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A Chatbot Student Support System in Open and Distance Learning Institutions

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Abstract: The disruptive innovation of artificial intelligence (AI) chatbots is affecting educational dominance, which must be considered by higher educational institutions. Open and Distance Learning (ODL) becomes imperative for the effective and interactive communication between the institutions and learners. Drawbacks of isolation, motivation, insufficient time to study, and delay feedback mechanisms are some of the challenges encountered by ODL learners. The consequences have led to an increase in students' attrition rate, which is one of the key issues observed by many authors facing ODL institutions. The National Open University of Nigeria (NOUN), one of the ODL institutions in Nigeria, is limited to an existing e-ticketing support system which is manually operated. A study on 2000 students of the NOUN using an online survey method revealed that 579 students responded to the questionnaire, equalling 29%. Further findings revealed significant delay time responses and inadequate resolutions as major barriers affecting the e-ticketing system in the NOUN. However, despite the quantitative method employed in the study, an artificial intelligence chatbot for automatic responses was also developed using Python 3.8+, ChatterBot (Version 1.0.5) Chatbot Framework, SQLite (default ChatterBot Storage, NLTK, and Web Interface: Flask (for integration with a web application). In testing the system, out of the 579 respondents, 370, representing 64% of the respondents, claimed that the chatbot was extremely helpful in resolving their issues and complaints. The adaptation of an AI chatbot in an ODL institution as a support system reduces the attrition rate, thereby revolutionising support services' potential in Open and Distance Learning systems.

Keywords: AI support systems; ODL learners challenges; chatbots; attrition rate

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1. Introduction

ODL is viewed as an effective tool that bridges the gap between learners and institutions, thereby widening access and providing flexibility for continuous professional development and lifelong learning [1]. ODL institutions are known as non-conventional institutions and use diverse means of instruction, rather than just the conventional face-to-face method. ODL depicts physical separation between the facilitators and the learners. However, instructions take place through a variety of media, including print and modern Information and Communication Technology tools [2]. ODL has merits, such as rapid

increases in student enrolment, cost effective instructions that are independent of time, location and pace, in addition to flexibility regarding space and time. Despite the plethora of merits in ODL, the learners still face challenges such as isolation [3–8], lack of motivation [9], lack of sufficient time to study [10], and delayed feedback [11–14]. One of the most important areas requiring immediate attention in ODL institutions is delay in students' feedback mechanisms. Timely and insightful feedback helps students perform better, participate more actively in the learning process, and maintain the connection between the facilitators and the students. All these challenges in ODL lead to the student attrition rate.

The attrition rate is the rate at which students abandon their programme of study before the assigned completion time due to some challenges [15]. However, both institutional and non-institutional challenges contribute to the student attrition rate, which is recognised as the most complex and important issue facing educational systems [16,17]. Different authors define student attrition differently. Attrition is defined by [18] as students who leave their programme before graduation for any reason other than death without transferring to another programme or institution. According to [19], attrition is linked to situations where students discontinue their education or are unable to complete their course of study. According to [20], attrition is a rise in the overall number of students who began their education but were unable to complete their programme. Attrition is also defined as the total number of students enrolled in a programme minus the total number of students who completed their programme [21].

Akmal [22] and Park [23] observed that only 50% of students enrolled in ODL institutions completed their studies, and the average attrition rate in an ODL system is between 10% and 20% lower than that of conventional institutions. The likelihood of a high attrition rate from non-conventional programmes is significantly higher than that from conventional (face-to-face) institutions was also confirmed by [24]. The high incidence of student attrition is one of the key issues facing ODL institutions. Attrition continues to be a significant concern for many educational institutions, and inadequate feedback from the instructors [22,25] contributes to the high rate of attrition. Additionally, significant delay time responses and inadequate resolutions [15,26–28] increase the attrition rate [29–39].

Attrition is categorised into three aspects, namely cohorts, status, and circumstantial [39]. Circumstantial attrition, according to [39], is the type of attrition that arises from all of the situations or events that are present in the students' environment at a certain moment, causing the students to abandon their programme.

Keeping the learners within the ODL institutions poses a lot of concern due to the institutions' inability to respond timely to enquiries from learners. The National Open University of Nigeria (NOUN) is one of the ODL institutions in Nigeria, with over five hundred thousand (500,000) student enrolments, based on the 2024 admission records, and the NOUN uses an e-ticketing platform to respond to student complaints. However, the responses are manually operated and, as a result, there are delays in the feedback mechanism, which leads to student frustration. The introduction of artificial intelligence (AI) chatbots in ODL institutions and using the correct mapping database will drastically reduce the attrition in ODL institutions [40]. Integrating chatbots into ODL institutions will result in beneficial inputs, including immediate responses to complaints [38] and immediate accessibility to students [37]. According to [41], providing students with a conducive learning environment and interactive technologies like chatbots can help maintain students' motivation and engagement with their studies. The nature of ODL institutions, such as the NOUN, where students work and learn while physically separated from facilitators via the use of effective support services, means that time management is of great importance to students [42].

This study introduced the development and implementation of a chatbot aimed at enhancing communication among the enrolled students at the NOUN and, in addition, presented the results of the pilot research to students who utilise a manually controlled e-ticketing system, with the goal of ascertaining the need for a more robust chatbot system.

In the context of education, support services are instructional services provided to students for their learning experience and also to improve educational environments. The academic, administrative, social, and psychological policies and practises that support and assist students' academic progress were also characterised as student services by [43]. One of the ODL research studies has been on requisite support services, which are the primary factors in student support and retention [40]. Support services are crucial components of a successful and long-lasting ODL system, according to [44,45]. Support services fill the gap between the management system and the students, particularly in cases where the students feel they are not involved. The success of the ODL system largely depends on the effectiveness of the support services in providing an adequate environment which in return creates a sense of belonging for learners [44].

