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Development of An Enhanced Personalized Ai-Powered Conversational Agent for Student Registration Support Using The Langflow Framework

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ABSTRACT

This study addresses the critical challenge of fragmented and inaccessible student support services in higher education by designing, implementing, and evaluating an enhanced AI-powered chatbot specifically tailored for prospective and new students at the Federal Polytechnic Bida. Leveraging the node-based visual architecture of Langflow, a conversational agent was developed and trained on a comprehensive knowledge base derived from mixed-methods data collection (N=400). The resultant system successfully centralized administrative information, providing immediate, personalized support. Rigorous performance evaluation demonstrated a robust Intent Classification Accuracy of 89% on unseen queries, an average response time of 1.2 seconds, and a high User Satisfaction Rate of 85%. Detailed F1-score analysis confirmed strong reliability across high-stakes intents, such as Fee Payment (94%). The findings validate Langflow's suitability for developing effective, transparent, and scalable AI solutions in resource-constrained educational settings, offering a practical model for institutions seeking to bridge operational gaps and improve the overall student experience.

Keywords: AI in Education, Langflow, Natural Language Processing, Student Support Services, Chatbots, Registration Process, Conversational AI.

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1. INTRODUCTION

The integration of artificial intelligence into educational contexts has evolved significantly over the past two decades, transforming from experimental applications to essential components of modern educational technologies *(Chen, Zou, Xie, Cheng, & Liu, 2022).* Research on AI in education has shown consistent growth, with focus areas including intelligent tutoring systems, natural language processing for language education, educational data mining for performance prediction, and recommender systems for personalized learning *(Chen et al, 2022).* Chatbots represent a particularly significant development in this progression, offering conversational interfaces that simulate human interaction while delivering educational services and support. These advanced technologies demonstrate a global shift towards systems that can respond dynamically and adaptively to individual student needs, moving beyond traditional one-size-fits-all educational models (Ayeni *et al.,* 2024).

Within this technological progression, chatbots represent a particularly significant development, offering conversational interfaces that simulate human interaction while delivering critical educational services and support (Hodge, 2022). In higher education, these agents have rapidly transitioned from rudimentary rule-based systems to sophisticated AI-powered assistants capable of advanced language understanding and personalized responses (Hodge, 2022). Examples such as George Washington University's Martha chatbot, which manages IT and administrative support functions, and the University of the People's Facebook Messenger-bot, which assists prospective students with program qualification and cost details, underscore the proven operational utility of conversational AI in the academic context (Hodge, 2022). The continuous demand for 24/7, immediate support, coupled with breakthroughs in NLP and machine learning, has created a critical technological convergence driving the rapid adoption of chatbots in universities globally (Kakhki et al., 2024).

Higher education institutions, exemplified by the Federal Polytechnic Bida, face chronic difficulties in providing timely, accurate, and personalized information to prospective and new students during their critical decision-making and initial transition phases (Moogan et al., 1999). This failure is rooted in the inherent limitations of reliance on traditional, manual support services (Kim, 2021). The existing support structure is characterized by severe fragmentation; services are delivered through disparate and often disconnected channels, relying on physical office visits, basic email, and telephone systems (Kim, 2021). This results in inconsistent information delivery, frequent delays, and the necessity for students to repeat requests across multiple departments to achieve resolution (Kim, 2021).

Furthermore, traditional support systems are constrained by fixed operational hours and staff availability, leading to significant scalability issues and bottlenecks, particularly during peak periods such as registration (Hodge, 2022). These constraints severely limit accessibility, often resulting in increased student stress, frustration, and a potential deterrence from enrollment (Moogan et al., 1999). Even with extensive online resources available, many students struggle to find the precise, relevant information required for informed decision-making regarding course selection and application procedures (Moogan et al., 1999). This institutional gap presents a clear opportunity for AI-powered solutions to deliver continuous, tailored support, thereby enhancing the student experience (Kim, 2021).

