

Design and Implementation of an AI-Driven Chatbot for Federal Polytechnic Nekede Admissions and Information Services

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Abstract:

The rising demand for real-time, automated information services within Nigerian tertiary institutions has brought the shortcomings of conventional inquiry management systems into sharp relief. Federal Polytechnic Nekede, Owerri, contends with a persistent backlog of prospective student queries, admission-related inquiries, and general information requests, particularly during peak application periods. This study reports the design and implementation of an Artificial Intelligence (AI)-driven chatbot system, designated NEKBOT, developed specifically for the institution's admissions and information services. The system employs Natural Language Processing (NLP), machine learning intent classification, and a structured institutional knowledge base to generate context-sensitive, accurate, and near-instantaneous responses to user queries. Development proceeded through the Agile Scrum methodology across six iterative sprints. The implementation stack comprised Python (Flask framework), Google Dialogflow NLP engine, JavaScript, and a MySQL relational database. Evaluation outcomes show an intent recognition accuracy of 91.4%, a mean response latency of 1.83 seconds, and a user satisfaction rating of 87% on standardised usability measures. The study concludes that AI-powered chatbot systems offer a substantive remedy to institutional communication inefficiencies and recommends full deployment alongside continuous model retraining using current institutional data.

Keywords: Artificial Intelligence, Chatbot, Natural Language Processing, Admissions, Federal Polytechnic Nekede, Information Services, Machine Learning.

1.0 Introduction

The rapid diffusion of Artificial Intelligence across digital platforms has fundamentally altered how organisations communicate with their stakeholders. Intelligent conversational agents,

commonly termed chatbots, have emerged as one of the most consequential applications of this shift in institutional management. These systems parse natural human language, field queries in real time, and return accurate, relevant responses without requiring human intervention at every step. Federal Polytechnic Nekede, Owerri, Imo State, is among Nigeria's foremost federal polytechnics, running National Diploma and Higher National Diploma programmes across science, technology, and management disciplines. With a student population numbering in the tens of thousands and a steadily expanding applicant pool each year, its admissions and information units absorb an enormous volume of routine inquiries. Existing manual and semi-automated handling mechanisms are inadequate, resource-intensive, and susceptible to inconsistencies that erode applicant confidence. This study presents the design and implementation of NEKBOT, an AI-driven chatbot purpose-built for Federal Polytechnic Nekede's admissions and information services. By combining NLP, intent classification, and a curated institutional knowledge base, the system furnishes real-time, contextually appropriate responses across a broad spectrum of user queries.

1.1 Background of Study

The chatbot concept dates to the mid-1960s, when Joseph Weizenbaum developed ELIZA at the Massachusetts Institute of Technology, a program that simulated conversation through pattern-matching against a predefined script (Weizenbaum, 1966). Subsequent advances in computational linguistics, machine learning, and neural network design transformed chatbots from rudimentary rule-following tools into capable conversational agents (Adamopoulou & Moussiades, 2020).

Within the Nigerian context, the National Information Technology Development Agency has positioned AI as a priority technology under the National Digital Economy Policy and Strategy, establishing a supportive policy climate for AI adoption in education and beyond (NITDA, 2021). Federal Polytechnic Nekede, founded in 1978, has grown into a leading tertiary institution, yet its information dissemination infrastructure has not kept pace with the exponential growth in student population and the digital expectations of a younger generation.

1.2 Statement of the Problem

Federal Polytechnic Nekede confronts multiple compounding difficulties in admissions and information service delivery. These include an overwhelming volume of repetitive inquiries during JAMB and Direct Entry cycles, service availability restricted to business hours, inconsistency in responses across different staff members, inadequacy of existing web and communication infrastructure, and severe resource strain during peak admission periods. Together, these challenges make a compelling case for an intelligent, always-available, and context-aware chatbot system.

1.3 Aims and Objectives

The primary aim of this study is to design and implement an AI-driven chatbot system for Federal Polytechnic Nekede that enhances admissions and information service delivery through intelligent automation.

