Online-Journals.org

iJEP International Journal of Engineering Pedagogy

iJEP | eISSN: 2192-4880 | Vol. 16 No. 6 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijep.v16i6.61849

PAPER

AI-Mediated Feedback in Computer-Aided Drafting Education: Exploratory Evidence on Student Performance and Perceptions

Víctor A. Erazo-Arteaga (✉), Santiago Marcelo Vacas Palacios, Marcelo Bayardo Cisneros Rúales

Universidad Técnica del Norte, Ibarra, Ecuador

vaerazo@utn.edu.ec

ABSTRACT

Large higher-education classes make timely feedback during practical sessions difficult, encouraging the use of artificial intelligence (AI) as a complementary resource in technical education. This study examined AI-mediated feedback during computer-aided drafting (CAD) activities using structured prompts and task segmentation, alongside instructor-provided feedback across alternating phases. Academic performance and student perceptions were analyzed in a classroom environment. A quasi-experimental within-subjects ABAB design was implemented with 34 first-year Industrial Engineering students over 20 weeks, as the curriculum progressed from two-dimensional (2D) drafting to three-dimensional (3D) modeling. Results showed significant performance variation, with lower scores in later phases involving greater procedural demands. Since feedback modalities were embedded within the curricular progression, these differences cannot be interpreted as isolated causal effects of feedback modality. Students rated both modalities positively and considered AI-mediated feedback useful for resolving specific doubts, although not more useful than instructor feedback, particularly in 3D tasks. AI-mediated feedback may complement CAD instruction, depending on task complexity, prompt precision, response reliability, and instructor guidance.

KEYWORDS

educational feedback, artificial intelligence (AI), academic performance, student perceptions, practical learning, quasi-experimental design, higher education, computer-assisted learning, AI-mediated feedback.

1 INTRODUCTION

Specialized literature recognizes feedback as an important element for identifying strengths and areas for improvement in teaching and learning processes. In this context, timely and meaningful feedback contributes to student engagement and

Erazo-Arteaga, V. A., Palacios, S. M. V., Rúales, M. B. C. (2026). AI-Mediated Feedback in Computer-Aided Drafting Education: Exploratory Evidence on Student Performance and Perceptions. *International Journal of Engineering Pedagogy (iJEP)*, 16(6), pp. 51–74. https://doi.org/10.3991/ijep.v16i6.61849

Article submitted 2026-04-07. Revision uploaded 2026-08-13. Final acceptance 2026-08-13.

© 2026 by the authors of this article. Published under CC-BY.

learning outcomes, whereas limitations in feedback may lead to dissatisfaction and difficulties in the educational process [1].

Feedback also promotes interaction between instructors and students through dialogic processes that facilitate the identification of errors and the resolution of specific difficulties, thereby supporting learning and skill development [2].

Ideally, during feedback sessions, instructors respond to students' questions as they arise, which helps consolidate learning before moving on to new content. However, the quality of feedback is often conditioned by the student-to-instructor ratio [3], [4]. This situation is particularly evident during the first year of engineering education, where feedback must be provided to large groups with different levels of prior knowledge, learning styles, and sociocultural backgrounds [5].

This heterogeneity is particularly evident in courses that integrate theoretical concepts with practical applications, such as Computer-Aided Drafting (CAD). In this discipline, learning requires the integration of geometric and mathematical knowledge with graphical representation and spatial visualization skills, competencies that are not developed uniformly among students. This complexity highlights the need for teaching strategies capable of addressing different learning paces, levels of understanding, and learning styles [6], [7].

The challenge of addressing this diversity has driven the development of automated approaches in education. In this context, artificial intelligence (AI) has demonstrated the potential to strengthen engineering education when incorporated into discipline-specific learning activities through adaptive learning environments and intelligent tutoring systems [8], [9].

More specifically, AI can support students throughout the learning process by explaining concepts, suggesting procedures, and providing guidance during problem-solving activities. This function is particularly beneficial for students who experience difficulties participating in class or feel hesitant to ask questions to the instructor, as it provides a more accessible and less restrictive learning environment [10].

From a pedagogical perspective, AI can also analyze learning patterns and identify students' specific learning difficulties, providing valuable information to support instructional decision-making. In this sense, its value extends beyond answering students' questions by strengthening monitoring, guidance, and feedback processes, provided that it serves as a facilitator of the learning process rather than replacing students' reasoning and problem-solving abilities [11], [12], [13].

However, within engineering education, the integration of AI with CAD tools is still in its early stages, and the available evidence is largely limited to studies published since 2024.

With the aim of analyzing engineering students' decisions to use or not use generative AI (GenAI) tools in academic projects within an engineering design course, an experiment was conducted with 403 students who were given voluntary access to a GPT-4.0-based chatbot. The results showed that 59.8% of the students used GenAI mainly for idea generation and feedback, whereas 40.2% avoided using it due to technical limitations and its limited alignment with their learning objectives. Although the study provides relevant evidence regarding the use of GenAI in engineering design contexts where CAD is a core tool, feedback was not the central focus and learning was not measured through quantitative instruments. Instead, the study focused on analyzing students' perceptions and experiences [14].

A systematic literature review was conducted to analyze 228 articles published between 2018 and 2023 and identify AI applications in mechanical engineering education. The results indicate that AI can support computer-aided design (CAD) learning. However, this conclusion is supported by only four articles that directly address the topic [15].

Similarly, a training program based on learning nuggets is proposed to develop skills in generative engineering. In this study, AI is not used as a pedagogical tool but rather as a subject of study, and assessment relies primarily on automated tests. The results suggest that participants perceive AI as useful in engineering design. However, although practical activities are included, they do not address the development or assessment of technical 2D and 3D modeling skills, focusing instead on understanding generative design, with no evidence of improvement in practical skills [16].

Another study presents an automated assessment system designed to compare students' CAD drawings with a reference solution. The system uses an AI-powered computer vision engine to identify errors, such as missing or incorrect lines, and highlight them visually, enabling iterative corrections. However, the study does not report experiments, pre- and post-tests, or evidence of improvement in practical skills [17].

A theoretical proposal is presented for a personalized computer-aided design (CAD) learning system within a design engineering course. The approach is based on surveys of students and instructors, with data analyzed through categorization. Although the study does not measure the development of practical skills, it provides insights into learning experiences and proposes the use of AI to generate personalized content [18].

Across these studies, AI has been applied primarily as an automated assessment tool or as a content-generation tool, with limited attention to its role as a real-time support resource during task execution and with no evidence regarding how its effectiveness may vary as content complexity increases.

This study analyzes the use of AI as a feedback tool during practical learning in a CAD course. Its contribution does not lie in establishing that AI improves CAD performance or in providing a causal comparison between AI-mediated and instructor-provided feedback. Rather, the study provides exploratory classroom-based evidence on how AI-mediated feedback may support students during practical CAD activities, particularly by helping them continue task execution when immediate instructor assistance is unavailable. At the same time, the study examines how this support is conditioned by task complexity, students' ability to formulate prompts, the reliability of AI-generated responses, and the continued role of instructor guidance.

Two research questions are posed: RQ1: What variation is observed in student performance across instructional phases involving AI-mediated feedback and instructor-provided feedback during practical CAD learning? RQ2: How do students perceive the usefulness of AI-mediated feedback and instructor-provided feedback during practical CAD learning?

2 MATERIALS AND METHODS

2.1 Study design

The study employed a quasi-experimental, longitudinal, within-subjects design conducted in an authentic classroom setting. Two feedback modalities were implemented during practical sessions: instructor-provided feedback (Condition A) and AI-mediated feedback (Condition B). These modalities were applied alternately following an ABAB sequence across four consecutive instructional phases.

Each phase lasted five weeks, and at the end of each phase, students completed a practical assessment (E1–E4). In Condition A, feedback was provided by the instructor without the use of AI tools. In Condition B, feedback was generated through AI

using multimodal prompts (text and images); during this phase, the instructor's role was limited to observation and did not involve providing solutions or intervening in task completion.

Unlike a classical reversal design, in which the second A phase aims to return to baseline levels, in this study the second A phase allowed observation of performance during a subsequent instructor-provided feedback phase after an AI-mediated feedback phase. The ABAB sequence was implemented within the natural structure of the course.

