2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC
Host Sponsor UNC Charlotte
Paper ID #51561

Enhancing Engineering Education with an AI-Powered Conversational Teaching Assistant

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Abstract

With support from SUNY Innovative Instruction Technology Grants (IITG), a retrieval-augmented, AI-powered conversational teaching assistant, eduBot, was developed and integrated into courses at SUNY Empire State University and SUNY Farmingdale State College. EduBot was developed to address common challenges in engineering and technical education, including limited access to timely academic support, early-course confusion, instructional scalability, and the need for responsible AI integration. The system was designed using instructor-approved materials and embedded within the learning environment to provide students with grounded responses related to course content, schedules, policies, and foundational concepts.

This paper reports findings from a matched pre/post survey study of students who used eduBot in an engineering course at Farmingdale State College. Twenty students completed both the pre- and post-surveys and were included in the matched analysis. Survey items measured student expectations and post-use perceptions related to usefulness, confidence, engagement, timely support, assessment preparation, user-friendliness, and willingness to use eduBot in other courses. Because the pre- and post-surveys used slightly different response formats, responses were converted to a standardized 0–100 scale before analysis.

Overall perceptions of eduBot improved from pre-survey to post-survey. The largest statistically significant gains were observed for using eduBot to access syllabus and schedule information and for receiving timely responses to student questions. Post-survey results also showed generally positive perceptions, with most students reporting favorable attitudes toward eduBot, its usefulness for course logistics, and its role in supporting engagement. These findings suggest that retrieval-augmented AI teaching assistants may be especially valuable for reducing

logistical uncertainty and increasing access to timely course support in engineering education. Results further show that the eduBot model—designed and managed using the ADDIE framework—contributes to measurable improvements in student self-efficacy in content-intensive courses.

1. Introduction

Artificial intelligence is rapidly reshaping higher education, particularly through tools that support student learning, engagement, and instructional scalability. Conversational AI systems offer the potential to provide continuous academic support, reduce administrative burden, and personalize learning experiences. However, integrating generative AI into credit-bearing courses—especially in engineering education—raises concerns related to accuracy, ethics, privacy, and cost. Engineering programs face additional pressures due to rigorous curricula, high attrition rates, and diverse student populations that include non-traditional, adult, and online learners. Early-course confusion regarding course organization, expectations, and foundational concepts is a well-documented contributor to student frustration and withdrawal. Addressing these challenges requires solutions that are pedagogically grounded and institutionally governed.

To respond to these needs, the eduBot was developed, a retrieval-augmented, domain-specific chatbot designed to provide reliable, low-risk instructional support across disciplines. This paper reports on the design and deployment of eduBot.

2. Literature Review

2.1 AI-Supported Learning in Higher Education

Artificial intelligence has been widely explored as a means to enhance instructional delivery, learner engagement, and administrative efficiency. Machine learning and adaptive systems have demonstrated the ability to personalize learning pathways, provide timely feedback, and support large-scale instruction (Chen et al., 2020; Guo et al., 2024). In online and high-enrollment courses, AI tools have been associated with improved learner satisfaction and perceived support.

However, research consistently emphasizes that AI effectiveness depends on pedagogical alignment. Holmes, Porayska-Pomsta, and Holstein (2022) argue that AI systems contribute meaningfully to learning only when designed around instructional goals rather than deployed as generic automation. This pedagogy-first principle is particularly relevant in engineering education, where conceptual accuracy and curricular alignment are critical.

2.2 Generative AI, Ethics, and Reliability

Despite growing interest, the use of generative AI in formal education is constrained by concerns about reliability and ethics. Large language models are susceptible to hallucinations—producing fluent but inaccurate or fabricated information—which can undermine academic rigor and student trust (Ji et al., 2023). These risks are especially pronounced in technical disciplines, where incorrect explanations may propagate misconceptions.

Ethical concerns include academic integrity, student overreliance on AI, and unclear authorship boundaries. Pan (2024) highlights that students often lack formal preparation in ethical AI use, increasing the risk of misuse. Bearman et al. (2022) argue that educational AI systems must operate within transparent constraints to prevent misinformation and unethical practices. From an institutional standpoint, privacy and data retention practices raise compliance concerns with FERPA (Family Educational Rights and Privacy Act) and institutional risk policies (Bouhia, 2022).