Langflow offers a promising platform for developing enhanced chatbots specifically designed to address these challenges. As described in its documentation, Langflow is a framework that enables the creation of flows (applications) that receive input, process it, and produce output, using a node-based architecture where components are connected by edges to form complete systems (Langflow, 2022). This approach allows for the development of sophisticated AI applications without requiring extensive programming knowledge, making it accessible to education professionals and researchers. By leveraging Langflow's capabilities, educational institutions can design chatbots that incorporate natural language processing, intelligent tutoring, and personalized recommendation systems to provide comprehensive support to prospective and new students.

This Research work, therefore, was conceived to bridge this gap. The primary aim of this study is to develop an enhanced chatbot for student support during registration using Langflow to provide comprehensive support to prospective and new students of the Federal Polytechnic Bida, Niger state. To realize this vision, the following specific, measurable objectives were established:

1. To create a structured Knowledge base from the data collected from the student through a questionnaire.
2. To develop an enhanced chatbot framework for student support during registration based on the Knowledge base.
3. To implement and rigorously evaluate the chatbot using Langflow, deploying it on the institution's website to test its performance.

2. LITERATURE REVIEW

2.1 The Evolution of Artificial Intelligence in Education (AIEd)

The field of AIEd is defined by its progression toward dynamic, adaptive, and personalized educational systems (Chen et al., 2022). A comprehensive review of literature reveals consistent growth, with key areas including Intelligent Tutoring Systems (ITS) that provide personalized guidance adapting to a student's pace, and Educational Data Mining (EDM), which leverages vast datasets to predict student outcomes and inform decision-making (Chen et al., 2022). Natural Language Processing (NLP) is particularly pivotal, enabling conversational interfaces to comprehend and generate human language (LinkedIn Pulse, 2024). This technological advancement allows educational institutions to provide personalized learning experiences that address individual differences in learning styles, paces, and preferences (Ayeni et al., 2024).

2.2 Chatbots in Higher Education: State-of-the-Art Applications

Chatbots have emerged as a practical and widespread application of AI in the higher education environment, functioning as sophisticated assistants capable of managing diverse administrative and academic inquiries (Kakhki et al., 2024). Modern implementations commonly aim to improve information accessibility, ensure consistent response accuracy, and alleviate the workload of administrative staff (Chen et al., 2022). These systems provide essential functions such as admissions assistance, academic advising, technical troubleshooting, and dissemination of general campus information (Hodge, 2022). The necessity for these systems is driven by students demanding immediate, around-the-clock access to support services, directly addressing the limitations imposed by traditional office hours (Kakhki et al., 2024).

2.3 The Criticality of Personalization and Integration in Student Support

Effective modern educational support necessitates personalization, which tailors information, recommendations, or interactions based on individual student characteristics, preferences, or behaviors (World Education, 2024). AI-powered chatbots achieve this by accessing and processing student-specific data (e.g., enrollment status, academic history) to provide contextually relevant responses, moving far beyond generic customer service applications (Comm100, n.d.). Research confirms that incorporating personalization significantly enhances relevance and effectiveness, leading to improved user satisfaction and engagement in chatbot interactions (Bhuiyan *et al.,* 2024). Advanced systems utilize this contextual awareness to track student progress and adapt communication style, ensuring support remains consistent and relevant across multiple interactions (Niche, 2025).

However, the value delivered by a sophisticated conversational agent is directly proportional to the integrity and accessibility of its knowledge base (Kakhki et al., 2024). Therefore, successful deployment is contingent upon the seamless integration of the AI system with existing institutional information technology infrastructure, such as student information systems and administrative databases (Xiao *et al.*, 2024). Integration gaps—a common challenge cited in the literature—directly translate into lower response accuracy and potential information inconsistency, fundamentally undermining the chatbot's effectiveness (Watermark Insights, 2024). The framework used must specifically support robust integration to ensure that information provided to students, such as fee schedules or registration deadlines, remains current and accurate in real-time .