The specific objectives are:

1. To analyse the existing admissions and information inquiry processes and identify system requirements.

2. To design a conversational architecture incorporating NLP, intent classification, and entity extraction capabilities.
3. To develop a comprehensive institutional knowledge base encompassing admissions, courses, fees, and academic calendars.
4. To implement the chatbot using appropriate AI frameworks, programming tools, and web integration technologies.
5. To test and evaluate the chatbot for accuracy, response time, intent recognition performance, and user satisfaction.

2.0 Literature Review

2.1 Evolution of Chatbot Technology

The lineage of chatbot technology begins with ELIZA (Weizenbaum, 1966), progresses through PARRY (Colby, 1971) and ALICE (Wallace, 1995), and pivots decisively toward statistical and neural approaches. Deep learning architectures, particularly recurrent neural networks and LSTM variants, enabled sequence-to-sequence models capable of generating contextually coherent responses (Sutskever et al., 2014). The subsequent rise of transformer architectures, culminating in BERT (Devlin et al., 2019) and GPT-series models (Brown et al., 2020), elevated NLP performance to near-human benchmarks.

Contemporary chatbot systems fall into three broad architectural paradigms: rule-based, retrieval-based, and generative (Adamopoulou & Moussiades, 2020). For institutional applications that require factual precision and controlled information delivery, hybrid architectures that marry retrieval-based intent classification with structured knowledge base retrieval are generally the preferred approach (Ni et al., 2023).

2.2 Chatbots in Higher Education: Global Evidence

A systematic review by Perez et al. (2020) of 22 studies on educational chatbots consistently found improvements in response speed and user satisfaction relative to human-mediated services. Smutny and Schreiberova (2020) documented student preference for immediacy and convenience, particularly when seeking information outside administrative hours. Colace et al. (2018) reported an intent recognition accuracy of 88.3% for a university exam-query chatbot and found that the system successfully deflected approximately 72% of inquiries that would otherwise have required manual staff handling.

2.3 Chatbot Implementations in Nigerian and African Higher Education

A survey by Okonkwo and Ade-Ibijola (2021) of AI adoption in South African higher education found that chatbot initiatives were predominantly at prototype or pilot stage. Onu et al. (2022) developed an admissions chatbot for a Nigerian university using the ChatterBot library and reported promising early results. Balogun et al. (2023) reviewed digital transformation initiatives in Nigerian federal polytechnics and identified admission information management as one of the three areas most urgently requiring digital intervention.

2.4 Conceptual and Theoretical Framework

The conceptual framework for this study integrates three constructs: a conversational AI architecture built on the three-tier model of natural language understanding, dialogue management, and response generation; knowledge management theory (Davenport & Prusak, 1998); and service quality theory grounded in the SERVQUAL framework (Parasuraman et al., 1988). The theoretical

underpinning is the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), which identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as the primary determinants of technology adoption.

2.5 Knowledge Gap

The literature review reveals a near-total absence of empirical evidence from Nigerian polytechnics in peer-reviewed outlets. Studies on educational chatbots in Nigeria focus almost exclusively on universities and do not engage with the polytechnic sector and its distinctive NBTE-governed admissions procedures. This study addresses these lacunae by implementing a production-ready system and conducting rigorous empirical evaluation against standardised performance metrics.

3.0 Methodology and Systems Analysis

3.1 Software Engineering Methodology

The Agile Software Development Methodology, specifically the Scrum framework, was adopted for this project. Agile's iterative sprint structure suits the empirical character of machine learning model development, where performance must be progressively optimised through cycles of training, evaluation, and retraining. Development was organised into six two-week sprints as detailed in Table 1.