One of the greatest challenges of ODL education is to respond to the high expectations of the students and stakeholders [1]. Support services concentrate mainly on learners and the learning environment, especially when there is a physical distance between the learners and the education providers, as observed by [46]. In the policy framework and best practice, the Africa Centre for Distance Education (ACDE) stated that for quality to be maintained in ODL, there must be structures and mechanisms to provide timely feedback to the learners [47,48]. This practice enhances quality in service delivery.

The principles of ODL to engage students in learning and motivate them to independently learn remain the same even as technology advances. Technology has helped to develop a more flexible, interactive, and personalised environment for students in distance education, and this has paved the way regarding providing support to students. The one-on-one communication and support services observed in the early years of ODL through educational materials and environments have developed into a form that supports both individual-oriented and intrapersonal (learner–learner, learner–instructor, learner–content–material/interface, etc.) interactions.

Chatbot is a technology where systems are made to engage in conversation with the users, especially over the internet. Chatbot engages in conversation with the users by using keyword matching and natural language processing (NLP). An artificial intelligence (AI) chatbot system is a computer programme that communicates with users, as stated by [46]. This technology has been engaged in industries and organisations where customers' requests need to be processed urgently. The goal of an AI chatbot is to provide feedback to clients for effective service delivery. Chatbots in educational institutions have made significant progress [49]. The proof that chatbots implemented in education systems can be beneficial to both learners and facilitators was established by [44]. Research on chatbots in education, especially in ODL systems, is still at its preliminary stage. Chatbots have been employed in institutions to handle issues that students encounter in a particular course. For example, [44] designed a chatbot for the University of Georgia to handle forum messages from students enrolled in a course. Since ODL institutions have problems of distance barriers and the isolation of learners, deploying a chatbot as a student support programme will cause a significant improvement in service delivery. Effective communication using AI chatbots for effective communication in ODL institutions will reduce the dropout rate of learners.

1.1. Chatbot and Feedback

Feedback in ODL is a tool that engages students in the process, encouraging participation and responsibility for learning outcomes. Student performance is improved through communication between facilitators and students, placing the students at the centre of the process as active participants [12]. Chatbots are feedback tools that have completely changed how institutions communicate with their students by offering prompt and effective responses to students' enquiries [49]. User feedback is a crucial component of improving chatbot performance, and the continuous improvement of institutions is made possible through feedback, helping institutions identify their operational strengths and flaws. AI-powered chatbots can collect feedback via conversational surveys, which aids in the collection of both qualitative and quantitative information regarding client experiences. Additionally, feedback is essential for enhancing the chatbot's natural language processing skills and handling more complicated enquires. The chatbot interface integration of feedback mechanisms also guarantees real-time data collection, which may be utilised to improve customer happiness and quickly fix problems. Institutions make sure that chatbots are reliable by utilising customer feedback and support the growth of motivation and positive self-confidence in the learning process of ODL (see Figure 1).

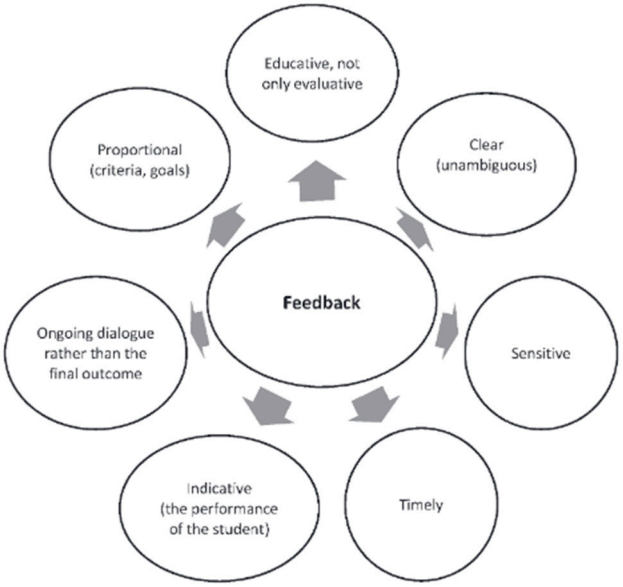


Figure 1. The elements of feedback [12].

In order to provide an adequate intuitive and user-friendly experience, learning environments in ODL institutions must integrate feedback into their support services. Institutions can determine typical difficulties expressed by students and areas that need development by examining user interactions and feedback. Feedback can also draw attention to the need for new features or functionalities that students want, like more individualised responses or service integration. The chatbot will adapt to its users' changing requirements and expectations if it is regularly updated based on user feedback, which will ultimately increase user satisfaction.

1.2. Chatbot and Machine Learning

Chatbots and machine learning (ML) is a powerful combination that enhances the capabilities of automated conversational agents [50]. ML algorithms enable chatbots to learn from interactions and improve over time. By analysing vast amounts of data, ML models can identify patterns and trends, allowing chatbots to provide more accurate and contextually relevant responses [51,52]. This continuous learning process helps chatbots

understand user intent better, handle complex enquiries, and offer personalised experiences. For instance, NLP, a subset of ML, allows chatbots to comprehend and generate human-like text, making interactions more natural and engaging.

ML enables chatbots to adapt to new information and scenarios without explicit programming [53]. This adaptability is crucial for maintaining the chatbot's relevance and effectiveness in dynamic environments in customer service; ML-powered chatbots can learn from past interactions to predict and address common customer issues proactively. Additionally, ML algorithms help chatbots detect anomalies and flag potential problems, enhancing their ability to provide timely and accurate support [53]. By leveraging machine learning, chatbots evolve from simple rule-based systems to sophisticated conversational agents capable of delivering high-quality, personalised interactions. NLP is a crucial component of ML that enables chatbots to understand and generate human-like text.

1.3. Chatbot and Programming

Chatbots and programming are in congress, as the development of chatbots relies heavily on various programming languages and frameworks. At the core of chatbot development, chatbots are built using languages like Python, JavaScript, and Java, which provide the necessary tools to create robust and scalable applications. Python, for instance, is popular for its simplicity and extensive libraries such as NLTK and spaCy, which are essential for NLP. JavaScript is widely used for building interactive web-based chatbots, leveraging frameworks like Node.js and React. These programming languages enable developers to create chatbots that can understand and respond to user inputs in a meaningful way, making interactions more seamless and efficient.

