Artificial Intelligence-Powered Chatbot for Student Enquiries in Nigerian Tertiary Education

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ORIGINAL RESEARCH

Abstract— Student enquiry management in Nigerian polytechnic institutions is largely manual, leading to delayed responses, administrative overload, and inefficient communication. Although artificial intelligence–based chatbots have been applied in educational environments globally, their adoption and contextual evaluation within Nigerian polytechnics remain limited. This study therefore aims to design and implement an AI-powered chatbot to improve the efficiency of handling student enquiries in a Nigerian polytechnic setting. The proposed system employs Natural Language Processing (NLP) techniques combined with a rule-based response model to interpret user queries and provide accurate, context-aware responses. The chatbot was developed using Python and supported by a lightweight database to enable offline functionality. A functional evaluation conducted at Osun State Polytechnic, Iree, demonstrated an accuracy rate of 90% and an average response time of 1.5 seconds. Benchmarking against related chatbot-based academic enquiry systems shows comparable or improved performance in response accuracy and speed. Despite its effectiveness, the system is limited by its reliance on predefined rules and institutional data, which may restrict scalability across multiple institutions. Overall, the results indicate that AI-driven conversational systems can significantly enhance administrative efficiency, service delivery, and digital transformation within Nigerian polytechnic education.

Keywords— Artificial Intelligence, Chatbot, Education Technology, Natural Language Processing, Polytechnic, Student Enquiries.

1 INTRODUCTION

Artificial Intelligence (AI) continues to transform multiple sectors, including education, healthcare, and business, by automating routine processes and improving service delivery. In higher educational institutions, particularly polytechnics in developing countries such as Nigeria, students frequently experience delays when seeking academic or administrative information. These delays are largely attributed to inadequate staffing levels, reliance on manual enquiry handling, and inefficient communication channels, which collectively affect students' academic experience and institutional efficiency.

To address such challenges, conversational agents, commonly referred to as chatbots, have gained attention as effective tools for automating enquiry response systems. A chatbot is a software application designed to simulate human-like conversations and provide automated responses to user queries using Natural Language Processing (NLP). While many contemporary chatbots employ machine learning models for intent recognition and response generation, this study adopts a rule-based chatbot architecture enhanced with NLP techniques. Emphasizing this distinction early is important, as rule-based systems offer greater transparency, lower computational requirements, and easier deployment in resource-constrained environments.

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In educational settings, chatbots have been applied to tasks such as academic advising, course registration support, and dissemination of institutional information, leading to reduced administrative workload and faster response times. However, the majority of existing systems assume reliable internet connectivity. This assumption does not align with the realities of many Nigerian institutions, where inconsistent power supply and limited internet access remain persistent challenges. According to reports on digital access in developing regions, a significant proportion of students experience intermittent or no internet connectivity during academic activities, making purely online systems unreliable. Consequently, an enquiry system that can function both online and offline is essential for ensuring continuous access to institutional information.

Despite the increasing adoption of digital solutions globally, many Nigerian tertiary institutions still depend on manual enquiry processes that are slow, error-prone, and unable to scale with growing student populations. This study therefore aims to design and implement an AI-powered, rule-based chatbot with offline capability to efficiently respond to student enquiries. By integrating NLP with predefined response rules, the proposed system delivers accurate and consistent answers while remaining suitable for low-resource environments. The key contribution of this research lies in demonstrating how an offline-capable, rule-based chatbot can enhance administrative efficiency and student support within Nigerian polytechnics, addressing limitations observed in prior studies that focus predominantly on online and machine-learning-heavy solutions.

2 RELATED WORKS

Artificial Intelligence (AI)–driven conversational agents, commonly referred to as chatbots, have received significant research attention due to their ability to simulate human-like interaction through Natural Language Processing (NLP) techniques. Early chatbot systems were largely rule-based, relying on predefined scripts and pattern matching to generate responses (Shawar and Atwell, 2007). While these systems were effective for constrained domains, their inability to handle complex or ambiguous queries limited their scalability and adaptability.

