the chatbot's machine learning models.

**Training and Model Iteration**

Machine learning models for intent recognition and entity recognition were trained and iteratively refined to enhance accuracy and coverage. The chatbot's knowledge base was continuously updated with new information.

**User Testing and Feedback**

In a controlled testing environment, users will interact with the chatbot, providing valuable feedback. This feedback will be used to identify areas for improvement, including refining responses and addressing common user queries.

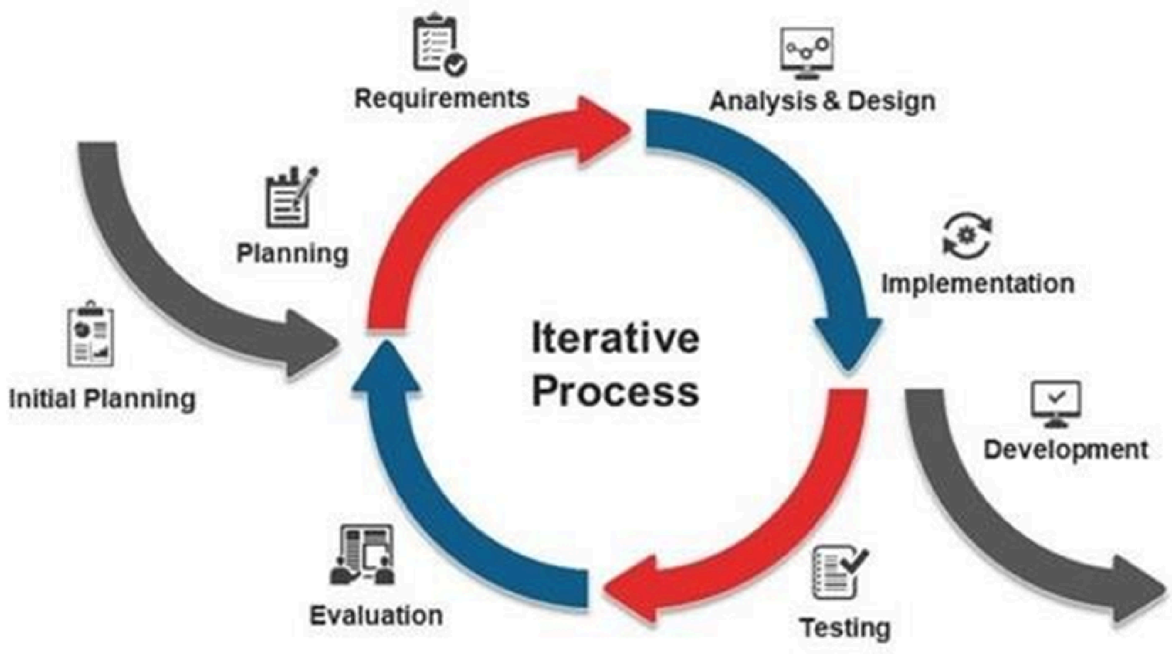



**Figure 3.7.1** Iterative development mode

## 3.8 User Interaction Design

The design of an effective chatbot for admissions targeting prospective students involves gathering information about different aspects of the admissions process. This section describes the interaction between the student and the chatbot.

### 3.8.1 Student Interaction with the chatbot

The chatbot starts with a warm welcome and a brief introduction clearly stating the bot's purpose in assisting the prospective student with the admission process.

The interaction between the student and the chatbot are in form of a question and answer

**1. Information Gathering**

The bot asks for basic information such as name, contact details, and the program of interest, which will be used as a conversational approach to make the process engaging.

**2. Program Details**

The bot can provide some information about some available programs, including details about them, so that students can ask specific questions about their programs.

**3. Admission Requirement**

The bot outlines the admission criteria and required documents while also breaking down the steps involved in the application process.

**4. FAQs and Complaints**

The bot provides a clear answer to some commonly anticipated questions and also implements the future for any issues students may encounter and log complaints.

**5. Application Assistance**

Guide student through the application form step by step

**6. Progress Tracking**

Provide an update on the application status and allow students to inquire about their progress in real time.

**7. Notification and Reminder**

The chatbot should notify prospective students of an important deadline or a missing application.

8. **Feedback**

The bot will be able to get feedback from students to improve future interactions and provide contact information for further assistance if needed.

### 3.8.2 User Experience (UX) Principle Application to the Chatbot

The user experience (UX) principle application with chatbot for admission processing is to provide a seamless and efficient experience for prospective students. Chatbots are designed to provide instant answers to queries, avoiding ambiguity and delayed replies, and streamlining interactions with digitally active students. (Beer, 2021)

Also, integration of visual elements such as images, videos, or interactive buttons when appropriate. Visual aids can enhance user engagement and understanding, especially in scenarios where visual information is essential, so as to enhance user experience.

**24/7 Availability**

Chatbots should be available 24/7 to answer questions from prospective students, providing them with instant answers to their queries and guiding them through the admission process.

**Personalization**

The chatbot is programmed to provide personalized responses to prospective students, based on their interests, academic background, and other relevant factors.

**Ease of use**

The chatbots can be designed to be easy to use, with a simple and intuitive interface that allows prospective students to find the information they need quickly and easily.

**Efficiency**

The chatbot can help streamline the admission process by automating routine tasks such as answering common questions, checking application status, and providing information on financial aid.

**Accessibility**

The chatbot is designed to be accessible to all students, including those with disabilities, by providing alternative text descriptions for images and other multimedia content.

## 3.9 Methodology Evaluation

The evaluation stage of the chatbot involves assessing its performance to ensure that it meets the desired goals and provides a positive user experience. The evaluation would typically encompass both quantitative and qualitative aspects.

### 3.9.1 Quantitative Evaluation

**Accuracy**

Measures the chatbot's ability to correctly understand user intents and provide accurate responses. This is particularly important for tasks like intent classification and entity recognition.

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions}$$

**Precision and Recall**

This metric is useful for evaluating the performance of the chatbot in tasks like entity recognition and question answering, where there may be a trade-off between precision (relevance of retrieved information) and recall (completeness of retrieved information).