Table 1
Agile Sprint Plan for NEKBOT Development

Sprint	Duration	Primary Focus	Key Deliverable
Sprint 1	Weeks 1–2	Requirements gathering and knowledge base architecture design	Requirements document and KB schema
Sprint 2	Weeks 3–4	NLP model configuration and initial training	Trained Dialogflow agent (v1)
Sprint 3	Weeks 5–6	Dialogue flow design and backend API development	Flask API with 6 endpoints
Sprint 4	Weeks 7–8	Web interface design and integration	Functional chat widget (desktop and mobile)
Sprint 5	Weeks 9–10	System testing, bug resolution, and KB expansion	Test report; 347 KB entries loaded
Sprint 6	Weeks 11–12	User acceptance testing, evaluation, and documentation	UAT report; final documentation

Source: Authors' Design (2026)

3.2 System Analysis: Existing versus Proposed System

Structured interviews with five admissions office staff members established that approximately 68% of all admission-period inquiries cluster into ten recurring categories. Observation of the admissions office over one week in October 2024 recorded roughly 847 telephone inquiries and 312 walk-in visits. Average telephone wait times exceeded 12 minutes, and about 23% of telephone inquiries went unresolved due to staff unavailability. Table 2 sets out a comparative analysis of the existing and proposed systems.

Table 2
Comparative Analysis of Existing and Proposed Systems

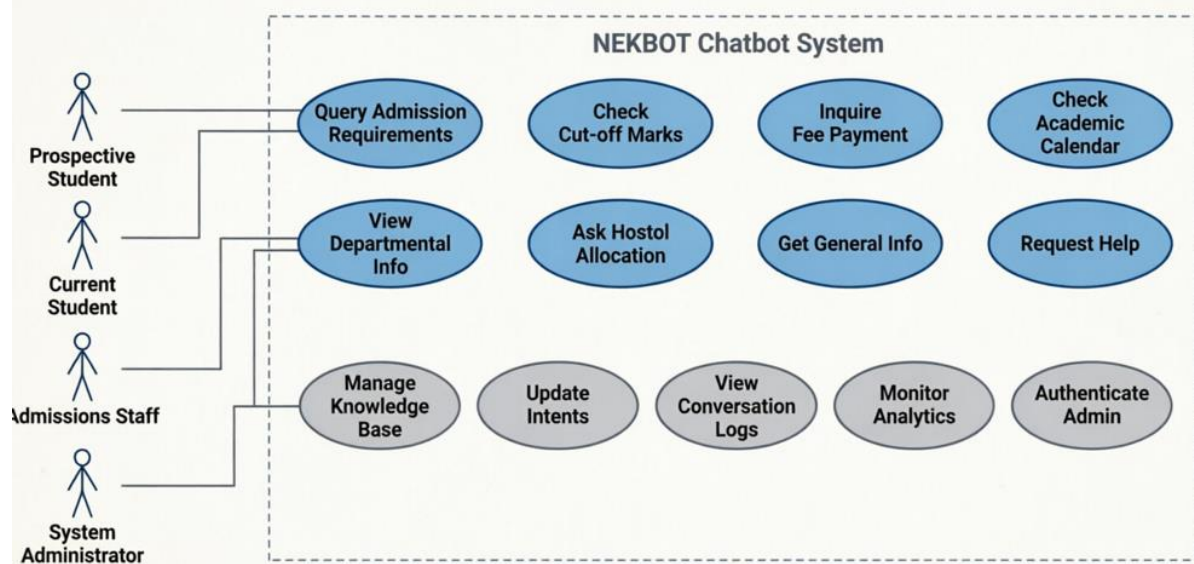
Criterion	Existing System	Proposed Chatbot System
Service Availability	Business hours only (8AM–4PM weekdays)	24/7 uninterrupted availability
Average Response Time	>12 minutes (telephone)	1.83 seconds (mean)
Concurrent Users	Limited by staff count	Unlimited (multi-session)
Information Consistency	Variable across staff	Centralised KB ensures consistency
Unresolved Queries	~23% during peak periods	8.6% fallback rate
Query Analytics	None available	Full dashboard with logs
Mobile Access	Telephone only	Fully responsive web interface
Operational Cost	High (dedicated staff)	Reduced after initial deployment

