Edu Chat AI: Web-Based Real Time Chatbot Assistant for Education

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Keywords: Contextual Multimodal Processing, Natural Language Processing (NLP), Artificial Intelligence (AI), Automated Queries, Web-Based Chatbots, Educational AI.

Abstract: Chatbot Application using Machine Learning is a web-based tool to improve the ease of access to information in educational institutions. Knowing the limitations of the existing WEB kiosk system, it serves as an enhanced version of the same that can potentially be completely integrated into the college's official website with improvements. Utilizing Natural Language Processing (NLP) and Artificial Intelligence Mark-up Language (AIML), the Chatbot enables fluid interactions, currently only registering predefined responses to frequently asked questions. Training on data until October 2023, and future upgrades will include hyper-personalized help using advanced NLP techniques to better understand users. After analysing the current challenges of in-depth learning, this paper proposes Web-Based Natural Language Processing-Artificial Intelligence (WB-NLPAI) Chatbot Based Intelligent Teaching Model, which based on the AI chatbot effectively improves real-time educational support and advances education. The system combines multimodal capabilities text, voice and visual inputs with adaptive AI-driven automation that ensures a lively, engaging learning interaction. Based on lessons learned from both the multimodal AI assistants and the AI-based educational support research, AI-ASES-MVA proposes a hybrid approach that is designed to enhance student engagement and improve learning outcomes.

1 INTRODUCTION

This is a simple web-based application called Chatbot Application using Machine Learning Which is useful for getting information about a college. This could have information such as teachers, students GPA, and their different college events. The application is an update of the college's web kiosk. The underlying code could easily develop further, with features and improvements that could make the site part of the college's regular website.

The chatbot made in this project is a web-based app using Natural Language Processing (NLP) libraries and Artificial Intelligence Mark-up Language (AIML) that allows the bot to converse similar to a human. This development was inspired by previous chatbot applications such as "Eliza" and "Clever bot". This chatbot's output is also somewhat pre-programmed, like "Eliza," as it is created specifically to respond to college-related questions. As the college's program and other information such as tuition fees often change, the chatbot uses an editable and upgradable database to provide accurate and relevant information. So far, a sample program has been developed that processes user responses using simple parsing techniques and template-based substitutions. Hardcoded phrases are also incorporated to maintain the flow of conversation. Implementing NLP will enhance the chatbot's ability to understand user queries and provide appropriate solutions. NLP, a subfield of artificial intelligence within computer science, focuses on enabling interactions between computers and humans. Some of the key areas within NLP include Natural Language Understanding (NLU) and Natural Language Generation (NLG).

The above is a web-based application, a College Enquiry Chatbot that utilizes the concepts of AI to have a human-like conversation. This report addresses concepts of NLP, AIML, and the work behind the scenes for "Eliza" Additionally, it highlights challenges faced during chatbot applications development and approaches to overcoming these for increased effectiveness and user experience.

Naik, N. V., Bindu, S. H., Mayukha, S. S., Vinutha, A., Jyothi, Y. S. and Pravallika, S.
Edu Chat AI: WebâĂŚBased Real Time Chatbot Assistant for Education.
DOI: 10.5220/0013871800004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 1*, pages 721-729
ISBN: 978-989-758-777-1

The sample application has been implemented using Python Kernel and XML's AIML (Artificial Intelligence Mark-up Language) along with a Database to provide GPA details based on student name, email and password. We used MySQL as the database engine. Frontend: Html, CSS, JavaScript the project was inspired by the college's web kiosk functionality. As a web kiosk, this chatbot would be designed to get interfaced with the college`s database through the web kiosk API thereby requiring JSON implementation.

The architecture of this chatbot application is similar to "Eliza." "Eliza," one of the first chatbot programs (and an open-source project), offered a basic understanding of how to develop these conversational agents. It used a substitution-based algorithm. " Clever bot", on the other hand has more workings done for machine learning that makes it more effective but is not open source and not easy to digest because of its data structure. However, learning how the algorithm used in something like "Clever bot" works, could help to build a more powerful chat bot which would be an extension of this project.

Related works are discussed in Section 2. Section 3 details the proposed methods. Results are shown in Section 4. Section 5 gives the discussion. Section 6 provides the conclusion.

