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Student Successes and Struggles when Adopting Text-based AI Activities in Structural Design Courses

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Abstract

Educators are at a crossroads with AI. Possible paths forward include active adoption, prohibition, or anything in between. While concerns remain about the effects of generative text-based AI on academic integrity and learning, AI is here to stay. Engineering educators must therefore thoughtfully explore how AI, particularly off-the-shelf tools already used by students, can advance domain-specific engineering education. With limited experimental evidence available on measured AI benefits vs challenges, current best practices are scarce. This gap is particularly acute for specific engineering tasks, as most publications focus on general activities such as writing and coding. For this study, two broad research questions are posed: "*how, and to what extent, does embedding text-based AI into structural design assignments influence student success or struggle?"* and *"What impact does AI have on performance?*"

This research explored leveraging text-based AI in two structural design courses, focusing on structural steel design due to its varying complexity and related industry efforts to supplement design with AI. Activities and demos were developed for four design situations of increasing open-endedness, where AI could inform design decisions, clarify processes, and promote understanding. Two separate cohorts were compared: Cohort 1 (future structural engineers) and Cohort 2 (students in other architectural engineering sub-disciplines: mechanical, electrical, and construction). Data on AI use and performance were collected via rubrics, alongside a pre-post survey assessing perceptions of AI attributes.

Results indicate mixed perceptions and performance. Some students actively curated prompts and verified outputs, while others overly relied on AI with limited validation or conceptual understanding. Enthusiasm toward learning with AI was similarly mixed. Cohort 1 was more engaged on average than Cohort 2. In aggregate, both cohorts trusted AI results beyond what would be expected of a professional engineer, as demonstrated by Pitts et al. [1] and Amoozadeh [2]. Cohort 1 frequently reported that completing activities by hand would have been faster than using AI—an observation that may change with increased familiarity, multimodality, and improved accuracy of next-generation tools. Nevertheless, Cohort 2 frequently achieved better performance in multiple contexts. Practical takeaways are provided to support early AI adopters in strategically integrating AI into technical courses.

Introduction

As educators, following ABET [3] and ASCE's BoK [4], our duties include equipping students with the knowledge and competencies needed to succeed as future professionals. Traditionally, this has been achieved through lecturing and textbook-based learning [5-6]. However, if leveraged appropriately, AI could further prepare students for their future careers, especially as the technology evolves [7]. Generative AI tools such as the ChatGPT, Perplexity, Gemini, CoPilot, and Claude have the potential to revolutionize how students engage with complex civil engineering concepts and applications, if proper critical thinking oversight is being applied [8-9].

Despite growing interest in leveraging AI in education, gaps remain due to largely ad hoc experiments with limited applied educational research-based evidence to support teaching claims. This lack of data is particularly acute for the scope of specific technical tasks found in civil engineering, since much of the generated evidence centers around the more general tasks of writing, coding, prompt engineering, and student versus faculty perceptions [8,10-11]. From a technical topic perspective, experimental evidence is available on how AI assistance in programming courses can aid students in the actual programming [12], be leveraged for spreadsheet development [13], and provide comparisons on how commercially available AI can perform against PE and FE exam questions [11,14]. While they can build on these foundations, future studies in engineering education must test more specific engineering tasks.

In response, this paper presents a comparative analysis on how leveraging text-based AI in two structural design courses affects student adoption of AI, performance on problems with AI, and perceptions of AI support. Through aggregated student data and survey results, this paper documents our adoption and delivery of AI, the creation of AI assignments / demos, and the resulting student trends.

Background

AI Potentials and Pitfalls in Civil-Structural Engineering Education

Insider Higher Education reports that nearly 75% of students (in 2024) felt that institutions should prepare them for an AI-enabled world to some degree, but only about 14% of universities have made this a focal point [15]. Educators must weigh potential benefits and risks to AI as we decide how to pedagogically deliver our curriculum. Educators can embrace it or resist it when adjusting our courses [16]. From reading published perceptions on AI as well as written discussions on social media/internet teaching forums, educators tend either embrace or purposefully resist. Faculty trying to resist AI adoption often see it as a mechanism to shortcut learning. Here, arguments center on students failing to grasp the technical concepts due to decreased critical thinking [7,17].