Across the instructional phases, the instructional content progressed from two-dimensional (2D) to three-dimensional (3D) modeling tasks, resulting in increasing procedural and spatial complexity throughout the course sequence.

2.2 Participants and context

Participants were first-year Industrial Engineering students enrolled in a compulsory CAD course. The study was conducted with an intact group; no random assignment was performed.

A total of 36 students were enrolled in the course. Prior to data collection, an informational session was held to explain the purpose of the study and to indicate that participation was voluntary. Students were informed that non-participation or withdrawal from the study would not affect their course grades, access to academic support, or classroom treatment, and that all students, regardless of participation, would receive the same instructional conditions and learning opportunities. Under these conditions, all students signed informed consent forms.

During the course of the study, two students withdrew from participation in the research, although they continued attending the course. Consequently, the final analysis included data from 34 participants, as incomplete data could not be incorporated into the repeated-measures analysis.

The study was conducted within a 20-week course (September 2025 to February 2026), with a weekly workload of five hours, consisting of one hour of demonstration, two hours of guided practice, and two hours of independent practice. All students received instruction under identical conditions (same instructor, schedule, classroom, and curricular sequence).

Data were anonymized prior to analysis. The study procedures and instruments were reviewed at the departmental level by an ad hoc committee composed of an educational psychology specialist and a Doctor of Education, which determined that the study did not involve physical or psychological risk. In accordance with institutional procedures, studies classified as minimal or no risk do not require further review by an external ethics committee.

The course instructor was also the principal investigator. To minimize potential bias associated with this dual role, all students were assessed using the same procedures and criteria within the standard course structure.

2.3 Teaching methodology

The course content was developed progressively through two thematic modules. The first focused on 2D drafting tools defined by geometric relationships and measurements. The second addressed 3D modeling and Boolean operations, followed by the introduction of model verification concepts, including physical properties and dimensional control.

The instructional methodology consisted of three instructional stages that were maintained throughout the experimental period: instructor demonstration, guided practice, and independent practice. This structure was maintained throughout the four instructional phases to preserve consistency in the teaching process.

During the demonstration stage, the instructor presented the commands and explained their application by solving a complete exercise, including a verbal description of the procedure and usage criteria. Students observed, took notes, and asked questions. During the guided practice stage, students developed an exercise collaboratively by following the instructor's step-by-step demonstration. Progress was paused at predefined points to review group performance, identify errors, and address questions before continuing. Feedback was concentrated in the independent practice stage, in which each student completed an exercise without prior demonstration.

Peer interaction was allowed throughout all phases of the study, including the exchange of problem-solving strategies. In the AI-mediated condition, this also included sharing variations of prompts. This practice was maintained consistently across both feedback modalities, without favoring either modality. No differential restrictions were imposed on peer interaction across modalities.

The exercises used across the three instructional stages featured different geometries but were designed to require similar theoretical foundations and comparable command usage, as shown in Figure 1. This design aimed to maintain relatively consistent procedural demands across sessions.

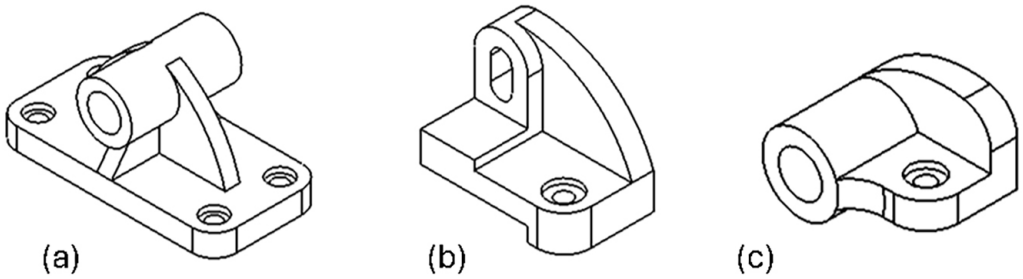
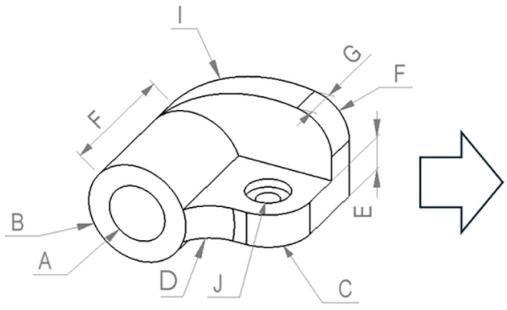


Fig. 1. Exercises used during the three class periods: (a) Instructor demonstration; (b) Guided practice; (c) Independent practice

During the independent practice session, each student completed a different exercise derived from a common geometric structure. While the geometry and underlying theoretical requirements remained the same, the measurements varied across students. This approach allowed students to work on structurally comparable tasks while performing the modeling procedure independently. These variants were generated using the parametric customization process proposed by [19], as illustrated in Figure 2.



Exercise	Dimensions (mm)									
	A	B	C	D	E	F	G	H	I	J
1	15	25	15	12	10	18	12	40	50	18-3-9
2	21	31	20	14	15	24	20	44	54	19-3-10
3	25	33	28	17	20	26	26	52	61	20-3-11
4	30	39	30	18	28	33	28	56	65	18-3-8
-	-	-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-	-	-
N	26	38	34	26	26	38	22	55	62	20-4-15

Fig. 2. Example of personalized exercise

2.4 Implementation of AI-mediated feedback

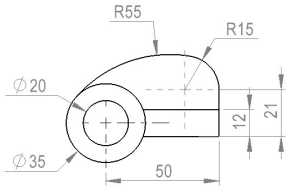
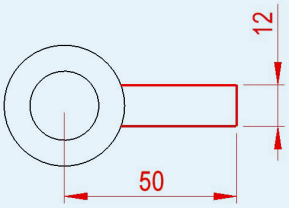
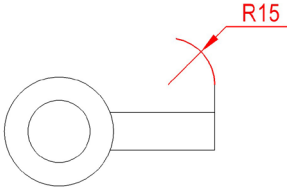
AutoCAD (educational version) and ChatGPT were the tools used during the course. Students accessed ChatGPT through their individual personal accounts using the free version available during the academic period.

During this time, the platform performed automatic model updates, meaning that the active version could vary without user intervention. Additionally, when the usage limits of the primary model were reached, the system automatically switched to versions with reduced reasoning capabilities. The number of interactions permitted by the free version also depended on how each student formulated and conducted their prompts, resulting in differences in the continuity and intensity of AI use during task completion.

Therefore, although the task structure, reference material, and general prompt template were common across students, the AI-mediated feedback modality was not fully standardized at the level of model availability, model version, interaction frequency, prompt formulation, prompt refinement, or response quality. The study also did not control or measure students' ability to critically evaluate AI-generated responses. These elements were part of the naturalistic implementation of AI-mediated feedback and were not experimentally controlled, because imposing stricter control over individual AI interactions would have altered the authentic classroom conditions under which the intervention was implemented.

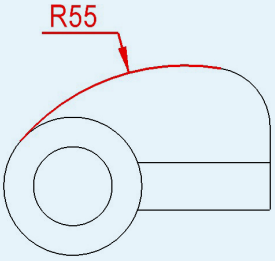
Since the CAD exercises were based on technical views, these views were used as visual inputs to formulate prompts for the AI system. From each view, students generated partial images corresponding to specific segments of the model in order to guide the feedback toward concrete actions in the modeling process rather than toward the complete resolution of the task. Table 1 presents an example of the prompt formulation process.

Table 1. Decomposition of a CAD view for prompt formulation

Sequence	Image Used According to the Exercise Status	Objective
Base view		View provided in the exercise from which the student performs the decomposition according to the needs of the problem.
Prompt 1		Request guidance on constructing the straight segment.
Prompt 2		Request guidance on building the arch.

(Continued)

Table 1. Decomposition of a CAD view for prompt formulation *(Continued)*

Sequence	Image Used According to the Exercise Status	Objective
Prompt 3		Request guidance to complete the geometry.

The knowledge source was restricted to a single reference in order to maintain alignment between the responses and the course content. The selected resource was the book *AutoCAD 2017: curso Práctico* [20], available through the institutional library via the eLibro platform, which allows the download of sections in PDF format for academic use. Students generated these excerpts individually and uploaded them to ChatGPT as a reference base to formulate their prompts during the completion of the exercises.

