ISBN: 978-628-96613-3-0. ISSN: 2414-6390. Digital Object Identifier: https://dx.doi.org/10.18687/LACCEI2026.1.1.2614

Educational chatbots in the classroom: student perceptions and their role in supporting learning in Mining Engineering

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Abstract– *AI-based educational chatbots have emerged as innovative tools in higher education, showing positive impacts on intrinsic motivation and student engagement. This study examines the application of an experiential framework for the strategic implementation of conversational systems in Mining Engineering courses, specifically through a discipline-specific database for the course on mining extraction methods, whose pedagogically validated contents aim to address critical metacognitive dimensions in educational innovation. Designed to foster autonomous learning and complement traditional instruction, the intervention follows a quasi-experimental design with pretest and posttest instruments to evaluate cognitive (conceptual understanding), motivational (self-efficacy), and perceptual (satisfaction) variables over eight weeks, progressively integrating theoretical-practical activities aligned with the syllabus and assessments mediated by the chatbot. Preliminary results reveal high technological acceptance and statistically significant improvements in motivational dimensions, particularly in students' confidence to tackle complex engineering problems and in the perceived pedagogical value of the chatbot as a support tool. Overall, the findings suggest that conversational systems, when designed with a student-centered approach and integrated with active teaching strategies, constitute a viable, transferable, and scalable pedagogical resource to strengthen personalized and interactive educational models aimed at developing specific competencies in Engineering education. These findings should be interpreted with caution due to the reduction in sample size and the absence of a comparison group, which limit causal inference*

Keywords-- *Educational chatbots; artificial intelligence in higher education; autonomous learning; Mining Engineering.*

I. Introduction

Engineering education in Mining requires innovative methodologies that articulate complex theoretical knowledge with practical applications in dynamic industrial environments through the integration of emerging technologies into the teaching learning process [1]. Artificial intelligence (AI) based chatbot systems emerge as transformative tools that can provide personalized support, continuous availability, and adaptive feedback to engineering students [2]. These systems facilitate the understanding of complex concepts through real-time assistance, guided problem solving, and idea generation for projects, thereby improving academic preparedness [3]. Comparative studies confirm that regular users outperform nonusers academically, with significant differences in performance [4]. Others demonstrate positive influences on student achievement, knowledge retention, and teaching efficiency [5]. A meta-analysis of 51 studies reveals that the use of systems such as ChatGPT produces a significant positive effect, reflected in improvements in grades and conceptual understanding in experimental groups [6]. A controlled experiment at Georgia State University showed that students with access to a chatbot increased their grade rate by 16% compared to the control group. The evidence converges to indicate that chatbots, when integrated with pedagogical strategies, optimize performance through immediate feedback and personalization [7–9]. Moreover, they enhance student engagement by facilitating deeper interactions and increasing participation in academic activities, suggesting a virtuous cycle among technology, active learning, and educational success.

To a large extent, current research reports focus on isolated indicators of academic performance or student perception, without incorporating a multidimensional evaluation that jointly considers cognitive, motivational, and metacognitive variables [10]. This fragmented approach limits the understanding of the real impact of AI conversational systems on the educational process and hinders their transferability to other disciplinary or institutional contexts [11]. Consequently, it is necessary to advance toward replicable, evidence-based frameworks that allow assessment not only of chatbots' technological acceptance but also of their contribution to autonomous learning, self-efficacy, and students' perception of pedagogical usefulness.

II. Methods

The chatbot architecture is designed to ensure smooth, high-efficiency operation through a system that operates via a continuous flow of information and processing stages (see Fig. 1). Prior to deployment, the course corpus (selected books, articles, and official documents) is cleaned, segmented into fragments, and indexed by generating vector embeddings with OpenAI models, which are stored along with their metadata in a vector database. At query time, the user input is captured and normalized, then transformed into an embedding with the same model. This vector is used to query the vector database restricted to the course corpus and retrieve only the most relevant fragments of that material. Using those fragments and the stored conversation history, a carefully crafted prompt is built that explicitly instructs OpenAI GPT to respond only based on the provided texts and to state when the requested information is not found in the course material. GPT then generates a contextual response traceable to its sources, which is shown to the user, completing the interaction cycle.

