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A CHATBOT FOR POSTGRADUATE INFORMATION DISSEMINATION

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Abstract

Information and Communication Technology (ICT) is defined as the acquisition, processing, storage and dissemination of information through the use of computer and related technologies. While information dissemination in most Nigerian tertiary institutions utilizes the potentials of the modern computer, the revolutionizing automation potentials of Artificial Intelligence Agents (AIA) has not been duly explored. This has resulted in communication gaps and delayed responses to crucial and time critical queries and requests. To curtail this lapses and to ensure timely delivery of information to users, this paper adopted mixed method research (i.e. design based approach and action research). Incremental software development model was used for software development, Decision Tree Algorithm was used for training the system whose database was populated with relevant and likely questions and corresponding responses. The Chatbot was designed using HTML, CSS, and ReactJava programming languages while the database was designed using PHP and MySQL Database. The result was a self-reporting, self-learning and interactive Chatbot for postgraduate information dissemination that autonomously create corresponding responses to user's queries in real time. User's Intent Understanding (UIU), Query Response Accuracy (QRA), Error Handling (EH) and Mean Response Time (MRT) were some of the metrics used for user -system's performance evaluation. Using a self-structured questionnaire, responses obtained from 130 student users purposively selected in TASUED with similar academic characteristics and needs were analysed using IBM SPSS v20. Findings show that on average, the system achieved 89% on UIU, 89% on QRA, less than 2 seconds on MRT (depending on processor's speed) and 95% on EH for all cases considered. The paper thus concludes that the decision tree algorithm is effective and efficient for developing self-reporting and self-learning chatbots and recommends further improvements based on these metrics using other machine learning algorithms.

Keywords: TASUED, COSIT, Self-reporting, Chatbot, Information Dissemination.

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1.0 INTRODUCTION

Internet facilities, Mobile computing and Ubiquitous computing are revolutionizing technologies that have changed our ways of acquiring, processing, transmission and storage of information in favour of real time data processing. In many corporate organizations, this has resulted in favourable outcomes like reduced cost of data processing and information management, availability of time crucial and decision critical information as and when due, and real time dissemination of results to time-critical information request and queries (Hansmann, *et al.* 2003). Nowadays, with the necessary infrastructures like internet facilities, Wi-Fi, firewall, virtual private networks (VPN), organizations, institutions and companies no longer have to spend huge sum of their income for adverts and publicity as was the case in the past, they rather make good use of interactive websites, mobile apps, social media handles etc. Thus, clients' demands and requests are met in real time.

Doherty and Curran (2018), opined that for the purpose of making crucial decisions regarding the goods and services in which investors might invest their money, clients need knowledge, this all the more makes Chatbot creation a welcome development. Compared to the traditional approach (hitherto in place) where customers and clients' queries were attended to by a specially hired human representatives, (also referred to as consultants or customer service agents, CSA), the world has now come to see robots (such as Siri, Alexa) replacing such human representatives effectively.

Despite the efficacies of human customer service representatives, several limitations had been on record. These includes cases of clients' dissatisfaction, inability to handle multiple clients' requests concurrently, error due to fatigue and the high cost of maintaining the human agents by the organizations (Doherty & Curran, 2018). However, with the advent of AI based computing, the modus operandi of many routine tasks in organization (CSA inclusive) began to be automated. A new technology known as Chatbot has emerged and has proven to be very effective in complementing human agents. Thus, this is an era where basic processes necessary for daily functioning of the society are being automated.

Chatbots, also known as conversational agents, have gained significant attention in recent years due to their potential to revolutionize human-computer interaction (HCI) (Kumar et al., 2020). Chatbots are computer programs designed to simulate conversations with humans, either through text or voice interactions (Smith, 2020). The concept of chatbots dates back to the 1960s, with the development of ELIZA, the first Chatbot (Weizenbaum, 1966). Since then, chatbots have evolved significantly, with advancements in natural language processing (NLP) and machine learning (ML) (Hirschberg & Manning, 2015). There are several types of chatbots, including: Rule-based chatbots (RBCs) (Chen et al., 2016); Machine learning-based chatbots (MLBCs) (Wang et al., 2018) and Hybrid chatbots (HCs) (Lee et al., 2019).

Also, chatbots have various applications, including: Customer service (CS) (Kumar et al., 2020); Healthcare (HC) (Liu et al., 2020) and Education (ED) (Wang et al., 2020). In education, literature shows that Jimoh, Adebayo, Akinfenwa and Abimbola (2022) developed a cloud based student information Chatbot system for University of Osun, but the response time was slow. Afonughe, Onah, Uzoma, Andor, and Orisakwe (2021) wrote on the integration of AI-Chatbot into teaching and learning as a panacea for improving Universities' educational and administrative duties in South-South, Nigeria, however it was theoretical, there was no implementation. Also, Lala, Okedigba and Aworinde (2020) developed an improved rapid response model for university admission enquiry system using Chatbot among others.