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

**F1-Score**

It is the harmonic mean of precision and recall, therefore, it will measure the balance of the chatbot's performance.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

**Response Time**

Also we will be considering the response time which is the Measure the time taken by the chatbot to respond to user queries. Lower response times are generally preferred, as users often expect quick responses. We will be monitoring and reporting response times for various user interactions.

**User Satisfaction Surveys**

We will be collecting feedback from users through surveys or feedback forms to gauge their satisfaction with the chatbot's performance and user experience. Also, we will make use of the Likert scales to quantify user satisfaction.

### 3.9.2 Qualitative Evaluation

**User Testing**

We shall be conducting user testing sessions where real users interact with the chatbots, observe how well they are able to accomplish their tasks and gather feedback on their experience.

**Human Evaluation**

We shall engage human evaluators who will manually assess the chatbot's responses for accuracy, coherence, and relevance.

**Conversation Logs Analysis**

We will analyze the chatbot's conversations to identify common user issues, misunderstandings, and areas for improvement.

**Error Analysis**

Examination of errors made by the chatbot, classifying them, and determining if they are systematic or random. This can help in fine-tuning the chatbot.

### 3.9.3 Metrics for Chatbot-Specific Tasks

**Task Completion Rate**

To determine the task completion rate, we will measure the percentage of user queries or tasks successfully completed by the chatbot.

$$Task\ Completion\ Rate\ = \frac{Completed\ Tasks}{Total\ Tasks}$$

**Conversation Length**

To measure conversation length, we will assess the average number of turns or messages exchanged in a conversation. Longer conversations might indicate user confusion or dissatisfaction.

## 3.10 Ethical Considerations

When building a chatbot for the university admission process, it is important to consider ethical concerns related to data collection, user privacy, and chatbot interactions. Chatbots should be designed with data privacy in mind, comply with relevant data protection laws and regulations, be transparent about what information is being collected, and provide accurate and unbiased information to users. (Naffi et al., 2022)

### 3.10.1 Data Privacy

Chatbots collect massive amounts of data, including personal information such as name, address, phone number, and email address. This data can be used to identify individuals and can be used for malicious purposes if it falls into the wrong hands. Therefore, it is important to ensure that chatbots are designed with data privacy in mind, and that they comply with relevant data protection laws and regulations. (*Ethics of Chatbots*, n.d.)

### 3.10.2 User Privacy

Chatbots can be used to collect sensitive information from users, such as academic records, financial information, and personal details. It is important to ensure that users are aware of what information is being collected, how it will be used, and who will have access to it. Users should also have the option to opt-out of data collection if they wish. (*Ethics of Chatbots*, n.d.)

### 3.10.3 Chatbot Interactions

Chatbots can be programmed to manipulate users into providing sensitive information or making decisions that are not in their best interests. It is important to ensure that chatbots are designed to provide accurate and unbiased information, and that they do not engage in deceptive or manipulative practices. (*Ethics of Chatbots*, n.d.)

## 3.11 Methodology Limitations

As with any research endeavor, it is crucial to acknowledge and transparently discuss the limitations inherent in the chosen methodology. Recognizing these limitations not only ensures the integrity of the study but also provides valuable insights into the boundaries of the findings. In this section, we identify the potential challenges and constraints encountered during the research on the development of a chatbot for the University of Ibadan's Admission Unit. Each limitation is carefully examined, and suggestions for mitigating these constraints and avenues for future research are offered to enhance the robustness and applicability of the study's outcomes.

1. **Sample Representativeness**: The participants in this study were drawn exclusively from the University of Ibadan, limiting the generalizability of the findings to a broader context. The demographic characteristics, technological exposure, and expectations of prospective students and admission staff at other institutions may differ significantly. Assuming the study were conducted at a more technologically advanced institution, the expectations and preferences for a chatbot's development might be influenced by a higher level of familiarity with technology, potentially leading to different findings.

2. **Self-Reporting Bias**: The reliance on self-reporting through interviews and surveys introduces the risk of participants providing socially desirable responses or aligning their answers with perceived expectations, thereby affecting the authenticity of the data. For example a prospective student might express enthusiasm for a chatbot's development, anticipating that it aligns with the university's technological advancements, even if their personal preferences or concerns might differ.

3. **Subjectivity in Thematic Analysis**: While thematic analysis is a powerful qualitative method, it is inherently subjective. The identification and interpretation of themes are influenced by the researcher's perspective and preconceptions, potentially introducing bias. For instance the identification of a theme related to the importance of 24/7 availability in the chatbot might be influenced by the researcher's personal experiences or beliefs about the significance of immediate access to information.

4. **Limited Exploration of Contextual Factors**: The study primarily focuses on expectations and preferences for chatbot development without extensively exploring contextual factors such as technological literacy, cultural nuances, or institutional dynamics that could significantly influence these expectations. Without considering

cultural differences in communication styles, the study may overlook the impact of cultural nuances on how users interact with and perceive a chatbot.

5. **Limited Accessibility to Documented Information**: One significant limitation pertains to the accessibility of documented information. Despite efforts to obtain relevant documents from the admission office for data extraction purposes, certain constraints may impede complete access. The sensitivity of certain admission records, data privacy concerns, or institutional policies may restrict the researcher's ability to extract comprehensive data. Consequently, the study's findings may be influenced by the partial availability of information, limiting the depth of insights that could be derived from a more exhaustive dataset. The inability to access detailed admission records, including specific criteria for program eligibility and historical data on admission trends, may hinder a comprehensive understanding of the factors influencing prospective students' expectations.

6. **Temporal Constraints**: The research timeline imposes inherent limitations, impacting the depth and breadth of the investigation. The cross-sectional nature of the study captures a snapshot of participants' expectations and preferences within a specific timeframe. This temporal constraint may not fully encapsulate the dynamic nature of attitudes towards chatbot development, potentially overlooking evolving trends or shifts in perspectives over an extended period. The study may not capture seasonal variations in admission inquiries or changes in technological trends that could influence participants' expectations.

7. **Language and Cultural Nuances**: The study acknowledges potential limitations related to language and cultural nuances in the interpretation of participant responses. The use of open-ended surveys and interviews, while valuable for capturing rich qualitative data, may introduce challenges in accurately capturing the subtleties of participants' perspectives, especially in a multicultural and multilingual context. The richness of participant responses may be lost in translation, and cultural nuances influencing expectations may not be fully captured.

