

## EduConvo: AI-Driven Student Feedback System

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### ABSTRACT

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Student feedback is a crucial tool for educational institutions to assess teaching effectiveness and improve course delivery. However, traditional feedback collection methods, e.g., static surveys, suffer from low engagement, vague responses, and a lack of actionable insights. To address these limitations, this paper presents a Conversational AI-based Student Feedback System that uses a Large Language Model (LLM) to facilitate dynamic, interactive, and adaptive feedback collection. The system personalizes questions based on course content, allowing in-depth responses while maintaining anonymity.

The system uses Next.js for the frontend, Flask for the backend, and a MongoDB database for data storage, integrating OpenAI's GPT model for conversational interactions. A real-time analytics dashboard enables faculty to interpret feedback effectively. To evaluate the system, a comparative study was conducted against a survey-based feedback approach, measuring student engagement, response quality, and usability of the system. The results indicate a significant improvement in feedback depth, participation rates, and user satisfaction.

This research highlights the role of AI-driven feedback systems in enhancing student engagement and providing richer insights for academic institutions.

**Keywords:** Conversational AI, Student Feedback, Large Language Models (LLMs), Educational Technology, Sentiment Analysis, Interactive Feedback

## I. INTRODUCTION

Student feedback plays an important role in evaluating teaching effectiveness and enhancing the learning experience. It provides educators with valuable insights into course content, teaching methodologies, and areas for improvement. Traditional feedback mechanisms, such as generalized surveys are widely used but suffer from several limitations. These methods often lead to low response rates, generic responses, and a lack of engagement from students, reducing their overall effectiveness.

Existing feedback systems primarily rely on predefined questions, which do not allow for interactive, contextual, or adaptive responses. Additionally, students may provide minimal or incomplete feedback due to survey fatigue, reducing the usefulness of collected data. Analyzing qualitative responses from open-ended questions remains a challenge, which requires manual intervention to extract meaningful insights. These limitations highlight the need for an improved, AI-based approach to collecting and analyzing student feedback.

To address these issues, this paper presents a Conversational AI-Based Student Feedback System that uses Large Language Models (LLMs) such as GPT4o-mini to make feedback collection dynamic and adaptive. Unlike static surveys, this system interacts with students through a natural, interactive dialogue, generating context-aware follow-up questions to gather more meaningful responses. The system adapts to student input, ensuring that feedback is relevant and detailed while maintaining anonymity.

The primary contributions of this research are as follows:

- Development of a dynamic feedback system that uses Artificial Intelligence to improve student engagement and response quality.
- Feedback is personalized by generating dynamic questions with course content and previous response as parameters
- Instructors are provided with actionable insights for curriculum improvement using feedback's sentiment analysis.

Hence, this research identifies the potential of AI-based conversational systems to improve student feedback collection and derive actionable insights for instructors.

## II. LITERATURE REVIEW

Previous studies underscore the drawbacks of conventional survey mechanisms for gathering feedback, as well as the promise of leveraging conversational AI to increase student engagement and improve educational results. Hence, in regular surveys like Google Forms the responses are often biased, with a small sample response (Andrade, 2020). In contrast, conversational AI applications allow such interactions and provide immediate feedback, which is interactive and more representative of the data. Vanichvasin (2022) showed that intuitive, natural interactions through AI-powered chatbots enhance student satisfaction and learning. For example, Cox (2023) noted that LLM-based systems of multiple conversational agents can simulate varied personas to provide more robust learning experiences.

Similarly, Jakesch et al. (2023) discovered that the nature of AI-assisted writing affects user responses, suggesting that AI could influence the quality of feedback received and welcome new ways of receiving constructive feedback.

Li et al. (2024) unveiled an EduBot that customizes responses according to student expertise, underlining AI's contribution to customized learning. Such situational feedback only disrupts the conversation, so these studies highlight the need of Conversational Feedback System to make sure that feedback will increase the relevance, engagement, and educational insights.

Year	Author and Journal	Methodology	Findings
2020	Chittaranjan Andrade, "The Limitations of Online Surveys"	The surveys, like Google Forms, SurveyMonkey, etc., are distributed through internet platforms like emails, mailing lists, and social media channels.	Compared to traditional survey methods, a conversational AI system improves generalizability by engaging users interactively, reducing non-representative samples, and improving feedback relevance.
2022	Patchara Vanichvasin, "Impact of Chatbots on Student Learning and Satisfaction"	Quasi-experimental study with 24 graduate students using Dialogflow and LINE-based chatbots mimicking entrepreneurs.	High ratings for chatbot appropriateness and satisfaction, with improved student learning, show that AI systems enhance education. The system supports intuitive, user-friendly interactions.