Despite these advancements, chatbots for institutions still faces several challenges and limitations, including: Contextual Understanding (CU) (Hirschberg & Manning, 2015); Emotional Intelligence (EI) (Smith, 2020) and Security and Privacy Concerns (SPC) (Kumar et al., 2020). Other challenges include Query Response Accuracy (QRA), Error Handling (EH) and Mean Response Time (MRT). These can be handled by chatbot systems that are able to self-learn and self-report in order to improve on cases not captured originally during their design. Thus, a self-reporting Chatbot which is capable of learning to overcome the above shortcoming with security of data is lacking, hence, the focus of this paper.

2.0 LITERATURE REVIEW

2.1 Concept of Chatbot

Chatbots are almost as ancient as computers. However, Chatbots or Virtual Personal Assistants (VPAs) driven by AI have swept the globe in recent years. A Chatbot is essentially a piece of software that mimics human-user communication through text, voice, image, or a combination of these elements (Newlands, 2018). Oxford Dictionaries (2018) defines Chatbot as 'a computer software designed to mimic human-to-human conversation, especially via the Internet.' It is a virtual sidekick or an associate that is incorporated into sites, applications or moment flag-bearers which speaks with us through instant messages.

2.1.1 Rule-Based Chatbots (RBCs)

A rube-based Chatbot uses pattern matching algorithms to interpret input and deliver responses based on established criteria. The core notion remains the same, despite the differences in complexity among pattern matching techniques. After classifying the user input as a pattern, the Chatbot compares the pattern with a list of previously stored answers to choose a predetermined response (Marietto *et al*. 2013; Xufei, 2021). Many Chatbots use pattern matching. For instance, early Chatbots like ELIZA, PARRY, and ALICE were particularly fond of it. The rule-based technique has the benefit of speed because it does not require a thorough analysis of the input text (Jia, 2009; Xufei, 2021). The responses, however, are repetitive and lack creativity and adaptability because the developer has already established the expertise or knowledge from the beginning (Pietroszek, 2007; Xufei, 2021).

2.1.2 Machine Learning Based Chatbots (MLBC)

Recent advances in machine learning have made it possible to design Chatbots that are more complex than ever before. Chatbots can now learn from previous encounters and use machine learning algorithms to collect data and generate responses (Xufei, 2021). According to Lin, D'Haro, and Banchs (2016), machine learning-based Chatbots need a large training set. Either generative or retrieval models can be applied. While generative models employ deep learning approaches to generate the response, retrieval-based models choose the best response from a series of responses (Wu, Wu, Xing, Zhou, and Li, 2016; Hien, Cuong, Nam, Nhung and Thang, 2018).

2.1.3 Hybrid Chatbots (HCs)

These are chatbots that are developed through a combination of rule-based and machine learning approaches. The result is usually improved performance, flexibility, and adaptability compared to single-approach chatbots. However, there are complexities that comes with these chatbots such as human expertise requirement and data quality.

2.2 Review of Relevant Literature

Literatures and scholarly works abounds concerning the subject of Chatbots and their application in tertiary institutions, ranging from general enquiries, admissions enquiries and students information provision respectively. For instance, Setaiji (2016) developed a Chatbot using knowledge in Database: An e-commerce website based Chatbot. The machine was embedded with knowledge stored in the database. The Chatbot identifies the sentences and answer questions on its own. But the Chatbot was made up of interfaces in relational DBMS for accessing the core which took a longer time. Also, Prashant *et al.* (2017), developed an online chatting system for college inquiries. They made us to the knowledgeable database and pattern matching algorithm to perform Chatbots' information retrieval. All the detailed working steps were clear with UML and various process diagrams, but the bot did not use ML approach, and was too rigid by rules for students and parents to use.

Similarly, Wadhwa (2017) worked on a college enquiry Chatbot, which uses AI algorithms to evaluate and comprehend user queries. The Chatbot was able to provides answers to students' queries, but was too difficult to use due to complexity in interface design. In the same vein, Thakkar *et al.* (2018) developed Erasmus – AI Chatbot. It was an end-to-end system using cloud services, api.ai (Dialogflow), Mlab (MongoDB cloud), IBM Bluemix (webhook API). The Bot was able to answer questions on university information, but the Chatbot took quite a long latency in responding to the users because it uses too many cloud services. Furthermore, Segura *et al.* (2019) developed a social Chatbot for football. It was deployed as a Slack client, for text-based interaction. It uses SPARQL to retrieve data from Wikidata to generate responses. It answers questions about the Spanish football league called "La Liga" but could not control the outputs delivered to clients.

Windiatmoko *et al.* (2020) developed a FB Chatbot based on DL using RASA framework for University enquiries. They used a generative Chatbot model based on sequence-to-sequence networks called encoder-decoder models. The researchers created a Chatbot integrated with MySQL DB and API for University inquiries with explanations step by step. However, the result was a Chatbot only capable of answering clients with a small number of intents. Harshala *et al.* (2020) on the other hand wrote on college enquiry Chatbot system to implement a virtual assistant based on AI that can solve any college related query. They described a model for Chatbot with information stored in its DB to identify inputs and make decisions as response to given questions. However, it was theoretical and there was no actual implementation of the model.