8. **Participant Availability and Recruitment Bias**: Recruitment and participant availability present inherent limitations. The study's reliance on willing participants may introduce recruitment bias, as those who volunteer may hold distinct views from non-participants. Additionally, participant availability may restrict the diversity of the sample, impacting the representativeness of the findings. Participants who are more tech-savvy or have specific interests in chatbot technology may be overrepresented, potentially skewing the study's insights towards a particular demographic.

## 3.12 Suggestion for further research

In contemplating the limitations listed in the preceding section, it becomes evident that the path to knowledge is an iterative journey, evolving with each study. The identified constraints present opportunities for future researchers to deepen their investigations, refine methodologies, and contribute to the ever-growing body of knowledge. This section delves into suggestions for future research endeavors, proposing avenues that, if explored, may unravel further intricacies and a subtle distinction in the domain of chatbot development for educational institutions. By considering these recommendations, researchers can contribute to the ongoing discourse, enhancing the depth and breadth of understanding in this dynamic field.

1. To address sample representativeness, future research could involve comparative studies across multiple educational institutions to capture a broader spectrum of perspectives. This would enable a more comprehensive understanding of expectations and preferences beyond the confines of a single university.

2. In order to reduce self-reporting bias, integrating behavioral metrics alongside self-reported data can provide a more holistic view. Tracking actual interactions with chatbots and comparing them with participants' self-reported preferences can help identify discrepancies.

3. Future studies may address subjectivity in rheumatic analysis by incorporating inter-rater reliability checks, involving multiple analysts independently coding and interpreting the data. Establishing consensus and addressing disparities in coding can enhance the reliability of thematic analysis.

4. For limited exploration of contextual factors, future research can conduct in-depth contextual studies, employing methodologies like case studies or ethnographic approaches. This would involve a detailed exploration of technological literacy, cultural nuances, and institutional dynamics that influence expectations.

5. To complement longitudinal studies, future research could explore experimental designs that manipulate specific variables to observe their impact on expectations over time. This would provide a more nuanced understanding of causality.

6. Future research should consider extending data collection periods to capture seasonal variations and account for evolving trends. This approach would enable a more dynamic and comprehensive analysis of participant expectations.

7. Conducting studies in multiple languages and cultural contexts can help mitigate language and cultural biases. Implementing cross-cultural analyses can uncover unique perspectives that might be overlooked in a single-cultural study.

# CHAPTER FOUR

# IMPLEMENTATION AND TESTING

## 4.1 Implementation

Here is the github repository containing the implementation of the chatbot

https://www.github.com/Timadey/uiadmit

### 4.1.1 Tools and Technologies Used

In the development of the admission chatbot for prospective students, a strategic selection of tools and technologies was employed to ensure an efficient and effective implementation. The technology stack encompasses:

**1. Programming Language**

Python was chosen as the primary programming language due to its versatility and suitability for natural language processing (NLP) tasks. And ReactJs was used in developing the frontend of the application. Figma was used in developing a prototype of the application.

**2. NLP Frameworks**

The implementation leveraged popular NLP frameworks, namely spaCy and NLTK. These frameworks facilitated critical tasks such as text tokenization, entity recognition, and intent classification.

**3. Chatbot Framework**

The Rasa chatbot framework served as the central component, providing comprehensive capabilities for natural language understanding, dialogue management, and conversation flow design.

**4. Web Framework**

The development of the user interface was accomplished using the Flask web framework. Flask, known for its simplicity and flexibility, contributed to the creation of a user-friendly chatbot interface.

**5. Cloud Services**

Amazon Web Services (AWS) was chosen as the cloud platform for deployment. AWS ensures scalability, reliability, and accessibility, allowing the chatbot to handle varying loads effectively.

This curated set of tools and technologies was instrumental in crafting a robust and scalable chatbot system. The combination of Python, spaCy, NLTK, Rasa, Flask, and AWS formed a cohesive technological foundation, enabling the chatbot to interpret user queries and provide accurate responses seamlessly.

### 4.1.2 User Interface Design

The user interface (UI) of the admission chatbot for prospective students was meticulously designed to ensure a seamless and intuitive interaction experience. A full list of the prototype can be viewed here. Key considerations in the UI design process include:

**1. Conversational Interface**

The UI was crafted as a conversational interface to mimic natural human-like interactions. This approach aimed to make users feel comfortable and engaged throughout the interaction with the chatbot.

**2. Clean and Minimalistic Design**

A clean and minimalistic design philosophy was adopted to avoid overwhelming users with unnecessary elements. The interface focused on clarity and simplicity to enhance user understanding and navigation.

**3. Intuitive Navigation**

The navigation flow was designed to be intuitive, guiding users through the chatbot interaction effortlessly. Clear prompts and easy-to-follow cues were implemented to ensure a user-friendly experience.

**4. Visual Feedback**

Visual feedback elements, such as typing indicators and response animations, were incorporated to provide users with real-time feedback on their interactions. This visual responsiveness enhanced the overall conversational experience.

**5. Personalization Features**

Personalization features, such as user greetings and the ability to remember context from previous interactions, were integrated to create a more personalized and engaging experience for prospective students.

