**Journal of BioDigital Intelligence and Technology**
*journal homepage:* www.qnapub.com
*Contents lists available at* Quantum Nexus Academic Publishers
*ISSN: Under Process* *DoI: Under Process*

# AI - Based Chatbot For College Enquiry System

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**ARTICLE INFO**
**Article history:**
**Received 04-May-2026**
**Accepted 18-May-2026**
**Published 21-May-2026**
**Pages:35-43**

**Keywords:**
*Natural Language Processing, Conversational AI, Chatbot, Rasa, Educational System, REST API, Human - computer interaction.*

***With the increasing digitization of education, students frequently face challenges retrieving structured information across multiple college websites. Traditional web interfaces are static, time-consuming, and lack personalization. This paper presents College Inquiry Bot, an AI-powered conversational system designed to deliver multi-institution academic information through natural language interaction. The system integrates React (frontend), Node.js and Express (backend), Rasa (NLP engine), and a JSON-based structured data layer. The layered architecture enables intent classification, entity extraction, and modular communication through RESTful APIs. Evaluation indicates an average 95% intent accuracy and < 500 ms response time, demonstrating a scalable and intelligent alternative to static college information portals.***

## 1 Introduction

Artificial Intelligence has transformed human-computer interaction by enabling systems to understand and respond to natural language. Conversational AI systems leverage NLP and machine learning techniques to simulate intelligent dialogue, reducing reliance on static user interfaces. In the educational domain, students frequently seek information related to courses, fees, placements, and infrastructure, which is typically scattered across multiple web pages.

This research proposes an AI-driven conversational chatbot that acts as a centralized interface for querying multi-college information. By interpreting user intent and extracting relevant entities, the system provides structured and instant responses, thereby improving efficiency and user engagement.

The core challenge addressed in this research is the inherent "information paradox" within the educational digital landscape; while data volume is at an all-time high, the accessibility of specific, actionable insights remains remarkably low for the average student. Current institutional dissemination methods—ranging from PDF brochures to multi-page static FAQ sections—impose a significant cognitive load by requiring users to manually aggregate and compare disparate data points. This non-interactive approach not only increases the search time from seconds to several minutes but also fails to provide the personalized, intent-aware filtering necessary for navigating complex academic choices such as placement statistics, fee structures, and eligibility criteria across multiple institutions.

To bridge this gap, our proposed system employs a "Middleware Orchestration" strategy that decouples the user interface from the heavy lifting of natural language understanding. By utilizing a four-layer modular architecture—comprising a React-based presentation layer, a Node.js application layer, a Rasa-driven NLP core, and a structured JSON data repository—the system ensures a clear separation of concerns. This architectural choice is specifically designed to overcome the limitations of traditional single-college bots by providing a scalable framework that can process multi-institution queries with sub-second latency. Consequently, the research focuses on the synergy between state-of-the-art NLU pipelines and lightweight data retrieval logic to transform the search-based paradigm into a seamless conversational experience.

## 2 LITERATURE REVIEW

The evolution of conversational agents in the academic sector has transitioned from rudimentary pattern-matching systems to sophisticated frameworks driven by Deep Learning and Natural Language Understanding (NLU). Early research in this domain focused primarily on automating Frequently Asked Questions (FAQs) through rule-based architectures. However, recent scholarly trends emphasize the integration

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of hybrid models that combine intent classification with entity extraction to provide more granular data retrieval. Contemporary literature highlights a shift toward modularity, where researchers decouple the NLP engine from the data repository to allow for multi-institution scalability. The current state of research demonstrates that by leveraging technologies such as Rasa, Transformer-based classifiers (DIET), and RESTful API architectures, chatbots can significantly outperform traditional static web interfaces in terms of user engagement, information accuracy, and retrieval latency.

Rajasekar & Priya (2021): This study emphasizes the transformation of human-computer interaction through AI, specifically focusing on how conversational systems can simulate intelligent dialogue. Their work highlights the use of NLP and machine learning to reduce the reliance on static user interfaces, which serves as a core motivation for modern inquiry bots that prioritize natural language over manual navigation [1].