Lala *et al.* (2020) also developed an improved rapid response model for University admission enquiry system using Chatbot. The model was implemented using IBM Watson to design a Chatbot for rapid response to admission enquiries. Botium was used to evaluate the performance of the Chatbot with an accuracy of 95.9% and instance of 212 successful test cases and 9 failed test cases. The approach introduces users to new and emerging technological solutions in the educational sector. However, Botium is a relatively new technology which not many people are familiar with. Additionally, Jimoh *et al.* (2022) developed a cloud based student information Chatbot system to provide answers to Frequently Asked Questions about Osun State University. The Chatbot shows ease of use, speedy responses generation, etc. however, there were few failed test cases. This paper thus intents to fill these gaps by developing a self-reporting and self-learning chatbot that ensures security of data.

2.3 Theoretical Framework

Any business or institution that implements a Chatbot would have to consider it a relatively novel phenomena, particularly if the technology's target users are accustomed to using more conventional methods to find the answers to their questions. Numerous theoretical frameworks and ideas have been proposed to elucidate the adoption of diverse technical advancements in both developed and developing nations. This paper thus adopts the Technology Acceptance Model (TAM). This is because technological innovation revolves around the following factors; individual, organizational, technology, and environmental characteristics. These factors in either determine the extent to which technologies are adopted (Ikumoro & Jawad, 2019).

Ikumoro and Jawad further states that the Technology Adoption Model (TAM), which reveals the effects of external variables like perceived usefulness (PU) and perceived ease of use (PEOU) as the determinants for IT users' intention to use an innovation (Awa *et al.* 2011), is the widely accepted theory for IT user acceptance and usage in a variety of domains. On the other hand, despite its applicability and validation, there are several drawbacks. For example, it performs best when producing statistically significant results, which can be further enhanced by including more components (Eeuwen, 2017).

To tackle this backlash, the researcher will administer copies of questionnaire to respondents during the testing stage of the College of Science and Information Technology (COSIT) Chatbot under view in order to obtain their feedback in terms of the usefulness and perceived ease of use which can be statistically computed to draw inferences base on the above. This is necessary since Awa *et al.* (2011) have indicated that the integration of TAM with other models to capture variables of human and social change processes, and those capable of influencing innovation adoption process is necessary when new innovations are introduced.

Because the TAM theory offers more thorough insights into taking perceived usefulness and perceived ease of use into consideration, the researchers have consequently adopted it in the development of the COSIT Chatbot. Additionally, a study by Chiemeke and

Evwiekpaefe (2011) claims that a variety of factors would affect users' decisions to embrace and use novel technology. However, since TAM offers a way to statistically determine the aforementioned components, it is regarded as a fairly comprehensive theory in this regard. It is a solid and powerful model for technological innovation adoption research.

3.0 METHODOLOGY

This paper adopted the mixed research method, utilizing both the qualitative and quantitative perspectives as its methodology. The qualitative method included a broad array of approaches such as review of related literature, expert opinions, content validation and development of the Chatbot. The quantitative approached entails the administration of questionnaire to elicit information from the respondents as regards to the performance of the developed Chatbot. The target groups for the questionnaire administration were the lecturers and postgraduate students of COSIT. Generally, information contained in official website and documents of the department served as the primary data for training the COSIT postgraduate Chatbot using Decision Tree Algorithm and secondary data were obtained from scholarly articles and publications.

Furthermore, the technical and other requirements needed to enable the Chatbot function effectively were analyzed appropriately. The adoption of Decision Tree algorithm in training the Chatbot is justified by Rahul, Jaya and Mani, (2021) who noted that the Decision Tree Algorithm is the most powerful Machine Learning algorithm to have existed. Despite all its flaws, it can work well with moderately large and complex datasets with 'n' different classes.

Rahul *et al.* (2021) noted that unless and until every instance is accurately identified, the decision tree implementation would keep building the tree with an increasing number of nodes. We call this phenomena over-fitting. This algorithm finds the best split by utilizing an impurity metric. DTA is hence effective with medium sized datasets rather than very big datasets. DTA generates an ideal split by measuring impurities. The two metrics of impurity that DTA uses most frequently are Gini Impurity or Entropy and Information Gain.

Entropy is the measure of impurities, randomness or uncertainties present in a given data set. Entropy should be low in the data. Information Gain (IG) on the other hand indicates how much 'information' a particular feature or variable gives us about the final outcome i.e. after the dataset is split. Information Gain should be high. The DTA was used in this paper as shown in equations (1) and (2):

$$Entropy\ (p, n) = -\frac{p}{p+n} \times log2\left(\frac{p}{p+n}\right) - \frac{n}{p+n} \times log2\left(\frac{n}{p+n}\right) \quad (1)$$

Where: p = current state or the probability that the given variable will be selected
n = is the selected attribute

$$Information\ Gain\ (IG) = entropy\ (p) - [weighted\ average] \times entropy\ (c) \quad (2)$$

Where: p = parent node or node before split
c = children or nodes after split

3.1 Data Collection and User Testing

After the design and development of COSIT CHATBOT, user testing was conducted using the questionnaire, their responses served as the basic statistical data for evaluating the performance of the Chatbot. The self-designed questionnaire titled "Chatbot for Postgraduate Information Dissemination Questionnaire (CFPIDQ)" was validated by two experts in the field in terms of the content and construct validity i.e. the layout and style, clarity of wording and ability of respondents to answer questions. Their comments, criticism and corrections were used to produce the final copy of the instrument. The reliability of the instrument was determined by conducting a pilot test in the Nigerian Army College of Education which is outside of the study area using 20 respondents. A correlation coefficient of Cronbach alpha α = 0.73 was obtained using the Siegle-Reliability-Calculator, thus, the instrument was considered appropriate.