As of the date of this study, the platform's terms of use contained no explicit prohibition against the academic use of partially downloaded excerpts in interactions with artificial intelligence tools. In addition, written authorization for this academic use was obtained directly from the publisher, Grupo Editorial RA-MA.

As shown in Table 2, two types of prompts were used. The first type restricted the knowledge source by loading PDF excerpts of the reference book and including a brief confirmation instruction. The second type of prompt was used during exercise completion and followed a defined structure that included context, role, student level, problem description, and commands mastered or in progress.

Table 2. Prompts used

Type	Prompt
Initial	You must use only the attached book to answer the questions in this chat. Do you understand? Please answer with a simple "yes" or "no."
Work	You must respond using only the book attached at the beginning of the chat. Act as a university instructor with expertise in CAD. Keep in mind that I am a first-year Industrial Engineering student. I am having difficulty creating the section marked in red in the image attached to this message in AutoCAD; I have already completed the section shown in black. Explain the procedure step by step, indicating the AutoCAD commands needed to correctly construct the red geometry. Keep in mind that I have mastered the following commands: (insert here the commands you have mastered), and I am currently learning the following: (insert here the commands you are learning).

At the beginning of each exercise, a new conversation was initiated, and interaction histories were not retained across sessions.

Students followed the prompt structure described in Table 2; however, the specific content of each interaction varied depending on the level of command proficiency and the geometric segments requiring guidance during task execution. Since the exercises were individualized, the elements addressed in the prompts were not uniform.

Interaction histories were not systematically collected, as imposing strict control over prompt formulation would have altered the naturalistic conditions of AI use that the study intended to observe. Additionally, systematic monitoring of individual interactions was deliberately avoided to prevent students from feeling pressured

to demonstrate either proficiency with the tool or favorable outcomes, which could have introduced response bias into both task performance and perception data.

Regarding data privacy, prompts, partial images of CAD exercises, and book excerpts were transmitted to OpenAI servers as part of the platform's normal operation. Students were informed that ChatGPT would be used as a support tool during the course.

2.5 Assessment instruments

A diagnostic assessment (T0) was administered before the beginning of the course to identify students' prior knowledge related to CAD. The instrument included 20 items focused on the interpretation of orthographic and axonometric views, recognition and application of basic CAD commands, and concepts associated with geometric constraints.

The four practical assessment occasions (A1, B1, A2, and B2, corresponding to E1, E2, E3, and E4, respectively) were conducted under standardized conditions and without instructor assistance or access to AI tools. Following the logic of the independent practice activities, each student completed an individualized exercise derived from a common geometric structure with variations in dimensions (see Figure 2). At the time of assessment, exercise variants were assigned individually through a non-repeated random selection process so that no exercise configuration was repeated among students.

The assessments were aligned with the curricular objectives corresponding to each instructional stage and were designed to match the expected level of difficulty associated with the planned progression of the course. E1 and E2 assessed 2D modeling tasks, whereas E3 and E4 assessed 3D modeling tasks. Although the procedural and spatial demands differed between these types of tasks due to the nature of the content, each assessment was intended to correspond to the competencies students were expected to demonstrate at that stage of the course.

All assessments were scored by the course instructor using a common analytic rubric with a scale from 0 to 10 points. The scoring procedure consisted of two stages. First, a visual inspection was performed to determine whether the model had the expected overall geometry; models that did not meet this basic criterion were not scored further.

Second, each model was scored using 20 scoring items, each worth 0.5 points. The rubric included ten-dimensional measurements, nine geometric joints or connections, and one physical property. The physical property corresponded to area for 2D sketches and volume for 3D solids. Dimensional measurements and physical properties were considered correct when they were within a 2% tolerance of the expected value. Each item was scored on a pass/fail basis: a correct item received 0.5 points, whereas an incorrect item received 0 points.

The rubric, exercises, and assessment materials were reviewed before implementation by three specialists in computer-aided design and manufacturing, each with more than eight years of teaching experience. The review process focused on alignment between the assessments, curricular objectives, and expected procedural demands at each instructional stage.

Prior to each assessment session, the scoring criteria and tolerance thresholds were reviewed to ensure uniform application across assessments. Assessment conditions, including classroom environment and allotted completion time, were maintained consistently across all assessments.

2.6 Characterization and perception instruments

Participants were identified using an anonymized code. At the start of the study, the researchers recorded basic demographic variables, including sex (F/M), age (in years), and regular access to a computer outside the classroom (yes/no). Information was collected on students' prior experience with technical drafting and CAD software using a five-level ordinal scale (1 = none, 2 = basic, 3 = intermediate, 4 = advanced, 5 = expert). The frequency of prior use of AI tools for academic purposes was recorded using a five-category ordinal scale (1 = never, 2 = almost never, 3 = occasionally, 4 =frequently, 5 = always).

At the end of the study, students completed a perception questionnaire regarding the feedback modalities used during practice sessions. The instrument included five-point Likert-scale items with response anchors ranging from 1 = strongly disagree to 5 = strongly agree, covering the following dimensions: perceived usefulness of instructor explanations, usefulness of AI-mediated feedback for resolving doubts, ability to continue exercises without immediate instructor intervention, and perceived appropriateness of AI as a learning support tool. A comparative item was also included to assess the relative usefulness of AI-mediated feedback versus instructor-provided feedback, using a scale from 1 = much less useful to 5 = much more useful.

For reporting purposes, responses were grouped into three categories: disagreement (scores 1–2), neutral (score 3), and agreement (scores 4–5). This grouping was applied to facilitate the descriptive interpretation of results and is consistent with the exploratory purpose of the instrument. Initial inspection and analysis of the questionnaire responses were conducted using the original five-point scale. The grouping procedure was applied only for descriptive reporting purposes and not for inferential statistical analysis.

The instrument also included an open-ended question about perceived difficulties during AI use. Responses were analyzed jointly by the three authors through a collaborative coding process. Each response was read individually, and relevant text segments were labeled inductively to describe the difficulty expressed. Categories were derived from recurring themes identified through this process, supported by word frequency. Given the collaborative nature of the process, in which all three authors read and discussed each response jointly, no formal discrepancies requiring resolution arose.

Given the compound nature of several responses, categories were not mutually exclusive; a single response could be assigned to more than one category if it referenced multiple difficulties. Multiple responses included references to difficulties associated with 3D modeling tasks, which led to their inclusion as a subcategory within the identified themes. The resulting categories are presented in Table 7.

The perception instrument was designed with a descriptive purpose and was not intended to measure a single latent construct. For this reason, the global internal consistency index was not calculated. These instruments were also reviewed by the ad hoc committee before their implementation.

2.7 Statistical analysis

The main instructional factor analyzed in the study was feedback modality, operationalized as instructor-provided feedback (Condition A) and AI-mediated feedback (Condition B). The dependent variables were academic performance, measured

through the practical assessments (E1–E4), and student perception, measured through the descriptive questionnaire administered at the end of the study.

Statistical analyses were conducted using jamovi version 2.6.44 through the Repeated Measures ANOVA module available under the Analyses menu, ANOVA, Repeated Measures ANOVA. Descriptive statistics were calculated for the assessment scores obtained at the four assessment occasions (A1, B1, A2, and B2). Normality was initially examined using the Shapiro–Wilk test and subsequently by visual inspection of model residuals through Q–Q plots. Although the Shapiro–Wilk test indicated deviations from normality, the Q–Q plots showed approximate alignment with the theoretical diagonal, without severe departures. Considering the repeated-measures design and the moderate robustness of parametric models to non-severe deviations from normality, repeated-measures analyses of variance were employed.

In all models, the within-subject factor Assessment was defined with four levels (A1, B1, A2, and B2), assigning the corresponding assessment variables to the repeated-measures cells. All models were estimated using Type III sums of squares. Sphericity was evaluated using Mauchly's test, and when this assumption was violated, the Greenhouse–Geisser correction was applied. Effect sizes were reported as partial eta squared (η^2p), adopting a significance level of $p < .05$. Pairwise comparisons for the factor Assessment were obtained from the fitted models using estimated marginal means (EMMs). Jamovi computed these comparisons with both Tukey and Bonferroni adjustments; however, only the Bonferroni-adjusted comparisons are reported and interpreted in this study.

