

## **MODELING UNIVERSITY ICT SERVICES AND SOLUTIONS USING AN ARTIFICIAL INTELLIGENCE CHATBOT**

**Nwankwo Godson Sunday, Dr. Nwobodo-Nzeribe Nnenna Harmony and Prof. Okafor  
Eric.Chilozie**

Department of Computer Engineering Enugu State University of Science and Technology, Enugu State

[godson@esut.edu.ng](mailto:godson@esut.edu.ng), [nnenna.nwobodo@esut.edu.ng](mailto:nnenna.nwobodo@esut.edu.ng), [okaforeric@esut.edu.ng](mailto:okaforeric@esut.edu.ng)

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**Abstract:** Modeling university ICT services and solutions using AI Chatbot is building an AI-powered virtual agent to represent the human staff in providing similar services and solutions to ICT users online via Facebook Messenger and Web Demo platforms to enhance the accessibility of the ICT services. This study aims to model an artificial intelligence (AI) for university information and communication technology (ICT) services and solutions delivery by providing responses to questions asked by ICT service users. The modeled Chatbot was implemented to solve the challenges that traditional ICT staff in universities faced, such as high volume of requests, long wait times, numerous repeated questions, duty hours constraints, and inability to provide personalized support to ICT users at all times due to human natural capacities. To address these challenges, universities need to explore the use of AI Chatbot as a means of providing more efficient, personalized, and accessible ICT support services 24 hours per week (24/7). In this study, text and voice-based Chatbot was developed with Google Cloud Dialogflow and integrated it into Facebook Messenger and Web Demo for interactive text and voice messaging that enabled ICT service users to receive solutions as text or voice responses from Chatbot at anytime and anywhere. First, we identified 17 ICT services and classified them into 42 intents for building the Chatbot with 381 training phrases that formed the dataset. Second, 42 intents was created using Google Cloud Dialogflow Essential Console. Chatbot was trained for 3 months using rule-grammar and machine learning matching with 92% accuracy. The results of this study proved that the developed system can help universities provide more efficient and accessible ICT services to their ICT service users, as well as contribute to the advancement of AI Chatbot technology applications in the field of education.

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**Keywords:** Modeling, ICT, Services, AI, Chatbot, Dialogflow, Training, intent, Dataset

### **INTRODUCTION**

The University Information and Communication Technology (ICT) consultancy services and solutions delivery can be modeled using a well-defined modeling language supported by Model-Based System Engineering (MBSE)(Sanford Friedenthal et al, 2022). System modeling can start from scratch or from the reuse of existing models in developing a new system (Xiaofei Wang et al, 2020). Modeling a system represents the system in an abstract view using graphical notation with unified modeling language (UML) and explains its different perspectives without altering the understanding of the system by the end users(Sommerville,2023). The graphical notation of the system model can show the input and output of the system, and represents all linkages that will

enable a better understanding of the system by the developing engineer (ER Deepak Gary, 2021). In system modeling, the developer considers factors such as assumption, simplification, limitation, constraints, and preferences as a part of the model (Hossein Arsham, 2021). The model based framework of a system serves as a way to include mass estimation and stability of the system (Pagliuca .G. et al, 2019). A system model can be classified as a physical model or an abstract model (like in mathematical and logical representation of a system) (Adiel T. A et al (2021).

The modelling of the proposed system features a hybrid model that comprises both the descriptive and analytical models of ICT consultancy services and solution delivery to ensure that the system planning, requirements, analysis, design and implementation are captured in the research work.

The university ICT department offers ICT services to students, staff, and management of the university. Generally, the ICT Unit of the University is responsible for deploying ICT infrastructure and services for administration, teaching, research, training, and learning to the University community. The services that most university ICT centres can provide vary depending on the level of their ICT infrastructures in both resource personnel and equipment. The study proposes that Enugu State University of Science and Technology ICT unit consultancy services and its solution delivery can be modeled using artificial intelligence (machine learning)-based Chatbot to demonstrate -alternative means of asking, telling, knowing, and providing solutions to students, guardians, staff, and management of the university in the absence of ICT staff and without restriction in location and time of the service. It simply denotes that any end user of ESUT ICT services can simply ask non-human staff (Chatbot) about his/her task anytime, anywhere, and any day and get answer(s) in real-time without visiting the ICT Unit or calling any ICT staff.

### MATERIALS AND METHODS

The materials used include a computer system with a high capacity Intel processor, hard disk drive (HDD), memory (RAM), and internet enabled for computing. The software used are Microsoft Windows 10 Operating System, Google Cloud Dialogflow Essential for Chatbot designing and training, Facebook Messenger for Chatbot deployment in social media for mobile device and Web Demo for desktop users.

The input data were collected as text documents from the university website, questionnaires and official memos in the ICT unit. The collected data were classified as the intents and processed as a natural language and stored as a dataset for training and testing Chatbots using machine learning (ML) matching in conjunction with a convolution neural network (CNN).

Fig. 1 shows the block diagram of the components of the system realized using the top-bottom design approach, which divides the system into subsystems for easy design.