Programming allows for the integration of chatbots with various APIs and services, enhancing their functionality and user experience. Chatbots can be connected to databases to retrieve and store information or can be integrated with third-party services like weather APIs, payment gateways, and social media platforms. This integration is achieved through RESTful APIs and webhooks, which facilitate communication between the chatbot and external systems. Additionally, programming enables the implementation of ML algorithms, allowing chatbots to learn from user interactions and improve over time [40]. By leveraging programming skills, developers can create sophisticated chatbots that not only provide accurate responses but also adapt to the evolving needs of users.

Table 1 demonstrates the various ways chatbots are used in educational institutions, highlighting how it can lessen students' search burden, offer real-time responses, improve academic achievements, and promote inclusive learning. Chatbots for certain applications, including the maintenance of academic records, processing admissions, and nursing education, were created using a variety of approaches, such as machine learning, natural language processing, and experimental designs. Limitations were noted, though, which include subject-specific applications, database restrictions, infrastructure issues, and a lack of diversity. These results imply that scalability, inclusivity, security, and adaptation to wider educational demands are critical for successful chatbot development.

Table 1. Summary of related works and methodology used to develop chatbots.

S/N	Ref.	Title	Methodology	Findings	Limitations
1.	[54]	NEEV: An Education Informational Chatbot	Supervised ML techniques and NLP using the Dialogflow framework from Google	The developed chatbot was used to reduce the overall pressure on the students' in search of other possible options	Only one programming language was used
2.	[55]	Chatbot for education system	Machine learning, NLP, pattern matching, and data processing algorithms	Encrypting of user queries to secure the chatbot and the use of the Apache Mahout to make the chatbot scalable	Responses limited to the local database
3.	[56]	Chatbot for E-Learning: A Case Study	NLP processing techniques	It provides real-time response to students' enquiries	The chatbot was developed for only computer science students
4.	[57]	Chatbot As an Educational Support System	Narrative review	The various benefits of using chatbot	The need to provide chatbot that takes care of both students and faculty members
5.	[58]	Developing Chatbot for Academic Record Monitoring in Higher Education Institution	Used webhook to receive messages and also used the Bot API to send messages	Alternative method to serving data requests from stakeholders	Requests were taken from the students and stakeholders only
6.	[59]	Chatbot-facilitated Nursing Education.	Experimental design	The knowledge-based chatbot system enhanced students' academic Performance	The study was limited to only nursing courses
7.	[60]	Intelligent Chatbot for admissions in Higher Education	ML algorithms, pattern matching, NLP	The admission chatbot scored 91.97% and the F-Score scored 95%	The chatbot was developed only for admission into higher education
8.	[61]	Integration of AI-Chatbot into Teaching and Learning.	Applied descriptive survey research design	The findings showed poor internet facilities, instabilities in governance, inadequate funding and poor power supply are factors inhibiting implementation of AI-chatbot	Full integration of the AI chatbot into teaching and learning is required
9.	[62]	Supporting inclusive learning using Chatbots? A chatbot-led interview study	Applied chatbot-led interview study and survey	Chatbots provide the opportunity to support students who are disadvantaged with diverse life environments, and with varied learning styles	Shortage of inclusive learning observed

2. Methodology

E-ticketing (a manually operated students' support system) is used in the NOUN for student support services, and an exploratory quantitative and qualitative study was conducted using a questionnaire that was created with Google Docs. The questionnaire was sent to the emails of students of the NOUN to ascertain the challenges faced while using e-ticketing. The questionnaire was anonymous and included two (2) questions that sought to learn about the level of awareness concerning e-ticketing and chatbots as student support services and the challenges they encounter while using e-ticketing in resolving problems. The questionnaire was sent out to approximately 4000 students to participate in the study; only 567 responded to the survey. The distribution among programmes was as follows: 452 respondents, representing 79.7%, were undergraduate, while 115 respondents, representing 20.3%, of the population were postgraduate students. Regarding gender, 313, representing 55.3%, were male respondents, while 251, representing 44.3%, were female.

2.1. Research Design

This study also adopts design and development research methodology to create a chatbot using the ChatterBot library. The development process follows a structured software engineering approach, including requirement analysis, design, implementation, and testing. The primary goal is to evaluate the chatbot's performance, accuracy, and usability in handling user queries.

2.2. Tools and Technologies

The chatbot was developed using the Python programming language, ChatterBot library, and Natural Language Toolkit (NLTK) as shown in Figure 2, which provided the machine learning-based conversational models, while the SQLite database was used for storage and the Flask framework provided the web interface for interaction with the chatbot in Figure 3.