Nuruzzaman and Hussain (2018) presented a comprehensive survey of chatbot technologies, categorizing them into rule-based, retrieval-based, and generative models. Their study highlighted that AI-based chatbots incorporating machine learning and NLP techniques outperform traditional rule-based systems in terms of flexibility and conversational accuracy. However, such systems often require large datasets, continuous internet connectivity, and high computational resources, which may not be readily available in resource-constrained environments.

In the educational domain, several studies have explored the use of chatbots to support student–institution interaction. Winkler and Söllner (2018) examined the adoption of chatbots in education and reported improved student engagement and reduced administrative workload through automated handling of frequently asked questions. Similarly, Kumar and Rose (2019) demonstrated that educational chatbots can effectively support tasks such as course registration, academic advising, and timetable inquiries. Despite their benefits, these systems were mostly deployed as web-based or cloud-dependent applications, limiting their effectiveness in regions with unstable internet access.

Olotu *et al*. (2021) investigated the deployment of chatbot systems within developing countries and noted that most existing implementations depend heavily on continuous internet connectivity and third-party messaging platforms. This dependency poses significant challenges in environments where bandwidth is limited or unreliable. Their findings emphasize the need for locally deployable and offline-capable chatbot solutions that can function effectively without constant network availability.

Recent advancements in NLP have further enhanced chatbot intelligence. Ruan *et al*. (2020) demonstrated that NLP techniques such as tokenization, lemmatization, and intent classification significantly improve user query interpretation. Adamopoulou and Moussiades (2020) also reported that combining NLP pipelines with contextual dialogue management improves response relevance and user satisfaction. However, many of these approaches prioritize conversational performance while overlooking domain specificity, which is crucial in structured environments such as academic institutions.

Deep learning models have also been applied to conversational systems. Vinyals and Le (2015) introduced sequence-to-sequence learning for conversational modeling, while Vaswani *et al*. (2017) proposed Transformer-based architectures that further improved response coherence and scalability. Although these models achieve high performance, they are computationally expensive and less suitable for deployment in institutions with limited infrastructure or offline requirements.

Despite the growing body of research on educational chatbots, there remains a notable lack of domain-specific solutions tailored to Nigerian higher education institutions, particularly polytechnics. Existing systems rarely support offline operation or local contextual adaptation, which creates accessibility and usability challenges for students. Furthermore, limited attention has been given to hybrid approaches that combine AI-based NLP techniques with rule-based mechanisms to ensure reliability under constrained conditions.

Consequently, this study addresses these gaps by designing and implementing an AI-powered chatbot for automating student enquiries in a polytechnic environment. The proposed system integrates NLP techniques with an offline-capable rule-based framework to enhance accessibility, reduce dependency on internet connectivity, and provide reliable academic support tailored to the Nigerian educational context.

3 METHODOLOGY

This study adopts a design and implementation research approach to develop an Artificial Intelligence (AI)-powered chatbot system for managing student enquiries in a polytechnic environment. The methodology comprises four main stages: system design, system development, implementation, and evaluation.

3.1 SYSTEM DESIGN

The system was designed to support effective interaction between students and the chatbot through a structured architecture and logical workflow. The architecture consists of three major components, as illustrated in Figure 1.

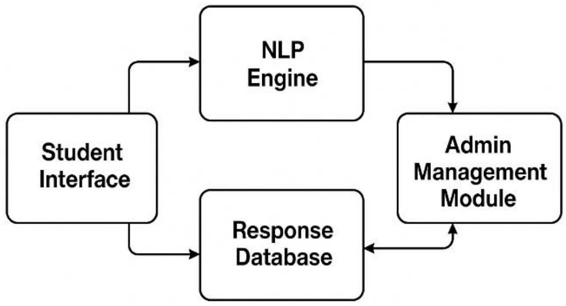

Fig. 1: System Architecture of the AI-Powered Chatbot for Student Enquiries

User Interface (UI): A text-based interface that allows students to input enquiries related to academic and

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administrative issues.