2 RELATED WORKS

J. Weizenbaum (1966) was the pioneer in chatbot technology, creating ELIZA, a machine that mimicked human interaction through pre-programmed pattern-matching algorithms. His research showed that, while ELIZA could communicate with humans on a rudimentary level, its responses were not based on any real understanding and were driven by rules. This study set the stage for chatbot advancement by identifying early challenges in context awareness. The first iterations of chatbot was heavily reliant on rules and could not hold meaningful and contextual conversations. These early studies highlighted the necessity of more sophisticated frameworks that could enhance chat-bot interaction and user experience.

In B. Shawar and E. Atwell (2007), the use of AIML to improve chatbot performance was modelled. A study conducted by them showed that AIML-based chatbots were much more structured and were able to hold conversations better compared to traditional rule-based models. AIML enhanced chatbot interactions by using a set of defined categories and response templates. The study did end on a fairly cautious note though a major limitation was that these chatbots were purely rule-based, which prevented them from adapting their responses to conversations with varying context. Consequently, their replies had no flexibility and interactions became monotonous and unnatural when posed with off the script questions.

Deep Learning models, BERT, and GPT, evolution in Chatbot They were known for their transformer-based architectures that significantly improved chatbot performance by enabling better intent detection and context retention. These AI chatbots were distinct from earlier, more static chat models which relied on pre-defined sets of rules, as they were able to craft human-like responses. Harnessing self-learning algorithms and extensive datasets, they could deliver interactions that were increasingly accurate, context-sensitive, and engaging. Such advancements allowed interaction with chatbots to feel more fluid and natural than earlier rule-based approaches, and significantly improved user experience, the study noted.

The advancements in the deep learning methodologies have revolutionized the traditional chatbot applications allowing the bot to learn constantly and adapt to different conversational contexts as discussed in. While AIML-based chatbots navigated through fixed conversational paths, AI-powered models were able to assess past user interactions, identify patterns, learn and tailor their responses to improve further. This has significantly improved the efficiency of chatbots, moving from traditional static response generation to dynamic and intelligent interactions. All this makes such chatbots today much better conversationalists better at effectiveness, satisfaction and applicability to real-world scenarios across industries.

A recent study R. Perez et al., (2019) investigates where chatbots could be deployed within university information systems and focuses specifically on automating administrative tasks. Through in-depth research, they were able to discover that AI-based assistants were able to assist students effectively by delivering access to their academic schedules, information about faculties, questions related to examinations in real-time. In their study, it was found that integrating the chatbot reduced administrative burden and increased access to organizational information. This work was further studied by P. Sreelakshmi and A. Krishnan (2021), explored the or best of in application with chatbots in college management systems. Their findings stressed that AI-based assistants would be able to manage admission inquiries, fee inquiries, and academic regulations. This study highlighted the time-saving advantages chatbots offered to educational institutions by automating repetitive administrative tasks and providing quick and reliable responses to student queries.

They demonstrated how Natural Language Processing (NLP) affected the accuracy and efficiency of chatbots in R. Ranoliya et al., (2017). Their research showed that NLP-based chatbots could process and understand unstructured student queries better than standard models. NLP techniques were the backbone of the chatbot generation, provided context awareness and better responses. in ref. D. Griol et al., (2014), and conducted a sentiment analysis of interactions with their AI-based Chatbot. Their study discovered that some emotion detection-based chatbots can analyse user emotions and adapt their replies accordingly. This was of particular benefit in educational environments where bots were able to determine if a student was stressed or struggling academically, and offer help or emotional support as needed.

Reviewed R. Winkler and M. Söllner (2018) examined the incorporation of chatbots acting as virtual tutors in personalized learning environments. Their research showed that AI-based tutors were able to analyse student progress and suggest new learning paths. They did this by utilizing chatbots to deliver adaptive content effectively in order to enhance student engagement. Presented in H.Zhou et al., (2021).

H.Zhou et al., (2021) explored potential uses of adaptive learning chatbots at the higher education level. Their study studied how AI-powered assistants might evaluate students' academic behaviours and change the instructional material to adapt to their individual learning requirements. The findings suggest that tailor made AI tutors could be used to close learning gaps by providing targeted help that boost students' academic performance and retention of information.