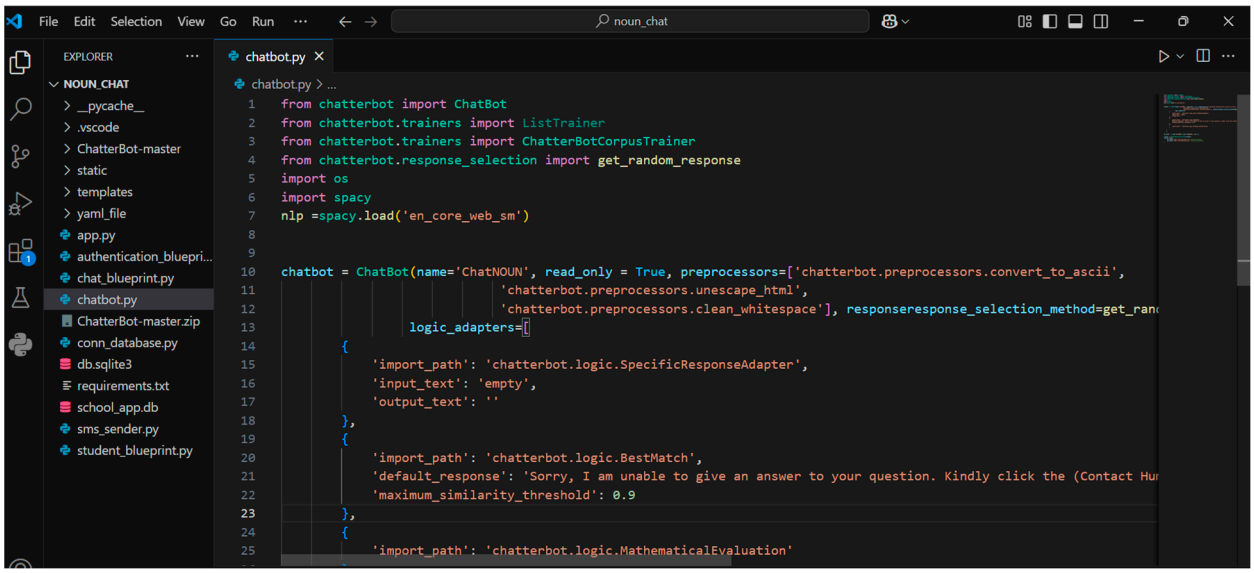


Figure 2. chatbot.py.

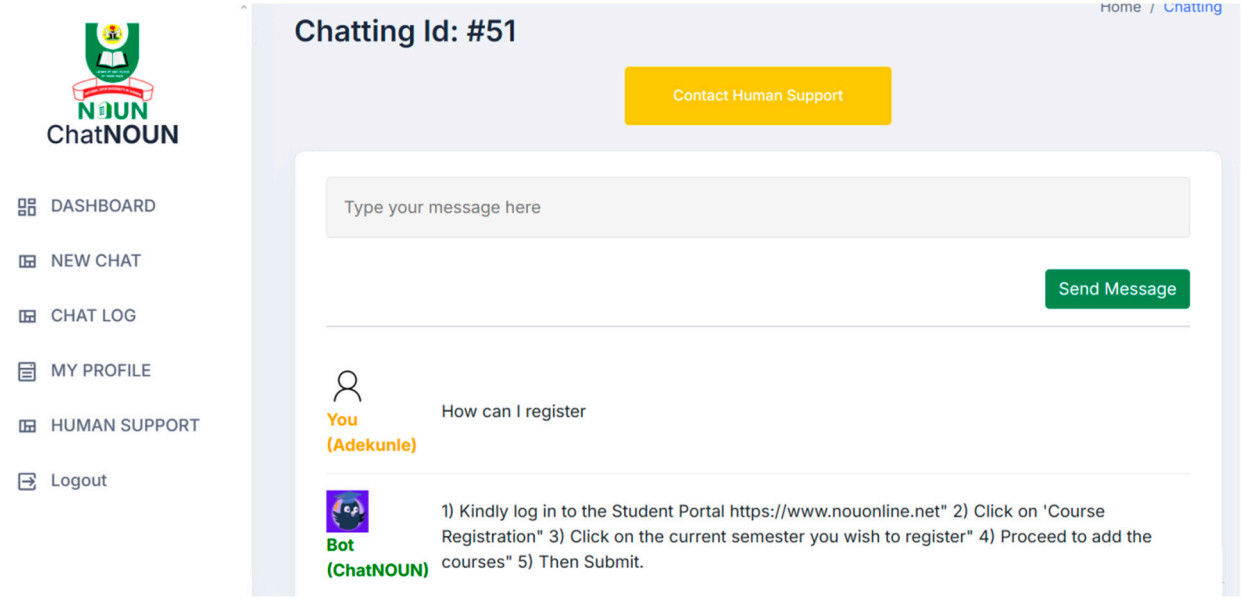


Figure 3. User interaction with the chatbot via web interface.

2.3. Traning Dataset

The dataset was made of a predefined dataset (greeting.yml) from ChatterBot that was made of 53 records and the custom data (noun_data.yml) shown in Figure 4; comprising 673 records, the custom dataset was collected from the NOUN academic support unit. The first time the application was executed, the ChatterBot library handled the training operation, which took about 20 s; this process automatically created and updated the default ChatterBot database db.sqlite3 in Figure 5.

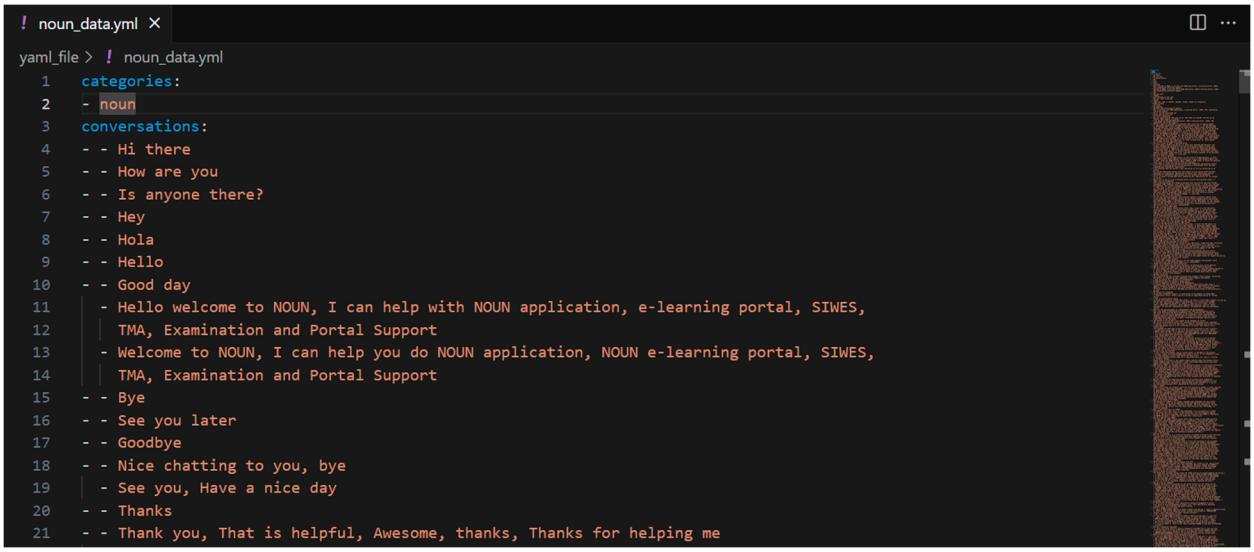


Figure 4. Custom data (noun_data.yml).