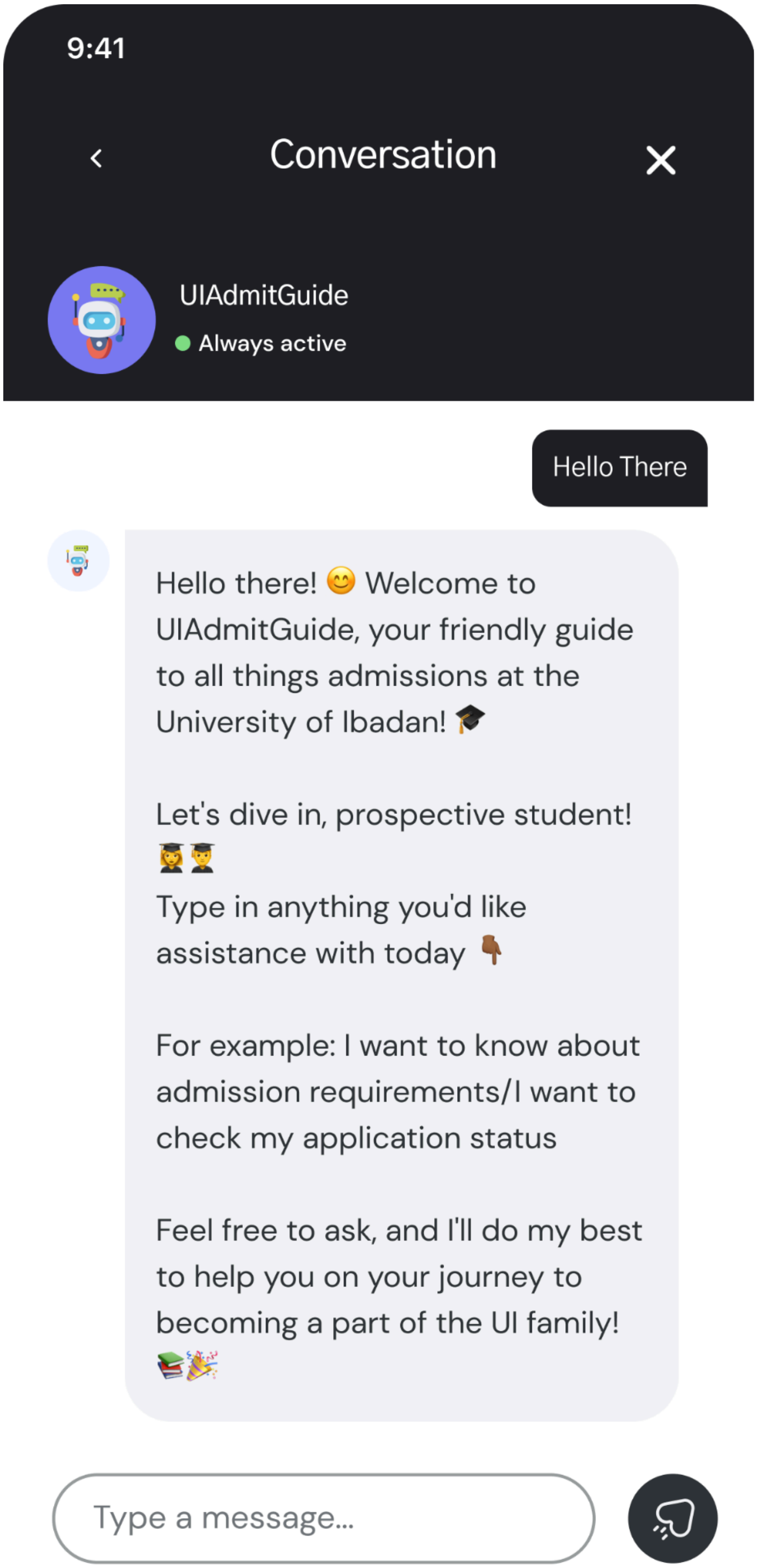
**6. Accessibility Considerations**

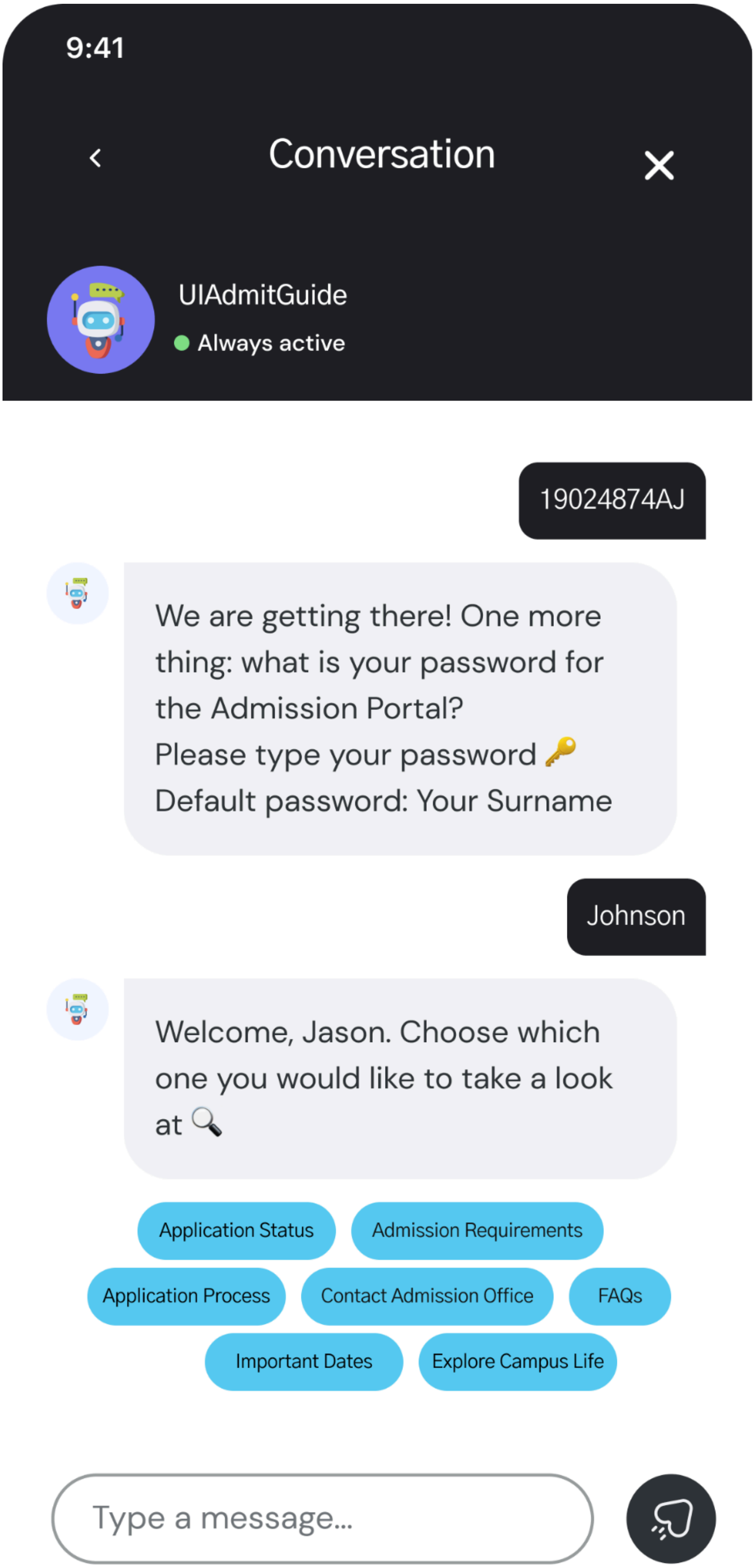
Accessibility was a key focus, with the UI designed to accommodate diverse user needs. Features like text resizing options and clear contrast were implemented to enhance accessibility for all users.