The paper adopted the chain referral sampling technique to select 130 respondents comprised of 10 lecturers and 120 students across different courses levels (undergraduates, PGD, MSc and PhD respectively) at 95% level of confidence. This sampling technique was necessary because it enabled the researcher to identify only a few postgraduate students in COSIT while others in their category were recommended by the few earlier contacted. The sample size was 130 respondents determined by the Yamane's (1976) statistical distribution which is shown in equation 3:

$$n = \frac{N}{1+N(e)^2} \tag{3}$$

where, n = sample size;
N = population of the study;
e = allowable sample error (0.05)
1 = constant

3.2 Architecture of the Proposed COSIT Chatbot

The architecture of the proposed COSIT Chatbot is shown in Figure 1. The Chatbot is made up of three main components, namely: user interface (client), chatbot engine and knowledge-base.

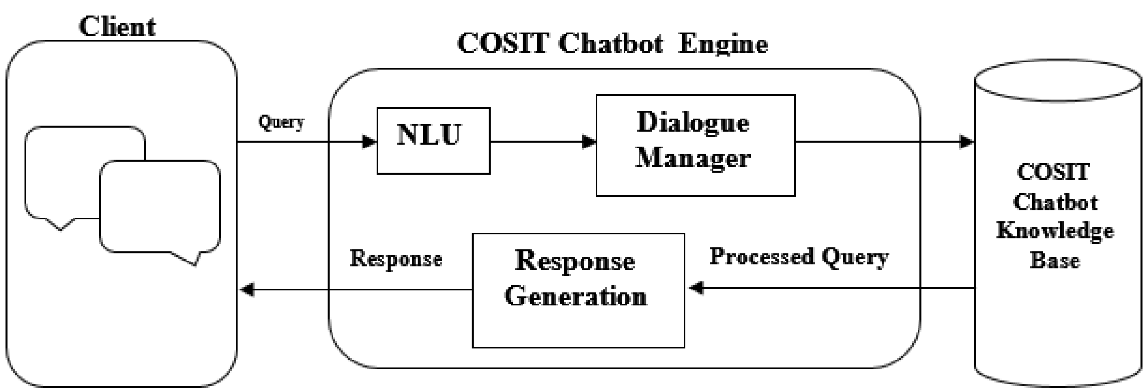

Figure 1: Architecture of COSIT Chatbot

The process begins with a user request to the Chatbot via the *User Interface*, such as "where is COSIT located?" After the reception of this message, the *Chatbot Engine*, using the Language Comprehension Component analyses the question that are being input to the Chatbot to infer information related to intents and entities. In order for the Chatbot to comprehend what the user is typing and offer an output value, the Natural Language Understanding (NLU) component of the Chatbot system is utilized to establish the context of the user's utterance by using keyword extraction. The purpose of Natural Language Comprehension is to interpret text. The basic element of Chatbots is Dialog Management. The Chatbot has to choose what to do next after figuring out which interpretation is the most accurate. It can respond to new information, retain what it has learned, and wait for what comes next.

Upon comprehending the request, the action is carried out and the data is retrieved. After receiving the NLU component's output, it creates a user-facing response. To make the data easily available to the conversation management component, the *Knowledge Base* (KB) or database component will formalize the data. Information relevant to the domain may be stored in this component. The Chatbot performs the necessary tasks or retrieves the needed information from its data sources, which could include a database referred to as the Chatbot's Knowledge Base. The query is handled once it has been searched via the knowledge base to produce a response. Using non-linguistic representations, Natural Language Generation (NLG), a branch of Natural Language Processing (NLP), produces text answers in natural language. The user finally receives a response via the Graphical User Interface (GUI) that is based on the intent defined in the knowledge base, after receiving the query results through natural language generation.

3.3 Flowchart Diagram

The flowchart diagram representing workflow of the activities that takes place in COSIT Chatbot between the users and the Chatbot is shown in Figure 2:

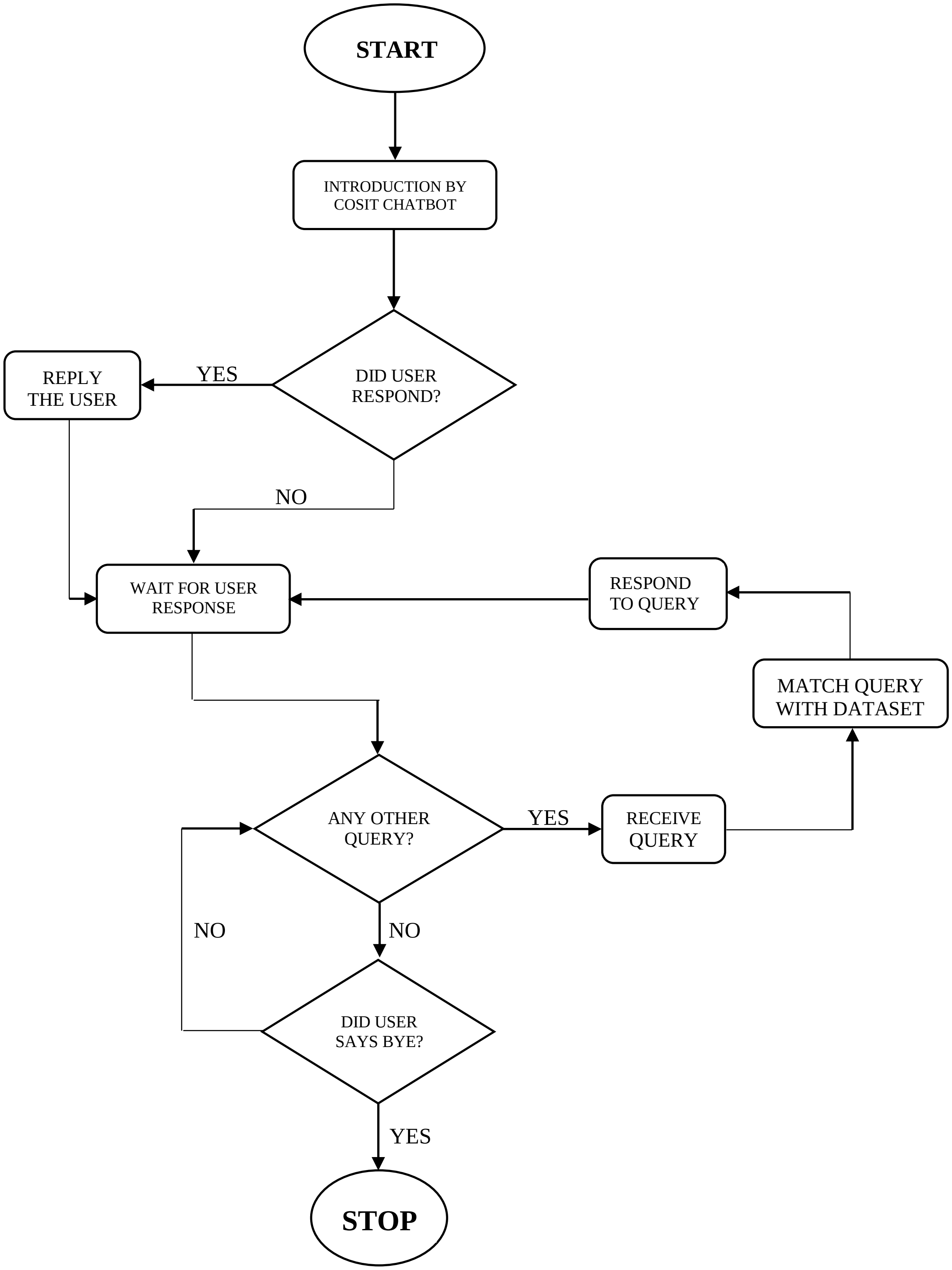

Figure 2: Flowchart diagram for COSIT Chatbot

3.4 Activity Diagram

The activity diagram in Figure 3 shows the different entities in the system, their functions and how they relate with one another.

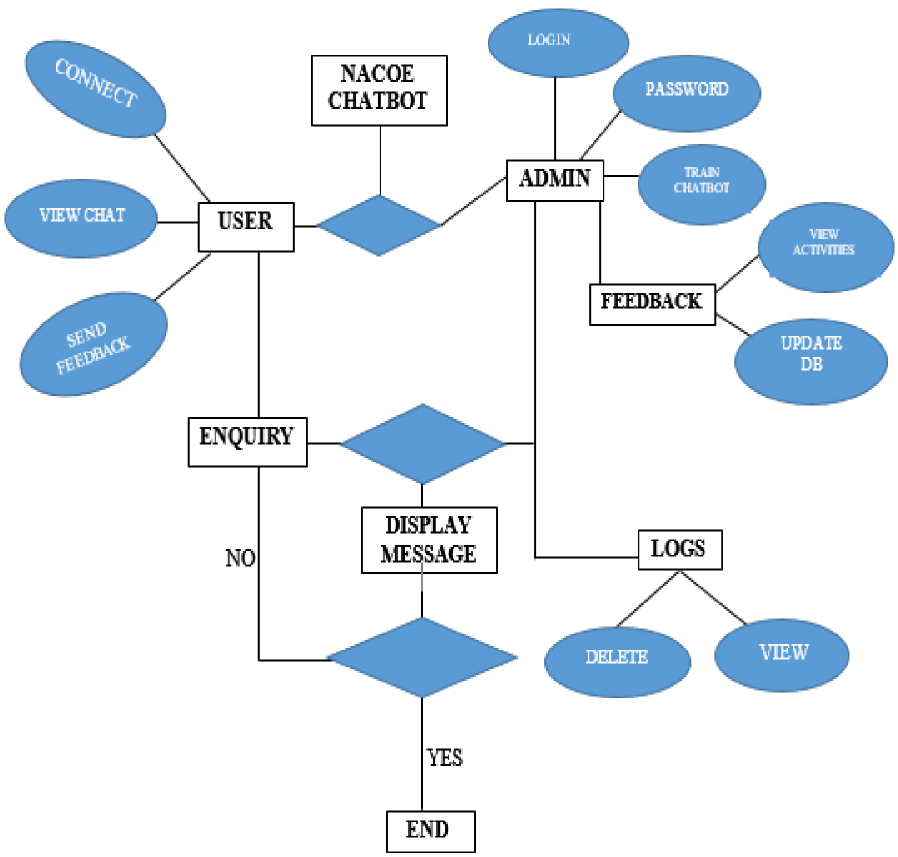

Figure 3: Activity Diagram for COSIT Chatbot

4.0 RESULTS AND DISCUSSIONS

The result of the implementation of the Chatbot is discussed in the following sections while screenshots presented in pictures are used to describe the output of the codes written in ReactJava, PHP, HTML and CSS and their interaction with MySQL database server. The pages are described with respect to their workings of functionality:

4.1 Admin Login Page: The admin login page in Figure 4 refers to the page where the Chatbot administrator in charge of training COSIT Chatbot is required to authenticate using his **Username** and unique **Password** to gain access to the bank end of the Chatbot.

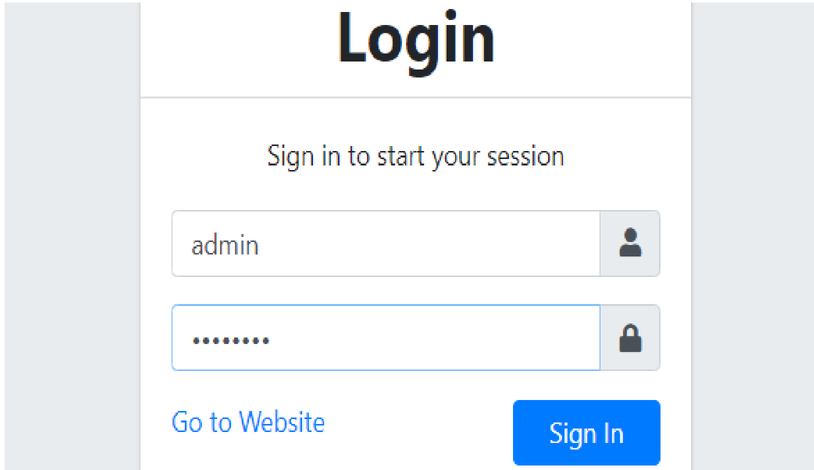

Figure 4: Admin Login Page

4.2 COSIT Chatbot Graphical User Interface: Figure 5 presents the interactive Graphical User Interface that pops up once the user access COSIT Chatbot. It presents the Chatbot **Introductory Message** and the **Input Placeholder** and **Send Button** where the user can type a query. COSIT Chatbot is designed to ensure timely dissemination of information to returning and prospective students, it is therefore an open source Chatbot to all enquirers. The Chatbot has similar features with those of Babu and Wilson, (2021) and Jimoh *et al.* (2022) respectively.

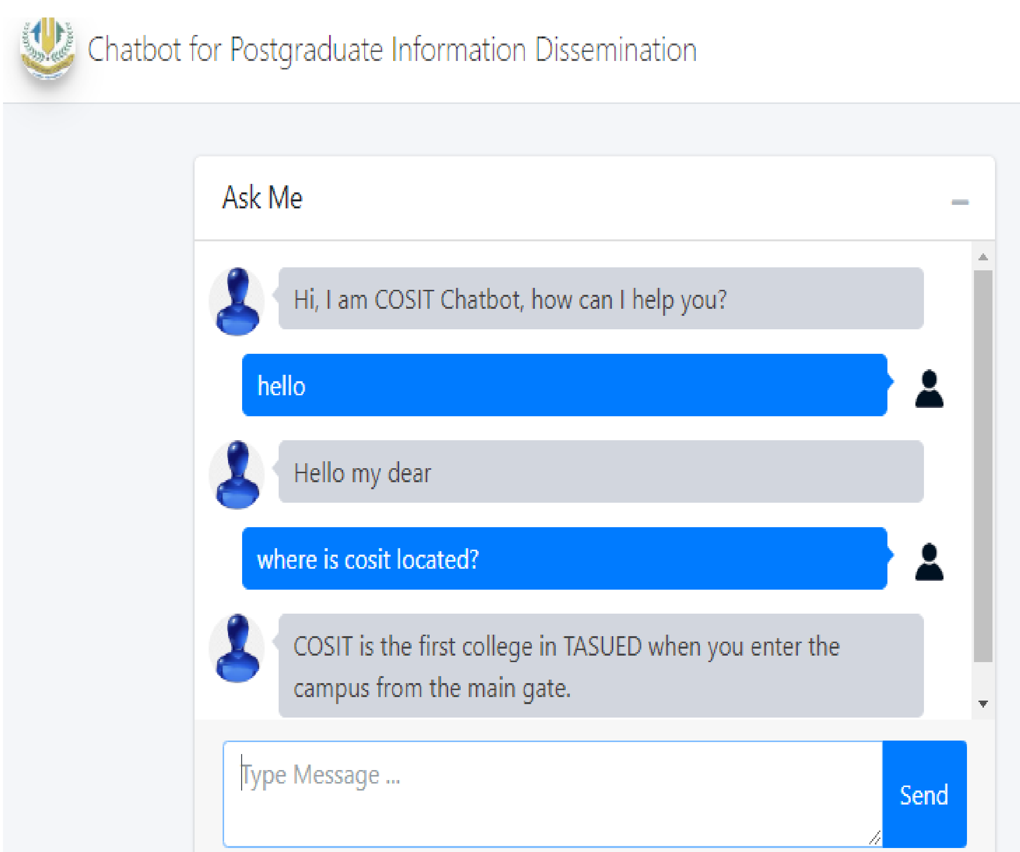

Figure 5: Chatbot Graphical User Interface

4.3 COSIT Chatbot Database: The system administrator can access COSIT Chatbot Database. The database is made up of six tables which are Frequent_asks; questions; responses; system_info; unanswered and users tables respectively as shown in Figure 6.