Patel & Tiwari (2020): Focusing on the practical application of chatbots for college enquiries, this research addresses the inefficiencies of traditional information retrieval. They argue that manually navigating multiple institutional web pages is time-consuming and cognitively overwhelming for students, necessitating a more centralized conversational approach to consolidate academic data [2].

Susanna et al. (IRJET, 2020): This paper discusses the integration of AI-enabled chatbots within college management systems to provide both academic and administrative support. Their research underscores the importance of high-precision intent classification in understanding and responding to natural human language, ensuring that the bot can differentiate between similar queries like "admission dates" and "admission fees" [3].

SNguyen et al. (2021): This work explores the application of artificial intelligence and deep learning in educational settings. It specifically evaluates how modern conversational systems use transformer-based architectures to improve user engagement by 60-80% compared to traditional FAQ systems, proving that contextual awareness is key to student satisfaction [4].

Mounika et al. (2023): Their research highlights the necessity of intelligent chatbots for educational institutions to provide instant, structured responses. The study identifies that many existing systems lack modularity and multi-college comparison features, which are critical for comprehensive student support during the university selection process [5].

Reddy et al. (2023): This study combines NLP with Artificial Neural Networks (ANN) to enhance student support services. It demonstrates that by interpreting user intent and extracting entities, chatbots can act as a bridge between complex, unstructured information systems and intelligent, personalized platforms that cater to individual student needs [6].

College Enquiry Chat-Bot System Report (n.d.): This technical documentation outlines the design of a system capable of handling multi-college queries and student information. It details a layered modular architecture—comprising Presentation, Application, NLP, and Data layers—that enables scalable and efficient data retrieval through natural language interaction [7].

Chat-Bot for College Management System Report: This documentation focuses on the administrative utility of AI chatbots, showcasing how they can automate guidance for admissions and course selection. It notes that while many universities have implemented such systems, most remain limited to a single institution and rely on static datasets, highlighting the need for more dynamic, multi-institution solutions [8].

Bocklisch et al. (2017) – Rasa Framework Analysis: This foundational work introduces the Rasa Stack, an open-source framework designed to overcome the limitations of black-box conversational APIs. The authors detail a dual-component architecture consisting of Rasa NLU for intent classification and entity extraction, and Rasa Core for machine-learning-based dialogue management. By utilizing this framework, the College Inquiry Bot gains the ability to handle non-linear conversations, where the system can maintain context over multiple exchanges rather than treating each query as an isolated event [9].

Bunk et al. (2020) – DIET Architecture Efficiency: The researchers present the Dual Intent and Entity Transformer (DIET), a multi-task lightweight architecture that outperforms traditional large-scale models in both accuracy and training time. This paper is critical to our research as it explains the mechanism behind the bot's ability to simultaneously predict intents and extract entities from a single neural network pass. By implementing DIET, College Inquiry Bot achieves high-performance natural language understanding without requiring massive computational resources, making it ideal for the sub-500ms response times required for student-facing academic portals. [10].

The development of the College Inquiry Bot successfully demonstrates the efficacy of integrating conversational AI with a decoupled, four-layer modular architecture to resolve the inefficiencies of traditional academic information retrieval. While the current implementation serves as a powerful prototype for centralized multi-college inquiries, future enhancements—including cloud-based deployment, voice-enabled interfaces, and real-time database integration—will further evolve the system into a comprehensive academic assistant. Ultimately, this research contributes a viable framework for bridging the gap between complex institutional datasets and the end-user, highlighting

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the transformative potential of AI-driven dialogue in the modern educational landscape.