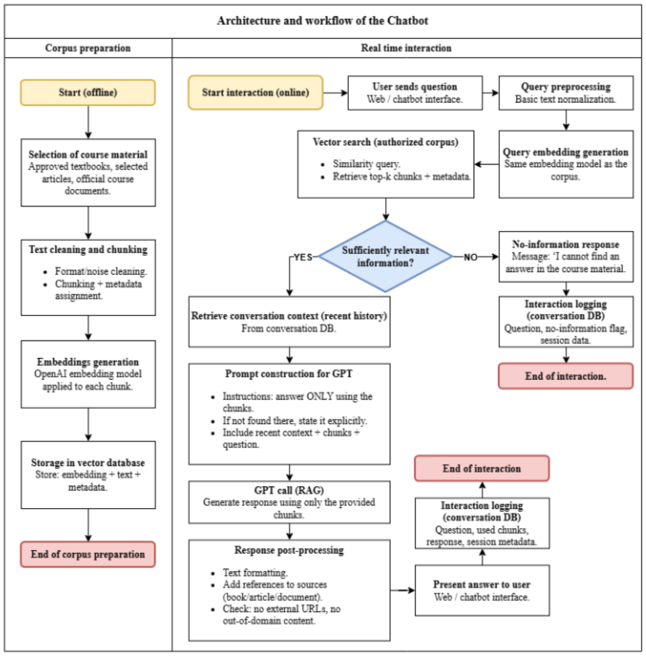

Fig. 1 Architecture and workflow of the academic chatbot (RAG restricted to the course corpus).

A. *Corpus Preparation (offline)*

On the left side of Fig. 1 it can be seen how the system begins with the selection of the authorized course material, a task in which the instructor identifies approved textbooks, relevant scientific articles, and official course documents such as notes, guides, or regulations. Next, that set of texts undergoes a cleaning and segmentation process, in which formatting elements and noise are removed and the content is divided into manageable fragments or chunks, to which metadata describing their source, section, page, or topic are assigned. Once segmented and annotated, the corpus is transformed into a vector space by generating embeddings, using an OpenAI embedding model that converts each fragment into a numeric vector capturing its semantic meaning. These vectors, together with the chunk texts and their metadata, are finally stored in a vector database that acts as the semantic index of the course corpus and is ready to be queried during real-time interactions.

B. *Real-time Interaction (online)*

On the right side of Fig. 1 the workflow activated each time a student interacts with the chatbot is shown: the question is first received through the web interface and subjected to basic preprocessing, in which the text is normalized to ensure a consistent representation. Next, an embedding of the query is generated using the same embedding model employed for the corpus, allowing the question to be compared with the fragments stored in the vector database. With this vector, the system performs a similarity search in the database, retrieving the top-k chunks that are semantically closest and their associated metadata. Once those fragments are obtained, the system evaluates whether the retrieved information is sufficiently relevant by applying criteria such as a minimum similarity threshold and a minimum number of useful chunks. If the decision is negative, the chatbot generates a response indicating that it cannot find the requested information in the course material and suggests that the student consult the instructor or the recommended bibliography; this interaction is recorded in the conversation database and the turn concludes. If, on the contrary, the information is considered adequate, the system proceeds to retrieve the recent conversation context from the history database so that it can maintain coherence in multi-turn dialogues. With the user's question, the relevant chunks, and the session context, it then constructs a prompt for GPT that includes explicit instructions to respond only from the provided fragments and to declare when the answer is not contained therein. The GPT model generates a natural language response conditioned by that prompt, which is subsequently post-processed to improve formatting, add references to the sources used, and perform basic domain checks. Finally, the system presents the response to the user in the interface, records the entire interaction, the chunks used, the response, and the session metadata in the conversation database, and leaves the flow ready to handle a new query.

C. *Chatbot Implementation*

From a methodological-operational perspective, the integration of technology is supported by the combination of the 5E instructional model [12], the ARC motivational model [13] and a competence-based learning approach, allowing the intervention to be structured in a systematic and replicable manner. The measurement instrument relies on student entry and exit tests, formulated as two assessments structured around five dimensions [14]: (1) *Physical* (*Df*), which captures students' perceived appropriation of the technological environment, including the accessibility, usability, and quality of interaction with the chatbot interface; (2) *Cognitive* (*Dc*), which refers to self-perceived conceptual understanding and the ability to connect new information with prior disciplinary knowledge; (3) *Motivational* (*Dm*), which assesses self-efficacy beliefs and the level of engagement and commitment toward learning tasks mediated by the tool; (4) *Emotional* (*De*), which reflects students' emotional regulation, academic confidence, and reduction of anxiety when facing complex technical problems with AI support; and (5) *Temporal Perception* (*Dt*), which evaluates the students' subjective sense of time invested and learning efficiency during chatbot-assisted study sessions.