2023	Samuel Rhys Cox, "The Use of Multiple Conversational Agent Interlocutors in Learning"	LLMs create multiple conversational agents with distinct personas and roles for diverse feedback.	LLMs simulate diverse personas to enrich educational interactions, offering benefits like social comparison and varied perspectives.
2023	Maurice Jakesch et al., "Co-Writing with Opinionated Language Models"	Online experiment (N=1,506) using GPT3 as a writing assistant with three groups: Control, Techno-optimist, and Techno-pessimist.	Opinionated models significantly influenced participants' writing, showing AI's potential to guide feedback constructively. This influence was stronger for participants spending less time writing.
2024	Yu Li et al., "Curriculum-Driven Edubot"	Created a chatbot framework integrating conversational AI with curriculum-based English textbooks by extracting topics and generating dialogues using LLMs.	By adjusting dialogue to user proficiency, EduBot shows how systems can provide feedback based on individual student levels, enhancing personalization.

### III. OBJECTIVES

This system aims to design and develop a dynamic, conversational feedback and quiz system that enhances student engagement and provides actionable insights for faculty. The system will use adaptive, real-time interactions to collect personalized feedback aligned with course syllabi, enabling more meaningful responses than traditional surveys. It will also include daily quizzes based on lectures, automatically marking attendance and gathering immediate feedback to help faculty refine teaching strategies. The system will be mobile-responsive and capable of summarizing both quantitative and qualitative data, supporting data-driven improvements in course delivery.

### IV. METHODS

The conversational feedback system allows students to interact with the system naturally. Instructors get feedback summaries and detailed insights to refine teaching methods and redesign the curriculum. The system uses a Large Language Model (LLM) to personalize the feedback collection. The approach used while designing the system involves: the selection of an LLM model, analyzing feedback parameters, deciding the strength of the model, choosing a relevant technology stack, analyzing data, testing, and security considerations.

#### A. LLM Model

We selected OpenAI's GPT-4o mini model due to its efficiency, accuracy, and speed. Compared to larger models like GPT-4 and alternatives such as Meta's LLaMA 2, Google's PaLM, and Mistral, GPT-4o mini offers lower latency, better contextual coherence, and reliable performance for real-time feedback generation. Its API accessibility and cost-effectiveness also make it ideal for deploying scalable, conversational feedback systems in an educational environment.