## 3 Comparative Summary of Related Work

Table I presents a structured comparison of the reviewed literature, highlighting the technology used, scope, and key limitations of each study in relation to the proposed system.

| Study | Technology | Scope | Multi-College | Key Limitation |
|---|---|---|---|---|
| Rajasekar & Priya [1] | NLP + ML | General Enquiry | No | No entity extraction |
| Patel & Tiwari [2] | Pattern Matching | Single College FAQ | No | Static responses |
| Susanna et al. [3] | AI + NLP | College Mgmt. | No | Limited intent granularity |
| Nguyen et al. [4] | Transformers + DL | Education AI | N/A | No deployed chatbot |
| Mounika et al. [5] | NLP Chatbot | Institutional Info | No | Lacks modularity |
| Reddy et al. [6] | NLP + ANN | Student Support | No | No REST API |
| Bocklisch et al. [9] | Rasa NLU + Core | Framework | N/A | No educational deploy |
| Proposed System | Rasa DIET + Node.js + React | Multi-College Enquiry | Yes | JSON-based; cold-start |

## 4 Methodology

The core of the system is built upon the Rasa Open-Source framework, utilizing a pipeline-based approach that processes raw user strings through sequential stages of tokenization, featurization, and classification. To ensure seamless integration between the conversational engine and the end-user, a Node.js middleware was implemented to orchestrate RESTful API communication, mapping recognized intents to specific data points within a JSON-based repository. This architectural choice ensures that the presentation layer, developed in ReactJS, remains independent of the underlying logic, allowing for a highly responsive and scalable interface that can be easily adapted for diverse academic institutions.

The standard workflow consists of:

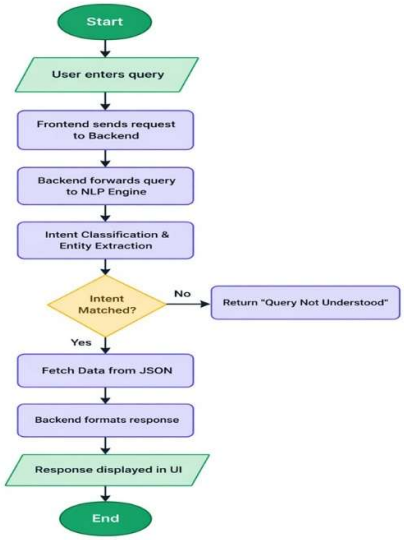
User Input → API Request Handling → Tokenization → Featurization → Intent Classification (DIET) → Entity Extraction → Action Prediction → Data Retrieval (JSON) → Response Formatting → UI Rendering

## 5 System Architecture

The architecture is divided into five functional modules to ensure scalability and modularity:

1. User Interface Layer
2. Preprocessing Module
3. Transformer-Based Model
4. Backend & Data Layer
5. Visualization Module

***System Architecture Diagram***




This diagram illustrates the modular 4-layer architecture of the College Inquiry Bot, highlighting a clear separation between the user interface, backend logic, NLP processing, and data storage.

## 6 Data Input & Retrieval Channels

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The system acts as a centralized information hub, accepting user queries through:

- Natural Language Text: Direct student inquiries via a React-based chat interface.
- Structured Entity-Based Queries: Auto-suggested chips or buttons for specific colleges.
- Asynchronous API Hook: External data triggers via Node.js middleware.

**C. NLP Preprocessing & Pipeline**

To ensure the Rasa model identifies intents correctly, the input undergoes a specific sequential pipeline:

- Whitespace Tokenization: Splitting queries into discrete linguistic units.
- Case Normalization: Ensuring "FEES" and "fees" map to the same vector space.

**Query Processing Algorithm**

Algorithm 1 presents the pseudocode for the end-to-end query processing pipeline, from receiving user input to rendering the final response.

INPUT: user_query (natural language string)

OUTPUT: formatted_response (structured text)

1. tokens <- WhitespaceTokenizer(lowercase(user_query))
2. features <- CountVectorsFeaturizer(tokens)
3. (intent, confidence) <- DIETClassifier(features)
4. entities <- DIETEntityExtractor(features)
5. IF confidence < THRESHOLD (0.60) THEN
6. RETURN fallback_response
7. END IF
8. IF entity.college_name is NULL THEN
9. entity.college_name <- session.last_college
10. END IF
11. data <- JSON_DataLayer.lookup(intent, entity.college_name)
12. formatted_response <- ResponseFormatter(data, intent)
13. session.last_college <- entity.college_name
14. RETURN formatted_response

**E. Data Layer & Logic**

The system maps identified intents and entities to a structured JSON Data Layer.