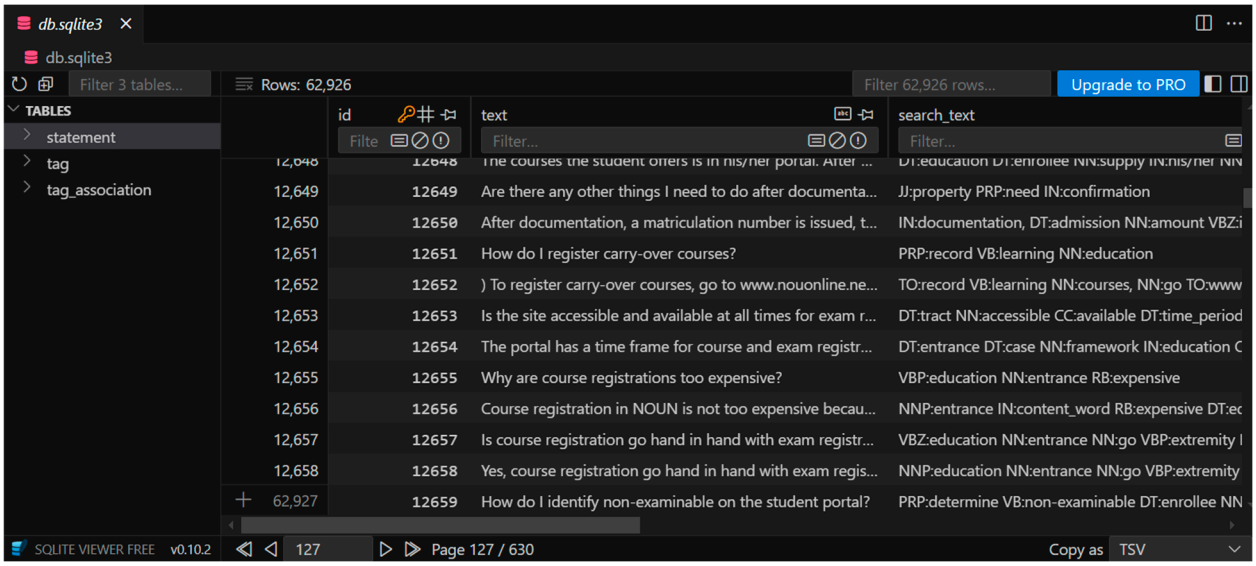


Figure 5. Default ChatterBot database db.sqlite3.

2.4. Users and Interaction

There are two categories of users that could login to the system: the student or prospective learner and the admin. Figure 6 shows the Use Case diagram that depicts the possible interaction of this user with the chatbot system.

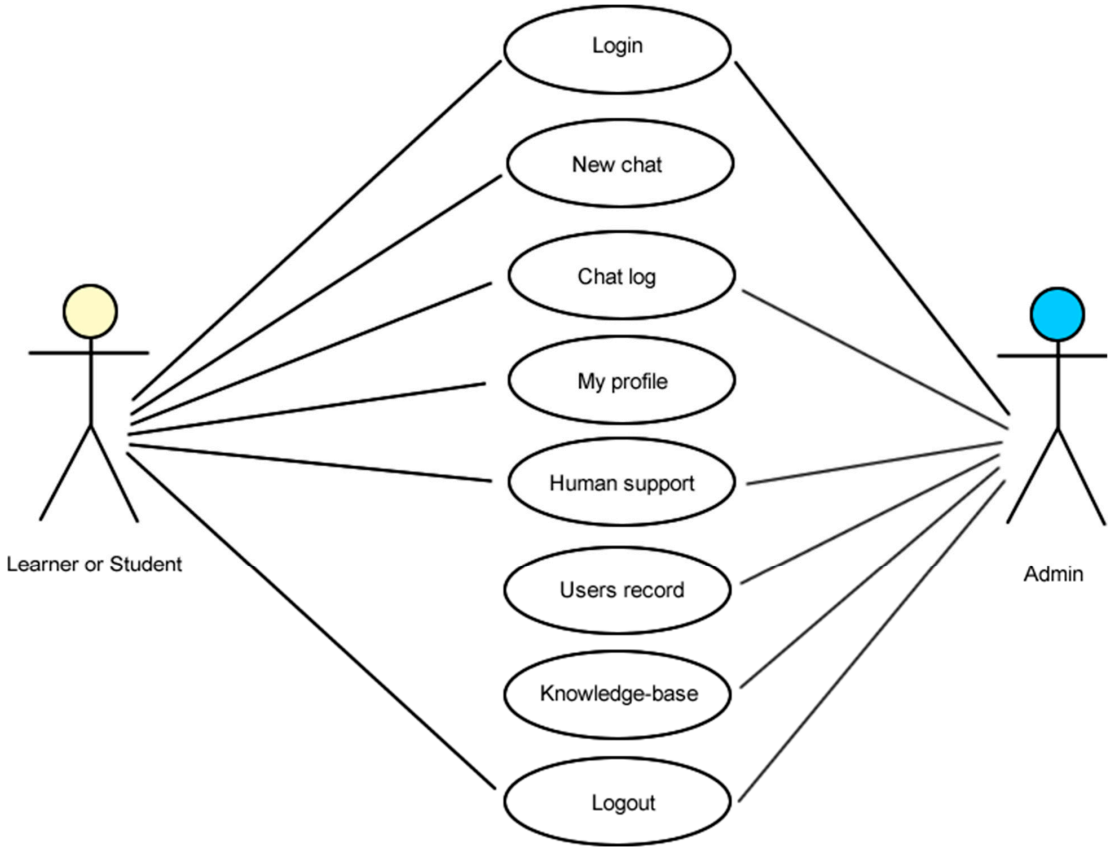


Figure 6. Use Case diagram.