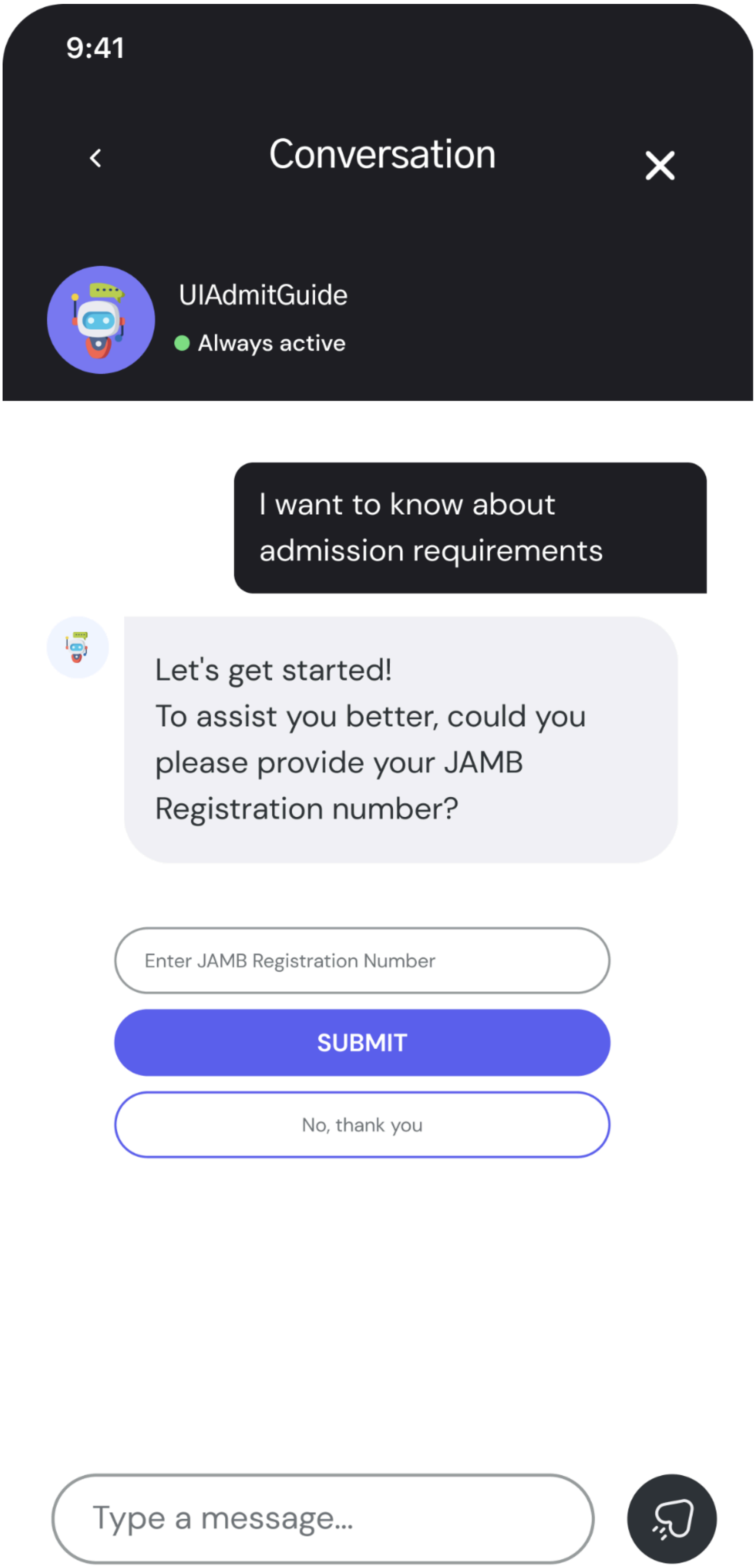
**7. Mobile Responsiveness**

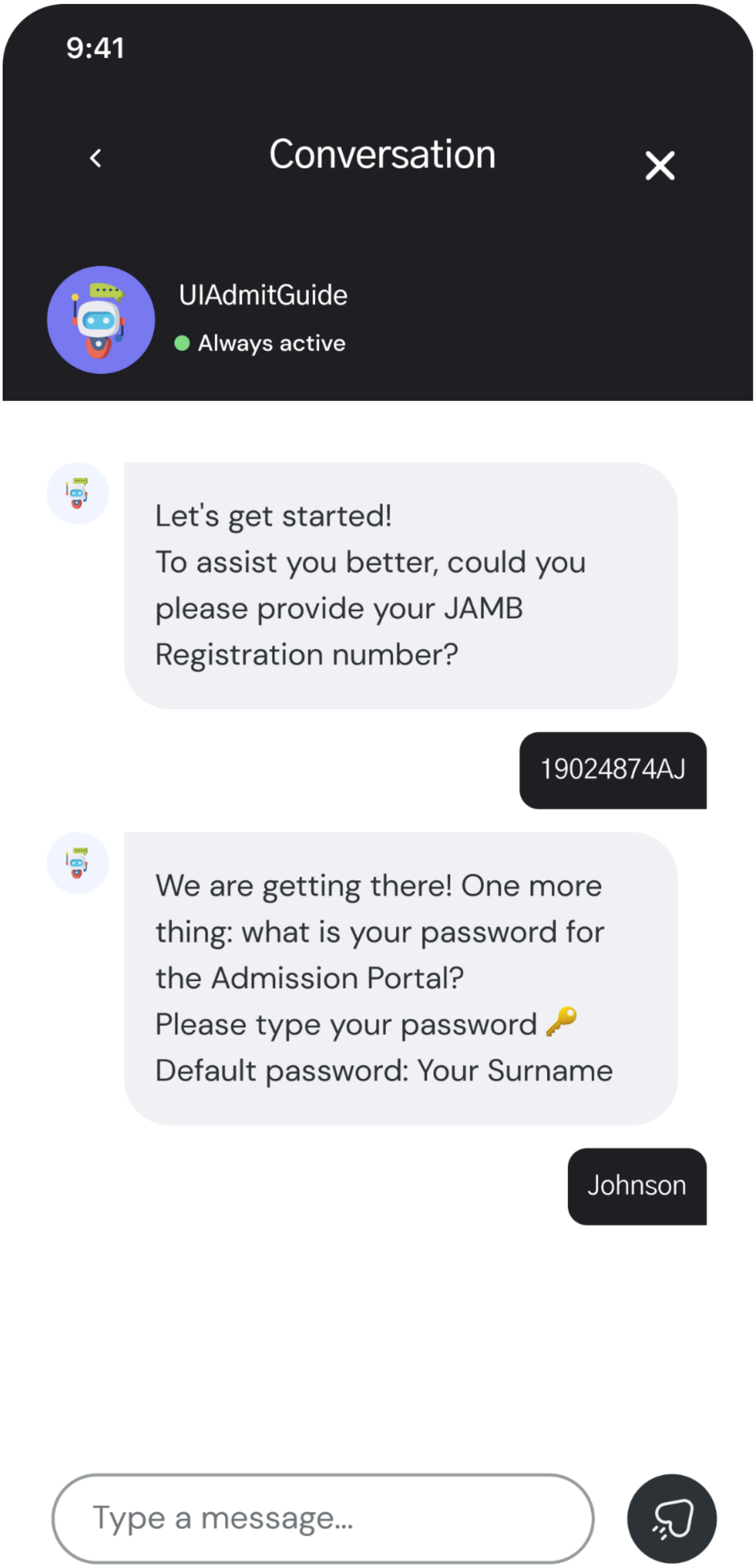
Recognizing the importance of mobile users, the UI was designed to be responsive, ensuring a consistent and optimal experience across various devices, including smartphones and tablets.

The resulting user interface successfully blends functionality with an appealing design, providing prospective students with an accessible, engaging, and user-centric platform to seek information and assistance related to admissions.


9:41
Conversation
UIAdmitGuide
Always active
Hello There
Hello there! 😊 Welcome to UIAdmitGuide, your friendly guide to all things admissions at the University of Ibadan! 🎓
Let's dive in, prospective student! 👩‍🎓👨‍🎓
Type in anything you'd like assistance with today 👇🏾
For example: I want to know about admission requirements/I want to check my application status
Feel free to ask, and I'll do my best to help you on your journey to becoming a part of the UI family! 📚🎉
Type a message...


9:41
Conversation
UIAdmitGuide
Always active
19024874AJ
We are getting there! One more thing: what is your password for the Admission Portal?
Please type your password 🔑
Default password: Your Surname
Johnson
Welcome, Jason. Choose which one you would like to take a look at 🔍
Application Status
Admission Requirements
Application Process
Contact Admission Office
FAQs
Important Dates
Explore Campus Life
Type a message...


9:41
Conversation
UIAdmitGuide
Always active
I want to know about admission requirements
Let's get started!
To assist you better, could you please provide your JAMB Registration number?
Enter JAMB Registration Number
SUBMIT
No, thank you
Type a message...


9:41
Conversation
UIAdmitGuide
Always active
Let's get started!
To assist you better, could you please provide your JAMB Registration number?
19024874AJ
We are getting there! One more thing: what is your password for the Admission Portal?
Please type your password 🔑
Default password: Your Surname
Johnson
Type a message...

### 4.1.3 Integration with the University Website

In the seamless integration of the admission chatbot, a strategic decision was made to embed the chatbot directly into the university website. This integration brings about several advantages:

**1. Centralized Access**

By embedding the chatbot within the university website, prospective students have centralized access to valuable admission-related information without the need to navigate to external platforms.

**2. Enhanced User Experience**

The integration contributes to an enhanced user experience by providing a cohesive and familiar environment. Users can seamlessly transition between exploring the website and engaging with the chatbot for real-time assistance.

**3. Increased Engagement**

Placing the chatbot within the university website increases user engagement. Prospective students can easily initiate conversations, seek information, and receive assistance within the context of their admission journey.

**4. Consistent Branding**

The integration ensures consistent branding and user interface elements, reinforcing the university's visual identity throughout the chatbot interaction. This consistency fosters a sense of reliability and professionalism.

**5. Efficient Navigation**

Prospective students can efficiently navigate the website and access specific information by interacting with the chatbot. This integration streamlines the information-seeking process, contributing to a more efficient and user-friendly website experience.