III. Applications

The implementation of the metacognitive instruments was carried out in a Civil Mining Engineering course, specifically in the subject Mining Extraction Methods. The sample comprised 35 students who participated in the pretest application and 35 students in the posttest phase. The study measured metacognitive variables and also included an additional variable aimed at capturing emerging dimensions associated with the use of AI assistants during the usage period. Data were collected using instruments based on a five-point Likert scale (from strongly disagree to strongly agree), focused on the five evaluation dimensions. The analysis did not include academic grades or formal course assessment performance, nor was it oriented toward relational analysis among variables given the implementation's evaluation period, adopting a descriptive and metacognitive approach centered on examining the implementation experience of these systems and their integration into the educational process of engineering students.

A. Methodological implementation approach

The pedagogical intervention was structured in four progressive phases (Introduction, Competency Development, Application of knowledge integration activities, and Evaluation-Reflection), combining synchronous and asynchronous activities with systematic integration of an AI assistant configured under a closed-corpus model. The methodological design was grounded in principles of active learning, adaptive scaffolding, project-based learning (PBL), and guided metacognition. In synchronous mode, introductory workshops, technical problem-solving sessions, industrial case analyses, guided simulations, and technical debates supported by the chatbot were conducted. Conversely, during asynchronous activities students were encouraged to explore the assistant autonomously, maintain weekly metacognitive journals, perform technical research for the integrative project, and conduct post-evaluation reviews with AI support, with a focus on consolidating self-regulation, strengthening conceptual understanding, and strategic use of the chatbot as a professional tool. Various techniques and application tools were defined (see Table 1) to enable the ethical, progressive implementation and use of the chatbot during the 8-week deployment.

Table 1. Implementation techniques and tools.

Modality	Teaching Technique	Main Tools	Function of the AI Assistant
Synchronous	Workshops and AI literacy	Chatbot RAG, projector, LMS	LMS Modeling use and prompt formulation
Synchronous	Technical problem solving	Chatbot + problem bank + specialized software	Immediate adaptive feedback
Synchronous	Case analysis and technical debates	Chatbot + forum + rubric	Disciplinary informational support
Synchronous	Controlled assessments	Presentations and infographics	Independent measurement of learning
Asynchronous	Autonomous exploration	Chatbot 24/7 + interaction logging	Self-regulated support
Asynchronous	Metacognitive journal	LMS + rubric + chatbot	Structured reflection
Asynchronous	Development of integrative project	Chatbot + digital library + collaborative document	Conditioned technical consultant
Blended	Continuous formative assessment	Adaptive quizzes + analytics	Identification of gaps
Blended	Post-assessment review	Chatbot + exam results	Conceptual consolidation

B. Complementary resources for pedagogical integration

With the aim of strengthening autonomous learning and the strategic appropriation of the tool, complementary resources were implemented specifically to support students within the experimental group. These resources included structured usage guides with examples of effective prompts, ethical interaction criteria, and guidelines for formulating contextualized technical queries. During sessions, the assistant was used as a support tool in problem-solving activities, disciplinary case analyses, and the preparation of academic products, such as technical infographics on underground mining methods, employing the assistant for search, synthesis, and validation of information exclusively within the authorized corpus, thereby promoting digital, disciplinary, and metacognitive competencies. Additionally, guided reflection instances were incorporated through metacognitive journals and post-assessment reviews supported by the assistant, enabling the identification of conceptual gaps and adjustment of study strategies, functioning as progressive scaffolding that favored self-regulation and the critical use of AI as an academic tool.

IV. Results

The comparative analysis of means between pretest and posttest revealed differentiated changes depending on the evaluated dimension (see Table 2). *Df* showed an increase of 30.2%, representing the largest percentage shift observed. *Dm* and *De* increased by 21.9%. In contrast, *Dc* remained stable with a variation of 0.8%, while *Dt* exhibited a slight decrease of 2.9%. The dimensions *Df*, *Dm*, and *De* showed statistically significant increases between pretest and posttest ($p < 0.001$), accompanied by large to extremely large effect sizes ($d > 1.9$). This pattern suggests that the intervention primarily affected variables associated with the subjective experience of technology-mediated learning.

Table 2. Comparison of means in metacognitive dimensions.

Dimension	Pre-test μ	Post-test μ	Diff. (%)	p-value

Df	3.404	4.433	30.2%	0.0000
Dc	4.316	4.283	-0.8%	0.7794
Dm	3.581	4.367	21.9%	0.0000
De	3.404	4.15	21.9%	0.0000
Dt	4.375	4.25	-2.9%	0.2708

Table 3 complements the analysis by incorporating Student's t values, 95% confidence intervals, and effect size (Cohen's d). The results confirm the statistical robustness of the differences observed in dimensions *Df*, *Dm*, and *De*. In these cases, the confidence intervals do not include zero, supporting the existence of a real change between pretest and posttest. Moreover, the reported effect sizes are large, substantially exceeding the conventional 0.8 threshold considered a large effect in educational research. This indicates that the magnitude of the impact is not only statistically significant but also meaningful from practical and pedagogical perspectives.