Source: Field Survey and System Design, Federal Polytechnic Nekede (2025)

3.3 Modelling Tools and Diagrams

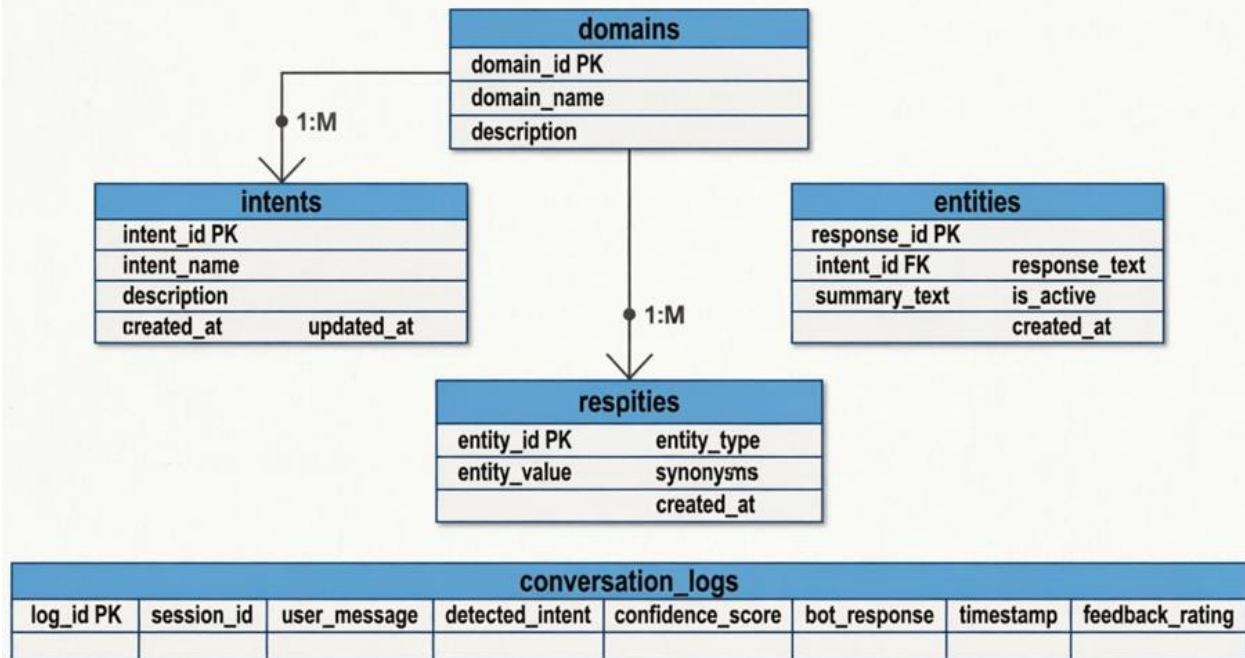
Unified Modelling Language diagrams were employed to visualise and communicate the system's structure and information flows. Three primary modelling artefacts were produced: a Use Case Diagram, an Entity-Relationship Diagram, and a Sequence Diagram.