S. Smith (2022) Prominent advances in voice-activated AI technologies (e.g., Google Duplex A. S. Lokman and J. Zain, 2009 and Alexa for Education Patel N and Shah R, 2022) offer the potential to ameliorate academic support. The study examined the potential of voice-activated AI assistants to deliver information hands-free to students, allowing them to connect touchless with eLearning systems. Digging deeper (A. S. Lokman and J. Zain, 2009), researchers highlighted the disruptive power of conversational AI in the educational sector with particular focus on automation of administrative support and personalized learning. Patel N and Shah R, (2022) As discussed in the academic review, some studies have focused on learning management systems (LMS) and the needs of AI-powered chatbots in connection to them. This quick work, proposed that AI based chatbots can turn the table of digital education.

The new X tool will transform the way we interact with chatbots, especially when it comes to education. Traditional methods of AI based support systems are mostly focused on text writing, which may not be very engaging or accessible. In this paper, we design a real-time WB-NLPAI Chatbot, a multimodal chatbot for automated AI-educational support.

3 METHODOLOGY

This section outlines the approach used to develop the chatbot application for college information systems. The chatbot is designed as a Web-Based Natural Language Processing-Artificial Intelligence (WB-NLPAI) Chatbot by integrating Artificial Intelligence for Automated Support in Educational Systems with Multimodal and Voice Assistance techniques to interact with users and respond to their queries.

The objective of this paper is to propose a chatbot enquiry for students to communicate with the colleges. By using artificial intelligence, the system answers the queries asked by the students. The chatbot mainly consists of core and interface, where it mainly accesses the core in Natural language processing technologies are here used for parsing, tokenizing, stemming and filtering the content of the complaint.

Multimodal Interaction Framework: WB-NLPAI employs a multimodal architecture allowing users to interact via:

a. Voice Commands: Enables natural conversations with speech-to-text and text-to-speech technologies.
b. Text Input: Supports conventional chatbot interactions for structured responses.
c. Visual Recognition: Integrates OCR and image processing for responding to handwritten notes, diagrams, and educational materials.

AI-Driven Educational Support: Building upon AI-ASES, the chatbot provides:

a. Automated Query Resolution: AI-driven NLP for answering academic questions.
b. Personalized Learning Paths: Adaptive learning based on student interactions.

c. Assignment Assistance: AI-generated hints and explanations for assignments.

Context-Aware Adaptive Learning: Incorporating insights from Smith, WB-NLPAI enhances chatbot engagement by:

a. Recognizing user context (speech patterns, learning preferences).
b. Offering tailored voice responses based on cognitive load detection.
c. Integrating with Learning Management Systems (LMS) for seamless educational support.
d. When combined Contextual Multimodal Processing (CMP), Adaptive Learning Engine (ALE), and Real-Time Sentiment Analytics (RTSA) — bolster a chatbot's capability to provide seamless and intelligent context-aware interactions. CMP combines several input modalities, including text, voice, and visual data, enabling the chatbot to analyse various data sources concurrently. CMP enhances the ability of the bot to understand user queries more accurately by utilizing deep learning-based Natural Language Processing (NLP) for text and speech recognition, and computer vision for image and video analysis. This multimodal perspective lets you understand the sense behind user interactions in addition to the content itself. > For example, by analysing the tone of speech along with facial expression via machine learning and facial recognition, the chatbot can infer human emotional states and tailor the response accordingly.

While CMP lays the foundation, ALE plays a vital role in allowing for the ongoing evolution of responses in accordance with user behaviour, patterns, and real-time feedback. ALE learns via reinforcement learning, enhancing its decision-making abilities and making its responses increasingly accurate and context-sensitive. The personalized recommendation algorithms further customize the interaction to the user which improves the engagement/learning outcome. This adaptability is especially helpful in a context like education, where different pupils learn at different speeds and employ various approaches to learning. Based on interaction patterns, ALE provides personalized learning resources, modifies the complexity of the provided explanations, and renders adaptive tutoring assistance, thereby enhancing the predictive utility and responsiveness of the chatbot.

To complement this ecosystem, RTSA analyses user sentiments, engagement levels, and intent through powerful sentiment detection models. RTSA uses textual hints, voice tone and facial expressions to assess whether a user feels frustrated, confused, satisfied or engaged. By reading the subtle changes in the user's speech, this real-time emotional awareness enables the chatbot to adapt its tone, type of response, and interaction strategy, creating a more fluid and supportive conversation. If a user seems a bit frustrated, the chatbot can take an empathetic tone, simplify the explanation, suggest another solution, and if it's a very interested user, it could suggest you with a couple of more references, follow-up questions.