Table 3. Results of the inferential pretest–posttest analysis by dimension (Student's t, 95% CI, and Cohen's d effect size).

Dimension	t-Student	IC 95% (lower)	IC 95% (upper)	Cohen's d
Df	-9.3412	0.818	1.24	2.9563
Dc	0.2818	-0.263	0.197	-0.0892
Dm	-7.0522	0.568	1.004	2.2328
De	-6.2999	0.522	0.969	1.9932
Dt	1.1143	-0.359	0.109	-0.3533

Fig. 2 shows the comparison of means between pretest and posttest for the five evaluated dimensions. Visually, a consistent positive shift is observed in *Df*, *Dm*, and *De*, where the posttest bars clearly exceed those of the pretest, corroborating the increase reported in the statistical analysis. In particular, the physical dimension exhibits the largest visual differential, reflecting the previously identified 30.2% increase, which suggests significant appropriation of the technological environment and use of the assistant as an academic resource. Similarly, *Dm* and *De* show sustained increases, consistent with strengthened self-efficacy and affective regulation when facing complex technical tasks.

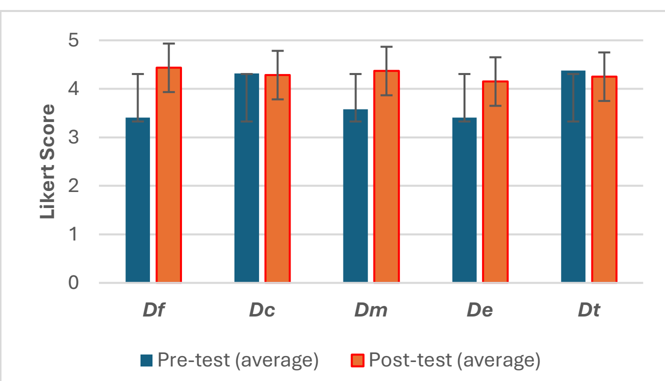

Fig. 2 Average dimension scores: pretest vs. posttest.

The error bars suggest a slight reduction in dispersion in some dimensions at posttest, indicating greater perceptual homogeneity following the intervention. The graphical representation supports the pattern identified in the inferential analysis, indicating that the chatbot's impact manifests mainly in experiential and motivational dimensions, consolidating favorable conditions for autonomous learning without substantially altering the initial cognitive self-perception.

V. Discussion

In the context of self-directed learning, it is relevant to discuss the formative gains afforded by a customized chatbot compared with the use of generic AI engines such as ChatGPT, DeepSeek, Gemini, and others. The proposed personalized system is constructed by regulating responses and ensuring uniformity of content and information. This advantage is grounded in three key aspects:

- *Disciplinary accuracy and content control:* Unlike generic models, which may generate responses based on unvalidated or outdated sources, the customized chatbot operates exclusively with curricular materials approved by instructors (guides, articles, textbooks). This eliminates the risk of "hallucinations" or information contradictory to the syllabus, enabling safe autonomous learning aligned with the educational objectives.

- *Pedagogical contextualization:* The system was designed with prompts and examples specific to the course, guiding students in formulating relevant queries and promoting domain-specific critical thinking skills characteristic of engineering. In contrast, generic assistants lack this layer of didactic mediation, which can lead to superficial interactions or disconnection from the competencies to be developed.

- *Integration with teaching methodology:* The chatbot was implemented as part of an active pedagogical ecosystem, complementing in-class demonstrations, practical activities, and assessments designed by the faculty. This integration fosters guided autonomy, where the student explores content within a clear frame of reference, unlike isolated use of generic tools that may encourage passive dependence on immediate answers without metacognitive reflection.

The results suggest that a closed RAG system, built on course-validated materials, is an effective strategy for addressing the problem of "hallucinations" in generative models, ensuring curriculum-aligned responses with traceability to their sources. This characteristic substantially differentiates the personalized chatbot from generic assistants like ChatGPT, whose extensive corpus can lead to irrelevant or contradictory information. In this context, the observed increase in motivational and emotional dimensions can be interpreted as evidence that discipline-specific chatbots foster student engagement and self-efficacy, reinforcing students' confidence in their ability to tackle more complex engineering problems.