2.3 Knowledge-Grounded Chatbots and Retrieval-Augmented Generation

Knowledge-grounded conversational systems offer a promising approach to mitigating hallucinations and improving trust. Retrieval-augmented generation (RAG) combines document retrieval with generative modeling to ensure outputs are grounded in verifiable sources (Lewis et al., 2020). Subsequent studies demonstrate that RAG-based systems significantly improve factual accuracy in domain-specific applications (Izacard & Grave, 2021).

In educational contexts, grounding chatbot responses in instructor-approved materials enhances transparency, reliability, and learner confidence (Holmes et al., 2022). By constraining the model’s response space, knowledge-grounded chatbots support academic integrity while retaining the accessibility benefits of conversational interfaces.

2.4 AI, Student Support, and Retention in Engineering Education

AI systems have also been explored as tools for improving student persistence and retention. Predictive analytics can identify at-risk students and enable early interventions (Ouyang et al., 2023), while personalized feedback mechanisms have been linked to improved engagement and persistence (Kizilcec & Brooks, 2018). In engineering programs, early-course engagement is a strong predictor of retention and success (Ohland et al., 2015).

For non-traditional and adult learners—who comprise a significant portion of online engineering enrollments—24/7 access to academic support is particularly valuable. Conversational AI systems that reduce friction related to course navigation and foundational understanding may therefore play a meaningful role in supporting retention.

2.5 Gaps in Scalable AI Implementations

Large-scale reviews of AI in higher education consistently identify a lack of validated, scalable implementation models that extend across disciplines (Zawacki-Richter et al., 2019). Many studies report isolated pilots without clear governance frameworks.

The eduBot initiative addresses this gap by evaluating a constrained, retrieval-based chatbot across business and engineering contexts using a consistent instructional and governance model.

3. System Design and Methodology

3.1 Instructional Design Framework

EduBot was developed using the ADDIE (Analysis, Design, Development, Implementation, Evaluation) instructional design framework (Branch, 2009), ensuring alignment between learner needs, course objectives, system functionality, and evaluation. The analysis phase identified high-frequency student questions related to course organization, policies, and foundational concepts—areas associated with early-course cognitive overload.

Building on a pilot study, eduBot was expanded to several courses using a structured ADDIE-based implementation model designed for cross-disciplinary replication.

3.1.1 Analysis

In late 2025, a systematic needs analysis was conducted for selected undergraduate courses. The analysis examined high-frequency student questions, common conceptual bottlenecks, and discipline-specific expectations related to digital and AI literacy. Particular attention was given to early-course challenges that contribute to cognitive overload and attrition in engineering pathways.

3.1.2 Design

Based on pilot study findings, three design enhancements were incorporated into the subsequent deployments:

1. improved query scaffolding to support novice users,
2. expanded FAQ coverage targeting course logistics and foundational concepts, and
3. adaptive instructional prompts to encourage productive engagement rather than answer substitution.

The retrieval-augmented generation workflow and LMS integration architecture remained consistent to preserve instructional governance and system reliability.

3.1.3 Development

eduBot was populated with instructor-approved course materials, including syllabi, policies, problem-solving guidelines, and curated conceptual explanations. All content underwent validation to ensure disciplinary accuracy and FERPA compliance. System testing focused on response grounding, retrieval precision, and LMS interoperability.

3.1.4 Implementation

In Spring 2026, eduBot was deployed in several courses. The system was embedded directly within the LMS, requiring no additional student accounts. Usage analytics was collected to quantify adoption, interaction frequency, and temporal patterns of use.

3.1.5 Evaluation

Effectiveness was evaluated using pre- and post-surveys measuring student self-efficacy, perceived usefulness, and system usability, mirroring the macroeconomics pilot methodology. Quantitative analyses included paired-samples comparisons and effect-size estimation to enable cross-course and cross-discipline comparisons.

In summary, framing eduBot's expansion within the ADDIE framework enables a transition from a single-course pilot to a scalable, evidence-based instructional support model appropriate for engineering education contexts. Rather than evaluating isolated chatbot deployments, this work seeks to validate a replicable architecture that engineering faculty can adopt without specialized AI development expertise.