2.4 Challenges in AI-Driven Support Implementation

Despite the clear benefits, the implementation of AI-driven support systems faces persistent challenges (NASPA, 2024). Technical limitations include difficulties achieving seamless integration with existing legacy systems, data management constraints, and the scarcity of adequate technical expertise within many institutions (NASPA, 2024). Ethical considerations are paramount, demanding rigorous safeguards for data privacy and security, as these systems handle highly sensitive student information (NASPA, 2024). Furthermore, concerns regarding algorithmic bias necessitate careful consideration to avoid disadvantaging minority students (NASPA, 2024). Studies also highlight communication limitations, noting that chatbots sometimes struggle to understand highly contextual, complex, or multi-intent queries, potentially leading to student frustration and reduced trust (NAGAP, 2024). The risk of over-reliance on automation must also be carefully managed to ensure that valuable human interaction and critical thinking skills are not diminished in the educational process (Saghiri, 2024).

3. MATERIALS AND METHODS

3.1 Research Context, Design, and Existing System Analysis

The methodology employed for this research utilized a comprehensive mixed-methods approach, incorporating quantitative surveys, qualitative interviews, document analysis, and systematic observation. This design was grounded in systems thinking principles, viewing the Federal Polytechnic Bida as an interconnected network where individual components influence overall performance.

Analysis of the current student support system at the Federal Polytechnic Bida revealed a traditional, largely manual infrastructure that relies on students physically visiting multiple administrative offices (e.g., Bursary, Academic Planning). Staff rely primarily on email and telephone, creating severe scalability limitations during peak registration periods. The study identified several critical shortcomings in this existing system that negatively impact the student experience, confirming the urgent need for a modernized, efficient solution as shown in table 1.

Table 1: Shortcomings of the Existing Student Support System

Shortcoming	Impact	Explanation
Limited Accessibility	Many students cannot get support in time	Service only during office hours
Fragmented Data and Processes	Frequent delays and errors	No centralized student data
Scalability Issues	Bottlenecks during registration	Manual handling of increasing requests
Communication Gaps	Misdirected or lost inquiries	Multiple contact points, no centralized channel

3.2 Data Collection and Sampling Methodology

Data collection employed a multi-pronged approach to ensure comprehensive coverage of stakeholder perspectives and requirements. Primary data was gathered using a structured survey instrument administered to a representative sample of the student body to capture measurable data on service satisfaction, challenges, and preferences. The target population comprised all registered students across the institution's seven academic schools which are School of Engineering Technology (SET), School of Applied and Natural Sciences (SANS), School of Business Administration and Management (SBAM), School of Environmental Technology (SET) and School of Basic and General Studies (SAAS), School of Financial Studies (SFS), and School of Information and Communication Technology (SICT). To ensure statistical rigor and generalizability, the sample size was determined based on established statistical methods (Yamane's formula approximation for a 5% margin of error on a large population), leading to a selected sample size of N=400 students. Stratified random sampling was used to proportionally allocate these 400 participants across the seven schools, maintaining balanced representation based on enrollment size as shown in table 2.

A commonly used formula for sample size determination in educational research is Yamane's formula:

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

where:

- n = sample size,
- N = population size,
- e = margin of error (typically set at 0.05 for 95% confidence level).

Assuming the total student population N*N* is approximately 8,000 students (an estimate based on institutional data), and using a margin of error of 5% (0.05), the sample size would be calculated as:

$$n = \frac{8000}{1 + 8000(0.05)^2} = \frac{8000}{1 + 8000 \times 0.0025} = \frac{8000}{1 + 20} = \frac{8000}{21} \approx 381$$

Rounding the calculated figure and considering practical aspects such as potential non-response, a sample size of 400 students was selected to ensure adequate statistical power and allow for attrition as shown in table 2. This size balances research feasibility with the need for a robust sample.

Table 2: Quantitative Survey Sample Distribution by School

School	Students Surveyed	Percentage(%)
School of Engineering Technology	75	18.75
School of Applied and Natural Sciences	60	15.0
School of Business Administration and Management	50	12.5
School of Environmental Studies	45	11.25
School of Financial Studies	40	10.0
School of Basic and General Studies	45	11.25
School of Information and Communication Technology	85	21.25
Total	400	100

Qualitative data, including observation notes and content analysis of student feedback logs, provided rich context for workflow inefficiencies and design requirements, informing the subsequent system development.