As depicted in the Use Case Diagram (see Figure 6), the prospective student or learner could chat with the chatbot and see the chat log. The admin can view all registered users and their chat log (see Figure 7); this helps the admin to know the effectiveness of the chatbot. The admin can also view complex questions that the chatbot could not handle and give corresponding solutions to it. The solution provided will be added to the knowledge base, as shown in Figure 8a, and the model will be retrained to update its knowledge base, as shown in Figure 8b.

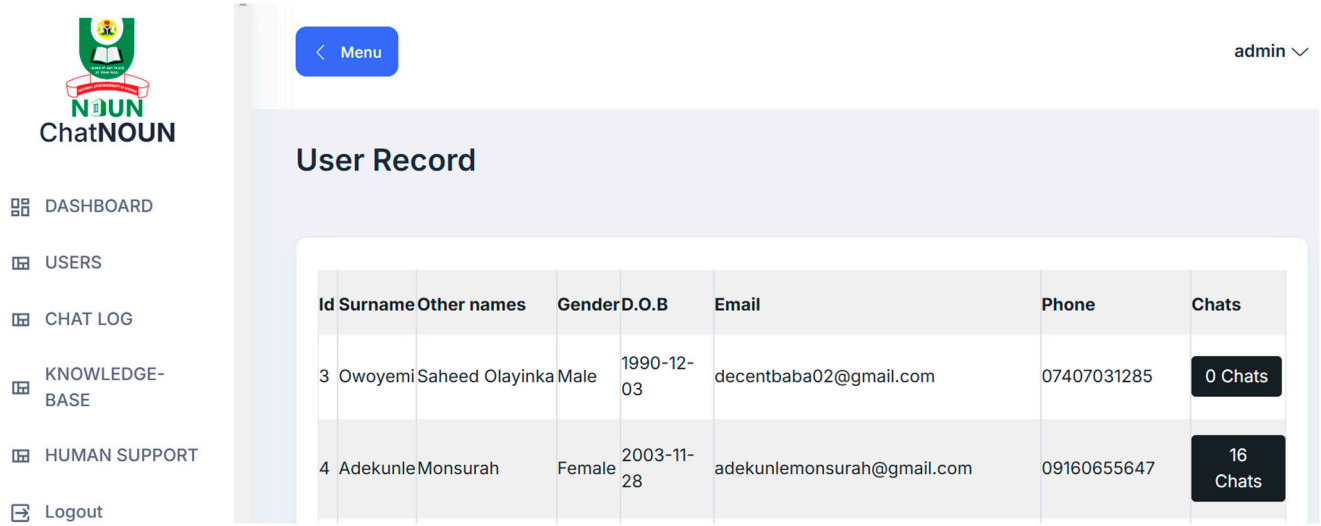
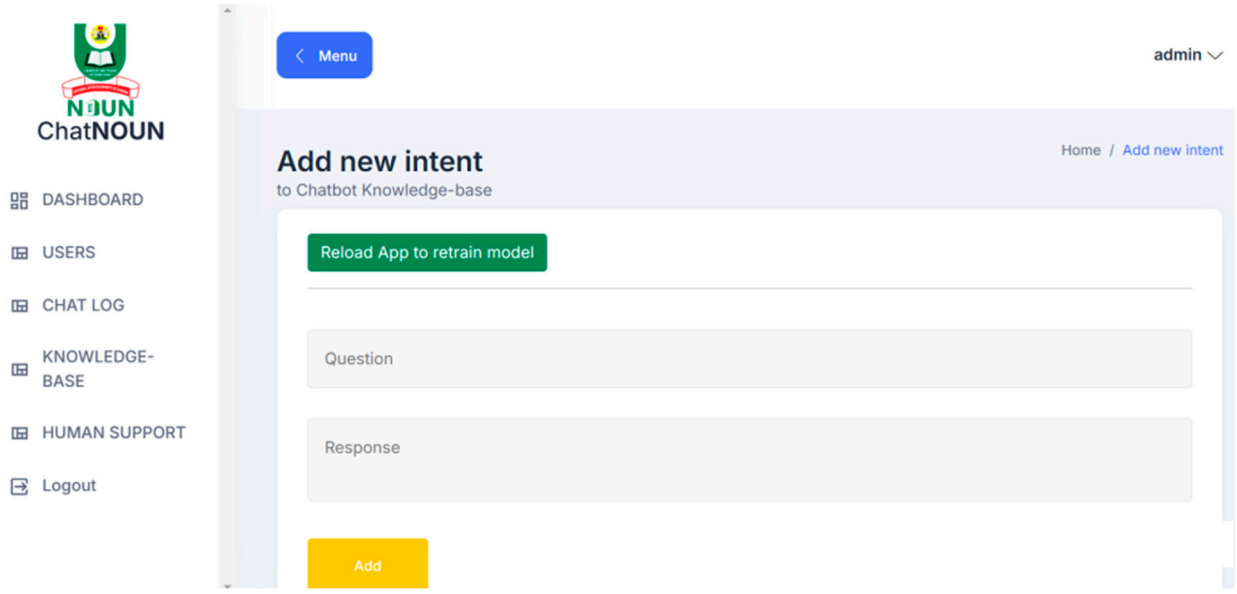
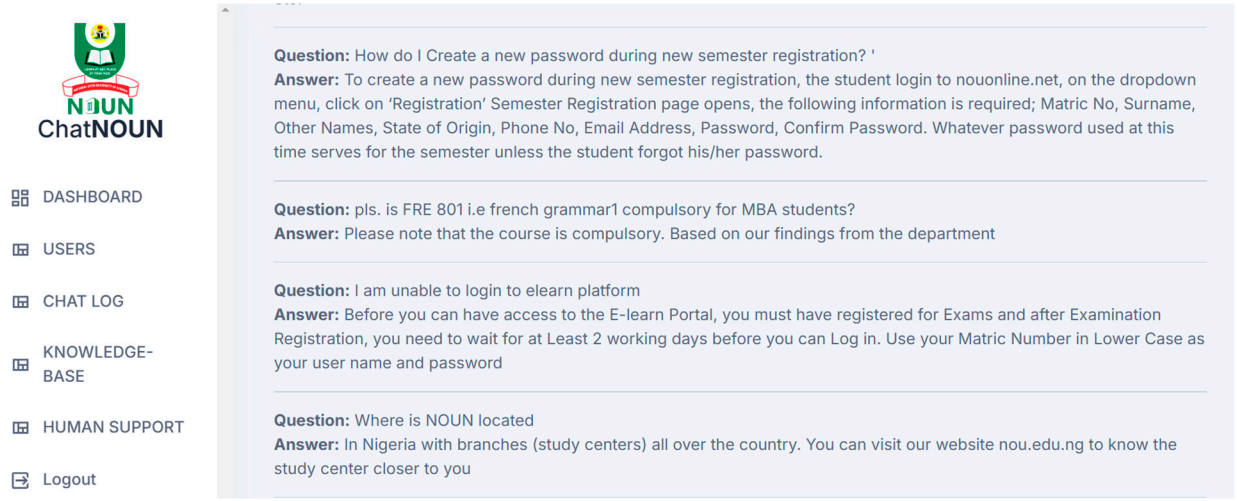