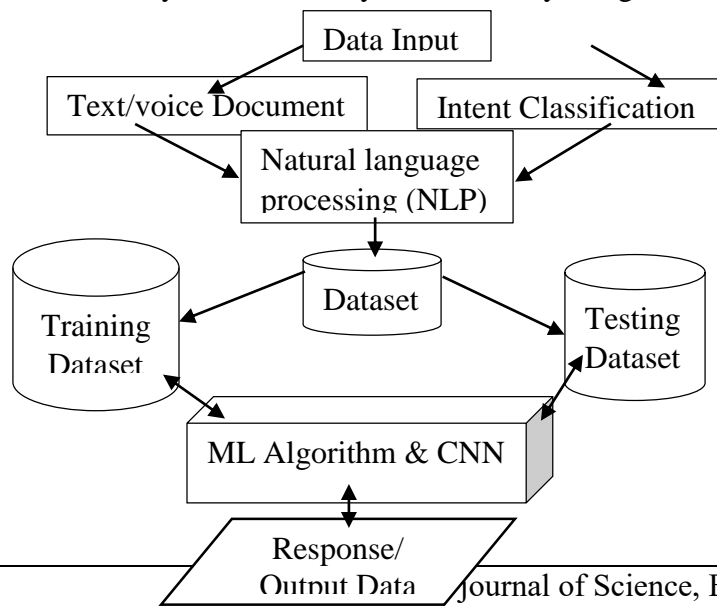


Fig. 1: Block diagram of the system components

The architectural model of the system shown in Fig.2 comprises the knowledge base of the ICT domain expert, the end users expression, the hardware devices for communication channel, the development and deployment platforms and online services such as Google cloud, webhook, API and Firebase database services.

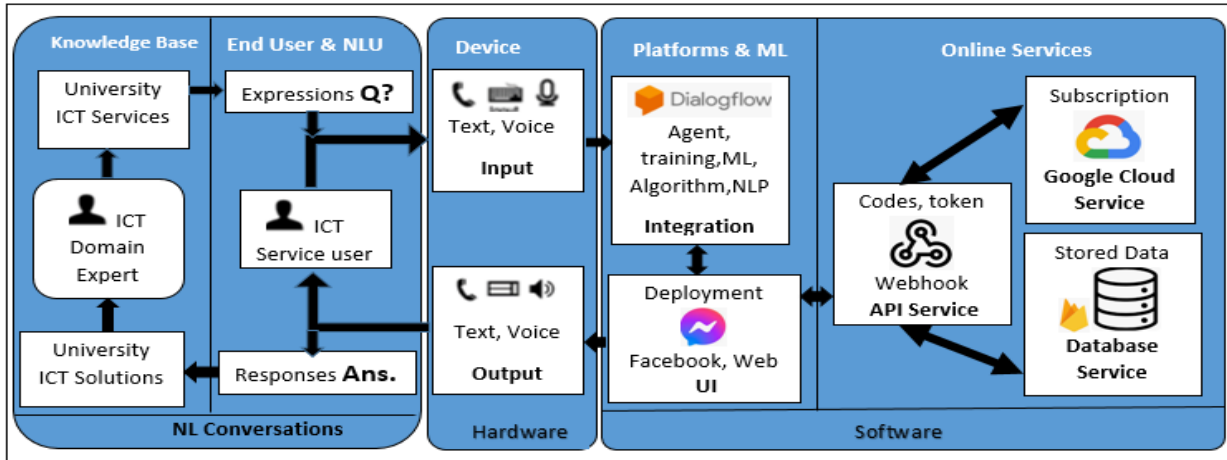


Fig. 2: System Architectural Model

The methods used are as follows:

**1. Identification of the ESUT University ICT Service.**

The ICT services of the Enugu State University of Science and Technology can be identified using Fig. 3. In Fig. 3, the services are divided into two categories: software advisory and hardware implementation services.