3.3 Chatbot System Architecture and Implementation

The enhanced chatbot system adopted a layered architectural framework to ensure flexibility, scalability, and maintainability (Langflow, n.d.). The system was designed around Langflow, leveraging its cloud-based capabilities and node-based visual workflow platform (Langflow, n.d.).
The architecture separates functional responsibilities into five distinct layers as shown in table 3:

Table 3: Layered System Design of the Langflow Chatbot Architecture

Layer	Description
Presentation Layer	Chatbot UI, mobile app interaction
Logic Layer	Dialogue manager (DM), intent recognition engine (NLU)
Data Layer	Knowledge base (KB), user profiles, logs
Integration Layer	APIs with student records, payment systems
Infrastructure Layer	Cloud servers, Langflow platform

The chatbot's architecture design illustrates a logical and interconnected flow, which is crucial for delivering effective, real-time, and personalized student assistance as seen in Figure 1. The Chatbot Architecture Diagram is not merely a conceptual model but a direct representation of the project's solution to the identified problems.

It demonstrates how each component, from user interaction to institutional data access, works in a synchronized manner to create a robust and enhanced student support system.

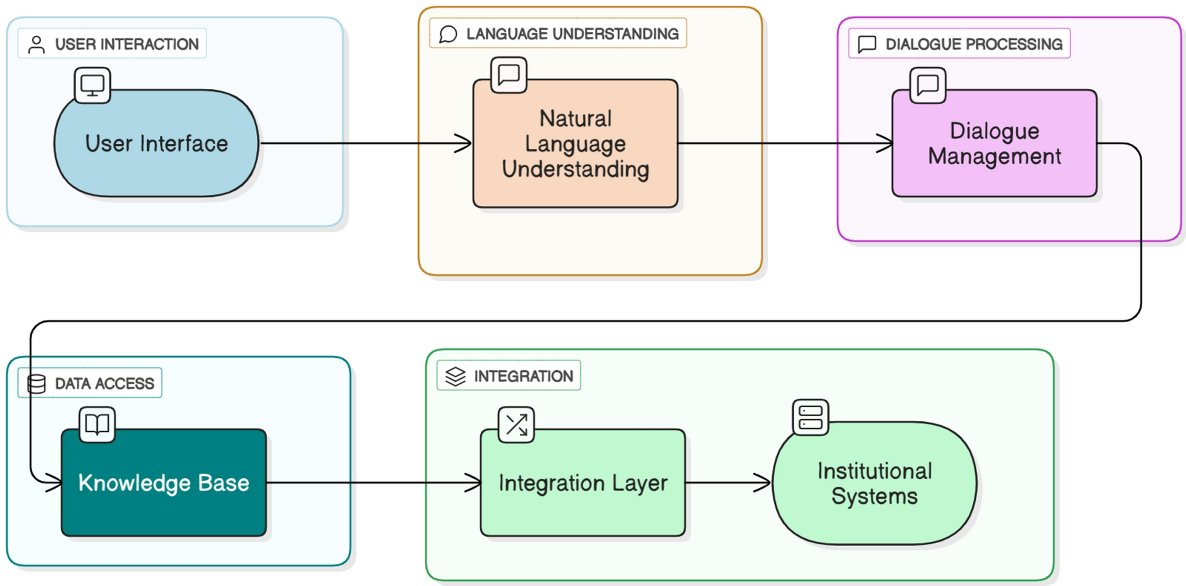

Figure 1: Chatbot Architecture Diagram

This architecture supports natural and interactive student queries, dynamic knowledge retrieval, and system integrations.
The core of the system is the chatbot engine, built using Langflow's "flows," which represent computational structures known as Directed Acyclic Graphs (DAGs) (Langflow, n.d.). In this framework, "nodes" (components) are connected by "edges" to define the systematic processing of information from input to response (Langflow, n.d.). This structure orchestrates user query analysis via the Natural Language Understanding (NLU) module, knowledge retrieval from the centralized Knowledge Base (KB), and the formulation of contextually appropriate responses. The conversational logic follows a decision-tree model designed to effectively direct user interactions for high-priority intents, such as 'Registration Assistance' and 'Fee Payment'. This logic is crucial for enabling personalization, incorporating steps that prompt the student for specific data (e.g., registration type or level) to ensure the guidance provided is contextually relevant. For instance, the 'Fee Payment' path integrates directly with the institution's financial databases to generate real-time payment links, a critical functional advancement over the existing manual system.