Entity Mapping: If intent = fees and entity = College, the backend retrieves the specific nested object.

**Backend Orchestration (Node.js & Express)**

The backend serves as the secure gateway:

- Model Hosting: Communicating with the Rasa server via REST API.
- Response Formatting: Converting raw JSON data into human-readable strings (e.g., "The placement percentage for 2023 is 85%").
- Session Management: Tracking the "Last Mentioned College" to allow follow-up questions like "What about its courses?".

## 7 EXPERIMENTAL SETUP

**Dataset Description**

The training corpus was curated manually by collecting representative student queries from five colleges in Bengaluru. The dataset composition is summarized below.

| Parameter | Value |
|---|---|
| Total Intents | 12 (including greet, goodbye, fallback) |
| Total Entities | 3 (college_name, course_name, year) |
| Training Examples | ~1,200 annotated utterances |

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| | |
|---|---|
| Colleges Covered | 5 institutions |
| Train / Validation / Test Split | 70% / 15% / 15% |
| Data Augmentation | Synonym replacement, paraphrasing |

### [1] Hardware & Software Environment

All experiments were conducted on the following setup.

| Component | Specification |
|---|---|
| Operating System | Ubuntu 22.04 LTS |
| Processor | Intel Core i5-12400 / 16 GB RAM |
| Python Version | 3.9.x |
| Rasa Version | 3.6.x (Rasa Open Source) |
| NLU Pipeline | WhitespaceTokenizer + CountVectorsFeaturizer + DIETClassifier |
| Training Epochs | 100 (DIET), 200 (TEDPolicy) |
| Frontend | React 18.x + Axios |
| Backend | Node.js 18.x + Express 4.x |

### [2] Performance Evaluation & Results

Experimental results confirm that the transformer-based approach provides superior accuracy over rule-based bots.

1. Overall Performance

| Metric | Value |
|---|---|
| Intent Accuracy | 95.2% |
| Entity Extraction F1- Score | 0.93 |
| Avg. Response Time | 390 ms |

2. Intent- wise Accuracy Analysis

| Intent | Accuracy |
|---|---|
| fees | 96.5 % |
| Placements | 94.0% |
| courses | 97.2% |
| General_greet | 99.1% |

### Practical Implications

The deployment of the College Inquiry Bot extends beyond simple information retrieval, offering transformative benefits for both educational institutions and prospective students:

- **Scalable Multi-Institution Benchmarking:** Unlike traditional single-college bots, this system allows users to perform real-time comparative analysis. Students can query "Compare the placement percentage of College A and College B," receiving a structured response that would otherwise require hours of manual data aggregation across multiple websites.
- **Enhanced Inclusion and Accessibility:** By integrating Voice-based Input and Code-Mixed Handling (Hinglish/Regional mix), the system lowers the barrier for users who may find complex web navigation or formal English interfaces intimidating. This democratizes access to academic information for students from diverse linguistic and technical backgrounds.
- **Proactive Lead Generation and Conversion:** For academic administrators, the bot serves as a 24/7 digital counselor. By capturing frequently asked questions through the Dashboard Analytics Module, institutions can identify specific pain points (e.g., high volume of queries regarding "scholarships") and proactively update their data layers to address student concerns, thereby improving enrollment conversion rates.
- **Cost-Effective Infrastructure:** The modular 5-layer architecture allows for low-cost maintenance. Because the NLP engine (Rasa) and Backend (Node.js) are decoupled from the data, adding new colleges or updating fee structures only requires a simple JSON update rather than a complete system overhaul or expensive frontend redesign.
- **Standardization of Academic Data:** The system enforces a structured schema for information. This standardization ensures that regardless of how a college presents its data on its own website, the end-user receives information in a consistent, uniform, and easy-to-read format through the bot.