3.2 Technical Architecture

EduBot employs a retrieval-augmented generation architecture. An open-source language model serves as the generator, while a semantic retrieval layer selects relevant passages from a curated corpus consisting of syllabi, schedules, institutional policies, and instructor-vetted instructional materials. Only retrieved content is passed to the model during inference, constraining outputs to approved sources.

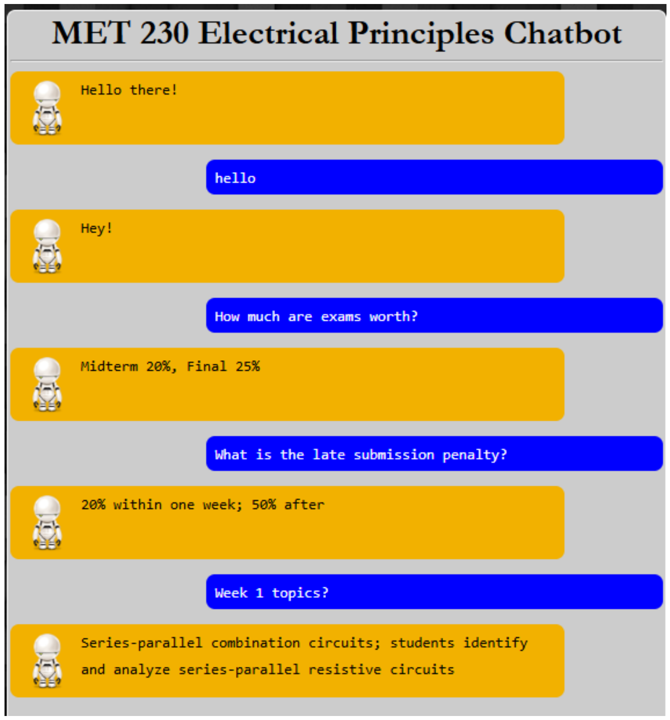
All components are hosted in a sealed, access-controlled cloud environment with no connection to the public internet. Student interactions are not used for external model training, supporting FERPA compliance and institutional data governance.

3.3 Integration and Deployment

EduBot is embedded directly within the university learning management system and inherits LMS authentication, eliminating the need for separate accounts. Students can query the system regarding course logistics, expectations, and concepts at any time. The initial pilot achieved 99.96% uptime and demonstrated stable performance throughout the term.

Figure 1

EduBot Interface for MET230: Electrical Principles course at Farmingdale State College



4. Results

4.1 Participants and Study Design

The study was conducted in an undergraduate engineering course using a matched pre/post survey design. A total of 20 students completed both the pre-intervention and post-intervention surveys and were included in the final analysis. Student identifiers were used solely for matching purposes and were removed prior to analysis to preserve confidentiality.

The sample consisted primarily of traditional undergraduate students, with the majority between 18 and 24 years old. Most participants were male and enrolled as full-time students, and all reported taking the course as a requirement for their major. A large proportion of students were employed part-time in addition to their studies. No missing data were observed in the matched dataset; therefore, all participants were retained for analysis.

Table 1
Demographic Characteristics of Matched Participants (N = 20)

Variable	Category	n	%
Age	18–24	19	95
	25–34	1	5
Gender	Male	18	90
	Female	2	10
Enrollment Status	Full-time	20	100
Course Requirement	Major requirement	20	100
Employment	Part-time	14	70
	Full-time	3	15
	Student only	3	15

Note. Percentages are based on matched participants only.

4.2 Measures and Statistical Analysis

Student perceptions of eduBot were assessed using multiple survey items capturing overall attitude, perceived usefulness, engagement, confidence, responsiveness, and usability. Higher scores indicated more positive perceptions.

Because pre- and post-surveys used different response formats, all responses were standardized to a 0–100 scale. Paired-samples *t*-tests were conducted to evaluate changes over time. Wilcoxon signed-rank tests were also performed to confirm robustness. Statistical significance was evaluated at $\alpha = .05$. Effect sizes were calculated using Cohen's *d* for paired samples.

4.3 RQ1 – Changes in Student Perceptions

Overall perceptions of eduBot increased from pre-intervention ($M = 63.25$, $SD = 13.21$) to post-intervention ($M = 67.96$, $SD = 19.65$). The Wilcoxon signed-rank test yielded consistent results.