The integration strategy emphasizes creating seamless, secure connections between the chatbot and existing institutional infrastructure. API development enables secure data exchange with student information systems and payment gateways, ensuring real-time synchronization. This capability is instrumental in overcoming common integration challenges, as it preserves institutional investments while ensuring the chatbot provides accurate and consistent information, thereby safeguarding data integrity and user trust.

3.4 Security and Privacy Framework

The implementation of the AI-powered chatbot required a robust security and privacy framework to protect sensitive student data, aligning with the principles supported by Langflow (NASPA, 2024). The framework leverages multiple layers of protection, including robust data encryption protocols to safeguard information during transmission and storage (NASPA, 2024). Langflow's flexible architecture allows for custom security logic to be embedded directly into the visual workflow via its "Custom Component" feature (Langflow, n.d.). This capability ensures that security measures, such as input sanitization and encryption enforcement, are applied at the application level within the conversational flow (Langflow, n.d.). Furthermore, best deployment practices recommend running AI models locally or on protected Virtual Private Clouds (VPCs), thereby achieving data sovereignty and reducing risks associated with third-party data exposure (NASPA, 2024). These security measures ensure the system remains resilient against cyber risks and protects student privacy, which is essential for institutional integrity and sustained student confidence in the support system (NASPA, 2024).

3.5 Performance Evaluation Methodology

The evaluation was designed to be multi-faceted, assessing the system's effectiveness, usability, and impact. Quantitative data included logs of chatbot interactions and accuracy scores. Key metrics measured were:

- Intent Classification Accuracy: The percentage of queries where the system correctly identified the user's intent.
- Average Response Time: Measured system efficiency and real-time responsiveness.
- Detailed Confusion Matrix Analysis: Calculated Precision, Recall, and F1-Scores for major intents to evaluate classification balance.
- Expert-rated Response Relevance: Subjective scoring by domain experts on the appropriateness of the answers.
- User Satisfaction Rate: Surveyed feedback from 50 pilot student users, assessing ease of use and helpfulness.

4. RESULTS AND DISCUSSION

4.1 Training Performance and Model Convergence Analysis

The Natural Language Understanding (NLU) model was developed based on a comprehensive knowledge base and trained iteratively using supervised learning techniques within the Langflow visual platform. The training process spanned 60 iterations to ensure robust convergence and generalization capability. The training accuracy demonstrated rapid initial improvement, indicating effective learning from the enriched dataset covering administrative policies and academic procedures. The accuracy reached a plateau at 92% after the 50th iteration and maintained this stability through iteration 60. This sustained convergence to 92% confirms the robustness and reliability of the model in recognizing the diverse array of student intents. Errors were primarily isolated to overlapping intents with similar phrasing, which were subsequently reduced through targeted dataset enrichment as shown in figure 2.