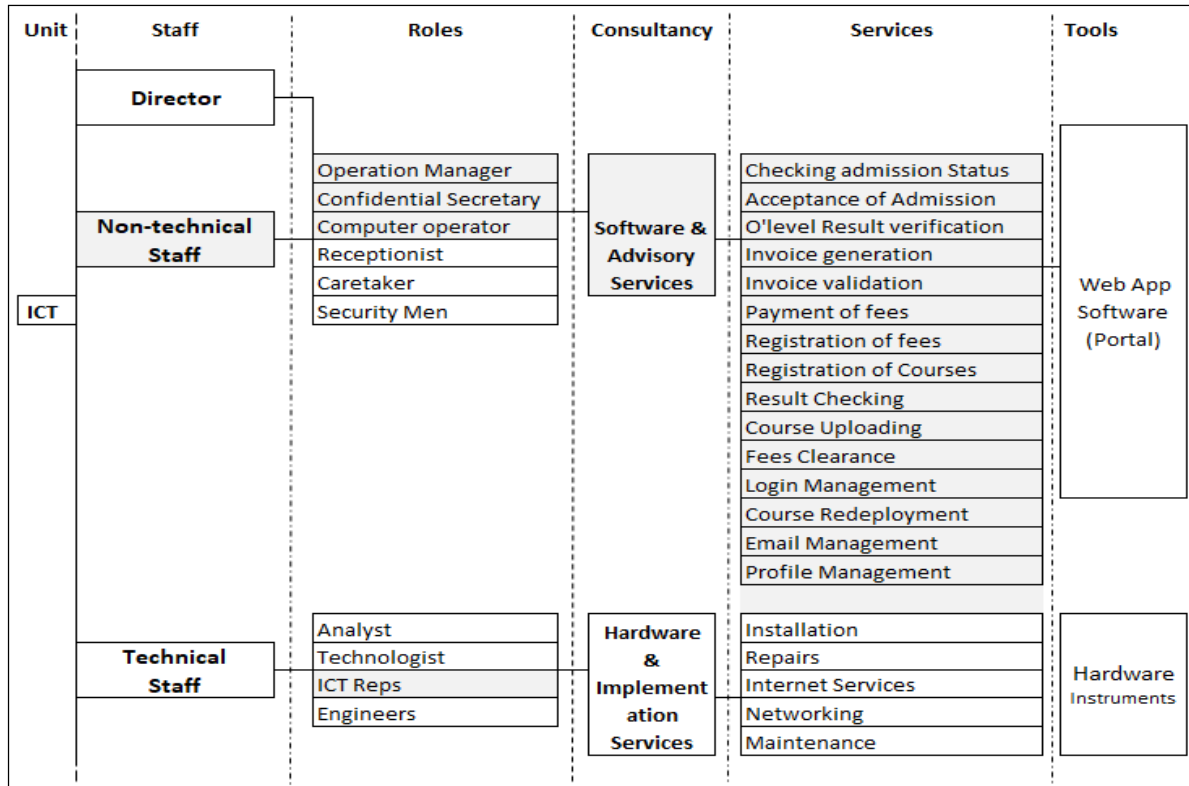


Fig. 3: Identified ICT service of ESUT University.

## 2. Characterization of ICT services into Intents.

The identified ESUT ICT services are classified into intents with their corresponding training phrases and responses to enable their individual building as an intent in the next stage of the method.

Table 1: Classified Intents and Training Phrases

ID	Intent	Training Phrases	Response
001	Greeting	Hello. Good morning sir.	Welcome. How are you?
002	Checking of admission status	Is the admission list out? Please help me check my admission status.	Visit <a href="http://www.portal.esut.edu.ng">www.portal.esut.edu.ng</a> to check your admission. Enter your Jamb number or Form No, and select the appropriate session and program.
003	Acceptance of admission	How long is the duration of acceptance of admission?	It can last between 2 weeks and 1 month, but do it as soon as possible so that your admission will not be denied.
004	Invoice generation	I want to generate an invoice. Can you help me?	Yes. What is your username and password, matriculation number, or registration number?

005	Invoice validation	My invoice is invalid and I cannot log in to my profile to generate a new invoice and pay school fees	I can understand your feelings. Kindly visit the ICT office for administrator' assistance in resetting your invoice to enable you to generate a new one and proceed for payment.
006	Payment of fees	I want to pay acceptance	Generate an invoice of 26100 naira, pay online or back. Log in to your profile and register it.
007	Registration of fees	Please, help me register my school fees.	Provide your payment printout, invoice, and login details.
008	Registration of courses	Help me register for my courses	Bring your course data and profile details
009	Uploading of courses	No course was assigned to me	Submit your departmental course allocation
010	Change of course and redeployment	New department have not reflected in my profile	Submit a copy of your deployment letter to the admission office
011	Checking of result	Can you help me check my results?	Submit your login details and make payment
012	Clearance of fees	I want to print my e-ledger for clearance. I want to do school fee clearance	Submit your login details or login into your profile and select fees clearance report
013	Login accessibility and authentication management	I cannot login to my profile	Submit your Matriculation number or jamb number if you are from 2017/2018 session upward
014	Profile management	I want to update my biodata	Submit your supporting document(s) to the ICT-administrator
015	Internet connection management	I cannot not browse with my system	Check your connection cable, Wi-Fi, or password
016	Creation of Institutional Email Addresses and Management	I want an ESUT institutional email address. Create institutional email for me	Supply your full name, phone number, and department to the ICT administrator
017	Verification of O'level results and obtaining the matriculation number	Where do I verify my O' level result? I have not obtained the matriculation number	Please hold on for a while to visit the admission office for clarification or check the ICT rep of your faculty

### 3. Creating ICT Service Intents in Google Cloud Dialogflow for Conversational Flow

The subscription to Google Cloud Service was done to create access to Google Dialogflow. The features for machine learning, language preference, among others, were configured to ensure smooth design, training, and deployment of Chatbot. The intents were created one after the other with their corresponding training phrases and expected responses. The fallback intent use for untrained words or phrases and follow-up intents use for conversational flow were also created.

The building of Chat in the Dialogflow environment offers a coldless, natural language processing environment with a machine learning algorithm.

#### **4. Training of the ChatUICs for Automated Conversations and Dynamic Responses**

The steps used in training the Chatbot in the Dialogflow console are as follows:÷

- 1) On the left pane menu of the Dialogflow console
- 2) Click on the “Training” module
- 3) View and select the training phrase for modification.
- 4) Scroll to view all the training phrases without a definite intent indicated by the “USERSAY” textbox content
- 5) Click on the “INTENT click to assign” marked in red colour
- 6) Scroll on the pop menu to assign an existing intent or create a new intent.
- 7) Click on the “approve” button to match the training phrase with the selected intent response following a given permutation performed by the machine learning algorithm.
- 8) Click on the “close” button to exit the training window.