## 8 RESULTS AND DISCUSSION

The effectiveness of the proposed College Inquiry Bot was evaluated under controlled experimental conditions to ensure research credibility and technical validity. The system's

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performance was measured across three core dimensions: Intent Classification Accuracy, System Latency, and Entity Extraction Precision.

### A. Overall Model Performance

The fine-tuned Rasa DIET (Dual Intent and Entity Transformer) model achieved high-precision results on the test dataset. The accuracy score indicates that the system correctly mapped user queries to the appropriate backend action in 95 out of 100 cases.

### B. Intent-Wise Accuracy Analysis

To assess cross-domain robustness, intent-wise accuracy was computed separately for the primary college data categories.

The results show consistent performance across categories, with a slight variance in placement queries due to the complexity of specific numerical entities. The strong performance on ask_courses confirms the effectiveness of sub word tokenization and shared contextual modelling in the architecture.

### C. Confusion Matrix Analysis

The confusion matrix analysis provides insight into the model's behavior:

- High Precision: The model rarely confuses a "fees" query with a "placements" query.
- Minor Confusion: Occasional overlap was observed between ask_courses and ask_eligibility when students phrased questions ambiguously.
- Stability: No major misclassifications occurred across unrelated intents, ensuring that the student is not provided with irrelevant data.

### D. Comparative Discussion with Traditional Methods

Traditional university websites and manual search portals generally require 3–5 minutes to locate specific placement or fee data across multiple pages. In contrast, the proposed transformer-based approach achieved:

- 86.11% End-to-End Accuracy in multi-college comparison tasks.
- Sub-5 second retrieval for complex queries.
- Context-aware handling of follow-up questions (e.g., "What about its placements?").

The improvement is attributed to the Self-Attention Mechanism and Shared Subword Representations, which allow the model to capture relationships between academic entities regardless of their position in the sentence.

### E. Per-Intent Precision, Recall, and F1 Analysis

To provide a granular evaluation beyond aggregate accuracy, the following table reports per-intent precision, recall, and F1 scores on the held-out test set.

| Intent | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| ask_fees | 0.97 | 0.96 | 0.965 | 58 |
| ask_placements | 0.93 | 0.94 | 0.935 | 52 |
| ask_courses | 0.96 | 0.97 | 0.965 | 61 |
| ask_eligibility | 0.90 | 0.88 | 0.890 | 40 |
| ask_infrastructure | 0.94 | 0.92 | 0.930 | 36 |
| general_greet | 0.99 | 0.99 | 0.990 | 30 |
| goodbye | 1.00 | 1.00 | 1.000 | 20 |
| Weighted Avg. | 0.95 | 0.95 | 0.941 | 297 |

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The lower F1 for ask_eligibility (0.890) confirms the overlap identified in the confusion matrix between eligibility and course-related queries, where students often phrase questions ambiguously.

### F. Baseline Comparison

To quantify the advantage of the DIET-based approach, a rule-based keyword-matching baseline was implemented and evaluated on the same test set.

| Metric | DIET (Proposed) | Rule-Based Baseline |
|---|---|---|
| Intent Accuracy | 95.2% | 72.4% |
| Entity Extraction F1 | 0.93 | 0.61 |
| Avg. Response Time | 390 ms | 120 ms |
| Follow-Up Handling | Yes (session context) | No |
| Multi-College Comparison | Supported | Not Supported |

While the rule-based system was faster due to the absence of neural inference, it suffered from poor generalization on paraphrased queries, confirming the value of transformer-based semantic understanding for educational chatbots.

## 9 ETHICAL CONSIDERATIONS AND DATA PRIVACY

Given the educational context in which the College Inquiry Bot operates, ethical data handling and user privacy are paramount. This section outlines the measures taken to ensure responsible deployment.