Figure 7. Admin viewing user record and chat log.



(**a**)



(**b**)

Figure 8. (**a**) Admin can add new conversation to knowledge base. (**b**) Updated knowledge base of retrained model.

2.5. Testing and Evaluation

The chatbot's accuracy was tested using unit testing to validate individual components and user testing by collecting feedback from selected real users.

3. Results

In relation to the question on the awareness of the use of e-ticketing in the NOUN, Table 2 shows the details of the responses provided by the respondents.

Table 2. Level of awareness on use of e-ticketing in NOUN.

I Am Aware of the NOUN Eticketing				
	Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Invalid	38	6.6	6.6	6.6
Completely Agree	412	71.2	71.2	77.7
Completely Disagree	14	2.4	2.4	80.1
Neither Agree nor Disagree	23	4.0	4.0	84.1
Partially Agree	84	14.5	14.5	98.6
Partially Disagree	8	1.4	1.4	100.0
Total	579	100.0	100.0	

Table 2 showed that, out of the 579 responses, 412 respondents, representing 71.2% of the total number of respondents, completely agree that they are aware of the use of e-ticking in channelling the issues they report to the support group, while 14 respondents, representing 2.4%, obliged that they were not aware. From the above, it can be deduced that few students in the NOUN are not aware of the e-ticketing platform which is provided by the institution to help solve students' various enquiries.

Table 3 shows the level of usage of the e-ticketing platform by the students of the NOUN.

Table 3. Level of usage of e-ticketing platform by NOUN students.

I Have Used the NOUN Eticketing				
	Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Invalid	47	8.1	8.1	8.1
Completely Agree	375	64.8	64.8	72.9
Completely Disagree	28	4.8	4.8	77.7
Neither Agree nor Disagree	32	5.5	5.5	83.2
Partially Agree	76	13.1	13.1	96.4
Partially Disagree	21	3.6	3.6	100.0
Total	579	100.0	100.0	

Out of 579 respondents, 375 agreed that they have used the e-ticketing platform to channel their issue to the support group. The percentage of those that have used e-ticketing is 64.8%, which showed that students are eager to use any communication channel that will help to resolve their respective academic issues.

Figure 9 shows the challenges that students encountered while using e-ticketing. It was found that the major challenge was the issue of slow responses from the support team;

there was a delay in the response time between the students and the support team, which caused boredom in the students and made them feel frustrated.

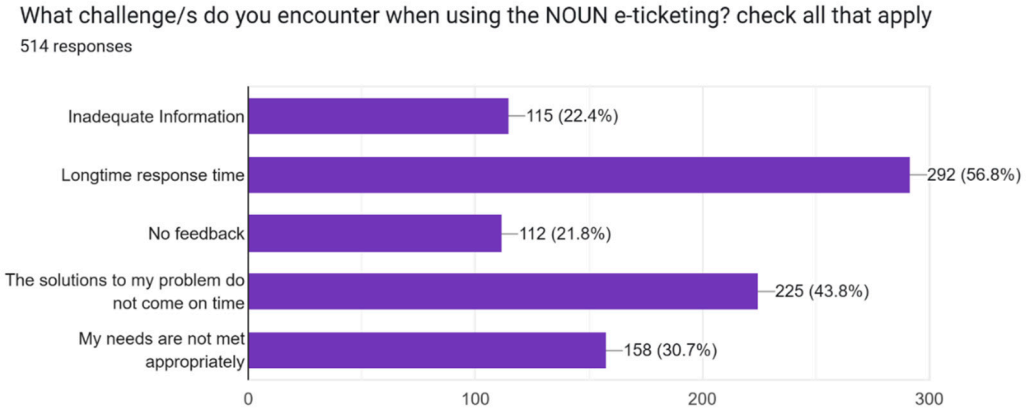


Figure 9. Challenges students encounter while using the e-ticketing platform.

Table 4 and Figure 10 display survey data regarding how beneficial users thought the developed chatbot was at answering their queries or problems.

Table 4. The level at which the chatbot was useful to the learners.