#### **5. Deployment of the Chatbot to Social Media using Facebook Messenger and web page using Web Demo.**

The integration of the system at this level was performed using a text-based platform called:

- i. Web Demo for a web application using a desktop computer to connect and
- ii. Facebook Messenger for mobile applications using both computers and mobile devices to connect.

Both deployment platforms are part of Google Cloud Dialogflow, and the steps below were followed to achieve the deployment.

- 1) Click on the integration modules in the left pane of the Dialogflow console and under the text-based option,
- 2) Select the Web Demo option for web page and messenger from Facebook for mobile deployment,
- 3) Click on the Web Demo icon and it will launch the URL shown in the next step.
- 4) Copy the URL “<https://bot.Dialogflow.com/64b3ad4d-a040-493a-ba21-81acecd005a1>” and paste it in any browser to launch the Chatbot on a webpage.

### **RESULT AND DISCUSSION**

The outcome of the created intents and training phrases stored as a dataset is displayed in Fig. 4. The column chart bears the intent name and their corresponding number of training phrases, summed up to 381 phrases.

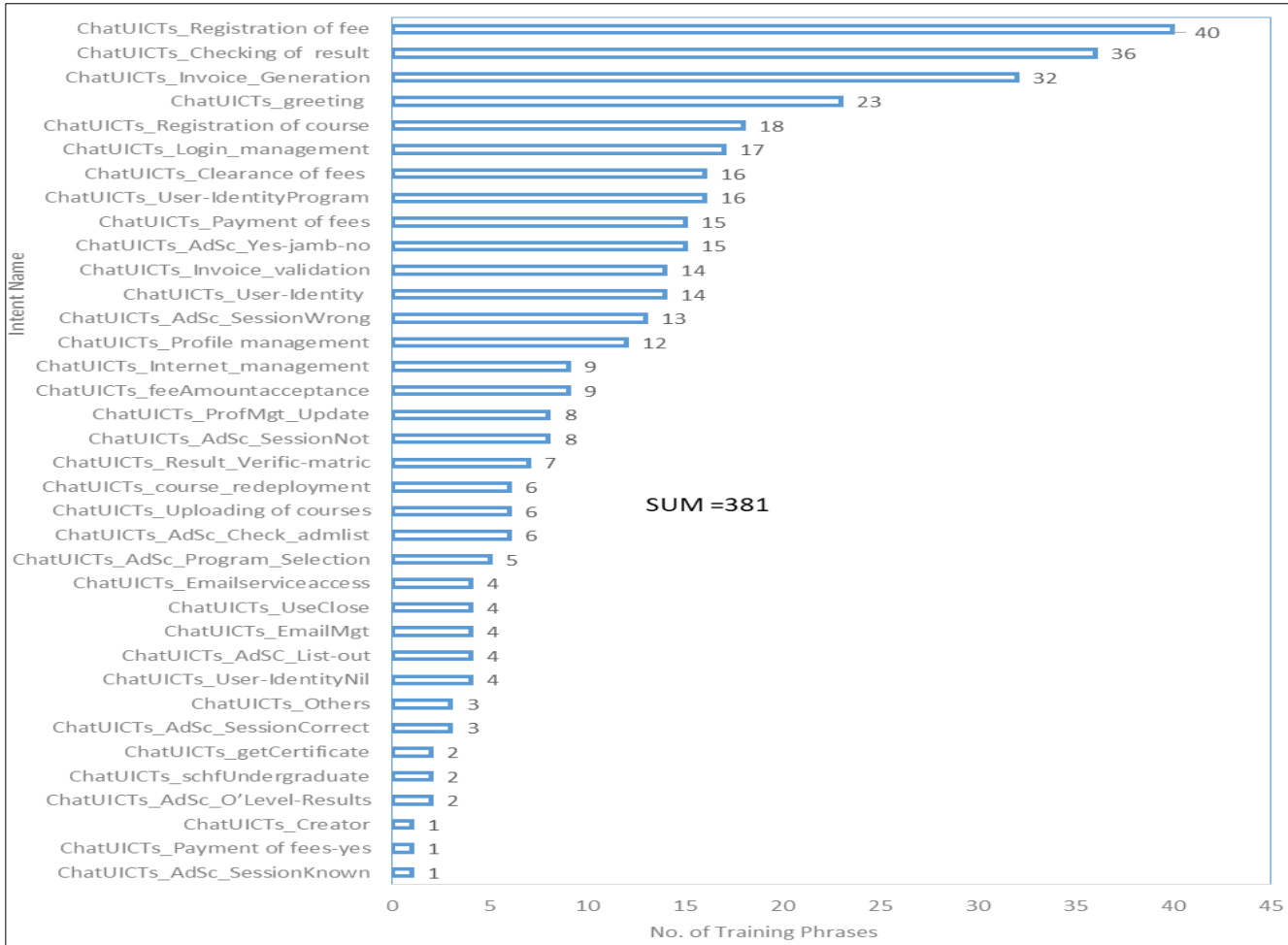


Fig. 4: Column Chart for Created Intents and Training Phrases

Fig. 4 presents the identified Seventeen -17 available ESUT ICT services were classified into 42 intents made up of parents, child, follow-up, and default fallback intents. The classified intents have approximately 381 training phrases/questions used to build an intent database/dataset stored in the Dialogflow Database Management System. The result proved that before training a Chatbot, utterance, intent, and entity must be established. This agrees with Jenna Alburger; (2021), who said that before diving into training a Chatbot, one needs to know these words: utterance, intent, and entity. Utterance is something that a user might say to your bot, intent represents what the user's utterance means, or what they intend to get from the AI Chatbot, and entity is a keyword that makes the user's intent more clear.