To control for possible baseline differences among students that could influence subsequent performance, the initial diagnostic assessment (T0) was included a priori as a covariate. Because T0 exhibited a restricted range (1.5–4.0 points out of 10), and because the interpretation of Type III main effects may depend on model parameterization when interaction terms are included [21], three complementary model specifications were evaluated.

Model 1 (ANCOVA with T0 in its original scale). Assessment was specified as the within-subject factor, T0 as the between-subject covariate, and the Assessment × T0 interaction was retained in the model.

Model 2 (ANCOVA with mean-centered T0; primary specification). The model retained the same structure as Model 1, replacing T0 with T0_centered as the covariate while retaining the Assessment × T0_centered interaction. Mean-centering shifts the covariate reference point from T0 = 0 to the sample mean. In models including interaction terms and estimated using Type III sums of squares, the Type III main effect is interpreted conditionally at that reference value [22], [23]. Accordingly, centering changes the value at which the main effect of Assessment is evaluated, without changing the underlying model specification. Consequently, the Assessment main effect in Model 2 is interpreted at the average level of diagnostic performance instead of at T0 = 0, a value that was not representative of the observed sample. In the present analyses, the change was restricted to the Type III test of the Assessment main effect, whereas the remaining model components showed negligible differences, indicating that centering modified the interpretation of the main effect rather than the fitted model itself.

Model 3 (Sensitivity repeated-measures ANOVA). Assessment was specified as the only within-subject factor, without including T0 as a covariate. This sensitivity analysis was used to evaluate the convergence of the Assessment main effect with that obtained from Model 2 under the assumption of homogeneous regression slopes, assessed through the Assessment × T0_centered interaction in Model 2.

The three model specifications were retained for transparency and reproducibility. Model 2 (mean-centered T0) constituted the primary specification for substantive

interpretation, Model 1 (original T0) was fully reported for traceability, and Model 3 was included as a sensitivity analysis. The complete jamovi project (.omv), statistical output, anonymized score matrix, codebook, and supplementary assessment materials are provided as supplementary material to enable independent reproduction and auditing of all statistical analyses.

Additionally, an exploratory 2 × 2 repeated-measures factorial analysis was conducted by defining two within-subject statistical factors: Feedback and Block. The Feedback factor represented a statistical contrast between assessment occasions labelled as instructor-provided feedback and AI-mediated feedback within the fixed ABAB instructional sequence, while Block represented the thematic progression from 2D to 3D modeling. T0_centered was included as the covariate. This analysis was treated as exploratory because the assessment occasions were embedded within the natural curricular progression of the course. Consequently, the model does not allow differences associated with the Feedback factor to be separated from temporal order, thematic block, cumulative learning, or the progressive complexity of the learning tasks.

The perception questionnaire was analyzed descriptively using frequencies and percentages. For reporting purposes, Likert-scale responses were grouped into disagreement (1–2), neutral (3), and agreement (4–5). Open-ended responses were summarized through inductive category grouping based on recurring themes identified during qualitative review.

3 RESULTS

3.1 Sample characteristics

The final analysis included 34 participants after excluding two students who withdrew from participation in the study before completing all assessment stages. Among the analyzed participants, 23 were male and 11 were female. The mean age was 18 years (range: 17–20 years).

Regarding regular access to a computer outside the classroom, 27 students (79.4%) reported having access, whereas seven students (20.6%) indicated that they did not have regular access to this resource.

Most participants reported limited prior experience with CAD software. Seventeen students (50.0%) indicated no previous CAD experience, sixteen (47.1%) reported a basic level, and one student (2.9%) reported an intermediate level. No participants reported advanced or expert experience.

Prior experience using AI tools for academic purposes was also limited. Twenty-five students (73.5%) reported occasional use, six (17.6%) indicated that they had never used such tools previously, and three (8.8%) reported frequent use. No participant reported permanent or daily use of AI tools for academic activities.

The mean score obtained in the diagnostic assessment (T0) was 2.46 out of 10 points (SD = 0.65).

3.2 Student performance on practical assessments

Table 3 shows the descriptive statistics for the practical assessment scores corresponding to the four phases of the instructional sequence: A1, B1, A2, and B2. These values are presented only as descriptive summaries because the phases differed simultaneously in feedback modality, thematic block, temporal position, cumulative learning, and task complexity.

Table 3. Descriptive statistics of practical assessments

Assessment	Average	SD	Min.	Max.
A1	7.676	1.2	4.5	9
B1	7	1.32	4	9
A2	6.573	1	3.5	8.5
B2	4.411	1.98	2.5	10

3.3 Inferential analysis

For completeness of reporting, the initial repeated-measures ANCOVA specification was examined, including T0 in its original scale as a covariate. In this specification, the main effect of Assessment yielded an F value of 5.14. However, this specification was not used for substantive interpretation because the main effect of Assessment is conditioned on the reference value of the covariate, which in the non-centered model corresponds to T0 = 0. This value lies outside the observed range of baseline diagnostic scores in the sample.

The primary interpretation was based on the specification with T0 mean-centered, following the procedure described in the Statistical Analysis section. In this model, the effect of Assessment is estimated at the mean diagnostic level of the sample, T0 = 2.46. As shown in Table 4, this specification yielded a significant effect of Assessment, with an F value of 40.82.

The Assessment × T0_centered interaction was examined as a test of the homogeneity of regression slopes assumption. The obtained value, F = 0.55, p = 0.559, provided no evidence that the association between initial diagnostic performance and practical scores differed across assessment occasions. Therefore, the results do not suggest that initial differences in T0 modified the performance trajectory across assessments.

Finally, the repeated-measures ANOVA without a covariate was included as a sensitivity analysis and showed a pattern consistent with the centered ANCOVA, yielding an F value of 41.40 for Assessment.

Although the Assessment test differed substantially between the non-centered and centered ANCOVA specifications, the Assessment × covariate interaction remained identical across both models, $F(1.76, 56.40) = 0.55$, $p = 0.559$, $\eta^2p = 0.017$. Likewise, the between-subject covariate effect remained unchanged, $F(1, 32) = 1.15$, $p = 0.292$, $\eta^2p = 0.035$, and the residual sum of squares for the within-subject model was identical in both specifications (SS = 159.17). These results indicate that centering did not alter the fitted model, the interaction term, the covariate effect, or the residual structure.

The discrepancy was restricted to the Type III test of the Assessment main effect. In the non-centered specification, the Assessment effect is evaluated conditionally at T0 = 0, a value outside the observed diagnostic-score range of the sample (1.5–4.0). In contrast, the centered specification evaluates the Assessment effect at the sample mean of the diagnostic assessment (T0 = 2.46). For this reason, the centered ANCOVA was retained as the primary specification for substantive interpretation, whereas the non-centered ANCOVA was reported for traceability, and the repeated-measures ANOVA without T0 was included as a sensitivity analysis.

Table 4. Repeated-measures models with Type III sums of squares for Assessment

Model	Covariate	Effect	df	F	p	η^2p
ANCOVA with T0 (original scale; reported for traceability)	T0	Assessment	1.76, 56.40	5.14	0.011	0.138
		Assessment × T0	1.76, 56.40	0.55	0.559	0.017
		T0	1, 32	1.15	0.292	0.035
ANCOVA with T0_centered (primary specification)	T0_centered	Assessment	1.76, 56.40	40.82	<0.001	0.561
		Assessment × T0_centered	1.76, 56.40	0.55	0.559	0.017
		T0_centered	1, 32	1.15	0.292	0.035
Sensitivity ANOVA	No covariate	Assessment	1.76, 58.09	41.40	<0.001	0.556

Notes: All models were estimated using Type III sums of squares in jamovi 2.6.44. Degrees of freedom for within-subject effects are Greenhouse–Geisser corrected. The two ANCOVA specifications included the interaction between Assessment and the corresponding covariate. In the non-centered ANCOVA, the Type III test of Assessment is evaluated at T0 = 0, a value outside the observed diagnostic-score range. In the centered ANCOVA, the Type III test of Assessment is evaluated at the sample mean of T0. The Assessment × covariate interaction, the covariate effect, and the residual sums of squares were identical across both ANCOVA specifications, indicating that centering changed the reference point of the Type III main-effect test rather than the fitted model.

Table 5 presents the post hoc comparisons between assessment time points from the repeated-measures ANCOVA with T0_centered as a covariate, adjusted using the Bonferroni correction.