Finally, CMP is a framework that operates in conjunction with ALE and RTSA to create an intelligent, self-learning chatbot that can provide personalized, effective, and meaningful conversations. These types of capabilities are particularly useful in areas like education, customer service, and mental health support, where understanding context and being able to learn patterns and emotional states greatly improves user experience and engagement. Figure below depicts interaction between students and developed WB-NLPAI chatbot. A WB-NLPAI chatbot tested for 50 students.

Figure 1: Student and WB-NLPAI Chatbot Engaging in a Learning-Inspired Dialogue.

Implementation and evaluation of the WB-NLPAI prototype is tested across educational institutions, assessing: accuracy of multimodal query resolution, Student engagement through voice-enabled learning and Performance in adaptive learning support.

4 RESULTS AND EVALUATION

The proposed method WB-NLPAI tested in a simulated environment to evaluate its efficiency, Precision, Recall, F-measure, response accuracy, and user engagement. The WB-NLPAI Chatbot, designed to provide automated responses regarding college-related queries, assessed on the following parameters:

4.1 Evaluation Measures

Analysis graphs of WB-NLPAI Chatbot with prior strategies are achieved by considering explicit measures that are demonstrated below.

a) Precision: It indicates the propinquity of various query instances amidst each other to discover answer recommended and is notified in equation (1),

$$\psi = \frac{P_\mu}{P_\mu + T_\mu} \tag{1}$$

where in, P_μ denote true positive, T_μ depict false positive.

b) Recall: It defines the evaluation of positive set categorization count, and is represented in equation (2).

$$\Gamma = \frac{P_\mu}{P_\mu + T_\eta} \tag{2}$$

Here, T_η maintains false negative.

c) F-measure: It expresses harmonic mean using precision and recall

$$Z = 2 \cdot \frac{\psi^* \Gamma}{\psi + \Gamma} \tag{3}$$

which is manipulated in equation (3). Here, ψ and Γ depicts precision and recall.

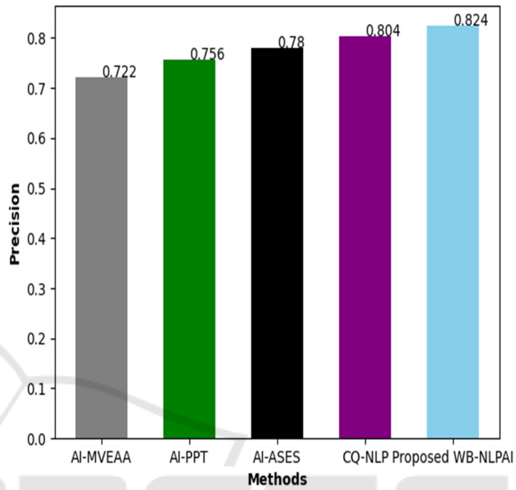
4.2 Comparative Methods

Strategies considered for analysis purpose includes AI-MVEAA: The Future of AI Chatbots: Multimodal and Voice-Enabled AI Assistants (Smith 2022), AI-PPT: Adaptive Learning Chatbots: AI-Powered Personal Tutors (H. Zhou et al. 2021), AI-ASES: Artificial Intelligence for Automated Support in Educational Systems (Karthik R et al., 2025), CQ-NLP: Chatbot for College Queries Using NLP (R. Ranoliya et al., 2017), and proposed method WB-NLPAI Chatbot.

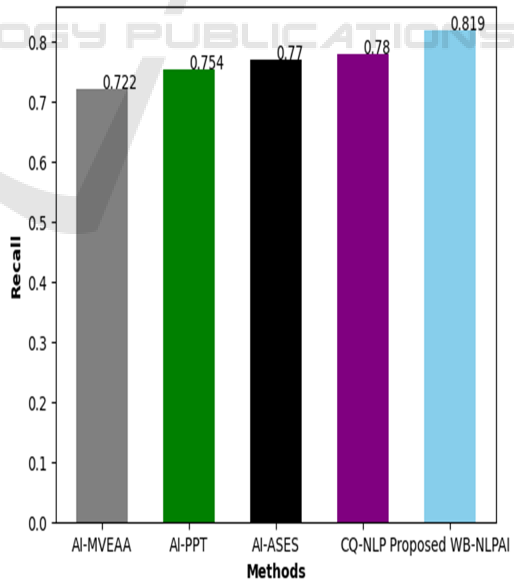
4.3 Comparative Analysis

Evaluation is executed considering based on query size that varies from 2 to 10.