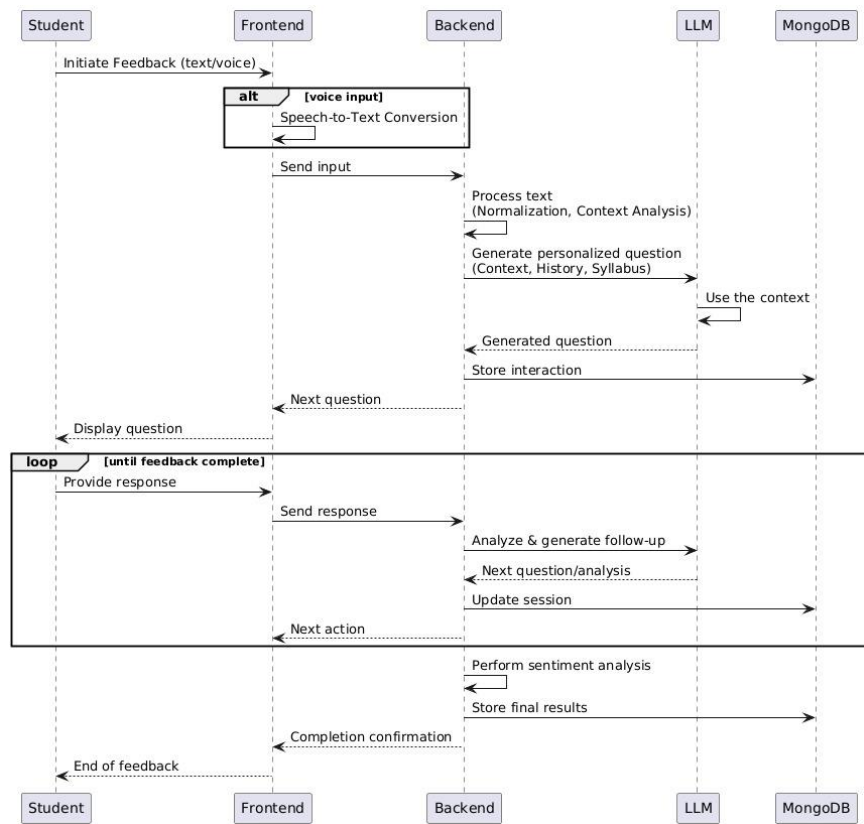


Fig.1. Flowchart

### B. Feedback Parameters

To ensure the LLM model generated relevant and structured questions, we defined a set of feedback parameters aligned with course evaluation goals. These parameters included topics related to student engagement with the overall course. By guiding the model with these parameters, we ensured that the conversation remained focused and contextually relevant.

#### Algorithm 1: Feedback Processing Pipeline

**Input:** input, course\_materials

**Output:** response

- Function** process\_feedback(input, course\_materials)  
  // Input handling
- If** input.type == VOICE
- text ← speech\_to\_text(input.content)
- Else**
- text ← normalize\_text(input.content)
- EndIf**
- // Context generation
- context ← generate\_context(text, course\_materials, previous\_messages)
- // LLM interaction
- prompt ← create\_prompt(  
    role = "feedback assistant",  
    context = context,  
    syllabus = course\_materials.key\_topics,

```
        feedback_rubric = STANDARD_PARAMS)
11. response ← llm.generate(prompt, max_tokens=500, temperature=0.7)
12. // Storage and continuation logic
13. store_interaction(
        session_id = input.session_id,
        message_pair = (text, response),
        embeddings = generate_embeddings(text))
14. Return response
2. End Function
```

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Parameters Considered for Feedback Capturing:

- Course Content
- Teaching Methods
- Resources and Materials
- Workload and Assignments
- Assessment Methods

This approach helped avoid generic questioning and enabled the system to generate personalized, course-specific, and actionable feedback prompts, enhancing both the depth and precision of responses. It also ensured consistency across different sessions while still allowing dynamic adaptation to individual student inputs.

#### C. *Strength of the Model*

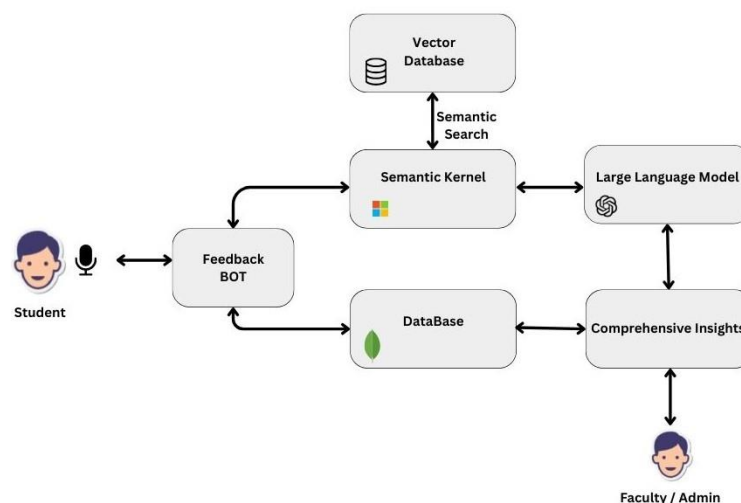
The parameters defined for feedback acted as a blueprint for the model, however, strong adherence to it, was limiting the natural interaction with students. Another consideration was the student response length, if too short (yes/no type or one word responses), limits the summarization relevancy (thus limiting the derivation of insights) and, on the other hand compelling long feedback inputs would reduce the engagement. Hence, the model was aligned to have a practical balance, enabling meaningful feedback generation without overwhelming the student or compromising the quality of summarization.

#### D. *Implementation*

The conversational feedback system is implemented through a structured, multi-stage pipeline that ensures accurate feedback collection, intelligent processing, meaningful analysis, and smooth deployment. The core tech stack comprises a Next.js frontend for responsive and interactive user interfaces, a Flask backend for handling API logic and integrating AI models, and MongoDB as the primary NoSQL database for efficient data storage and retrieval. The system uses OpenAI's GPT-4o mini, a lightweight LLM, for adaptive question generation and summarization.