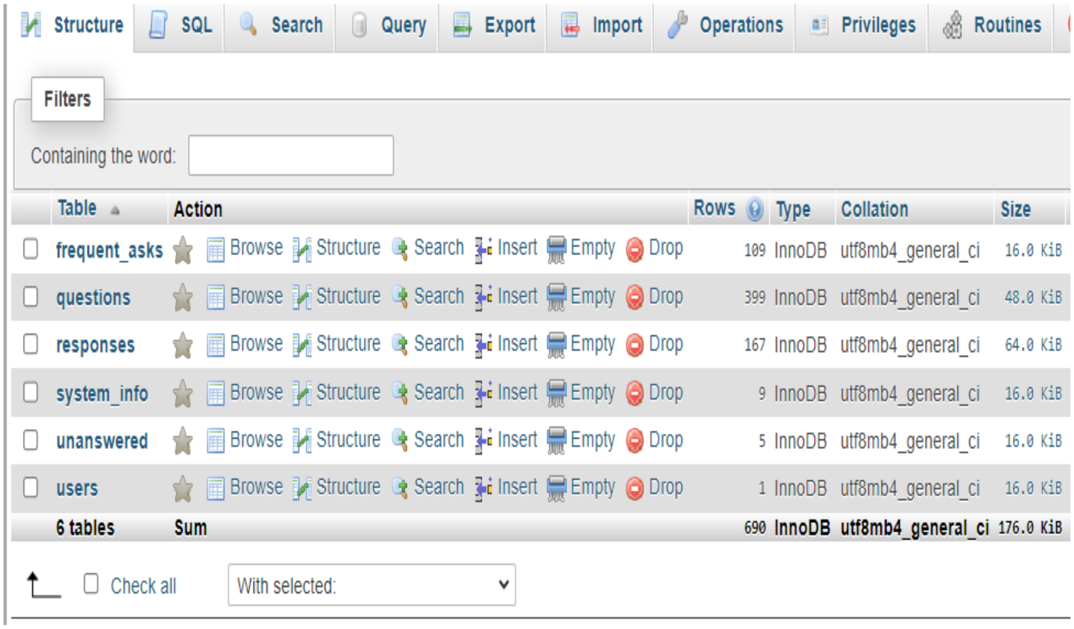

Table	Action	Rows	Type	Collation	Size
frequent_asks	Browse Structure Search Insert Empty Drop	109	InnoDB	utf8mb4_general_ci	16.0 KiB
questions	Browse Structure Search Insert Empty Drop	399	InnoDB	utf8mb4_general_ci	48.0 KiB
responses	Browse Structure Search Insert Empty Drop	167	InnoDB	utf8mb4_general_ci	64.0 KiB
system_info	Browse Structure Search Insert Empty Drop	9	InnoDB	utf8mb4_general_ci	16.0 KiB
unanswered	Browse Structure Search Insert Empty Drop	5	InnoDB	utf8mb4_general_ci	16.0 KiB
users	Browse Structure Search Insert Empty Drop	1	InnoDB	utf8mb4_general_ci	16.0 KiB
6 tables	Sum	690	InnoDB	utf8mb4_general_ci	176.0 KiB

Figure 6: Database Tables

5.0 Evaluation of COSIT Chatbot

To evaluate COSIT Chatbot, 129 questionnaires were retrieved from users randomly selected to test the performance of the Chatbot by providing feedback in terms of its quality and efficiency. The standard metrics used to evaluate the performance attributes and the results were the speed of answering, error management, intelligence, ease of navigation, personalization and input understanding of the Chatbot among others.

5.1 Demographic Information of Respondents

Table 2 shows the demographic information of 129 respondents that participated in this paper with 89 (69%) being less than 40 years of age while 40 (31%) were adult of 46 years and above. Seventy seven (60%) are male and 52 (40%) are female. Seventy one (55%) of the respondents are Christian while 58 (45%) practice Islam. Those that were single were 93 (72%) while 36 (28%) were married. Furthermore, 70 (54%) of the respondents were undergraduate students, 49 (38%) were postgraduate students, while 10 (8%) were lecturers.