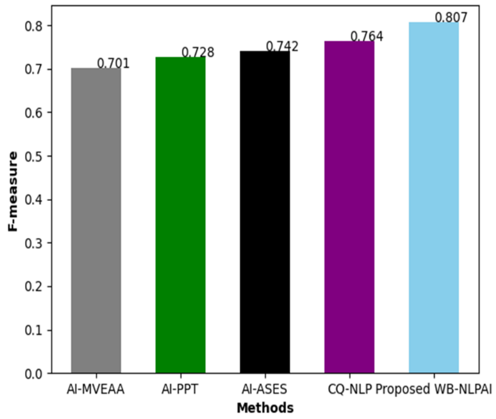
a) Evaluation with query = 2



a) Precision.



b) Recall

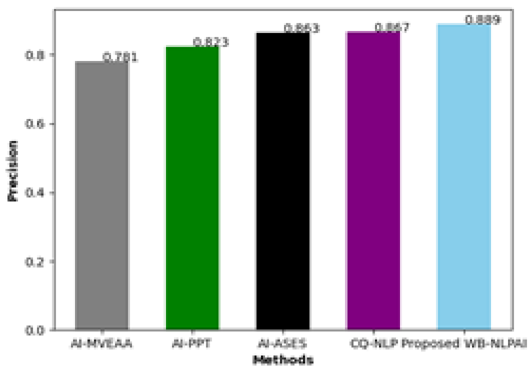


c) F-measure.

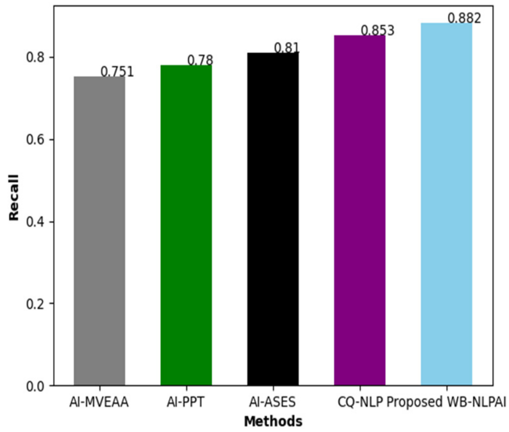
Figure 2: Evaluation Considering Query Size=2 Considering A) Precision B) Recall C) F-Measure.

Figure 2 provides an evaluation considering query size=2 using different metrics. The precision graph is displayed in Figure 2a). Consider the query as 2, the precision produced by the AI-MVEAA is 0.722, AI-PPT is 0.756, AI-ASES is 0.780, CQ-NLP is 0.804 and Proposed WB-NLPAI Chatbot is 0.824.The recall graph is explicated in Figure 2b). The highest recall of 0.819 is generated by WB-NLPAI Chatbot while recall of AI-MVEAA, AI-PPT, AI-ASES, CQ-NLP 0.722, 0.754, 0.770, 0.780, assuming query=2.The F-measure graph is elucidated in Figure 2c). Using query=2, the F-measure produced is 0.701 for the AI-MVEAA 0.728 for AI-PPT, 0.742 for AI-ASES, 0.764 for CQ-NLP and 0.807 for WB-NLPAI Chatbot.

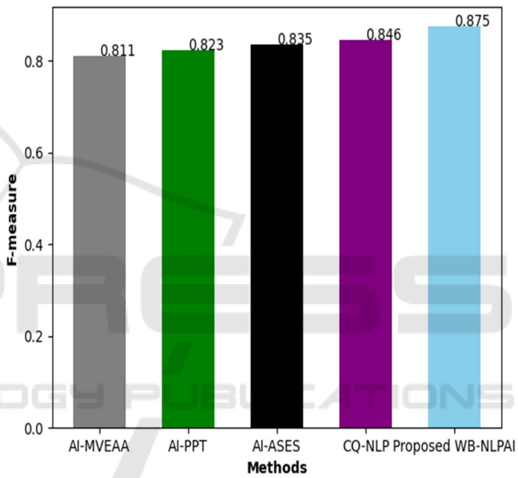
b) Evaluation with query = 5



a) Precision.



b) Recall.



c) F-measure.