Table 5. Post hoc comparisons between assessment time points (Bonferroni correction)

Comparison	Difference of means	p (Bonferroni)
A1 – B1	0.676	0.086
A1 – A2	1.103	<0.001
A1 – B2	3.265	<0.001
B1 – A2	0.426	0.198
B1 – B2	2.588	<0.001
A2 – B2	2.162	<0.001

Notes: Pairwise comparisons were based on estimated marginal means (EMMs) obtained from the repeated-measures ANCOVA with T0_centered as the covariate and adjusted using the Bonferroni correction. The centered ANCOVA was retained as the primary specification for substantive interpretation.

The exploratory 2 × 2 repeated-measures ANCOVA was conducted with T0_centered as a covariate. In this model, the Feedback factor represents only a statistical contrast between assessment occasions labelled as instructor-provided feedback and AI-mediated feedback within the fixed instructional sequence, rather than an independently manipulated experimental factor. Table 6 presents the results of this exploratory analysis together with the thematic block. Block 1 corresponded to 2D modeling, and Block 2 corresponded to 3D modeling.

Table 6. Exploratory repeated-measures ANCOVA for statistical factors representing feedback modality and thematic block

Effect	df	F	p	η^2p
Feedback	1.00, 32.00	32.00	<0.001	0.500
Feedback × T0_centered	1.00, 32.00	0.05	0.822	0.002
Block	1.00, 32.00	87.37	<0.001	0.732
Block × T0_centered	1.00, 32.00	1.01	0.323	0.031
Feedback × Block	1.00, 32.00	12.43	0.001	0.280
Feedback × Block × T0_centered	1.00, 32.00	0.85	0.364	0.026
T0_centered	1.00, 32.00	1.15	0.292	0.035

Notes: The Feedback term should be interpreted only as a statistical contrast between assessment occasions labelled as instructor-provided feedback and AI-mediated feedback within the fixed instructional sequence, not as an independent causal estimate of feedback modality. The Feedback × Block interaction reflects an exploratory association within the same fixed sequence. The model was estimated using Type III sums of squares. Degrees of freedom for within-subject effects are Greenhouse–Geisser corrected. T0_centered corresponds to the between-subject covariate effect. Accordingly, the Feedback and Feedback × Block terms are discussed only as exploratory statistical contrasts within the fixed instructional sequence.

3.4 Student perceptions of feedback modalities

Figure 3 presents the distribution of students' perceptions of instructor-provided feedback and AI-mediated feedback during practice.

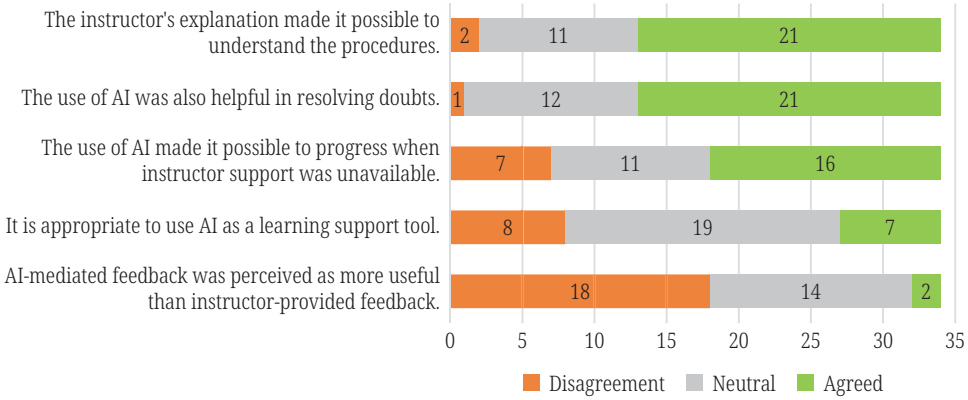


Fig. 3. Distribution of student perceptions

Table 7 presents the categories derived from the open-ended responses. These categories include errors or a lack of precision in the answers, difficulties in formulating instructions, and comprehension problems with AI. Mentions related to modeling 3D objects were also included in these categories. A small number of students did not report any limitations.

Table 7. Categories in open-ended responses regarding limitations of AI use

Main Category	Frequency	Difficulty 3D
Inaccurate or erroneous answers	13	6
AI difficulty interpreting student prompts	11	4
Difficulty in formulating appropriate prompts	7	2
Without perceived limitations	3	0

3.5 Illustrative analysis of AI-mediated feedback

To complement the qualitative findings derived from student perceptions, two illustrative cases of interaction between students and the AI tool used during the intervention are presented below. Because no systematic analysis of all conversations generated during the study was conducted, these examples should not be interpreted as statistically representative evidence but rather as intentionally selected cases used to illustrate different behaviors of AI-mediated feedback when addressing the same CAD modeling task.

In the first case, the student submitted five prompts during the interaction. Initially, the student used the image shown in Figure 4a together with the recommended prompt, indicating that the cylindrical components had already been completed and requesting guidance to construct the front geometry highlighted in red.

The initial AI response was extensive and difficult to follow due to its format and excessive use of icons. Subsequently, the student requested that the explanation be reformulated first into paragraphs and later into numbered steps. The resulting response generated a 13-step procedural sequence that initially appeared consistent; however, beginning at step 8, it included inconsistencies related to the construction of the triangular geometric body in an incorrect spatial position. The student identified these inconsistencies and pointed them out in a new prompt, after which the AI reformulated the guidance and generated a corrected 14-step sequence.

Later, using the image shown in Figure 4b, the student requested instructions to complete the 3D solid. In this interaction, the AI generated a 16-step sequence that again presented inconsistencies in the relative position of certain elements, as well as dimensional and spatial inaccuracies. The student identified these inconsistencies and requested additional corrections before reaching the result shown in Figure 4c.

In this case, the AI-mediated feedback consisted primarily of step-by-step procedural instructions. Although the responses presented limitations in spatial interpretation and in the positioning of some geometric elements, the student was able to continue progressing through the task by interpreting the instructions and engaging in an iterative refinement process based on the observed modeling results.

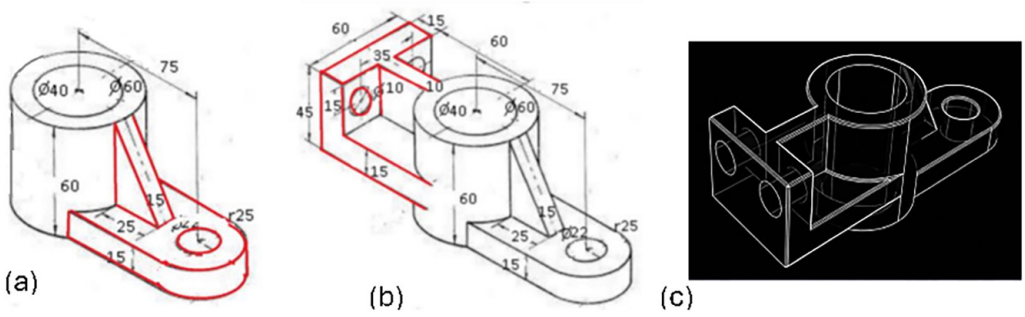


Fig. 4. Case 1: Iterative interaction process during AI-mediated feedback in CAD: (a) Image used in the initial prompt; (b) Image used in a later corrective interaction; (c) Final modeled geometry

In the second case, the student used several images during the interaction. In the initial prompt, the student followed the recommended template, although no previous progress was specified and uncertainty was expressed regarding how to begin the exercise. Additionally, the student requested guidance to start from the lower section of the solid, based on the geometry highlighted in red in Figure 5a. The AI generated an extensive response containing a sequence of steps to construct the 2D sketch. However, during execution, the student identified inconsistencies in

the construction of the front section. Using the image shown in Figure 5b, the student indicated that the front section was not producing the expected result. The AI recognized the inconsistency and proposed an alternative procedure that allowed the student to complete the 2D sketch successfully.

In the following prompt, using the image shown in Figure 5c, the student requested guidance to construct the elevations of the solid, beginning with the connection between the cylinder and the triangular rib. The AI generated a new procedural sequence; however, the instructions provided did not allow the student to complete the 3D solid correctly.

Subsequently, using the image shown in Figure 5d, the student indicated that the model remained incomplete and that a set of surfaces had been generated instead of a solid. The AI reformulated the instructions once again; however, the student did not continue following the proposed procedure. The final result obtained is shown in Figure 5e.