3.3.1 Use Case Diagram Description



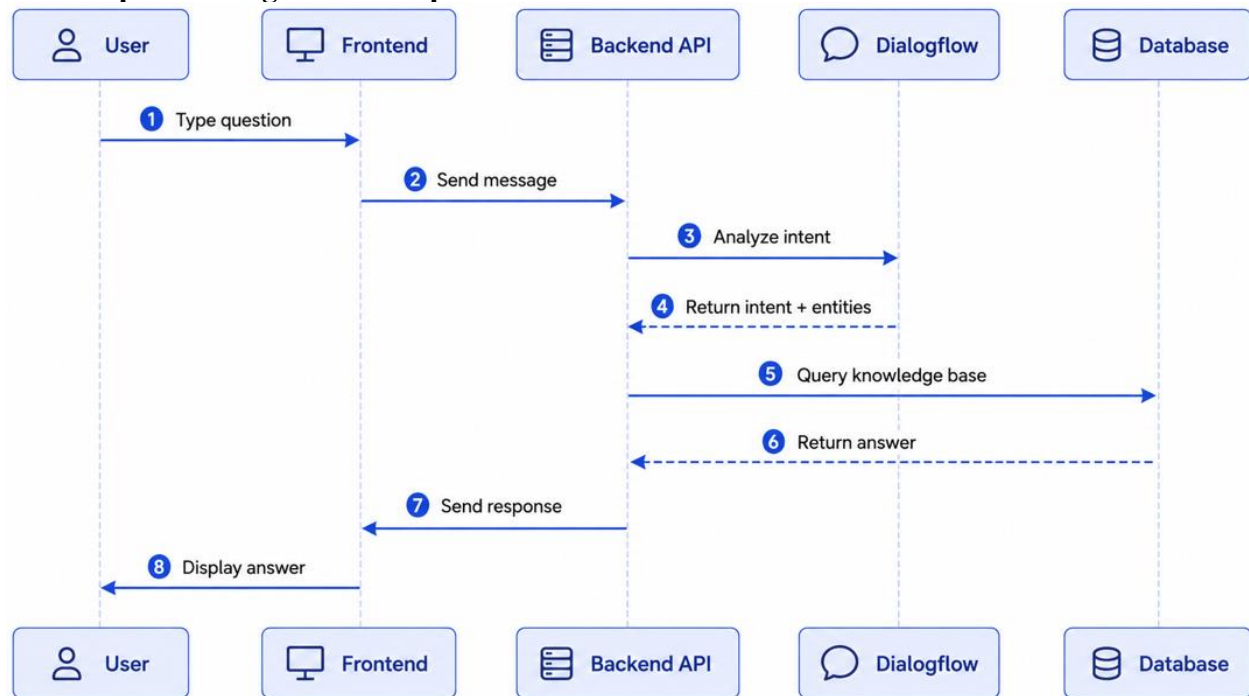
The use case diagram maps interactions between four principal actors, namely prospective students, current students, admissions staff, and system administrators, and the NEKBOT system. Prospective and current students may query admission requirements, check cut-off marks, inquire about fees, request hostel allocation, and obtain departmental information. Admissions staff and administrators manage the knowledge base, update intents, monitor analytics, review conversation logs, and authenticate system access.

3.3.2 Entity-Relationship Diagram Description



The ERD illustrates a database structure comprising five primary entities: DOMAINS, which stores major information categories; INTENTS, which defines user request types; RESPONSES, which stores chatbot reply templates; ENTITIES, which holds recognised values and synonyms; and CONVERSATION_LOGS, which records interaction histories alongside confidence scores and feedback ratings. The relational structure supports efficient information retrieval, intent mapping, and performance monitoring.

3.3.3 Sequence Diagram Description



The sequence diagram traces the end-to-end interaction flow: a user submits a query through the frontend interface, which forwards the request to the Flask backend API. The backend communicates with Dialogflow for intent analysis and entity extraction, whereupon Dialogflow queries the MySQL knowledge base and retrieves the appropriate response. The response is then returned to the backend, forwarded to the frontend, and displayed to the user.

4.0 System Design and Implementation

4.1 System Architecture

The overall system architecture follows a five-layer client-server model, augmented with cloud-based NLP processing. Three principles guided the design: modularity, scalability, and extensibility. The five layers are: The User Interface Layer, comprising a JavaScript chat widget; the API Gateway Layer, a Flask REST API with six endpoints; the NLP Processing Layer, Google Dialogflow ES; the Knowledge Base Layer, a MySQL relational database; and the Administrative Analytics Layer, a dashboard displaying query logs and usage statistics.