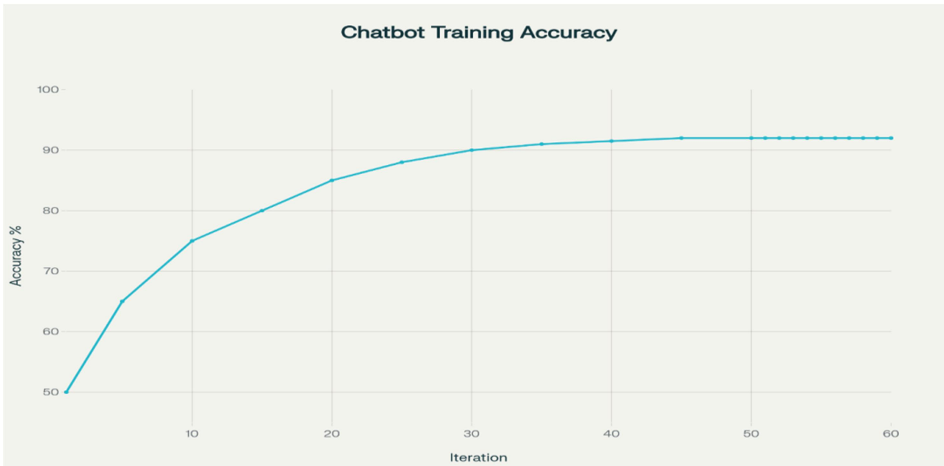

Figure 2: Training Result of Iterations

The system successfully learned to classify student intents with an accuracy rate reaching approximately 92% after 60 iterations of training.

4.2 Overall System Performance Metrics

Testing was conducted on a withheld dataset of student queries not encountered during training, ensuring a valid evaluation of the chatbot's generalization capabilities and practical utility. The overall system performance validated the design objectives, yielding strong operational metrics as presented in table 4.

Table 4: Overall Performance Test Results

Metric	Value	Significance
Intent Classification Accuracy	89%	High generalization capability on unseen queries
Average Response Time (seconds)	1.2	Responsive, real-time user experience
Expert-rated Response Relevance (out of 5)	4.3	Answers are contextually appropriate and accurate
User Satisfaction Rate (%)	85	High student acceptance of the AI-driven support

The Intent Classification Accuracy of 89% on unseen queries is slightly lower than the final training accuracy, which is expected, but confirms the model's effective generalization to real-world scenarios. Crucially, the average response time of 1.2 seconds represents a significant operational improvement, drastically reducing the time students previously spent waiting for responses, which could range from "1–2 business days" to "never received a response" under the fragmented manual system . Furthermore, the expert-rated Response Relevance score of 4.3 out of 5 indicates that the information delivered was accurate and contextually appropriate, directly resolving the problem of inconsistent information delivery. The 85\% User Satisfaction Rate among pilot students confirms high student acceptance of the AI-driven support model as shown in table 4.

4.3 Detailed Intent Classification Analysis

To provide a deeper understanding of model performance, detailed metrics were calculated for key student query categories using precision, recall, and F1-scores as presented in table 5.

Table 5: Per-Intent Classification Metrics (Precision, Recall, F1-Score)

Intent	Precision (%)	Recall (%)	F1-Score (%)
Admissions Requirements	90	88	89
Registration Procedure	92	90	91
Fee Payment	95	93	94
Academic Calendar	88	85	86.5
Document Submission	85	84	84.5

The analysis of these metrics highlights the balanced classification capability of the model. Specifically, the highest F1-score was observed for the Fee Payment intent at 94\%. This administrative function is arguably the most critical and high-stakes task during registration, where accuracy is paramount to ensure successful enrollment. The model's exceptional performance in this category demonstrates that the system design and training effectively prioritized reliability for institutionally critical functions.

Conversely, the lowest F1-score was recorded for the Document Submission intent at 84.5\%. This category often involves complex, multi-faceted queries and ambiguous phrasing—a known limitation of current NLU systems. The lower score here suggests that while the system performs robustly overall, complex procedural inquiries remain areas for targeted improvement and validate the necessity for the system's built-in human escalation path (the hybrid support model). Overall, the high precision (90%) for high-volume intents like Registration Procedure and Fee Payment confirms the chatbot's strength in minimizing false-positive classifications.

4.4 Attainment of Research Objectives and Operational Impact

The research study successfully achieved its primary aim by developing and rigorously evaluating an enhanced chatbot using the Langflow platform, providing a robust, scalable solution for student support during registration. The first objective was met through the successful creation of a centralized Knowledge Base derived from student needs and institutional documents, effectively resolving the problem of fragmented and inconsistent information. The subsequent development and evaluation phases (Objectives 2 and 3) confirmed that the Langflow-based framework delivers accurate, personalized, and scalable support.