The process begins with capturing feedback via both text and voice. Voice responses are converted into text using a speech-to-text (STT) module, and all inputs are normalized to prepare them for downstream processing. Educators provide course materials, and using semantic search combined with the GPT-4o mini model, the system generates dynamic, personalized follow-up questions mapped to relevant topics, fostering deeper engagement. Student feedback is anonymized to ensure data privacy and allow students to provide feedback without hesitation.

Subsequently, Natural Language Processing (NLP) techniques perform sentiment and thematic analysis on student responses, categorizing them into positive, neutral, or negative sentiments and identifying key discussion areas. These are then visualized using interactive dashboards that display insights, trends, and statistical summaries for faculty.

**Fig.2.** Functional Diagram*E. Data Analysis and Insight Derivation*

Each student response is individually analyzed to generate a concise summary along with an overall rating, which is presented to the faculty for quick review. Using Natural Language Processing techniques, all responses are categorized into positive, negative, or neutral sentiment. A collective summary is then generated from the combined feedback, highlighting common themes and concerns. These aggregated insights help faculty identify strengths and weaknesses in course delivery, enabling data-driven decisions for academic improvement.

*F. Testing*

The system was tested with third-year students by deploying it in a real academic setting for the Laboratory of Machine Learning course. A feedback task was created, and quizzes were scheduled daily to collect topic-wise feedback. The system's functionality and performance were evaluated in terms of responsiveness, scalability, and reliability under actual usage conditions. Feedback summaries and corresponding ratings were generated and analyzed to validate the accuracy of the conversational model. The test ensured that the system could effectively handle dynamic feedback and support real-time educational improvement.

**Algorithm 2: Dynamic Question Generation**

**Input:** feedback\_history, syllabus

**Output:** question

1. **Function** generate\_question(feedback\_history, syllabus)
  - // Retrieve course context
2. course\_topics ← syllabus.extract\_key\_topics()
3. topic\_embeddings ← create\_embeddings(course\_topics)
4. // Semantic matching
5. feedback\_embedding ← create\_embedding(feedback\_history.last\_response)
6. // Find relevant topics
7. relevant\_topics ← find\_top\_matches(
  - feedback\_embedding,
  - topic\_embeddings, top\_n = 3)
8. // Construct LLM prompt
9. prompt ← "Generate follow-up question about " + relevant\_topics +



" considering previous responses: " + feedback\_history +

" Maintain conversational flow and focus on teaching effectiveness."

10. question ← llm.generate(prompt, temperature = 0.5)

11. **Return** question

2. **End Function**

### G. Security & Data Privacy Considerations

To ensure data privacy, all student feedback responses are anonymized before being processed or viewed by instructors. Identifiable information is removed, allowing faculty to access only the content summaries and ratings without linking them to individual students. This approach safeguards student identity and encourages honest, unbiased feedback while maintaining confidentiality throughout the system.

## V. RESULTS

The assessment of the Conversational Feedback System proved its potency in generating questions based on syllabus content and examining for student feedback as actionable insights. This system had a high question 95%, rate of relevance, guaranteeing a consistent alignment with course material via semantic embeddings. Sentiment and thematic analysis provided valuable insights into student understanding, highlighting areas of confidence and those requiring additional support. Positive feedback correlated with well-structured topics, whereas complex or less-covered areas elicited constructive feedback. Additionally, the system's real-time processing capabilities facilitated immediate transcription and dynamic question adaptation, fostering an interactive and responsive feedback loop that enhanced student engagement and the depth of responses.