Amongst the embrace or resist mindsets, there has been exponential growth of papers on AI in education over the past several years [7,16,18]. This research can largely be subdivided into the following domains:

- Teaching the computational mechanics of developing AI [23]
- Leveraging pre-programed, off the shelf AI packages in the classroom [8,13,21]
- Perceptions on AI from student and faculty perspective [15,16,22]
- Ethics and Academic Integrity of Leveraging AI [24]

For those actively adopting or experimenting with AI, faculty are attempting to capture AI benefits within an already packed curriculum. While some are developing new AI-specific courses [19], others are integrating it into existing courses [10] or adopting it as an optional resource through AI-friendly course policies [20]. Naser [11] and Rezaei [10] observed that AI can improve engagement and motivation via multimodality interaction and collaborations as well as building a more dynamic and responsive educational environment. Uddin et al. [9] recorded several concerns of AI adoption including AI tools to perpetuate biases, provide misinformation, risk of plagiarism and maintaining originality of student works, over reliance on AI tools, and ethical implications. In both cases, there is a rapidly growing breadth of topics and guidance being published. Of the four listed, bullet two has the most potential for specific engineering disciplines to consider.

Parker [18] conducted workshops that established several key themes for educator consideration: critical thinking skills, ethics [24], and a comprehensive understanding of the problem to be solved. A structural engineer using an AI tool to identify stress points within a building design must have the critical thinking skills necessary to scrutinize the underlying assumptions and limitations of the model, as well as its real-world applicability [18].

Although it is less commonly discussed, another potential AI use is helping to connect currently taught topics that need later application in the program (advanced classes or capstones) where students often forget or struggle to expand and apply their knowledge [6-7]. This long-term connection / expansion of knowledge disconnect has been documented specifically in our program, as well as historically in others [5]. From faculty observations, students tend to have overreliance and adoption of examples that are not correct for new scenarios [25], or they seek out advice from instructors too late (which leads to frustration) [26], or they trust classmates who are equally confused [27], or they "just guess their way to what they need". This is specifically true within design classes. Regularly, faculty observe students struggling to apply project class design knowledge to new scenarios [5]. This is partially due to limited in-class / textbook examples for them to reference [13]. Given the possibilities for AI to advance learning, it was broadly hypothesized that maybe AI could be a valid mechanism to help students get over some of these hurdles in future classes.

Importance of AI for Structural Engineers

Many view structural engineering as difficult because it requires learning both the theory behind structural behavior and the many reference standard specifications for design. Although advancements in AI are increasing, the civil engineering domain approaches such advances slowly, with hesitation [11]. If the civil, architectural, and structural engineering communities can embrace AI-based methods, it could allow for improved quality of work and open the door for innovative solutions [11]. While students and existing research have focused on commercially available platforms like ChatGPT and Gemini, engineering profession-based platforms are just starting to be developed with refined scopes.

AI tool initiatives are already in development or testing by leading firms [28] and leading engineering societies [29]. The two most available are the National Council of Structural Engineering Associations (NCSEA): 1) SEGPT that is trained on NCSEA documents and Structures Magazine Articles, and 2) AISC Clark that is trained on AISC's published data. Beyond LLM development, societies such as ACI, AISC, and NCSEA are developing and executing task forces to investigate applications of AI for structural engineering. Leading AEC firms are also developing AI platforms for decision support by focusing on tasks such as predicting structural quantities [30], improving communication and reducing project risk [31-32], or automating structural design [33]. While some of these tools are multi-modal or incorporate geometric and simulation data, with the rise of agentic AI, these may increasingly be engaged with text-based interfaces.

As professionals and firms continue to implement AI in the real world, it has the potential to foster safer, more sustainable, and more efficient infrastructure systems and construction practices, ultimately reshaping the future of the built environment [18]. As such, this AI study is meant to build mechanisms for self-learning where students can leverage AI for guidance and support when they encounter new scenarios.

Research Methods

This exploratory investigation is built on the integration of existing, widely available, text-based generative AI tools into two engineering courses. The domain of structural steel design was selected as it has naturally varying levels of design complexity and open-endedness, which will inform the suitability of AI for design activities and provide clearer guidelines on teaching AI in design. Furthermore, structural steel design is a common topic across both Civil Engineering (CE) and Architectural Engineering (AE) at most US universities, meaning the findings have wide relevance.

Two different courses (AE 401 and AE 404) teaching steel design were selected from within an AE Curriculum. Both courses primarily enroll 4th year students in a 5-year AE program. AE 401 is basic steel design, while AE 404 is a structural system design course for non-structural disciplines. While AE 401 and AE 404 have different cohorts, there is ~40% topical overlap. The topics selected for this study included an initial activity on structural analysis, which offered a bridge to previous courses without AI, and then three additional topics with increasing levels of rigor and detail.

Based on these activities, a mixed-method qualitative/quantitative approach was used to extract both numerical and reflective rich information to advance AI education [34]. The following research questions are addressed:

1) Do students use AI for conceptually determining their process, directly solving analytical problems involving equations, or both? If both, which is more successful?
2) Do student perceptions of AI change when they use it to design?
3) How does design complexity affect the benefits, challenges, or accuracy of leveraging AI?
4) What can we learn from how students leverage AI to teach more proactively?