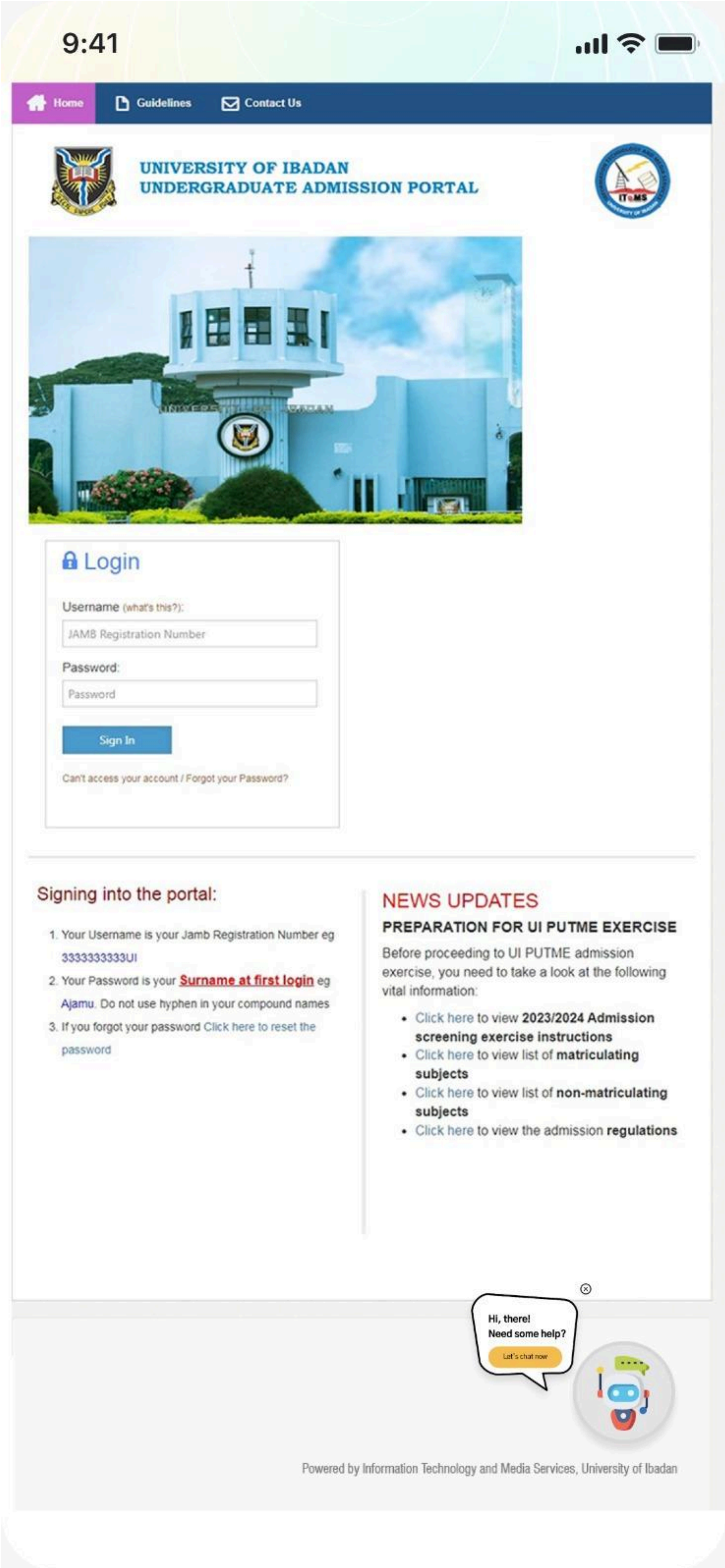
**6. Real-time Assistance**

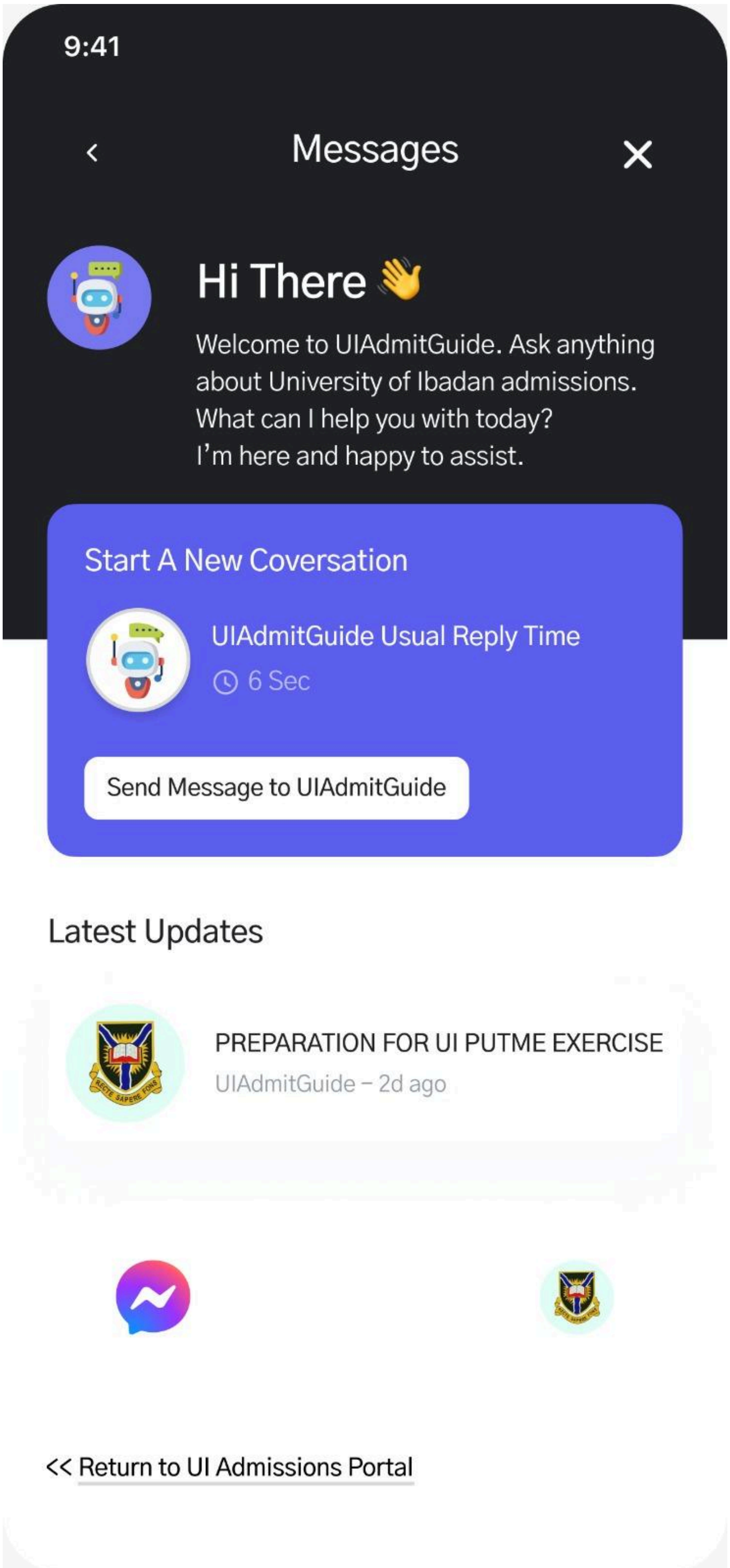
Offering real-time assistance directly within the website context allows the chatbot to address user queries promptly, providing prospective students with instant support and information during critical stages of the admission process.