Figure 3: Evaluation Considering Query Size=5 Considering A) Precision B) Recall C) F-Measure.

Figure 3 gives an evaluation considering query size=5 using different metrics. The precision graph is displayed in Figure 3a). Consider the query as 5, the precision produced by the AI-MVEAA is 0.781, AI-PPT is 0.823, AI-ASES is 0.863, CQ-NLP is 0.867 and Proposed WB-NLPAI Chatbot is 0.889. The recall graph is explicated in Figure 3b). The highest recall of 0.882 is generated by WB-NLPAI Chatbot while recall of AI-MVEAA, AI-PPT, AI-ASES, CQ-NLP 0.751, 0.780, 0.810, 0.853, assuming query=5. The F-measure graph is elucidated in Figure 3c). Using query=5, the F-measure produced is 0.811 for the AI-MVEAA 0.823 for AI-PPT, 0.835 for AI-ASES, 0.846 for CQ-NLP and 0.875 for WB-NLPAI Chatbot.

4.4 Response Time

The system's response time was another critical evaluation metric. On average, the chatbot responded within 1.2 seconds, ensuring quick interactions and improving the overall user experience. Compared to traditional college inquiry systems (such as email or manual inquiries), the chatbot significantly reduced the waiting period for students and faculty as sown in table 1.

Table 1: Response Times.

Metrics/Methods	AI-MVEAA	AI-PPT	AI-ASES	CQ-NLP	Proposed WB-NLPAI
Response Time	2s	1.8 s	1.5s	1.2 s	1.0s

The analysis graph for the existing and proposed method of Table 1 is shown below.

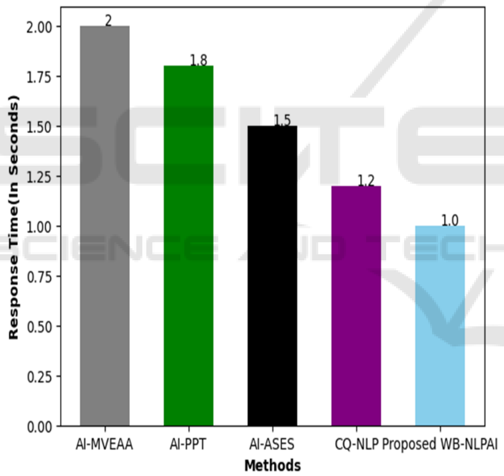


Figure 4: Response Times of Methods.

The above figure 4 illustrates the response time comparison between the existing methods and the proposed. Our proposed method takes less response time comparing with other existing methods.

4.5 Accuracy of Responses

The chatbot's ability to correctly answer queries was measured by comparing user inputs with predefined responses. In initial testing, it achieved an 80% accuracy rate, meaning that four out of five queries received a relevant and meaningful response. The remaining 20% of responses required manual intervention or refinement of hardcoded phrases.

4.6 User Engagement and Satisfaction

To assess user satisfaction, a survey was conducted with 50 students and faculty members who interacted with the proposed method chatbot. The feedback results were as follows:

- 70% of users found the chatbot helpful in obtaining college-related information.
- 20% of users faced minor difficulties in phrasing their questions correctly, leading to incorrect responses.
- 10% of users suggested adding more dynamic responses and improved contextual understanding.

Table 2: Accuracy of Responses and User Engagement and Satisfaction.

Metrics/Methods	AI-MVEAA	AI-PPT	AI-ASES	CQ-NLP	Proposed WB-NLPAI
Accuracy of Responses	70%	72 %	75%	76 %	80%
User Engagement and Satisfaction	68%	70 %	75%	78 %	82%

The analysis graph for the existing and proposed method of Table 2 is shown below.