In this case, the AI-mediated feedback was useful for supporting the iterative construction of the 2D sketch, but it was insufficient for guiding the 3D modeling stage, where the generated instructions did not allow successful completion of the required solid.

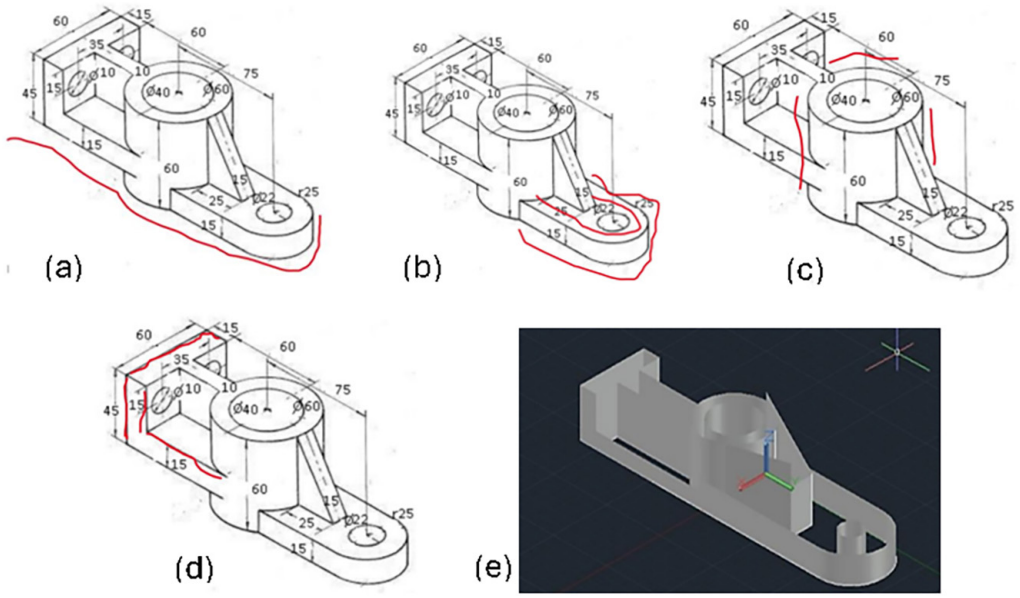


Fig. 5. Case 2: Iterative interaction process during AI-mediated feedback in CAD: (a) Initial prompt requesting guidance to begin the lower section of the solid; (b) Corrective interaction associated with the front section of the 2D sketch; (c) Prompt requesting guidance for the 3D modeling stage; (d) Corrective interaction after incomplete solid generation; (e) Final modeling result obtained by the student

4 DISCUSSION

4.1 Task complexity and performance variation across the instructional sequence

The exploratory repeated-measures analysis identified significant statistical terms associated with the thematic block and with the assessment occasions labelled by feedback modality, as well as a significant interaction between these terms.

However, these findings should be interpreted with caution because the assessment occasions were embedded within the natural curricular progression of the course. Consequently, the statistical model does not allow complete separation of the Feedback term from temporal sequence, increasing task complexity, cumulative learning, and thematic progression. Therefore, the observed interaction cannot be interpreted as causal evidence of differential effectiveness of AI-mediated feedback across task types.

A significant statistical term associated with thematic progression was observed, indicating that student performance varied across the instructional sequence as activities progressed from 2D to 3D modeling tasks. Descriptive results also showed lower average scores during the later phases of the instructional sequence.

The decrease in performance observed during the later instructional stages, regardless of the feedback modality implemented, could be explained by the increased cognitive load involved in the transition from 2D to 3D modeling.

This interpretation is consistent with the findings in [6], which indicate that converting 2D representations into 3D representations constitutes one of the main difficulties in engineering education. This process requires advanced reasoning skills due to the highly abstract nature of the task. The authors note that this difficulty is reflected in students' academic outcomes, as the diagnostic reports reviewed show recurrent low performance in activities involving the conversion of 2D views into 3D projections.

Complementarily, the authors in [7] point out that the challenge is not merely drawing but correctly interpreting depth, orientation, and the way objects relate to one another in space. They indicate that this difficulty requires students to visualize and mentally transform objects through axonometric and orthogonal views. Therefore, in CAD learning, the challenge does not lie solely in producing the graphical representation but in understanding the spatial structure of the object. Furthermore, this skill is necessary in engineering because many problems in areas such as design, physics, mathematics, and chemistry require spatial reasoning and graphical representation to be solved.

The present findings are better interpreted as classroom-based evidence regarding the interaction between progressively complex CAD tasks and the practical use of AI-mediated feedback. The study does not provide causal evidence regarding the comparative effectiveness of AI-mediated feedback and instructor-provided feedback, and interpretations connecting feedback modality to performance outcomes should therefore be considered preliminary.

4.2 Interaction with AI: formulating prompts and ensuring accurate feedback

As practical tasks became more complex, students appeared to require increasingly detailed instructions and iterative interactions with the AI system in order to obtain useful guidance. Under these conditions, the use of AI-mediated feedback appeared to involve not only task execution but also the ability to formulate prompts that adequately described the modeling problem. This is relevant because AI can present limitations in tasks that require nuanced interpretation and the application of multiple evaluation criteria [24].

In this sense, the usefulness of AI-mediated feedback may not depend solely on the capabilities of the system but also on the students' competencies to construct precise, contextualized, and progressively refined prompts. Interaction with AI tools may therefore involve an iterative process of formulating and reformulating

instructions, in which the quality of the responses obtained may be related to the clarity and specificity of the prompts used [14].

Prompt formulation appears to be more complex for the generation of 3D objects. This conjecture is based on the difficulties reported by students, who mentioned problems related to geometric interpretation, uncertainty regarding the modeling sequence, imprecise AI-generated responses, and difficulty formulating instructions.

These observations are qualitative in nature and should not be interpreted as statistically demonstrated effects of feedback modality. The quality of the information provided and metacognitive regulation were not directly measured in this study.

However, similar difficulties have been reported in CAD education research, where students frequently experience challenges in constructing 3D objects due to limited understanding of the procedural structure required for modeling tasks [18]. These challenges may involve not only technical execution but also difficulties related to organizing the sequential operations necessary to complete the model. According to [25], the effectiveness of AI-based educational systems depends, in part, on students' ability to critically engage with the feedback provided by the system, as this may influence the usefulness of the generated responses and the depth of learning achieved.

Although the present study did not directly examine prompt quality, interaction frequency, model variation, response accuracy, metacognitive regulation, or students' ability to critically evaluate AI-generated responses, the qualitative findings suggest that interaction with AI systems in CAD learning environments may involve additional procedural and communicative demands beyond the execution of the modeling task itself. These demands may become more salient in instructional contexts involving progressive transitions from 2D to 3D modeling tasks, as occurred in the present course sequence.

4.3 AI-mediated feedback during practice and student perception

AI-mediated feedback appeared to function as an additional instructional resource during practical activities. This interpretation is consistent with the perception results, in which most students identified AI as useful for resolving specific doubts and maintaining progress during exercises when direct instructor guidance was not immediately available. One of the most relevant characteristics of AI-mediated feedback was therefore the possibility of obtaining rapid responses to specific questions during task completion. However, students generally continued to assign greater importance to instructor-provided feedback for understanding and validating modeling procedures, especially during more complex activities. Thus, AI-mediated feedback should be interpreted as a complementary resource within classroom instruction rather than as evidence of differential effectiveness between feedback modalities.

These findings are consistent with those reported by [14], who states that GenAI primarily functions as a support tool for idea generation during engineering design learning. However, the author warns that its adoption should not be assumed to be generalized or uncritical, as a significant proportion of students rejected its use due to concerns regarding the reliability and technical accuracy of the generated responses.

In this study, the qualitative responses additionally suggest that students' perceptions of AI-mediated feedback varied according to the procedural complexity of the task and the type of assistance required during the modeling process. While many

students valued the immediacy of AI-generated responses, they also reported limitations associated with procedural interpretation and response precision during 3D modeling activities.

Previous studies in engineering education have similarly proposed that AI-mediated tools may function as complementary instructional resources while maintaining instructor guidance as a central component of the learning process [18]. In this regard, it has been proposed that instructor-provided feedback may contribute contextualization, procedural explanation, and pedagogical mediation, whereas AI systems may provide rapid and continuous access to operational support during practice activities [16].