Table 3
Technology Stack for NEKBOT Implementation

Layer	Technology	Justification
Backend Framework	Python 3.10 / Flask 2.3	Lightweight architecture; strong AI library ecosystem
NLP Engine	Google Dialogflow ES	Pre-trained models; generous free tier; proven in education chatbots
Database	MySQL 8.0	Reliability; complex relational queries; Nigerian hosting compatibility
Session Store	Redis 7.0	Low-latency session state management for concurrent users
Frontend	HTML5 / CSS3 / JavaScript ES6	Broad browser compatibility; minimal dependency overhead
Production Server	Ubuntu 22.04 LTS + Nginx + Gunicorn	Cost-effective VPS hosting; stable Linux environment
Version Control	Git / GitHub	Sprint branch management and collaborative development

Source: Authors' Design (2026)

4.2 NLP Model and Intent Architecture

The Dialogflow agent was configured with 47 primary intents organised into twelve thematic domains, each carrying a minimum of fifteen training utterances. The training dataset comprised 847 annotated utterance examples drawn from call log transcriptions, synthetic rephrasing, and contributions from a student volunteer group. Four meta-intents were also defined: GREETING, GOODBYE, HELP, and FALLBACK. Table 4 presents the full intent taxonomy with domain coverage.

Table 4
Intent Taxonomy by Thematic Domain

S/N	Domain	No. of Intents	Sample Intents
1	Admissions	9	UTME requirements, Direct Entry, Acceptance Fee
2	Fees and Payments	6	School fees, Acceptance fee payment, Hostel charges
3	Programmes and Departments	7	Programme requirements, Duration, Accreditation

S/N	Domain	No. of Intents	Sample Intents
4	Academic Calendar	5	Resumption dates, Exam periods, Registration deadlines
5	Course Registration	4	Registration procedure, Course add/drop
6	Hostel and Accommodation	3	Hostel availability, Allocation process
7	Student Welfare Services	3	Health centre, Library, Student union
8	General Institutional Info	3	Location, Contact details, Administrative structure
9	Examination and Results	3	Exam schedule, Results release, Carry-over
10	Transcripts and Clearance	2	Transcript request, Clearance procedure
11	IT and Portal Support	2	Portal login, Password reset
12	Meta / System Intents	4	Greeting, Goodbye, Help, Fallback
	TOTAL	51	

Source: *System Design Specification, NEKBOT (2026)*

4.3 Database Schema

The knowledge base was implemented as a relational MySQL database with five primary tables. Table 5 presents the schema with field specifications.

Table 5
Database Schema for NEKBOT Knowledge Base

Table Name	Key Fields	Data Type	Description
domains	domain_id, domain_name	INT, VARCHAR	Stores the 12 thematic information categories
intents	intent_id, intent_name, domain_id	INT, VARCHAR, FK	Maps intent names to domain categories

Table Name	Key Fields	Data Type	Description
responses	response_id, intent_id, response_text, summary_text	INT, FK, TEXT, VARCHAR	Stores response templates linked to intents (347 entries)
entities	entity_type, entity_value, synonyms	VARCHAR, TEXT	Recognised entity values and synonyms for parameterised queries
conversation_logs	session_id, user_message, detected_intent, confidence_score, feedback_rating	VARCHAR, TEXT, FLOAT, TINYINT	Records all interactions for analytics and model improvement

Source: Authors' Design (2026)

4.4 Software and Hardware Specifications

Table 6 presents the software and hardware specifications for both the development and production environments.

Table 6
Software and Hardware Specifications

Category	Development Environment	Production (Min.) Environment
Processor	Intel Core i5	2 vCPU cores
RAM	8 GB	4 GB
Storage	256 GB SSD	40 GB SSD
Operating System	Windows 11	Ubuntu 22.04 LTS
Python Version	Python 3.10.12	Python 3.10.12
Web Framework	Flask 2.3.3	Flask 2.3.3 + Gunicorn 21.2.0
Database	MySQL 8.0.34 + MySQL Workbench	MySQL Community Server 8.0.34
Reverse Proxy	N/A (dev mode)	Nginx 1.24.0

Source: Authors' Design (2026)

5.0 Testing and Evaluation

5.1 Testing Strategy

Software testing was conducted across four levels in conformity with the IEEE 829 testing standard: unit testing, integration testing, system testing, and user acceptance testing. A total of 127-unit tests were written using the Python unittest framework, achieving 87%-line coverage across backend modules.