**7. Seamless Deployment**

The integration process was executed seamlessly, ensuring minimal disruption to the existing website structure. This strategic deployment allows for the chatbot to seamlessly blend into the website's overall architecture.

The integration of the chatbot into the university website stands as a testament to the commitment to providing prospective students with a unified, informative, and engaging digital experience throughout their exploration of admission-related information


9:41
Home
Guidelines
Contact Us
UNIVERSITY OF IBADAN
UNDERGRADUATE ADMISSION PORTAL
Login
Username (what's this?):
JAMB Registration Number
Password:
Password
Sign In
Can't access your account / Forgot your Password?
Signing into the portal:
1. Your Username is your Jamb Registration Number eg 3333333333UI
2. Your Password is your Surname at first login eg Ajamu. Do not use hyphen in your compound names
3. If you forgot your password Click here to reset the password
NEWS UPDATES
PREPARATION FOR UI PUTME EXERCISE
Before proceeding to UI PUTME admission exercise, you need to take a look at the following vital information:
Click here to view 2023/2024 Admission screening exercise instructions
Click here to view list of matriculating subjects
Click here to view list of non-matriculating subjects
Click here to view the admission regulations
Hi, there!
Need some help?
Let's chat now
Powered by Information Technology and Media Services, University of Ibadan


9:41
Messages
Hi There 👋
Welcome to UIAdmitGuide. Ask anything about University of Ibadan admissions.
What can I help you with today?
I'm here and happy to assist.
Start A New Coversation
UIAdmitGuide Usual Reply Time
6 Sec
Send Message to UIAdmitGuide
Latest Updates
PREPARATION FOR UI PUTME EXERCISE
UIAdmitGuide – 2d ago
<< Return to UI Admissions Portal

## 4.2 Testing

### 4.2.1 Testing Processes

The testing phase for the admission chatbot project was meticulous and strategic, encompassing various essential processes:

**1. Testing Objectives**

Rigorous testing was undertaken to validate chatbot functionalities, assess performance, and ensure alignment with specified requirements.

**2. Comprehensive Testing Types**

A multi-tiered approach covered unit testing, integration testing, system testing, and user acceptance testing (UAT), ensuring a thorough examination of the chatbot's capabilities.

**3. Scenario-Based Testing**

Carefully designed test scenarios simulated diverse user interactions, covering expected positive interactions and challenging negative scenarios to validate the chatbot's robustness.

**4. Performance and Usability Evaluation**

Performance testing gauged responsiveness, scalability, and resource utilization. Simultaneously, usability testing focused on the overall user experience, emphasizing navigation and response clarity.

**5. Iterative Refinement and Bug Fixing**

An agile approach to addressing identified issues ensured prompt bug fixing and iterative development, reflecting a commitment to continuous improvement.

**6. User Feedback Integration**

Valuable user feedback, particularly from usability testing, played a pivotal role in refining dialogue flow, response generation, and overall user interaction.

**7. Post-Deployment Monitoring**

Vigilant post-deployment monitoring mechanisms were instituted to proactively address any emerging issues, ensuring a smooth user experience in real-world scenarios.

**8. User Acceptance Testing (UAT)**

The culmination of testing involved UAT, where real users interacted with the chatbot, contributing valuable insights that informed final refinements and improvements.

This rigorous testing process underscores our commitment to delivering a reliable, user-friendly chatbot experience for prospective students, aligning seamlessly with the university's admission processes.

# CHAPTER FIVE

# SUMMARY, CONCLUSION AND RECOMMENDATION

In this concluding chapter, we bring together the threads of our research journey, culminating in the development and implementation of the admission chatbot for prospective students.

## 5.1 Summary

### 5.1.1 Objective Recap

Our research set out to create an intelligent chatbot tailored for prospective students navigating the intricacies of university admissions. We successfully achieved this objective through a comprehensive exploration of methodologies and technologies.

### 5.1.2 Implementation Highlights

The chatbot's implementation showcased a carefully selected technology stack, including Python, spaCy, NLTK, Rasa, Flask, and AWS. The integration into the university website ensured a centralized, user-friendly experience.

### 5.1.3 Testing Rigor

Our testing processes, spanning unit, integration, system, and user acceptance testing (UAT), were characterized by meticulous scenario design and iterative refinement. Performance and usability evaluations underscored our commitment to delivering a robust and user-centric solution.

## 5.2 Conclusion

### 5.2.1 Achievements

The successful development and deployment of the admission chatbot mark a significant achievement, poised to enhance the user experience for prospective students.

### 5.2.2 Impact on User Experience

The chatbot's anticipated impact on user experience lies in its ability to streamline inquiries, provide real-time assistance, and contribute to a smoother admission process.

### 5.2.3 Contributions to the Field

Our research contributes to the evolving landscape of chatbot development, particularly within the context of educational institutions, offering insights and practices that can inform future endeavors.

### 5.2.4 Limitations and Future Work

Acknowledging limitations, we envision future work addressing these constraints and exploring new opportunities for refinement and innovation.

## 5.3 Recommendations

### 5.3.1 Further Refinements

We recommend ongoing refinements to enhance the chatbot's capabilities, leveraging insights from testing and user feedback.

### 5.3.2 User Training and Engagement

Suggesting strategies for user training and engagement to optimize the chatbot's effectiveness and foster user adoption.

### 5.3.3 Continuous Monitoring

Recommendations include the establishment of continuous monitoring mechanisms to promptly address evolving challenges and identify opportunities for improvement post-deployment.

## 5.4 Concluding Thoughts

### 5.4.1 Reflection on the Journey

Our journey reflects a commitment to excellence and innovation, navigating challenges, and celebrating successes in the pursuit of a user-centric chatbot solution.

### 5.4.2 Gratitude and Acknowledgments

Expressing heartfelt gratitude to all contributors, advisors, and stakeholders whose support and guidance were instrumental in bringing this research to fruition.

### 5.4.3 Closing Remarks

As we conclude this chapter and our research endeavor, we look ahead with optimism, confident in the positive impact our admission chatbot will have on the university's engagement with prospective students.

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