VI. LIMITATIONS

The study has several methodological limitations that should be considered when interpreting the results. First, its scope is restricted to a single engineering course over one academic semester, which limits the generalizability of the findings to other educational contexts. To enhance replicability and external validity, future research should expand implementation to multiple courses across different engineering disciplines and institutional settings. This would enable interdisciplinary comparisons of the chatbot's impact on perceptual and motivational outcomes. Additionally, longitudinal designs involving successive student cohorts could help determine whether improvements in the physical, motivational, and emotional dimensions are consistent across diverse populations or specific to the current sample. Second, the absence of a comparison group prevents causal attribution of the observed changes exclusively to the chatbot intervention. Factors such as the natural progression of the course, instructor influence, or increased familiarity with the content may have contributed to the reported variations. Consequently, the findings should be interpreted as temporal associations rather than causal effects. Future studies employing equivalent assessment tools to compare groups with and without chatbot access would strengthen causal inference and provide more robust evidence to support institutional adoption of conversational AI in higher education. Finally, the results rely solely on self-reported perceptions and lack objective measures of academic performance. This restricts the ability to directly link the intervention to improvements in disciplinary learning. Future research should incorporate performance-based indicators, such as course grades, standardized test scores, or competency assessments, to complement the perceptual evidence and provide a more comprehensive evaluation of the chatbot's educational impact.

VII. CONCLUSION

The intervention was designed to bridge the gap between traditional content-transmission approaches and current demands for active, autonomous, technology-mediated learning, integrated within a structured instructional design and positioned as a complementary resource to the teacher's role. The findings can be interpreted in light of constructivism: the tool's integration facilitated active knowledge construction processes through continuous interaction, immediate feedback, and guided exploration of disciplinary content, also enabling an association between autonomy and motivation and how these relate to self-regulated learning theory by showing that the tool promoted planning, monitoring, and adjustment of students' own study processes in a structured digital environment. The system's design, based on prompts oriented toward reflection and the formulation of pertinent questions, contributed to strengthening metacognitive processes, fostering awareness of problem-solving strategies and conceptual understanding. The physical/environmental, motivational, and emotional dimensions showed increases accompanied by large to extremely large effect sizes, suggesting the intervention primarily impacted dimensions associated with the subjective experience of technology-mediated learning. In the physical dimension, the increase may be interpreted as an improvement in perceived accessibility, usefulness, and coherence of the digital environment, indicating progressive technological appropriation and reduced friction in interacting with the system. This pattern is mirrored in the motivational dimension as a positive shift reflecting strengthened perceived self-efficacy and commitment to more complex tasks, consistent with motivational models such as ARCS, where relevance and confidence are consolidated through immediate feedback. Regarding the emotional dimension, the observed increase suggests a reduction in academic anxiety and a rise in confidence when facing technical problems, supporting the assistant's role as affective as well as cognitive scaffolding.

Conversely, the cognitive and temporal-perception dimensions did not show statistically significant changes. This stability should not necessarily be interpreted as absence of effect; rather, it can be explained from several complementary perspectives. First, both dimensions exhibited high baseline values in the pretest, suggesting a possible ceiling effect that limited the observable magnitude of change. Second, it is plausible that the intervention activated self-regulation and metacognitive recalibration processes, whereby students adjusted their initial perceptions after real-use experience, tempering idealized expectations toward more realistic and critical evaluations. Likewise, stability in the cognitive dimension may reflect that the assistant functioned as a support tool rather than a substitute for formal conceptual learning, preserving previously consolidated self-perceptions of competence. In the case of the temporal dimension, the absence of significant change could be associated with natural maturation effects over the academic term or with the instrument's limited sensitivity to capture subtle variations in perceived learning time during a relatively brief intervention period.

In conclusion, the incorporation of personalized educational AI systems, articulated with active teaching orientation, constitutes an effective strategy to promote innovation, student engagement, and learning personalization in university engineering programs. This approach contributes both to strengthening the institutional training model and to developing a sustainable digital educational culture aligned with the competencies required in the current professional context. For future research, it is recommended to incorporate a sixth dimension related to student performance by comparing grades across different academic periods to analyze possible correlations with metacognitive dimensions.

ACKNOWLEDGMENT

The authors thank the Faculty of Engineering and Business of Universidad Santo Tomás for the institutional support and funding provided for the participation and registration of this work at the 24th LACCEI International Multi-Conference for Engineering, Education and Technology "Engineering without Borders: Artificial Intelligence, Knowledge, Innovation, and Alliances for a Future from the Americas," held from July 15 to 17, 2026, in Santiago, Chile.

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