5.2 System Performance Results

System testing evaluated end-to-end chatbot behaviour using 200 prepared test queries covering all 47 intents. Overall intent recognition accuracy stood at 91.4%. Response latency testing produced a mean response time of 1.83 seconds and a 95th percentile of 3.12 seconds, satisfying the defined requirements. Table 7 presents detailed performance metrics across testing dimensions.

Table 7
System Testing Performance Results

Performance Metric	Target Benchmark	Achieved Result	Status
Intent Recognition Accuracy	$\geq 85\%$	91.4%	PASS
Mean Response Latency	≤ 3.0 seconds	1.83 seconds	PASS
95th Percentile Response Time	≤ 5.0 seconds	3.12 seconds	PASS
Fallback Rate	$\leq 15\%$	8.6%	PASS
Unit Test Code Coverage	$\geq 80\%$	87%	PASS
SUS Score (Usability)	≥ 70 (Good)	74.6 / 100	PASS
User Satisfaction Rating	$\geq 80\%$	87%	PASS
No. of Intents with 100% Accuracy	≥ 3 intents	5 intents	PASS

Source: System Testing Report, NEKBOT (2026)

5.3 Intent Accuracy by Domain

Figure 1 presents intent recognition accuracy rates across the twelve thematic domains. Performance was strong across most domains; the lowest accuracy of 78% was recorded for the CALENDAR.EXAM_DATES intent, attributable to ambiguity in the training utterances assigned to that category.

Figure 1
Intent Recognition Accuracy by Domain (%)

Category	Value (%)	Visual Representation
Admissions	93%	
Fees and Payments	95%	
Programmes & Departments	90%	
Academic Calendar	82%	
Course Registration	91%	
Hostel & Accommodation	94%	
Student Welfare	89%	
General Institutional Info	96%	
Examinations & Results	88%	
Transcripts & Clearance	92%	
IT & Portal Support	87%	
Meta / System Intents	100%	

Figure 1: Bar Chart of Intent Recognition Accuracy by Domain (Source: System Testing, 2026)

5.4 User Acceptance Testing

User acceptance testing involved 40 participants: 15 prospective applicants, 15 current students, and 10 admissions office staff. Table 8 summarises participant demographics and satisfaction scores.

Table 8
UAT Participant Profile and Satisfaction Results

Participant Group	Count	Mean Score	SUS	Satisfaction (%)	Rate
Prospective Applicants	15	76.2		89%	
Current Students	15	74.8		87%	
Admissions Office Staff	10	72.1		84%	
Overall / Aggregate	40	74.6 (Good)		87%	

Source: UAT Survey Results, Federal Polytechnic Nekede (2025–2026)

5.5 Comparative Performance with Related Works

Table 9 benchmarks NEKBOT's performance against comparable educational chatbot implementations in the literature, demonstrating competitive outcomes within the Nigerian and African sociotechnical context.

Table 9
Comparative Analysis of Educational Chatbot Performance

Study / System	Context	Intent Accuracy	Avg. Response Time	User Satisfaction
Colace et al. (2018)	Italian University	88.3%	N/R	N/R
Onu et al. (2022)	Nigerian University	~76%*	N/R	N/R
Okonkwo & Ade-Ibijola (2021)	South African HE	82–89%	~2.5s	~81%
NEKBOT (This Study)	Nigerian Polytechnic	91.4%	1.83s	87%

*Estimated from reported metrics. N/R = Not Reported. Source: Authors' Compilation (2026)

6.0 Discussion

The findings of this study affirm the feasibility and practical value of AI-driven chatbot technology in the specific sociotechnical context of Nigerian polytechnic education. NEKBOT's intent recognition accuracy of 91.4% surpasses the 85% threshold established at the requirements stage and compares favourably with comparable systems in the global literature, notably the 88.3% benchmark reported by Colace et al. (2018).