Table 2: Demographic Information of Respondents

Factors	Categories	N	%
Age	<20 – 29	51	40%
	30 – 39	38	29%
	40 – 49	25	19%
	50 – 59	15	12%
	Total	**129**	**100**%
Gender	Male	77	60%
	Female	52	40%
	Total	**129**	**100**%
Religion	Christianity	71	55%
	Islam	58	45%
	Total	**129**	**100**%
Marital status	Single	93	72%
	Married	36	28 %
	Total	**129**	**100**%
Occupation	Undergraduates	70	54%
	Postgraduates	49	38%
	Lecturers	10	8%
	Total	**129**	**100**%

Source: Researcher's field work, 2024

5.2 Respondents Opinion of COSIT Chatbot Performance

The result in Table 3 shows that 129 (100%) respondents claims there is ease of starting a conversation with COSIT Chatbot, 110 (85%) respondents equally claims that access to COSIT Chatbot is easy and it meets your expectations but 19 (15%) respondents disagreed and 124 (96%) respondents agreed that COSIT Chatbot shows flexibility in communication while 5 (4%) disagreed. In the same vein, 121 (94%) respondents agreed that COSIT Chatbot has the ability to maintain a themed discussion but 8 (6%) disagreed and 129 (100%) respondents claimed that COSIT Chatbot ensures users' privacy and security by not requesting for personal or sensitive details, more so, 122 (95%) respondents agreed that COSIT Chatbot recognizes and facilitates users' goal and intent while 7 (5%) respondents disagreed.

Furthermore, 126 (98%) respondents claimed that COSIT Chatbot provides relevant information to users while 3 (2%) respondents disagreed, 117 (91%) respondents agreed that COSIT Chatbot is resilient to failure while 12 (9%) respondents disagreed, also, 119 (92%) respondents claimed that COSIT Chatbot shows understandability and politeness during conversation while 10 (8%) respondents disagreed. Furthermore, 126 (98%) respondents agreed that COSIT Chatbot has conversational credibility while 3 (2%) respondents disagreed.

Also, 129 (100%) respondents claimed that COSIT Chatbot returns answers to users queries speedily, the response time is very fast and COSIT Chatbot's responses in unexpected situations or to queries not understood is polite and friendly respectively. In addition to the above, Table 3 shows that interaction with COSIT Chatbot creates a sense of enjoyment or satisfaction as 111 (86%) respondents agreed to the research item while 18 (14%) respondents disagreed and 123 (95%) claimed that conversation with COSIT Chatbot creates a feeling that it has a great personalization while 6(5%) respondents disagreed.

The above findings thus implies that on average, the system achieved 89% on User's Intent Understanding (UIU), 89% on Query Response Accuracy (QRA), less than 2 seconds on Mean Response Time (MRT) (this also depends on systems processor's speed) and 95% on Error Handling (EH) respectively for all cases considered, hence, the Chatbot satisfies the user and system requirements for the test cases.

Table 3: Respondents Opinion of COSIT Chatbot Performance

Variables	Response	N (%)
There is ease of starting a conversation with COSIT Chatbot	Yes No	129 (100%) –
Access to COSIT Chatbot is easy and it meets your expectations	Yes No	110 (85%) 19 (15%)
COSIT Chatbot shows flexibility in communication	Yes No	124 (96%) 5 (4%)
COSIT Chatbot has the ability to maintain a themed discussion	Yes No	121 (94%) 8 (6%)
COSIT Chatbot ensures users' privacy and security by not requesting for personal or sensitive details	Yes No	129(100%) –
COSIT Chatbot recognizes and facilitates users' goal and intent	Yes No	122 (95%) 7 (5%)
COSIT Chatbot provides relevant information to users	Yes No	126 (98%) 3 (2%)
COSIT Chatbot is resilient to failure	Yes No	117 (91%) 12 (9%)
COSIT Chatbot shows understandability and politeness during conversation	Yes No	119 (92%) 10 (8%)
COSIT Chatbot has conversational credibility	Yes No	126 (98%) 3 (2%)
COSIT Chatbot returns answers to users queries speedily	Yes No	129 (100%) –
The response time is very fast	Yes No	129(100%) –
COSIT Chatbot's responses in unexpected situations or to queries not understood is polite and friendly	Yes No	129(100%) –
Does interaction with COSIT Chatbot create a sense of enjoyment or satisfaction?	Yes No	111 (86%) 18 (14%)
Conversation with COSIT Chatbot creates a feeling that it has a great personalization	Yes No	123 (95%) 6 (5%)

Source: Researcher's field work, 2024

6.0 CONCLUSION AND RECOMMENDATIONS

The paper yielded a successful result. The postgraduate enquiry Chatbot was capable of receiving and processing users' queries with a reasonable degree of speed and accuracy and presenting outputs for the processed data in real time. The Chatbot is reasonably secure and enforces data integrity resulting from the use of a secured Database Management System. The paper thus concluded that the Chatbot has a high degree of User's Intent Understanding (UIU), Query Response Accuracy (QRA), Error Handling (EH) and Mean Response Time (MRT). This is because access to the Chatbot is easy and it meets users' expectations, the Chatbot shows flexibility in communication, the Chatbot has the ability to maintain a themed discussion and the Chatbot ensures users' privacy and security by not requesting for personal or sensitive details, more so, the Chatbot recognizes and facilitates users' goal and intent. Thus, the decision tree algorithm is effective and efficient in designing and implementing self-reporting and self-learning chatbots like those implemented using other cloud based platforms. The paper thus recommends the following: that institutions should incorporate Chatbots into their websites to ease users' access to information in real time; that further improvements should be done on the test metrics used; that other machine learning algorithms should be used to determine their prospects and constraints in chatbots development.

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