Class Cohorts

Students in AE 401 were of the structural discipline, whereas students in AE 404 were students focusing on mechanical (HVAC), lighting/electrical, and/or the construction management discipline. AE 404 is the terminal required structural course for non-structural students in the program. AE 401 had a total of 38 students, 8 of which were female, 30 were male, and 0 were non-binary. For AE 404, 60 students made up the cohort of which 21 were female, 39 were male, and 0 were non-binary. Both courses were 15 weeks, each averaging nine hrs. of work per week for the typical student. Instructors split time differently between in-person and out-of-class. AE 401 met for 3–50-minute sessions each week for a total of 45 meetings. AE 404 met for 2–80-minute sessions each week for a total of 30 meetings. AE 401 was structured as a flipped class with videos to be watched prior to class (~80% of class periods have videos), while AE 404 was structured to typically have traditional lectures / discussions on Tuesdays and interactive activities on Thursdays. To better understand the course structure, the primary topics and traditional assessments of each course are listed in Table 1.

Table 1: Topical Organization and Key Assessments

Attribute	AE 401	AE 404
Main Coverage (days taught)	Load and analysis review (1) Design methodology (1) Deck and OWSJ (4) Tension members (4) Compression members (5) Gravity layout (3) Non-composite beams (7) Composite beams (7) Work sessions (11)	Load and analysis review (5) Deck and OWSJ (2) Steel Design (6) • Non-composite Beams • Compression Members Concrete Design (6) • Rectangular Beams • Columns • Conceptual Slab Layout
Assessment	12 homework sets 1 mini-project 3 exams Participation	9 homework sets Participation 3 quizzes 3 exams

Note: (#) indicate number of days per topic.

The main difference in learning objectives between the two courses is the student mastery level. AE 401 students are expected to be at an "analyze" up to "create" levels on Bloom's Taxonomy, which indicates they are comfortable critically reviewing and then applying key AISC 360 provisions to future scenarios. In AE 404, students are expected to be at an "understanding" to "evaluating" levels, with the intent of knowing enough about design to engage with structural designers later in their careers. AE401 covers all appropriate steel limit states, while AE 404 covers simplified assumptions on common practices in many topics. For example, in AE 404, Table 4-1a in the AISC Manual is called upon for all column compression design as the course assumes the weak direct controls, whereas AE 401 covers these tables for design but also AISC 360 Specification Provisions in Chapter E that are used to generate these tables along with how to determine K, bracing, and support impacts.

Delivering the AI Content

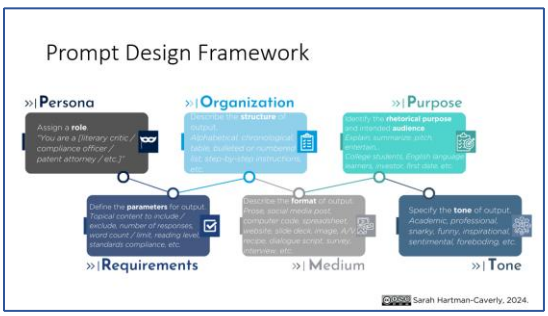
To incorporate AI into already full class schedules, both AE 401 and AE 404 leverage prior built-in time for interactive activities / float work session days. To limit additional burden on students, time was made for the new AI activities by (1) replacing older activities with the AI-based ones, and/or (2) recording parts of "spillover" lectures / leverage the flipped classroom format. In both classes, text-based generative AI was strategically demonstrated live in class with students or though recorded snap shots that were discussed live.

In the development of the demos, new AI "lectures / activities" provided short backgrounds on what is AI, how is AI trending in our industry (to showcase relevance), and how to perform good prompt engineering interactions with AI. Here, students were shown the positives, as well as discussed caution areas like AI hallucinations. Fig. 1 shows several representative "lecture" slides. Table 2 provide more insight into these "lecture compositions". None of the developed content provided any in-depth AI theoretical underpinnings. In all cases, connections to structural engineering were made.

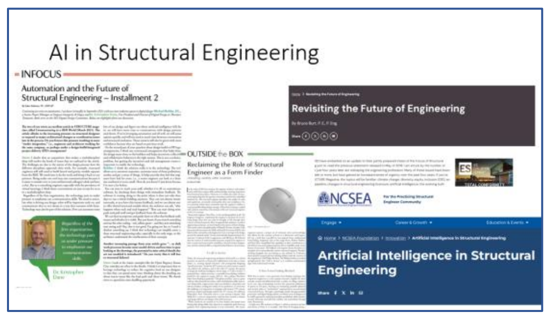
In total, 3 days were used in AE 401 and parts of 4 days in AE 404. A differing point was that AE 404 gave more real time demos and interactive exercises while AE 401 balanced live and pre-completed demos with animated notes. All demo lecturing portions were purposefully not long (<15min between demos) before students had a chance to interact with an AI platform.