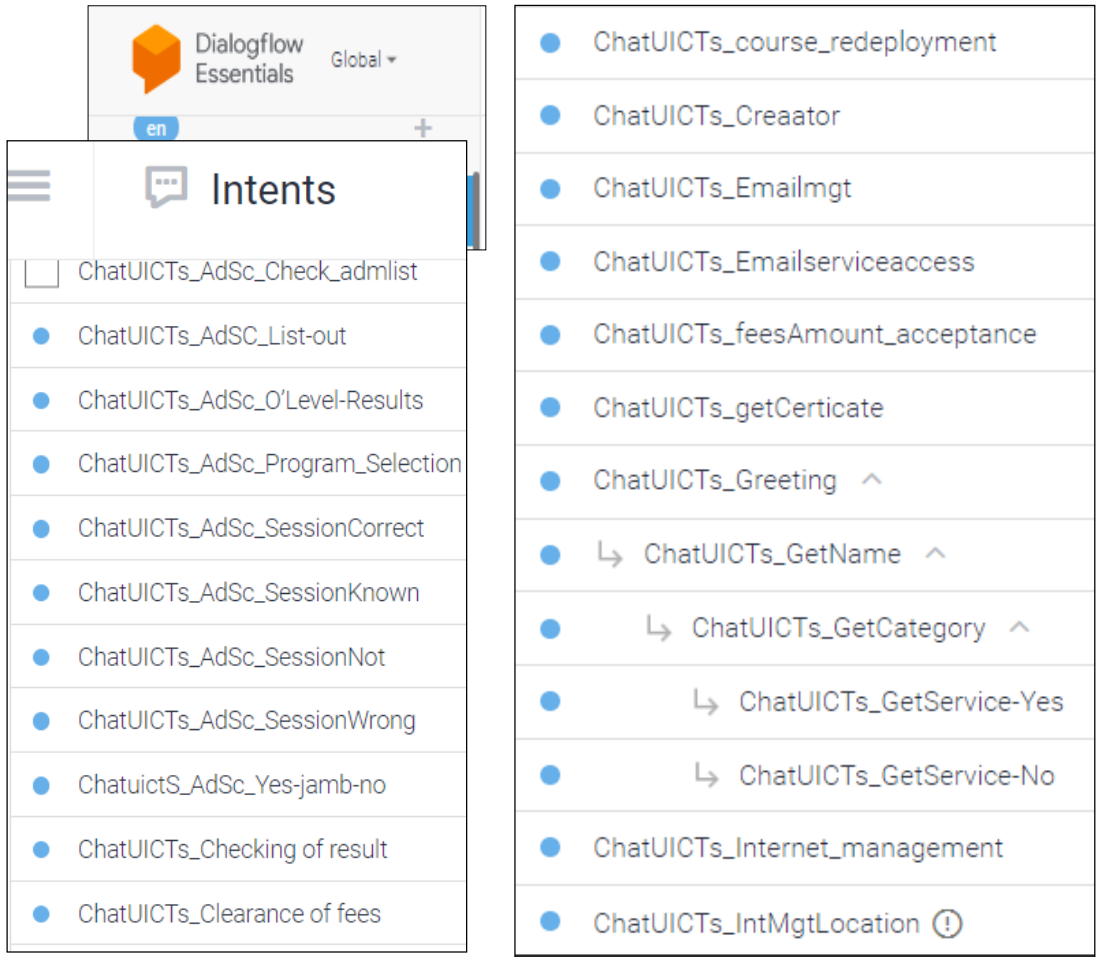


Fig. 5: Created intents in the Dialogflow Console

Fig. 5 clearly presents the image of the classified list of intents in Fig. 4 built with the Google Cloud Dialogflow Essential Console. This implies that the Google Cloud Dialogflow console has been proved in this study to be a suitable non-coding, visual flow builder environment for building Chatbot intents with an inbuilt natural language processing engine for good Chatbot and human conversational flow using a machine learning model. This result is supported by the study of Albert Smith (2020) that machine learning technology is useful for the classification of intents to allow the training of the Chatbot and decrease the tedious tasks of manual programming of the patterns offers. Nghia, D.T. and Nguyen T. P. (2020) study on university admission services designed and implemented Chatbot based on Long-Short-Term Memory (LSTM) Network model of machine learning. Moreover, the study has shown that Dialogflow has the advantage of no-coding over other conversational agent-developing platforms such as Tensorflow. The developers do not bother with writing codes or scripts or selecting libraries by themselves for designing the interactive interface compared to the study by Usman .H. et al, (2020) where the interface was designed by writing HTML script, CSS, and JavaScript for interactivity. In addition, intents, training phrases, and entities formed the primary training data that was stored in line with the work of (Gopis M 2023). The training data were useful for building a machine learning model for Chatbot- ChatUICts, and the trained data were stored and referenced as the machine learning data label in support of the study of Gopis M.(2023).