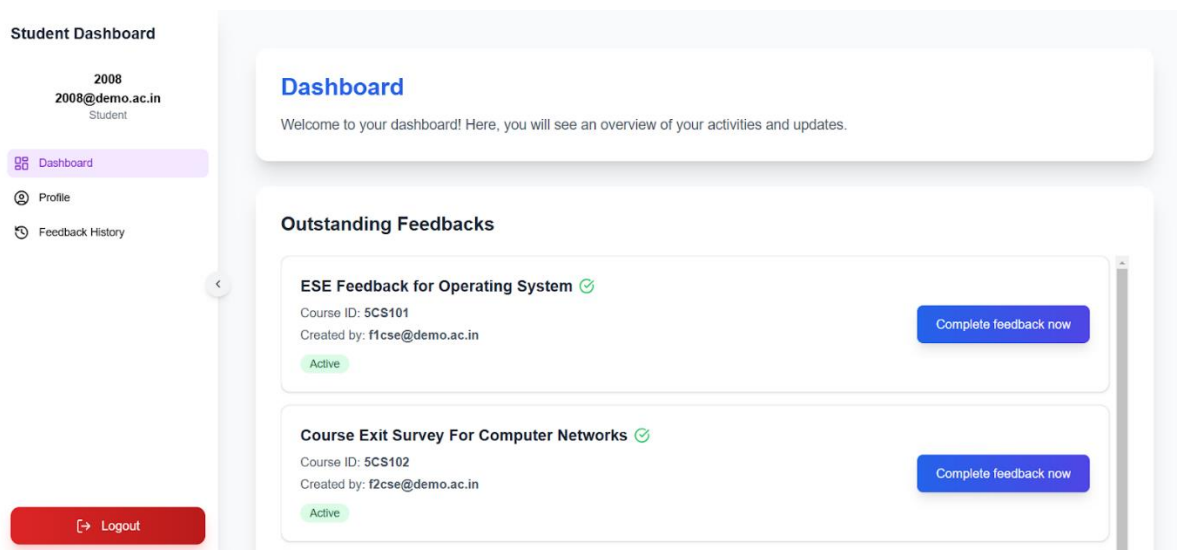


Fig.3. Student Dashboard

1. **Personalized questions:** The feedback questionnaire is generated dynamically based on the student responses. Students are encouraged to provide more specific feedback so that deep actionable insights can be derived to improve the course delivery. The GPT model generates the next question based on the context of the current chat, feedback parameters, and the student response. [Fig.4]

**Course Feedback Assistant**

Course: Operating System | Course ID: 5CS101 | Faculty: ffce@demo.ac.in

Welcome! I'd like to collect your feedback about the Operating System course. On a scale of 1-10, how would you rate your overall experience with the Operating System course?

I would rate it 8

Thank you for your rating! Now, let's delve into specific aspects of the Operating System course.

How would you rate the Course Content of the Operating System course on a scale of 1-10? The syllabus covers topics such as process management, memory management, and file systems. If possible, please provide a few comments or feedback on this area.

Type your feedback here... 0 / 3000 Send

**Fig.4. Personalized Questions**

2. **Course Specific Feedback:** The GPT4o-mini LLM model is given a few feedback parameters along with the course syllabus or course contents. Thus, the model sequentially generates questions that cover the feedback targets while making it relevant for that specific course. [Fig.5]

**Admin Portal**

- Dashboard
- Courses**
- Faculty
- Students
- Feedback

**Course Dashboard**

**Course Management** Search courses... + Add Course + Assign Courses

**5CS101 Operating System**

Introduction to OS: Overview, types, and functions of operating systems. Process Management: Process scheduling, threads, synchronization, deadlocks. Memory Management: Allocation, paging, segmentation, virtual memory. File Systems: Structure, directory and file management, permissions. I/O Management: Device drivers, interrupts, and DMA. Concurrency and Multithreading: Parallelism, issues, and solutions. Security and Protection: Access control, authentication, malware defense. Case Studies: Analysis of popular OS like Linux, Windows, or macOS.

**5CS102 Computer Networks**

1. Introduction to Computer Networks Network types: LAN, WAN, MAN, PAN Network topologies and protocols OSI and TCP/IP models 2. Physical Layer Transmission media: wired and wireless Data encoding and modulation Multiplexing techniques 3. Data Link Layer Error detection and correction Flow control and protocols (e.g., HDLC, PPP) MAC addressing and ARP 4. Network Layer IP addressing (IPv4 and IPv6) Routing algorithms (e.g., distance vector, link state) Subnetting, NAT, and CIDR 5. Transport Layer TCP and UDP protocols Flow and congestion control Port numbers and socket programming basics 6. Application Layer HTTP, FTP, SMTP, DNS, and DHCP protocols Client-server and peer-to-peer models Web technologies and