How Helpful Were the Chatbot's Responses in Resolving Your Issue or Question?					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	Invalid	47	8	8	8
	Extremely helpful	370	64	64	72
	Helpful	32	5.5	5.5	77.5
	Neutral	32	5.5	5.5	83
	Unhelpful	76	13.5	13.5	96.5
	Very Unhelpful	21	3.5	3.5	100
	Total	579	100	100	

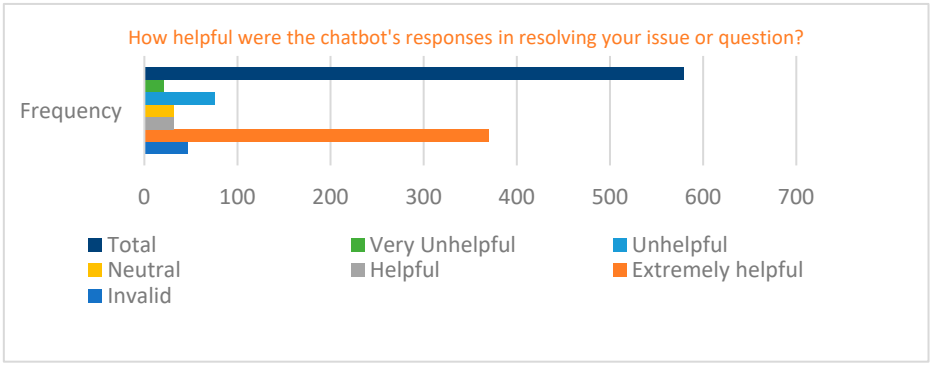


Figure 10. The level at which the chatbot was useful to the learners.

4. Discussion

From Figure 9, it can be seen that delayed response time is the major challenge NOUN students encounter in e-ticketing, agreeing with [49], which stated that delays in feedback are the main cause of attrition.

Figure 9 also shows that 43.4%, representing 215 respondents, indicated that after the delayed time, the response to the complaints may not be provided, making the student develop impatience and anxiety during their studies [9], thereby making them lack the motivation to continue their studies.

Figure 9, further provided information that 153, representing 30.8%, indicated that the students' needs were not met through e-ticketing, while 112, representing 22.5%, indicated that the information the support team provided was inadequate and 106, which represents 21.3%, indicated that there was no feedback entirely. Delayed feedback has become one of the critical areas that need urgent intervention, as stated by [13,14] and authenticated by the findings from Figure 1 above. When there is delayed feedback, students tend to feel isolated, losing a sense of belonging, thereby abandoning their studies.

The data presented in Table 4 and Figure 10 highlight how beneficial users found the developed chatbot in resolving their queries or challenges. Among 579 respondents, 375, which represents 64%, rated the chatbot as "Extremely helpful", and 5.5% rated it as "Helpful", which cumulates to a total of 69.5% favourable ratings. Additionally, 5.5% of respondents were "Neutral", meaning they were neither satisfied nor dissatisfied. But 13.5% of users rated the chatbot as "Unhelpful", and 3.5% opined that it was "Very Unhelpful". Unfavourable ratings were provided by 17% of students. In addition, 42 invalid responses, representing 8% of the total respondents, were also noted. These results imply that the chatbot works effectively for the majority of users, although it could be improved to do a better job of attending to the issues raised by the unfavourable minority. Even though the chatbot performed very well as rated by the majority of the respondents, scalability [56] is a major drawback to consider. As the user base expands, the chatbot may find it difficult to handle a growing number of concurrent enquiries without seeing a drop in accuracy or response time. This may result in inaccurate or irrelevant information being provided and a misconception of the user's purpose. In the developed system, complex questions are channelled and handled by the support team.

There are serious ethical issues with the employment of chatbots driven by AI, especially when it comes to bias and data protection. Sensitive user data, such as behavioural, academic, or personal information, is frequently gathered and processed by chatbots. If these data are not adequately secured, it may result in privacy violations or unauthorised access [63]. It is crucial to make sure that data processing is transparent and that laws like the GDPR are followed. Furthermore, biases from training data may be inherited by AI chatbots, resulting in unfair or discriminatory responses, especially in scenarios involving education or decision-making [64,65]. To address these biases and guarantee fair and impartial interactions for all users, meticulous dataset curation, ongoing monitoring, and algorithmic fairness measures are needed. However, obtaining a variety of training data to enhance the performance of the chatbot is also a challenge. This problem is persistent in educational environments, especially in the ODL systems, where fair access to reliable and helpful information is essential for the learners. More research is needed in this area to bridge the gap by providing inclusive and scalable systems that meet the diverse needs of the learners.

5. Conclusions

In this study, the authors presented preliminary findings on the effectiveness of the use of e-ticketing in NOUN support services and developed a chatbot as a NOUN support system. A survey was created to ascertain the level of awareness of e-ticketing, which the NOUN is using for its learner support system. In the findings, it was found that the e-ticketing system is not very effective, since there is always a delayed response whenever an issue is submitted for resolution by learners to the support team. However, the need

for the introduction of a chatbot is inevitable as it provides a timely response to issues raised by the students. Based on the findings, a chatbot was developed to provide solutions to the needs of the students by removing the barrier of delayed response. The system is automated and renders self-service due to its AI capabilities. The system automatically resolves issues raised by the learners by searching through its database knowledge system for keywords with the data in the knowledge base, automatically alerting the support team through a built-in SMS alert system that notifies the support team on complex issues that cannot be handled by the chatbot. Giving quick, easily accessible, and individualised help to learners in real time makes chatbots essential to learner support services in an Open and Distance Learning (ODL) environment. Students' questions about academic materials, course navigation, and administrative procedures can be answered in real time by chatbots using natural language processing and machine learning. This quick response guarantees that students receive timely instruction regardless of their location or time zone and minimises the delay that is frequently associated with traditional support systems. By doing this, chatbots empower learners by providing reliable, round-the-clock help, which fosters engagement, retention, and academic success.

The issue of data security and privacy has become a great concern because chatbots frequently gather and handle private user data, including academic records and personal information. These data may be susceptible to breaches or illegal access in the absence of strong encryption and data protection measures. To preserve confidence, user data processing, sharing, and storage must be transparent. Additionally, an over-reliance on AI assistance, like chatbots, by the institutions runs the risk of limiting opportunities for human connection and tailored advice. Even though chatbots can respond quickly and effectively, they might not have the empathy and contextual knowledge that human advisors do—two qualities that are especially crucial when dealing with complex issues. Continuous improvement and oversight are needed in this area, including diversifying and growing training datasets by integrating superior natural language processing techniques. The authors recommend that researchers should critically develop an ethical consideration policy on private user data which includes academic records and personal information. This will guide how these data are handled to avoid violating data privacy rules.

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