The results of the Chatbot training statistics for three months are summarized in Table 2.

Table 2: Summary of trained data on conversations from July to September 2023

Months	Days of Connection	No. of Successful Chat Connections	Tot. No. of Match Questions	Tot. No. of non-match Questions	Total Users
July	5	229	200	29	3
August	5	339	327	12	8
September	10	93	81	12	5
<b>SummationΣ</b>	<b>20</b>	<b>661</b>	<b>608</b>	<b>53</b>	<b>16</b>

The deductions from Table 2 are:

- 1) 20 days of training sessions
- 2) 661 requests were made for the conversational flow of the training
- 3) 608 requests matched the questions from the Chatbot dataset
- 4) 53 requests did not match the stored database information and were retrained
- 5) 16 different names of users found in the conversions as test users.

These deductions were used to calculate the accuracy of the Chatbot training from the result data in Table 2 as follows:

Total trained questions(Tq) = 661,

Total Matched question(Tmq) = 608,

Total non-match(Tnq) = 53

Training Accuracy =  $Tq/Tmq = 608/661 = 0.91982$

Percentage of training accuracy =  $Tq/Tmq*100 = 91.98 \approx 92\%$

The training of the modeled Chatbot took approximately 3 months (July-September) 2023 with a successful training accuracy of 92.4% as calculated with summation data in Tables 2. The summary of the Chatbot training proved that 661 successful chat requests were made, 605 requests matched, and 25 did not match in the training, resulting in re-training as the total number of 16 users tested the Chatbot. The “**matched requests**” showed Chatbot understanding based on the stored words or phrases in the training database, while “**non-match request**” denote the absent of the words or phrases from the training database/dataset, which caused the Chatbot to lack understanding of them.

Fig. 5 and 6 are the results of the deployment of the trained Chatbot to social media Facebook Messenger and Web Demo platforms, which achieved the objective of smart interaction between the Chatbot and humans using mobile devices and desktop web browsers,, respectively. This result proves that Chatbot is an artificial agent that made human-to-computer communication possible, in line with the statement made by Cem Dilmegani, (2018) that conversational artificial intelligence enables automatic messaging and conversation between computers and humans. This is supported by the study of Indra Ayu, Susan Mckie, and Bhuva Narayan (2019), who declared that the deployment of the project Lib-bot helps the researcher discover that asking research questions on academic libraries reveals much about the researcher’s academic level and library experience. Another study by Usman H, et al. (2020), writes that the implemented Chatbot has ability to communicate with users in Hausa language, tell some funny stories, and above all can learn from users new simple Hausa words. This further

supports the study of Nghia D.T and Nguyen T. P (2020), he posits that his implemented Chatbot was used for instant messaging applications of Facebook Messenger to support university admission.