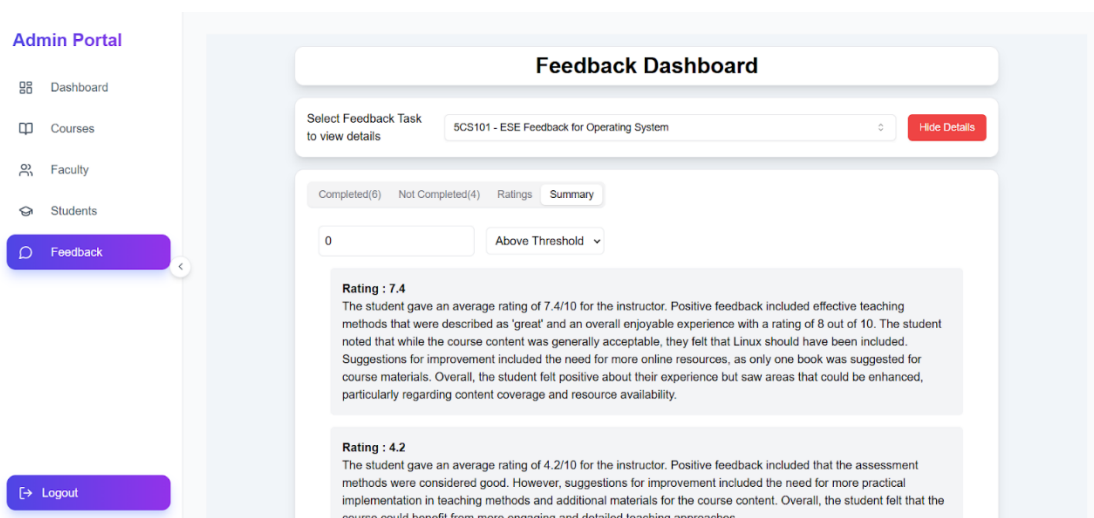
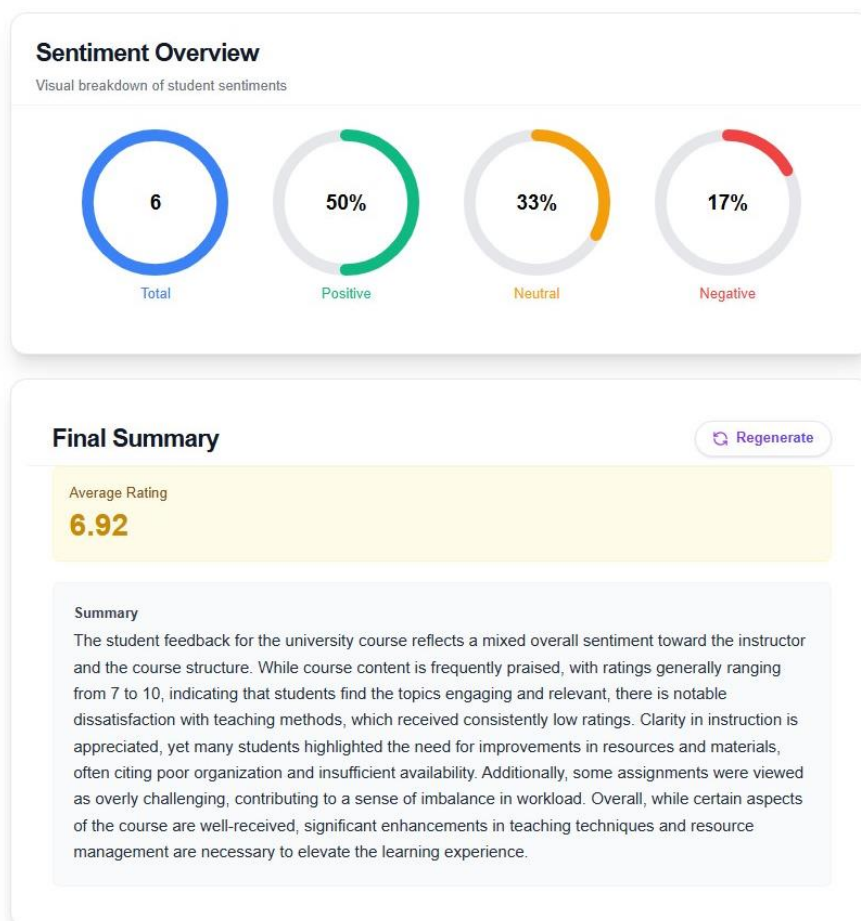
**Fig.5. Course Specific Feedback**

3. **Enhanced Student Engagement:** Conversational Feedback System helps students to express their thoughts regarding the course delivery, syllabus, and teaching methods. The anonymity of the feedback makes it easy to express real thoughts. Thus, conversational feedback system improved student engagement and encouraged them to be involved in the feedback loop.