The empirical data establishes the operational viability of the system. The 89% intent classification accuracy surpasses performance benchmarks (e.g., 75% to 85% accuracy reported in similar higher education deployments) (Liu, 2021). This superior accuracy, coupled with the rapid 1.2-second response time, demonstrates that the system is functionally capable of replacing significant portions of the manual administrative workload, particularly during peak registration periods, thereby achieving necessary scalability. The high 85% user satisfaction rate further validates the success of the user-centric design philosophy and the benefits of deep personalization in academic support systems, aligning with findings that link personalization depth to increased student acceptance (Bhuiyan *et al.,* 2024).

4.5 The Strategic Role of Langflow in Educational Technology Adoption

The successful implementation of this system provides significant validation for utilizing low-code visual frameworks like Langflow in public and resource-constrained educational settings (Langflow, 2022). The traditional barrier to advanced AI implementation—the high cost and scarcity of specialized machine learning engineers—is substantially lowered by Langflow's visual, node-based architecture (NASPA, 2024). This design enables domain experts, who possess abundant institutional knowledge but limited programming skills, to participate directly in the flow design and maintenance (Langflow, 2022). This strategy effectively shifts AI development management from a demanding technical specialty to an approachable, domain-driven administrative function, which is a crucial strategic advantage for institutions seeking to leverage advanced AI and Large Language Models (LLMs) without incurring unsustainable technical overhead (Xiao *et al.,* 2024).

Furthermore, the framework's inherent transparency addresses key ethical concerns in AI deployment (Kim, 2021). The capability to view the underlying Python code and trace the visual logic flow prevents the "black box" phenomenon that often leads to distrust among students and staff (UNESCO, 2019). This feature enables institutional domain experts to audit the chatbot's decision path, verify information accuracy, and detect potential algorithmic biases, thereby satisfying recommendations for ethical AI deployment and fostering long-term trust and widespread adoption among the student body (UNESCO, 2019).

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The developed enhanced AI-powered chatbot, built on the Langflow visual workflow platform, represents a highly effective and practical solution for addressing the critical challenges of fragmentation, limited accessibility, and lack of personalization in student registration support services at the Federal Polytechnic Bida . Empirical evidence confirms the system's operational success, with an 89% intent classification accuracy, a rapid 1.2-second response time, and an 85% user satisfaction rate. The robustness of the model, particularly its 94% F1-score reliability for the high-stakes Fee Payment intent, affirms its capability to handle critical administrative tasks efficiently and accurately. The research validates the strategic selection of Langflow, demonstrating that low-code visual frameworks are ideal for developing effective, transparent, and scalable conversational AI solutions, thereby enabling resource-constrained institutions to adopt advanced educational technologies successfully (Langflow, 2022.; Xiao *et al.,* 2024).

5.2 Strategic Recommendations for Institutional Deployment

Based on the robust performance and strategic advantages validated by this research, the following recommendations are put forth for the Federal Polytechnic Bida and similar educational institutions seeking to implement AI-driven support:

1. Formal Implementation and Scaling: The enhanced chatbot should be formally implemented as the primary, 24/7 support channel for prospective and new students, expanding its knowledge base and scope to cover other student lifecycle phases, such as academic advising and technical troubleshooting, to maximize institutional efficiency .
2. Maintain and Optimize Hybrid Support: The institution must rigorously maintain the hybrid support model, ensuring complex, ambiguous, or emotional queries are seamlessly

escalated to trained human advisors . Continuous monitoring of the escalation process is necessary to ensure optimal operational efficiency and a smooth transition between AI and human staff.

3. Prioritize Continuous Data Governance and Ethical AI: A rigorous protocol must be established for the continuous enrichment of the knowledge base and monitoring of NLU performance. Concurrently, the institution must strictly adhere to the established security framework, emphasizing data encryption, robust access controls, and transparent flow management—a capability facilitated by Langflow—to maintain student trust and safeguard sensitive data.
4. Scale Personalization Features: The institution should leverage Langflow's modular capabilities to deepen personalization, tailoring conversational flows and recommendations based on individual student roles, prior interactions, and specific academic profiles to enhance engagement and effectiveness.

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