The acceptance of AI among students is related to its ease of use, rapid access to information, and the time savings it provides in complex academic activities. However, its use should be critical and responsible, as concerns regarding the accuracy and reliability of the generated responses still persist. Therefore, it is considered a complementary learning tool rather than a substitute for reliable academic sources or for students' own analysis and reasoning [26].

According to [24], caution should be exercised when using AI autonomously in academic processes. Although AI can generate consistent responses and provide support in certain tasks, its level of agreement with experts remains insufficient to replace human judgment. Furthermore, AI may introduce systematic biases and exhibit limitations in the interpretation of complex criteria.

Other authors have emphasized the importance of instructor–student interaction for the development of reflection, self-regulation, and knowledge organization, suggesting that feedback processes may remain more effective when students actively engage with instructors rather than relying exclusively on automated support systems [1], [2], [3].

Taken together, the findings of this study provide exploratory classroom-based evidence that AI-mediated feedback may help students continue practical CAD work when immediate instructor support is unavailable. However, its usefulness appears to depend on task complexity, students' ability to formulate prompts, the reliability of AI-generated responses, and the continuing role of instructor guidance.

4.4 Limitations of the study

This study presents several methodological limitations that should be considered when interpreting the findings.

First, the study employed a quasi-experimental within-subjects design conducted with an intact classroom group and without random assignment. Although instructional procedures were maintained consistently throughout the course, the design does not allow complete control over potential threats to internal validity associated with authentic educational settings.

A central limitation of the study is that the instructional phases were directly aligned with the natural curricular progression of the course. The transition from 2D to 3D modeling tasks occurred simultaneously with the alternation of feedback modalities in the ABAB sequence. Consequently, differences associated with feedback modality cannot be fully separated from task complexity, cumulative learning, procedural demands, and content progression. For this reason, the findings should be interpreted as exploratory evidence obtained in an authentic instructional context rather than as causal evidence regarding the comparative effectiveness of AI-mediated feedback and instructor-provided feedback.

Additional limitations are associated with the implementation of the AI-mediated feedback modality. Students accessed ChatGPT through personal accounts using the free version available during the academic period. During this time, the platform underwent automatic model updates, and system limitations could lead to temporary changes in model availability or reasoning capacity.

These operational conditions were not experimentally controlled; therefore, the AI-mediated feedback modality was not fully standardized in terms of model version, model availability, reasoning capacity, number of interactions, prompt quality, prompt refinement, response accuracy, or students' ability to evaluate AI-generated responses. Consequently, the study cannot determine how these factors affected student performance or perceptions. These factors represent sources of uncontrolled variability inherent to the naturalistic conditions under which AI-mediated feedback was observed; imposing stricter controls over individual interactions would have altered the naturalistic character of AI use that the study intended to examine.

Additionally, no systematic records were kept regarding the number of prompts submitted, interaction frequency, prompt modifications, model availability during each interaction, or AI-generated responses. Although students followed a common prompt structure, the specific content of interactions varied according to individual needs and task progression. Consequently, the study cannot determine how prompt quality, interaction frequency, prompt refinement, model availability, model variation, response accuracy, or students' ability to critically evaluate AI-generated responses may have affected performance or perceptions. This limitation is consistent with the quasi-experimental and naturalistic nature of the study, in which AI-mediated feedback was observed under authentic classroom conditions rather than under a fully controlled laboratory protocol.

The study also did not directly examine prompt quality, metacognitive regulation, or the accuracy of AI-generated responses. Therefore, interpretations regarding the possible role of prompt formulation and interaction strategies remain hypothetical and should be interpreted as qualitative inferences rather than directly measured variables.

Because all assessments were scored by the course instructor, who also served as the principal investigator, the possibility of scorer expectancy bias cannot be entirely excluded. Although the objective and binary nature of the scoring procedure reduced dependence on evaluator judgment, this dual role represents a limitation that should be acknowledged.

The diagnostic assessment (T0) presented a restricted score range and limited variability across participants, which reduced its strength as a covariate within the repeated-measures model. Although T0 was included a priori to account for potential baseline differences in prior CAD-related knowledge, its limited variability may have constrained the robustness of the adjustment. To improve the interpretability of Type III main effects in the presence of interaction terms, the covariate was mean-centered. Nevertheless, a sensitivity analysis indicated that the overall pattern of findings remained consistent regardless of whether the covariate was included.

The qualitative analysis was conducted collaboratively by the three authors, and therefore a formal inter-rater reliability analysis was not considered necessary. Categories were derived inductively from brief descriptive responses, and the findings should be interpreted as recurring student perceptions rather than exhaustive qualitative representations.

Finally, the study was conducted with a relatively small and homogeneous sample composed of first-year engineering students from a single course context. This

limits the transferability and broader generalizability of the findings to other educational levels, disciplinary contexts, or instructional environments.

4.5 Implications and future research directions

The integration of AI into technical courses should be analyzed considering the procedural and progressive nature of the content involved. From a pedagogical perspective, this implies that the incorporation of AI-based tools can hardly be standardized, as their usefulness may vary depending on the type of task, the level of complexity, and the procedural demands required during the learning process.

In courses focused on the development of practical skills, instructor-provided feedback continues to play a relevant role, particularly in activities that require spatial interpretation, procedural analysis, and the sequential execution of operations. In this context, it is important to examine the extent to which virtual environments and AI-mediated feedback can complement face-to-face teaching dynamics without fully replacing the pedagogical mediation provided by the instructor.

Future research should employ designs that allow a clearer separation between the effects associated with AI-mediated feedback, instructor-provided feedback, and curricular progression during practical activities in engineering education. In addition, studies involving broader and more diverse student populations across different educational contexts and engineering disciplines will be necessary to expand the scope and applicability of the findings obtained in this study.

This study also suggests potential future research directions focused on examining AI-mediated feedback within specific contexts of professional engineering practice. In particular, it would be relevant to explore its application in areas related to CAD, such as CAM (CNC programming) and CAE, as well as in technical disciplines involving procedural reasoning and sequential problem solving, including electronics, PLC programming, and relay logic.

5 CONCLUSIONS

The exploratory analyses identified statistically significant differences in performance across the instructional sequence, including terms associated with thematic progression and feedback modality. Because the feedback modalities were aligned with the curricular progression of the course, these findings should be interpreted as exploratory classroom-based evidence rather than as causal effects attributable to either feedback modality.

The practical use of AI-mediated feedback appeared to be shaped not only by task complexity but also by students' ability to formulate precise prompts, interact iteratively with the system, and critically evaluate the reliability of AI-generated responses, demands that become more evident as procedural requirements increase.

Students perceived AI-mediated feedback and instructor-provided feedback as serving complementary rather than interchangeable functions in CAD learning, attributing to AI-mediated feedback the role of providing immediate operational support during practice and to instructor-provided feedback the role of offering procedural interpretation and validation.

The study contributes exploratory classroom-based evidence that AI-mediated feedback may help students continue practical CAD work when immediate instructor

support is unavailable. However, this support depends on task complexity, students' ability to formulate prompts, the reliability of AI-generated responses, and the continuing role of instructor guidance; therefore, future research should examine these interactions in more controlled designs incorporating direct analysis of prompt formulation, AI-generated responses, and metacognitive strategies.

6 ACKNOWLEDGMENTS

The authors acknowledge the financial support of the Universidad Técnica del Norte through the research project InvestigaUTN-2025-1501.

The authors are also grateful to Grupo Editorial RA-MA for authorizing the academic use of excerpts from the book AutoCAD 2017: Curso Práctico for research and educational purposes.

7 DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used ChatGPT to support the improvement of writing clarity and the rephrasing of certain parts of the text. After using this tool, the authors carefully reviewed and edited the content and take full responsibility for it.