4. **Feedback Summary:** The system analyzes overall insights from all the student responses and prepares a statistical summary for the feedback. This includes average rating for the course, positive and negative responses, and number of students fields. [Fig.6]

5. **Actionable Insights For the Instructors:** Conversational Feedback System creates a summary of each feedback for the easy analysis of the student responses. Instructors can see the summarized versions along with the rating of each, which makes it feasible to derive actionable insights. [Fig.9]



**Fig.6.** Summarized Responses with Rating**Fig.7.** Statistical Feedback Summary

6. **Daily Quiz and Attendance Integration:** A daily quiz system is implemented where students attempt quizzes based on the topics taught on that particular day. Attendance is automatically considered based on quiz participation, ensuring active engagement. [Fig.8]

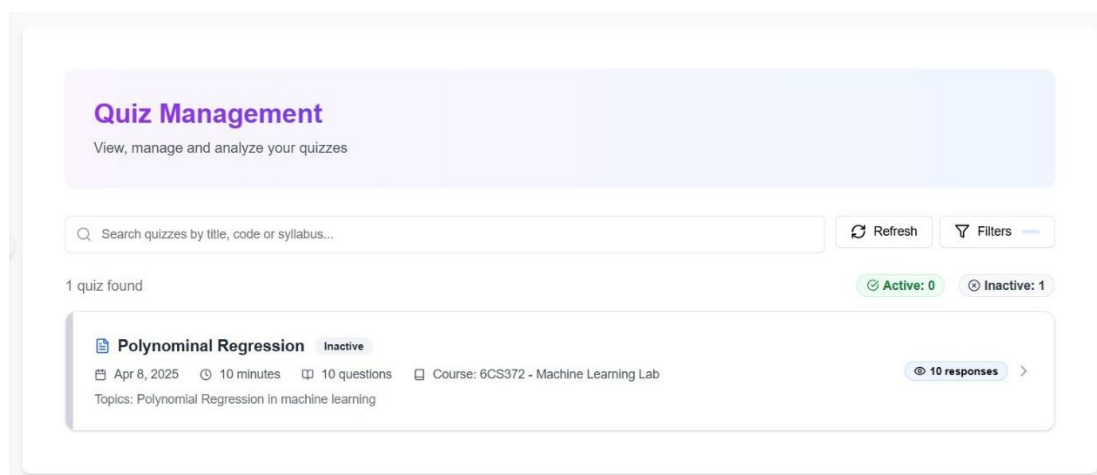


Fig.8. Daily Quiz System

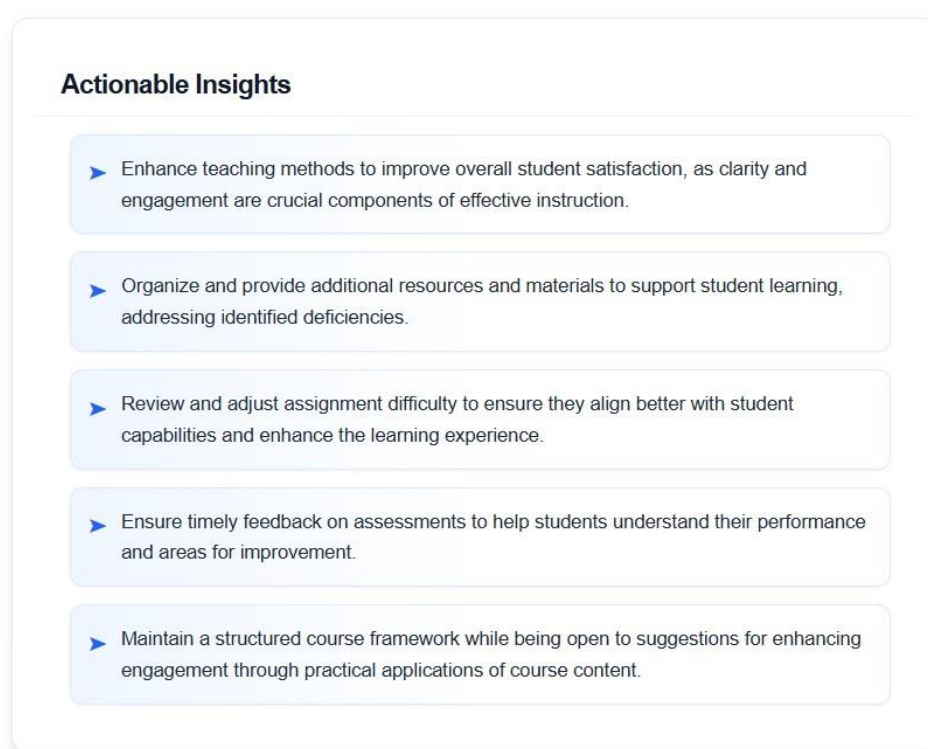


Fig.9. Actionable Insights

At the end of the quiz, students provide feedback regarding the teaching of the topic. This feedback, along with quiz performance, helps the instructor to analyze student understanding and prepare better for the next lecture. The system provides actionable insights to the instructor for improving topic delivery, clarifying doubts, and revising content if needed.

## VI. DISCUSSION

This study explored how a Conversational AI-based feedback system can reshape the way feedback is collected in educational settings. The goal was not just to gather responses, but to make feedback more engaging, honest, and useful for both students and instructors. Based on our observations, students interacted more meaningfully with the system compared to traditional survey methods, and the insights gathered were richer and more detailed. Here, we consider two major takeaways: how the system facilitated student reflection and thinking, and how its central concepts can be used outside the classroom.

### A. Cognitive Engagement and Reflective Learning

One of the most striking consequences was the way the system provoked students to consider more deeply what they had acquired. Rather than ticking boxes or jotting brief comments as in typical surveys, students engaged with the AI that prompted them to remember particular points, think through their grasp, and even convey challenges they experienced. Such reflective feedback served to elicit nuances that may otherwise go unnoticed. A few students said that the questions were more personal and natural-sounding, so it was simpler to give their true reactions. Having the anonymity feature was a double dose of comfort—students could express themselves freely without fear of judgment. It minimized the so-called "politeness bias" wherein students refrain from criticizing due to fear of influencing the quality of the teacher-student relationship. Notably, when the AI prompted follow-up questions from previous answers, students tended to provide more detail, particularly on confusing or difficult material. This amount of interaction provided teachers with more precise and usable information on where students were struggling—something that static surveys rarely provide.