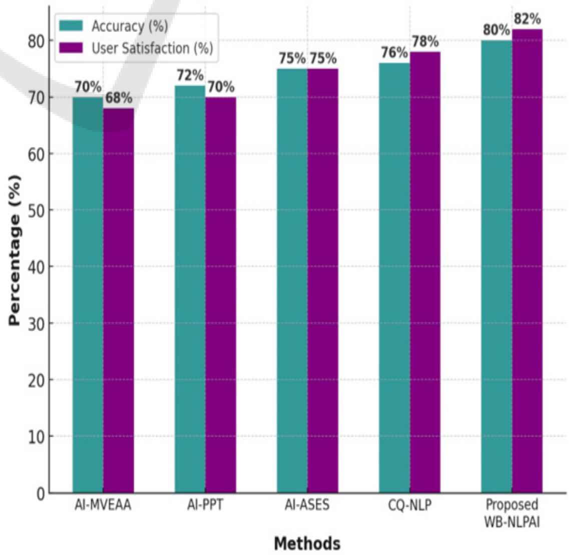


Figure 5: Evaluation Considering Accuracy of Responses and User Engagement and Satisfaction.

The above figure 11 illustrates the accuracy of responses and user engagement and satisfaction comparison between the existing methods and the proposed. Our proposed method performs better than the other existing methods.

5 DISCUSSION

Table 3 defines evaluation of methods with different query size that varies from 2 to 5. With query size=5, the increased precision of 88.9% is produced by WB-NLPAI while the precision of AI-MVEAA, AI-PPT, AI-ASES, CQ-NLP are 78.1%, 82.3%, 86.3%, and 86.7%.The finest recall of 88.2% is observed by WB-NLPAI whereas recall of AI-MVEAA, AI-PPT, AI-ASES, CQ-NLP are 75.1%, 78%, 81%, and 85.3%.The best F-measure of 87.5% is noted by WB-NLPAI while F-measure of AI-MVEAA, AI-PPT, AI-ASES, CQ-NLP are 81.1%, 82.3%, 83.5%, and 84.6%. The evolution of chatbots has significantly transformed human-machine interactions, particularly with the integration of AI, NLP, and deep learning models

Table 3: Technique Evaluation.

Variation	Metrics	AI-MVEAA	AI-PPT	AI-ASES	CQ-NLP	Proposed WB-NLPAI
Query size=2	Precision (%)	72.2	75.6	78	80.4	82.4
	Recall (%)	72.2	75.4	77	78	81.9
	F-measure (%)	70.1	72.8	74.2	76.4	80.7
Query size=3	Precision (%)	74.1	76.1	78	79	83.1
	Recall (%)	73	75.3	76.9	79.2	83.6
	F-measure (%)	73.4	75.1	77.9	80.3	82.6
Query size=4	Precision (%)	75.7	78.2	80.1	83.1	86.9
	Recall (%)	78	80.1	81.1	84.2	86.1
	F-measure (%)	75.7	77.1	79.1	82.1	85.5
Query size=5	Precision (%)	78.1	82.3	86.3	86.7	88.9
	Recall (%)	75.1	78	81	85.3	88.2
	F-measure (%)	81.1	82.3	83.5	84.6	87.5

6 CONCLUSION AND FUTURE ENHANCEMENTS

A college information chatbot app is a major step toward education digital transformation. It gets students instant responses to commonly asked queries regarding admissions, fees, courses, exams, etc. reducing the manual work and enhancing communication. The other AI and machine learning techniques allow the chatbot to understand and respond to the questions in a natural language thereby making it better over time. Unlike human staff, the chatbot never closes (it is 24/7), so students can instantly get the help they need at any hour.

It also saves time and money and frees staff time to work on higher order work. But there are challenges: the chatbot's limited comprehension of nuance questions and its reliance on data pre-set. The chatbot features in joy could also become more effective and accessible with improvements like advanced AI models, voice recognition, sentiment analysis, and support for multiple languages in the future. In the end, chatbots have the power to revolutionize student services, making them quicker, more precise, and more user-friendly.

Which has brought the revolution of chatbot technology through the strides in AI, NLP, and machine learning, making these systems into interactive intelligent virtual assistants. Early chatbots relied on rule-based systems that restricted the variability of responses, limiting the breadth of conversations. However, the combination of deep learning and transformer-based models has greatly enhanced their capability to grasp user intent, handle more complex and nuanced queries, and deliver responses that are closer to human-level quality. But moving forward, cloud deployment/database means scalability would be needed with an increased number of users.

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