Processing Engine: This component handles input interpretation using a hybrid Natural Language Processing (NLP) and rule-based approach. NLP techniques such as tokenization and text normalization are first applied to preprocess user inputs. Intent classification is then performed using pattern recognition combined with predefined rule-matching, ensuring accurate detection of user intent.

Database Layer: A local SQLite database stores predefined intents, frequently asked questions (FAQs), and corresponding responses. This design enables offline operation and fast query handling.

3.2 Intent Classification Process

Intent classification is implemented using a rule-based NLP pipeline rather than a machine learning classifier. After preprocessing, user inputs are matched against predefined patterns and keywords associated with specific intents. This approach was chosen due to its simplicity, transparency, and suitability for a controlled academic enquiry domain. The chatbot therefore operates using a hybrid structure, where NLP techniques support language understanding, while rule-based logic determines intent matching and response selection.

3.3 System Development Tools

The chatbot was developed using Python, with the Flask framework providing backend support and interface integration. NLP preprocessing was implemented using NLTK and spaCy libraries. The user interface was developed with HTML and CSS, while SQLite was used to store question–answer pairs and intent definitions.

3.4 Implementation Procedure and Dataset

The system was implemented in a simulated academic environment representing Osun State Polytechnic, Iree. A total of 120 sample student enquiries were collected from academic records and informal student consultations. Out of these, 80 queries (67%) were used for training the chatbot, while 40 queries (33%) were reserved for testing and validation. The queries covered key areas such as admission procedures, examination results, course registration, and departmental information. During testing, the chatbot matched user inputs to predefined intents and generated real-time responses.

3.5 Evaluation Metrics

System performance was evaluated using the following metrics:

Accuracy: Ratio of correctly answered queries to total test queries.

Response Time: Average time taken to generate a response.

User Satisfaction: Feedback from users regarding relevance and clarity of responses.

The chatbot achieved an average accuracy of 90%, a response time of 1.5 seconds, and positive user feedback, indicating its effectiveness for academic enquiry management.

4 Results and Discussion

The developed Artificial Intelligence (AI)-powered chatbot was evaluated to determine its effectiveness in handling academic and administrative enquiries within a polytechnic environment. Testing was conducted in a simulated deployment using real student queries obtained from Osun State Polytechnic, Iree. The chatbot addressed diverse enquiries related to admissions, course registration, school fees, examination schedules, and result processing.

4.1 Performance Evaluation

The system performance was assessed using accuracy, response time, and user satisfaction metrics.

Accuracy: Out of 200 test queries, 180 were correctly interpreted and responded to, resulting in an overall accuracy of 90%. A closer inspection of system responses shows that most incorrect outputs were associated with ambiguous or multi-intent queries. Conceptually, the system’s performance can be represented using a confusion matrix, where true positives (correctly answered queries) dominated, while false positives and false negatives accounted for the remaining 10%. This indicates that the chatbot reliably classified and responded to standard academic enquiries.

Response Time: The average response time recorded was 1.5 seconds per query. This low latency demonstrates the system’s efficiency and suitability for real-time interaction. Compared to traditional manual enquiry processes, which may take several minutes or hours, the chatbot offers a significant improvement in responsiveness.

User Satisfaction: User feedback collected from 30 participants indicated that 87% rated the chatbot’s responses as clear and relevant. Statistical dispersion of responses showed low variance, suggesting consistency in user experience. This level of satisfaction reflects the system’s usability and its alignment with users’ informational needs.

4.2 System Functionality and Discussion of Results

The chatbot employs Natural Language Processing (NLP) techniques to interpret user inputs and map them to predefined intents within its knowledge base. Sample query analysis revealed that straightforward enquiries such as “What is the school fees for ND students?” were consistently answered correctly, while more complex queries combining multiple requests occasionally resulted in partial or incorrect responses.