### B. Broader Applicability and Future Considerations

Though the system was created for feedback in the classroom, its development has potential application beyond that as well. Add-ons such as daily quizzes and quiz-based tracking of attendance enabled students to engage on a daily basis, more than just an add-on feedback feature—it was incorporated into their daily learning environment. Concurrently, some issues were noticed. The sentiment analysis module, for instance, occasionally had trouble with indirect feedback such as sarcasm or cultural expressions. This indicates a future area of improvement by incorporating more sophisticated language models that are better at understanding context and tone. All in all, the findings imply that conversational AI has the potential to turn feedback into something more meaningful and dynamic—not just in learning, but potentially in corporate training, or customer support where continuous feedback is relevant. As it further develops, these systems have the potential to make individuals share their opinions more freely, and enable organizations to respond more reflectively.

## VII. CONCLUSION

This research demonstrates that AI-driven conversational feedback systems represent a significant step forward in educational assessment methodology. By combining the accessibility of digital platforms with the help of natural conversation, we've created a tool that not only collects more meaningful feedback but also encourages greater student participation in the improvement of their educational experience.

The success of our implementation suggests that the future of student feedback lies not in replacing traditional methods entirely, but in augmenting them with intelligent systems that can adapt to individual student responses while maintaining consistency in data collection. The high relevance rate of generated questions and improved student engagement levels indicate that AI can indeed bridge the gap between standardized assessment and personalized interaction.

Our findings have important implications for educational institutions considering the adoption of AI-based feedback systems. While the initial investment in such technology may be significant, the returns in terms of improved course delivery, student satisfaction, and administrative efficiency make a compelling case for implementation. As we continue to refine these systems, the potential for creating more responsive, student-centered learning environments becomes increasingly achievable.

In closing, while our system has shown remarkable promise, we acknowledge that technology alone cannot solve all challenges in educational feedback. Rather, it serves as a powerful tool that, when properly implemented, can help create more dynamic, responsive, and effective educational environments. The key to success lies in striking the right balance between technological innovation and human insight, ensuring that we enhance rather than replace the crucial human elements of education.

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