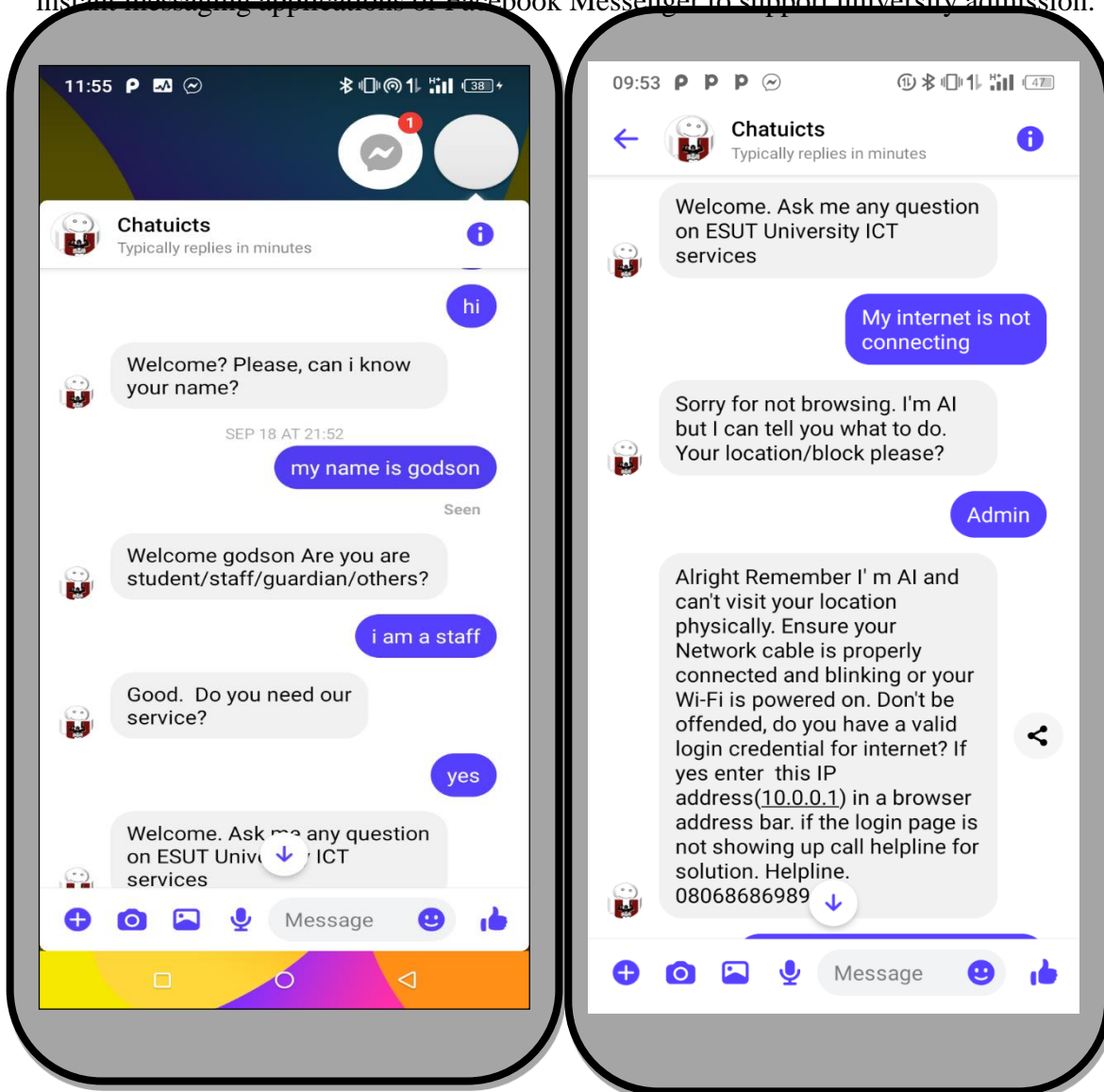


Fig. 6: ChatUICts Interactive Interface on Facebook Messenger for Internet Service



Fig. 7: Conversations for admission status and invalid invoice in the Web Demo Interface

The performance efficiency of the deployed chatbot can be determined from user feedback in Table 3 and analytic statistics from Dialogflow in Fig. 8.

Table 3: User Feedback on Performance

<b>Solution Delivery Performance</b>	<b>sD(1)</b>	<b>D (2)</b>	<b>N(3)</b>	<b>A(4)</b>	<b>sA (5)</b>
System response to questions immediately	0	0	0	3	13
Response is relevant to ICT solutions	0	0	0	3	13
The system is available at any time	0	0	0	0	16
Access to the system does not discriminate user	0	0	0	0	16
The system works only with the Internet	0	0	0	0	16
System deployment can bring innovation to existing ICT solution delivery	0	0	2	2	12
The system virtual mimics how the ICT staff delivers ICT solutions	0	0	0	3	13
The system understands questions like a human agent	0	0	2	2	12
The system dialog interface is interactive	0	0	1	1	14
<b>_ Degree of Agreement DoA</b>	<b>0</b>	<b>2</b>	<b>5</b>	<b>16</b>	<b>105</b>
<b>Summation</b>	<b>128</b>				
<b>TDoA</b>					

Table 3 summation indicates that:

0 feedback comment strongly disagrees *with solutions delivered by the system*

2 *feedbacks disagree with some solutions delivered*

5 feedbacks were not sure of some solutions delivered

16 feedbacks agreed on the solutions delivered by the system

105 feedbacks strongly agreed on the delivered solutions

To determine the performance efficiency using the percentage of system acceptance and rejection, Mathematically,

Degree of acceptability(aDoA) and degree of rejection(rDoA) of the system by the users using the records in Table 3 can be derived by finding the percentage of the degree of **strongly agree(sA)** comments and **strongly disagree(sD)**

Acceptability model equation =  $aDoA = \text{DosA} / \text{TDoA} * 100$  in percentage

Rejection model equation =  $(rDoA) = \text{DorA} / \text{TDoA} * 100$

Where = TDorA is the total of strongly disagree for rejection

TDosA is the total of strongly agree for acceptance

$$\text{TDorA} = 0$$

$$\text{TDosA} = 105$$

$$aDoA = 105/128 * 100 = 82\% \text{ accepted}$$

$$rDoA = 0/128 * 100 = 0\% \text{ rejected}$$

Therefore, the performance efficiency of the deployed Chatbot was established using a total of **105** feedback out of **128** feedback from the **16** users, which was calculated to be **82% of strongly agree(SA) feedback**. The Chatbot model as proposed by the researcher will be significant to ICT services and solution delivery in reducing workload from the ICT staff if applied to the university in line with the study of Kshitija Shingte, et al. (2021) on the design and implementation of Chatbot that will help students to know admission processes of the institute from anywhere using internet connection. At the end of the deployment, they achieved a reduction in workload from the departmental admission office trying to answer all the queries of the students, and the required information was given to students and parents at fast replies.