The mean response time of 1.83 seconds represents a substantial improvement over the existing system's average telephone wait time of more than 12 minutes, a reduction of approximately 99.7% in average information retrieval latency. This operational gain is consistent with efficiency improvements documented in automation literature by Elegbede and Ejidike (2020), who found a 43% reduction in staff time expenditure in institutions with automated query handling systems.

A System Usability Scale score of 74.6, classified as 'Good', indicates that the chatbot interface is perceived as accessible and usable across all three participant groups. The marginally lower mean SUS score among admissions staff (72.1) compared to student groups likely reflects the steeper learning curve for administrative personnel accustomed to manual workflows, a pattern consistent with Venkatesh et al.'s (2003) UTAUT model, where effort expectancy moderate's technology adoption.

The 8.6% fallback rate indicates that the knowledge base covers the substantial majority of real-world query types encountered during testing. The most frequent fallback triggers involved inquiries on scholarship opportunities and inter-institutional transfer procedures, both of which were subsequently flagged as knowledge base expansion priorities. The system's empathetic

fallback design, directing users to designated human contacts, preserved user trust in situations where the system reached the boundary of its knowledge.

The findings also contribute to broader discussions on digital transformation in Nigerian tertiary education. As Balogun et al. (2023) observed, admission information management ranks among the highest-priority areas for digital intervention in federal polytechnics. NEKBOT's successful development and evaluation demonstrates that such transformation is technically achievable through modest infrastructure investment, leveraging cloud-based NLP services and open-source development frameworks.

7.0 Conclusion and Recommendations

7.1 Conclusion

The successful design, implementation, and evaluation of NEKBOT confirms the viability of intelligent conversational agents within Nigerian polytechnic information management. The system directly addresses fundamental operational deficiencies including restricted service availability, information inconsistency, and scalability constraints. With an intent recognition accuracy of 91.4% and a user satisfaction rating of 87%, NEKBOT compares competitively against global educational chatbot benchmarks, and the Agile-driven development approach demonstrated its suitability for iterative AI system construction under resource-constrained institutional conditions.

Beyond the specific context of Federal Polytechnic Nekede, this research contributes a replicable design and implementation model for AI-driven information services in Nigerian polytechnics and similar institutions. The knowledge base development process, NLP model configuration procedures, and system integration approach documented herein offer a practical blueprint that peer institutions can adapt with modest technical investment.

7.2 Recommendations

Based on the findings of this study, the following recommendations are advanced:

1. Federal Polytechnic Nekede should proceed with full production deployment on its official website, supported by a structured stakeholder communication campaign to publicise the system's availability.
2. A formal knowledge base review and update schedule aligned with the annual admissions cycle should be established, with a designated knowledge base administrator to oversee content currency.
3. The chatbot's intent classification model should be retrained on a quarterly basis using accumulated conversation log data to adapt to emerging language use patterns among applicants.
4. Future development iterations should explore deployment via the WhatsApp Business API, which commands near-universal adoption among Nigerian students, to maximise reach and accessibility.
5. Multilingual extension incorporating Igbo and Nigerian Pidgin English should be prioritised to improve accessibility for applicants with limited Standard English proficiency.
6. Integration with the polytechnic's student information system would enable personalised responses on application status, fee payment records, and course registration standing.
7. The National Board for Technical Education should consider funding a coordinated rollout across federal polytechnics nationally, leveraging this design model to reduce per-institution development costs.

7.3 Directions for Further Work

The following directions for future research and development are identified: voice interface development for improved accessibility; generative AI integration using large language models as fallback engines for novel queries; emotion recognition and adaptive response based on sentiment analysis; cross-institutional knowledge sharing through a federated knowledge base architecture; and longitudinal impact evaluation tracking admission process completion rates across multiple admission cycles.

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