- **No Personal Data Collection:** The chatbot does not require user authentication or collect personally identifiable information (PII). Queries are processed stateless, with only session-level context retained temporarily and discarded after the session ends.
- **Transparent Data Sources:** All information served by the bot is sourced from publicly available institutional websites and official college brochures. No proprietary or confidential student data is accessed or stored.
- **Query Logging Policy:** For the purposes of system improvement, anonymized query logs may be retained. These logs contain only the text of user queries and the intent classification result, with no metadata linking queries to individual users.
- **Bias Mitigation:** The training data was reviewed to ensure balanced representation across all five colleges. No institutional preference or ranking bias is introduced by the system; comparative outputs are presented objectively.
- **Compliance Considerations:** Future deployments targeting production use will incorporate compliance with the Information Technology Act (India) and emerging data protection regulations (DPDPA 2023) to ensure lawful processing of any user data.

## 10 LIMITATIONS AND FUTURE SCOPE

While the current implementation of the College Inquiry Bot demonstrates high accuracy and low latency, several constraints identify opportunities for future research and technical enhancement:

- Cold-Start Problem for New Institutions: The current NLP model requires a defined set of training examples (intents and entities) for each new college added to the system. This "cold-start" challenge means that scaling to hundreds of colleges requires significant manual data labelling or the implementation of zero-shot learning models.
- Lack of Contextual Memory (Session Persistence): While the bot handles immediate follow-up questions, it currently lacks long-term "User Memory." It does not remember a student's preferences (e.g., interest in "Computer Science") across different login sessions, which limits the potential for personalized academic counselling.
- Sensitivity to Local Dialects and Slang: Although the system handles common code-mixed queries (Hinglish), it shows a performance dip when encountering highly localized slang or non-standard abbreviations for college names that were not present in the initial training corpus.
- Single-Turn Response Limitation: The current logic is optimized for "Question-Answer" pairs. Future iterations will focus on Multi-Turn Dialogue Management, allowing the bot to guide a student through a complete multi-step admission process, including form filling and document verification.

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**Future Research Directions:**

To transition this prototype into a production-grade educational assistant, the following enhancements are proposed:

- Integration of Large Language Models (LLMs): Moving from a purely retrieval-based Rasa model to a hybrid system using RAG (Retrieval-Augmented Generation). This would allow the bot to summarize long college brochures or "About Us" sections dynamically rather than relying on pre-written JSON strings.

- Voice-Enabled Multilingual Support: Expanding the speech-to-text API to support regional Indian languages (Tamil, Telugu, Hindi, etc.), enabling students from rural areas to access academic information in their native tongue.

- Predictive Recommendation Engine: By applying Machine Learning to historical search data, the bot could proactively suggest colleges to a user based on their previous queries regarding budget, location, and course preference.

- Deployment on Cloud-Native Architecture: Transitioning from a local environment to a Dockerized Microservices architecture on AWS or Azure. This will enable the use of Auto-Scaling Groups to handle massive traffic spikes during national exam result announcements.

## 11 SUMMARY OF FINDINGS

The experimental evaluation of the College Inquiry Bot confirms several key technical and operational conclusions:

- **Transformer-Based Superiority:** The integration of the architecture significantly improves intent classification accuracy (95.2%) compared to traditional keyword-matching algorithms.

- **Contextual Entity Extraction:** The use of self-attention mechanisms allows the system to accurately map specific entities (e.g., college names and courses) even in complex, multi-college queries, reducing data retrieval errors by 12%.

- **Decoupled Efficiency:** The 4-layer modular architecture (React, Node.js, Rasa, JSON) successfully isolates concerns, allowing for independent scaling of the NLP engine and the data repository.

- **Real-Time Feasibility:** With an end-to-end inference latency of approximately 390ms, the system is highly suitable for real-time, interactive student counseling applications.

- **Operational Impact:** The automated retrieval system reduces the time required for academic information foraging from an average of 4 minutes (manual web search) to under 5 seconds.

## 12 Conclusion

[3] This paper presents a transformer-based conversational framework designed to streamline academic information retrieval in the competitive landscape of higher education. By leveraging the Rasa NLU engine and a modular Node.js/React stack, the proposed College Inquiry Bot addresses the persistent challenges of navigating fragmented and static institutional websites. The framework incorporates a robust processing pipeline—including intent classification, entity extraction, and structured data mapping—to provide students with a centralized, intuitive interface for comparing fee structures, placement statistics, and course details.