Table 2
Paired-Samples Comparison of Overall eduBot Perceptions

Measure	Pre M	Pre SD	Post M	Post SD	Mean Difference	t(19)	p	Cohen's d
Overall Perception Score	63.25	13.21	67.96	19.65	4.71	1.10	.286	0.25

Note. Scores standardized to 0–100 scale. Positive differences indicate improvement.

Item-level analysis revealed statistically significant improvements in two areas. Perceived usefulness for accessing syllabus and schedule information increased significantly, $t(19) = 3.94$, $p < .001$, with a large effect size ($d = 0.88$). Perceptions of timely responses also improved significantly, $t(19) = 2.95$, $p = .008$, with a moderate effect ($d = 0.66$).

Other variables showed positive but non-significant trends, while a few showed small non-significant decreases.

Table 3
Item-Level Matched Pre/Post Comparisons

Construct	Pre M	Post M	Mean Diff.	t(19)	p	Cohen's d
Overall attitude	62.50	76.25	13.75	1.87	.077	0.42
Syllabus/schedule access	58.75	77.50	18.75	3.94	< .001	0.88
AI tools for learning	73.75	68.75	-5.00	-0.64	.532	-0.14
Integration into courses	63.75	73.75	10.00	1.71	.103	0.38
Understanding materials	60.00	60.00	0.00	0.00	1.000	0.00
Timely responses	67.50	81.67	14.17	2.95	.008	0.66
Clarification of content	50.00	58.33	8.33	1.06	.304	0.24
Assessment performance	62.50	51.67	-10.83	-1.31	.205	-0.29
Engagement	58.75	63.33	4.58	0.86	.400	0.19
User-friendliness	75.00	68.33	-6.67	-0.90	.380	-0.20

Note. All values standardized to 0–100 scale.

4.4 RQ2 – Post-Intervention Perceptions

Post-intervention responses indicated generally positive perceptions of eduBot. Students reported the highest satisfaction with course logistics support and responsiveness.

Table 4

Percentage of Positive Post-Survey Responses

Construct	Positive (%)
Syllabus/schedule access	95
Timely responses	95
Overall attitude	90
AI tools for learning	85
Integration into courses	85
Understanding materials	80
Engagement	80
User-friendliness	80
Clarification of content	60
Assessment performance	55

Note. Positive includes responses at or above the “positive” category.

These results suggest that students primarily perceived eduBot as a tool for improving accessibility and course navigation rather than directly enhancing performance outcomes.

4.5 Summary of Findings

The findings indicate that eduBot was most effective in supporting logistical aspects of learning, particularly access to course information and timely responses. These functions are critical in engineering education, where course complexity and structure can create early barriers to engagement. By providing immediate, accurate, and course-specific support, eduBot enhances instructional accessibility and offers a scalable solution for supporting students in high-demand learning environments.

However, the impact on deeper learning outcomes, such as conceptual understanding and assessment performance, was limited. This suggests that AI teaching assistants are best positioned as complementary tools that support, rather than replace, traditional instruction.

Overall, the results demonstrate that eduBot was positively received and effectively supported course navigation and responsiveness. While broader impacts on learning require further investigation, the findings support the use of knowledge-grounded AI systems as scalable support tools in engineering education.

5. Conclusion

This study examined the implementation of eduBot, a retrieval-augmented conversational teaching assistant, in an engineering education context. Using matched pre/post survey data from 20 students, the findings suggest that eduBot was most effective in supporting course navigation and timely access to information. Students reported significant gains in their perceptions of eduBot's usefulness for accessing syllabus and schedule information and in its ability to provide timely responses to questions. These findings align with the original purpose of eduBot: to reduce logistical uncertainty, improve access to instructor-approved course information, and support students outside traditional class meeting times.

The overall composite perception of eduBot improved from pre-survey to post-survey. Students generally viewed eduBot positively with its strongest immediate value in practical and logistical support rather than in directly improving perceived assessment performance or conceptual understanding. Post-survey results showed that most students viewed eduBot as a tool for accessing course information, receiving timely support, and supporting engagement. These results provide preliminary evidence that knowledge-grounded AI teaching assistants can be useful in engineering education when they are carefully designed, constrained to instructor-approved materials, and integrated into the learning environment.

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