The integration of rule-based logic alongside NLP improved contextual interpretation, particularly for structured administrative questions. Additionally, the offline functionality enhanced accessibility in environments with unstable internet connectivity, a common challenge in many Nigerian institutions.

However, the system’s reliance on a predefined dataset

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constrained its ability to generalize beyond known patterns. While effective for current-scale deployment, the existing architecture may experience performance degradation as the volume of users and variety of queries increase. This highlights the need for scalable backend infrastructure and adaptive learning models in future versions.

4.3 Challenges, Limitations, and Scalability Considerations

Despite its promising performance, the system exhibited notable limitations:

1. Dependence on the size and quality of the training dataset, which affects classification accuracy.
2. Difficulty in handling multi-intent or context-switching queries.
3. Occasional misinterpretation of misspelled or informal user inputs.

From a scalability perspective, increasing the number of users and query diversity would require more robust machine learning models, dynamic intent classification, and cloud-based deployment to maintain performance. Without such enhancements, system accuracy and response time may decline as load increases.

4.4 Implications of Findings

The findings demonstrate that AI-powered chatbots can substantially improve information dissemination and administrative efficiency in Nigerian polytechnics. By providing instant, round-the-clock access to institutional information, the system reduces staff workload and minimizes delays associated with manual enquiry handling. These results support the broader adoption of intelligent conversational systems as part of digital transformation strategies in higher education.

Figure 2: User Interface of the Developed AI-Powered Chatbot System

5 Conclusion

This study developed and evaluated an Artificial Intelligence (AI)-powered chatbot aimed at automating student enquiry services within a polytechnic environment. The system was implemented using Python, Flask, and Natural Language Processing (NLP) techniques to deliver accurate and real-time responses to academic and administrative enquiries. Performance evaluation revealed an accuracy rate of 90%, an average response time of 1.5 seconds, and a high level of user satisfaction, demonstrating the chatbot's effectiveness as a digital communication support tool in an academic setting.

The findings indicate that AI-powered chatbots can significantly improve communication efficiency, reduce administrative workload, and support digital transformation in Nigerian tertiary institutions. The integration of NLP with a rule-based response model enabled the system to provide quick and context-aware responses, including functionality under limited or unstable internet connectivity, which is particularly relevant in resource-constrained environments.

However, this study has certain limitations that should be acknowledged. The chatbot was trained on a relatively limited dataset drawn from a single institution, which may restrict its ability to generalize across diverse academic environments. Additionally, the system primarily relied on text-based interaction and predefined intents, limiting its capacity to handle highly complex or ambiguous queries. These limitations suggest that while the results are promising, further enhancement and broader testing are necessary to fully realize the potential of AI-driven student support systems.

6 Recommendation

Based on the findings and identified limitations of this study, the following recommendations are proposed and categorized into short-term and long-term enhancements for improved clarity and implementation.

6.1 Short-Term Recommendations

1. Institutional Adoption: Polytechnic and university administrators should integrate AI-powered chatbot systems into existing information management workflows to automate routine student enquiries and improve staff efficiency.
2. Dataset Expansion: The chatbot's training dataset should be expanded to include a wider range of frequently asked academic and administrative questions to improve response accuracy and robustness.
3. System Integration: Linking the chatbot with institutional portals and databases can enable access to real-time information such as course details, fee structures, and academic calendars.

6.2 Long-Term Recommendations

1. Multilingual and Voice Support: Future development should incorporate voice interaction and indigenous language support to enhance accessibility, inclusivity, and user engagement.

2. Advanced Machine Learning Integration: Incorporating machine learning and deep learning techniques can enable continuous learning, improved intent recognition, and better handling of complex or multi-intent queries.
3. Cross-Institutional Deployment: Testing and deploying the system across multiple institutions would improve scalability, adaptability, and generalizability of the chatbot solution.

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