To further evaluate the performance of the deployed Chatbot, the analytics for integration, sentiment analysis, speech, intent path, and statistics of all requests by intent were viewed. Fig. 7 shows only sentiment analysis for August 2023. The Sentiments analysis for August analyzed with the Chart graph indicated a corresponding increase in the sessions and interactions. The Chatbot received more training on 7<sup>th</sup> August -and it declined till 27<sup>th</sup> August and rise again as the number of the queries analyzed indicated better performance on Chatbot's positive understanding of users' questions.

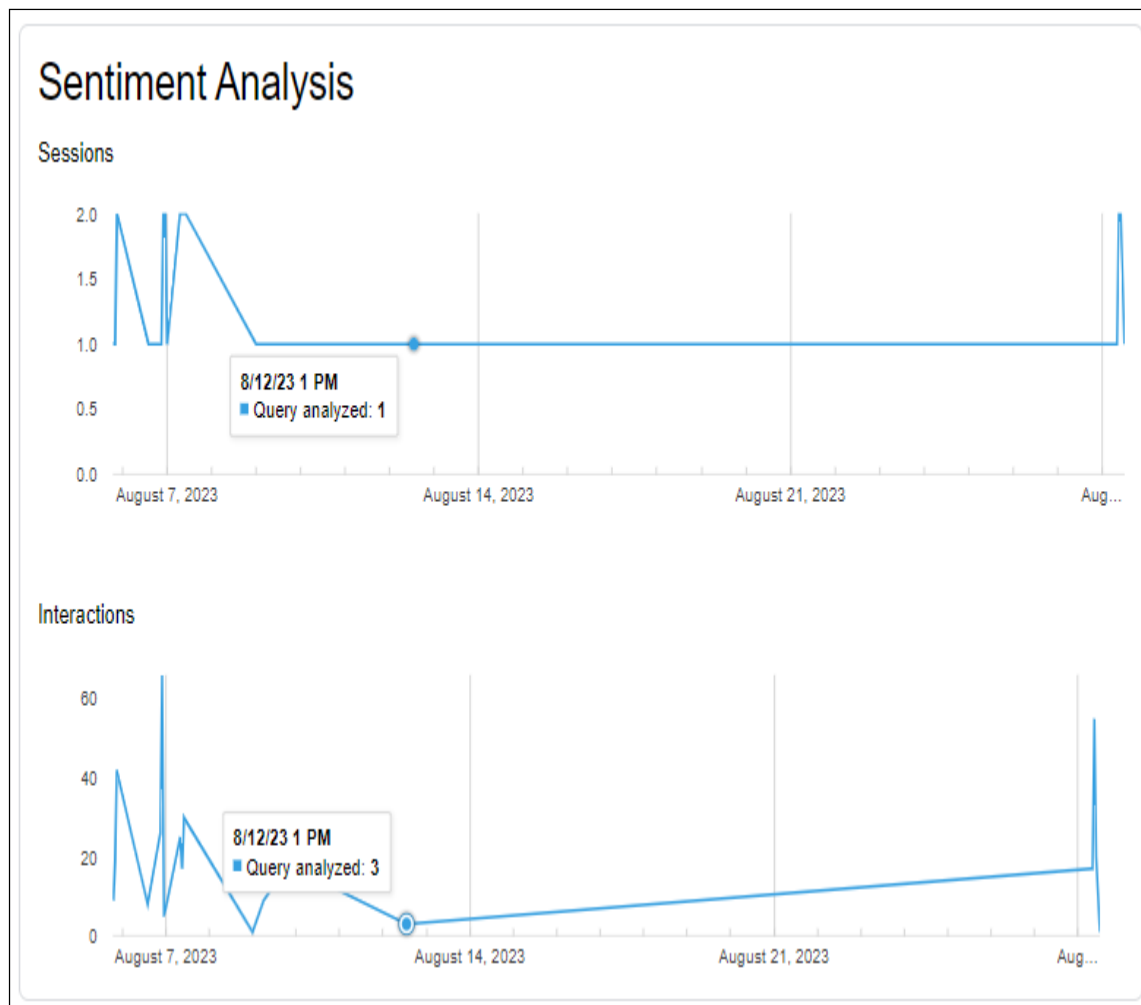


Fig. 8: Sentiment Analysis for August 2023 Sessions and Interactions

The sentiment analysis clearly showed that Chatbot understands text patterns with a machine learning model and a neural network, similar to the human brain, and processes natural language faster based on familiarity. Chatbot understanding increases with the increase in more sessions and more interactions with a particular word or sentence. This is supported by the words of Chris Knight, (2020) that CNNs can analyze text to determine the sentiment expressed, such as positive, negative, or neutral. They learn to capture important features and context from the text, enabling sentiment analysis in social media, customer reviews, and opinion mining.

## CONCLUSION

Conversations between university ICT service providers and ICT service end users on university ICT services and solutions can be represented virtually using a Chatbot application successfully built with Google Cloud Dialogflow Essential Console for natural language processing(NLP) with inbuilt Google Machine Learning. The university ICT services can be modeled using an AI-based Chatbot as a smooth alternative to an efficient and effective means of asking questions to the ICT unit and accessing solutions using text or voice messages in a minimal period of seamless online conversations.

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