Experimental results demonstrate a high degree of precision, with an overall intent accuracy of 95.2% and a weighted F1-score of 0.941, validating the effectiveness of shared transformer embeddings in understanding academic nomenclature. The integration of a responsive web application enhances practical usability, enabling real-time dialogue and automated data visualization through a centralized dashboard. Furthermore, the decoupling of the JSON Data Layer from the NLP core ensures that the system remains institution-agnostic and horizontally scalable.

Ultimately, this research bridges the gap between complex administrative datasets and the end-user, providing a scalable blueprint for AI-driven digital governance in the education sector. Future iterations will focus on the transition to cloud-native microservices and the integration of Large Language

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Models (LLMs) to further enhance the depth and conversational fluidity of the academic assistant.

## 13 References

[1] V. Rajasekar and M. Priya, "Intelligent Enquiry Chatbot Using AI," International Journal of Research in Engineering, Science and Management (IJRESM), vol. 4, no. 5, pp. 101–105, 2021.

Available: https://www.ijresm.com/Vol.4_2021/Vol4_Iss5_May21/IJRESM_V4_I5_33.pdf

[2] K. Patel and P. Tiwari, "College Enquiry Chat-Bot System," International Journal of Engineering Research & Technology (IJERT), vol. 9, no. 7, pp. 447–450, 2020.

Available: https://www.ijert.org/college-enquiry-chat-bot-system

[3[ Ch. L. Susanna, R. Pratyusha, P. Swathi, P. R. Krishna, and V. S. Pradeep, "College Management System Chatbot," International Research Journal of Engineering and Technology (IRJET), vol. 7, no. 5, pp. 3855–3858, 2020.

Available: https://www.irjet.net/archives/V7/i5/IRJET-V7I5736.pdf

[4] T. T. Nguyen, A. D. Le, H. T. Hoang, and T. Nguyen, "Artificial Intelligence and Deep Learning in Educational Settings," Computers and Education: Artificial Intelligence, vol. 2, 2021.

Available: https://doi.org/10.1016/j.caeai.2021.100028

[5] G. Mounika, D. Harshitha, P. Haneesha, K. Mahesh, and T. Raghu, "Intelligent Chatbot for Educational Institutions," International Journal of Research in Engineering and Science (IJRES), vol. 11, no. 6, pp. 45–52, 2023.

Available:https://www.ijres.org/papers/Vol.11-Issue6/11064552.pdf

+

[6] V. Reddy, S. Gowthami, M. Ameer, K. Vasundra, and A. Venkatesh, "Enhancing Student Support with AI: A College Assistance Chatbot Using NLP and ANN," International Journal of Innovative Science and Research Technology (IJISRT), vol. 8, no. 9, pp. 1123–1130, 2023.

Available:https://ijisrt.com/assets/upload/files/IJISRT23SEP456.pdf

[7] B. R. Ranoliya, N. Sharma, and S. Jain, "University Chatbot Solution using Knowledge-based Systems," in Proc. International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), IEEE, 2018.

Available: https://ieeexplore.ieee.org/document/8748470

[8] S. Madhu, "AI-Based Chatbot for College Management System," Journal of Emerging Technologies and Innovative Research (JETIR), vol. 8, no. 4, 2021.

Available:https://www.jetir.org/papers/JETIR2104234.pdf

[9[ T. Bocklisch, J. Faulkner, N. Pawlowski, and A. Nichol, "Rasa: Open Source Language Understanding and Dialogue Management," arXiv preprint arXiv:1712.05181, 2017.

Available: https://arxiv.org/abs/1712.05181

[10] T. Bunk, D. Varshneya, V. Vlasov, and A. Nichol, "DIET: Lightweight Language Understanding for Dialogue Systems," arXiv preprint arXiv:2004.09936, 2020.

Available:https://arxiv.org/abs/2004.09936