8 REFERENCES

[1] N. K. Mandal, "Importance of student feedback in improving mechanical engineering courses," *International Journal of Mechanical Engineering Education*, vol. 47, no. 3, pp. 227–245, 2019. https://doi.org/10.1177/0306419018759800

[2] M. Thurlings and M. van Diggelen, "Perceptions of practical knowledge of learning and feedback among academic teachers," *European Journal of Engineering Education*, vol. 46, no. 1, pp. 139–160, 2019. https://doi.org/10.1080/03043797.2019.1677559

[3] D. Alique and M. Linares, "The importance of rapid and meaningful feedback on computer-aided graphic expression learning," *Education for Chemical Engineers*, vol. 27, pp. 54–60, 2019. https://doi.org/10.1016/j.ece.2019.03.001

[4] L. Hua, L. Guo, N. Zheng, Y. Lu, J. Xu, and J. Deng, "Proactive framework for evaluating retrieval-augmented generation-based learning assistants in engineering education," *Computer-Aided Civil and Infrastructure Engineering*, vol. 40, no. 26, pp. 4651–4668, 2025. https://doi.org/10.1111/mice.70063

[5] A. Lathigara, P. Tanna, N. Bhatt, H. Durani, and K. Thumar, "Reimagining fairness by inclusive assessment practices for diverse engineering cohorts," *Journal of Engineering Education Transformations*, vol. 39, no. S2, pp. 195–201, 2026. https://doi.org/10.16920/jeet/2026/v39is2/26024

[6] Z. Ngcobo, "Keeping pace with 21st century skills: The role of computer-aided design in teaching engineering graphics and design," *International Journal of Learning, Teaching and Educational Research*, vol. 24, no. 12, pp. 546–568, 2025. https://doi.org/10.26803/ijlter.24.12.24

[7] B. N. Guler, S. Sajadi, A. Alenezi, and D. Bairaktarova, "From doubt to drive: How instructional modality and self-efficacy shape motivation in remedial spatial visualization courses," *International Journal of Engineering Pedagogy*, vol. 14, no. 5, pp. 37–50, 2024. https://doi.org/10.3991/ijep.v14i5.46097

[8] A. Rahman *et al.*, "Artificial Intelligence innovations challenges and emerging trends in engineering education," *Discover Education*, vol. 5, no. 1, Art. no. 179, 2026. https://doi.org/10.1007/s44217-026-01137-1

[9] T. Alasmari, "Artificial Intelligence and M-learning in Arabic countries: Innovations, trends, and regional perspectives," *International Journal of Interactive Mobile Technologies*, vol. 19, no. 5, pp. 170–194, 2025. https://doi.org/10.3991/ijim.v19i05.52735

[10] L. T. Ameen, M. R. Yousif, N. A. Jasim Alnoori, and B. H. Majeed, "The impact of Artificial Intelligence on computational thinking in education at university," *International Journal of Engineering Pedagogy*, vol. 14, no. 5, pp. 192–203, 2024. https://doi.org/10.3991/ijep.v14i5.49995

[11] L. Li and M. Bertrand, "Fostering critical thinkers and future designers: Design fiction pedagogy in AI education," *Think. Skills Creat.*, vol. 59, Art. no. 101962, 2026. https://doi.org/10.1016/j.tsc.2025.101962

[12] L. Holubnycha *et al.*, "AI-Powered teaching: Literature review of ChatGPT's impact on university educators," *International Journal of Interactive Mobile Technologies*, vol. 19, no. 15, pp. 41–65, 2025. https://doi.org/10.3991/ijim.v19i15.54275

[13] D. A. Varsos, N. C. Zygouris, K. M. Kolomvatsos, A. N. Dadaliaris, and G. Dimitriou, "Prediction of secondary-school student cognitive performance in informatics," *International Journal of Engineering Pedagogy*, vol. 16, no. 1, pp. 66–86, 2026. https://doi.org/10.3991/ijep.v16i1.56637

[14] Y. Dai, "Why students use or not use generative AI: Student conceptions, concerns, and implications for engineering education," *Digital Engineering*, vol. 4, Art. no. 100019, 2025. https://doi.org/10.1016/j.dte.2024.100019

[15] M. Alghazo, V. Ahmed, and Z. Bahroun, "Exploring the applications of Artificial Intelligence in mechanical engineering education," *Front. Educ.*, vol. 9, Art. no. 1492308, 2025. https://doi.org/10.3389/feduc.2024.1492308

[16] T. Köring, D. Gerhard, and M. Neges, "Design and implementation of a skill development program in AI driven generative engineering," in *DS 131: Proceedings of the International Conference on Engineering and Product Design Education (E&PDE 2024)*, Institute for Product and Service Engineering, Digital Engineering Chair, Ruhr-University Bochum, Germany, 2024, pp. 223–228. https://doi.org/10.35199/EPDE.2024.38

[17] L. W. Jianwu *et al.*, "Artificial Intelligence-enabled evaluating for computer-aided drawings (AMCAD)," *International Journal of Mechanical Engineering Education*, vol. 52, no. 1, pp. 3–31, 2024. https://doi.org/10.1177/03064190231175231

[18] O. Kravchenko and S. Green, "Future proofing computer-aided design education through AI-driven e-learning," in *DS 131: Proceedings of the International Conference on Engineering and Product Design Education (E&PDE 2024)*, H. Grierson, E. Bohemia, and L. Buck, Eds., United Kingdom: Imperial College London, 2024, pp. 336–341. https://doi.org/10.35199/EPDE.2024.57

[19] V. A. Erazo-Arteaga, "Personalization of tasks as a learning methodology to avoid dishonesty in higher education," *Formacion Universitaria*, vol. 16, no. 6, pp. 47–60, 2023. https://doi.org/10.4067/S0718-50062023000600047

[20] C. Cebolla, J. Santoro, and J. García, *AutoCAD 2017. Curso práctico*. Madrid, España: RA-MA Editorial, 2017.

[21] L. Graefe, S. Hahn, and A. Mayer, "On the relationship between ANOVA main effects and average treatment effects," *Multivariate Behav. Res.*, vol. 58, no. 3, pp. 467–483, 2023. https://doi.org/10.1080/00273171.2022.2068122

[22] D. Afshartous and R. A. Preston, "Key results of interaction models with centering," *Journal of Statistics Education*, vol. 19, no. 3, pp. 1–24, 2011. https://doi.org/10.1080/10691898.2011.11889620

[23] S. W. Jarantow, E. D. Pisors, and M. L. Chiu, "Introduction to the use of linear and non-linear regression analysis in quantitative biological assays," *Curr. Protoc.*, vol. 3, no. 6, Art. no. e801, 2023. https://doi.org/10.1002/cpz1.801

[24] G. Zacharis and S. Papadakis, "Can AI grade like a human? Validity, reliability, and fairness in university coursework assessment," *Educational Process: International Journal*, vol. 19, pp. 1–22, 2025. https://doi.org/10.22521/edupij.2025.19.591

[25] C. R. Patel, S. Patel, C. B. Rathod, A. Vagadia, R. R. Modi, and A. Kumar, "AI-powered gamification in computer engineering education: A mixed-methods study on engagement, learning outcomes, and personalization," *Journal of Engineering Education Transformations*, vol. 39, no. Special Issue 3, pp. 42–48, 2026. https://doi.org/10.16920/jeet/2026/v39is3/26096

[26] S. Altikriti and Z. Nemrawi, "The use of ChatGPT as a learning tool among jordanian students in technical universities: Attitudes and perceptions," *International Journal of Interactive Mobile Technologies*, vol. 19, no. 5, pp. 144–158, 2025. https://doi.org/10.3991/ijim.v19i05.52049

9 AUTHORS

Víctor A. Erazo-Arteaga is a Mechanical Engineer with a Master's degree in Design and Industrial Automation. His academic background also includes university studies in Technical Pedagogy, followed by a Master's degree in Educational Research Methods. He is a professor and researcher at Universidad Técnica del Norte, Ecuador. His research interests include engineering education, artificial intelligence in education, computer-aided design (CAD), manufacturing technologies, and educational innovation (E-mail: vaerazo@utn.edu.ec).

Santiago Marcelo Vacas Palacios is an Agroindustrial Engineer with a Master's degree in Administration, Quality Management, and Productivity. He is a faculty member and researcher in the Industrial Engineering Program at Universidad Técnica del Norte, Ecuador. His research interests include research methods, pedagogy, engineering education, university-level teaching, and optimization techniques (E-mail: smvacas@utn.edu.ec).

Marcelo Bayardo Cisneros Rúales is a Commercial Engineer and Business Administrator with a Master's degree in Business Administration. He is a faculty member and researcher in the Industrial Engineering Program at Universidad Técnica del Norte, Ecuador. His research interests include educational research, industrial engineering, and management education (E-mail: mbcisneros@utn.edu.ec).