Table 2: Delivered AI Topics and Broad Scope

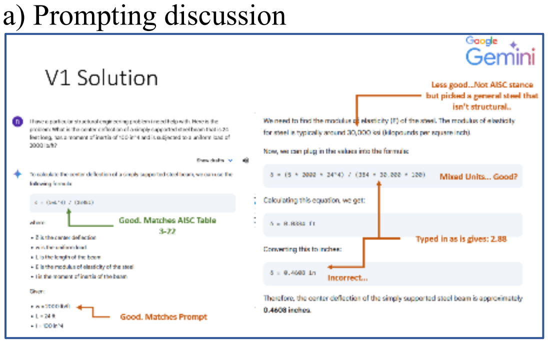
AE 401	AE 404
Lecture Day 1: what is AI, AI cautions (hallucinations), prompt engineering: **demos on**: analysis questions and prompt iterating on the topic of loading. *Leveraged*: ChatGPT and Gemini.	Lecture Day 1: discuss possible uses of AI in structural engineering**: demos on**: calculating shear and moment for a beam. *Leveraged*: Claude.
Lecture Day 2: AI in the building industry and structural industry; **demos on**: structural system suggestions and layout help. *Leveraged*: Perplexity and ChatGPT	Activity Day 2: interactive exercise on determining loads in a historic structure. Students were encouraged to use AI for research. *Leveraged*: Student Choice
Lecture Day 3: Ethics and cautionary tales of AI, knowing how to critically think about output, and open-source vs professional AI platforms; **demos on**: capacity calcs and design calcs. *Leveraged*: Gemini, ChatGPT and NCSEA SEGPT	Lecture Day 3: prompt engineering, cautionary tales of AI, knowing how to critically think about output; **demos on**: structural system suggestions, layout help, and capacity and design calcs. *Leveraged*: Perplexity and ChatGPT.



a) Prompting discussion



b) Connecting to industry



c) AI Results Review

Figure 1: Representative Sample slides used in the "lecturing portion"

Assignment Development

As this project was exploratory, four assignments looked at varying aspects of structural engineering that varied the level of open-endedness, complexity, and scenario compositions. Table 3 provides a summary of 4 professional scoped scenarios. While students were capable of doing all of these "by hand / without AI", the intent was to see the advantages or disadvantages that AI provided students. For both classes, older non-AI equivalent assignments were replaced by these new AI activities. For AE 401, all graded AI activities started in class but were finished out of class whereas for AE 404 was largely all completed in class.

Set 1 had students try to have AI directly solve the problems concurrent with hand calculations with a critical review of the output. Set 3 centered on finding a problem in a design and fixing it which led to AI opportunities to aid in the redesign (recommendations or numerically). Set 2 and 4 were created to leverage AI by asking it questions related to the scenarios. Here, students should have used AI recommendations to finish the tasks (not direct solving). Fig. 2 highlights images from the scenarios to provide better context in Table 3.

Table 3: Context of the AI Assignments, Scope, and onset intended AI interactions

Set #	Scenario Type	Context	Description	Intended AI Scope	Hopeful AI Interactions to Avoid
1	Close-ended analysis scenario	Math Problem Solving Prior Application	Students are asked to solve prior structural analysis problems they have seen in a prior course to get comfortable with AI and fill in gaps.	Adopt AI help solve problem(s) w/ technical rigor. Students compare AI to hand methods to understand the pro-con & any items to be cautious of.	Have students use it to just solve and accept results. Not check the output for hallucinations.
2	Semi-open-ended design scenario	Conceptual	Students will lay out beams, columns, and girders for a series of bays that have complex geometric that extends beyond what is covered in lectures.	Adopt AI to provide inspiration and additional best practices to help them conceptualize.	Let AI do it completely. Accept recommendations that don't match the scenario.
3	Semi-open-ended design scenario	Math Problem Solving Critical Thinking	Students are given floor design doesn't work and they need to fix it, but it has a series of technical constraints that need to navigate.	Adopt AI help solve problem(s) w/ confusing / broad wording that is different than examples in class.	Have students use it to just solve and accept results. Not check the output for hallucinations. Accept recommendations that don't match the scenario.
4	Open-ended design scenario	Math Critical Thinking Conceptual	Students will be given a problem where several design strategies could work for, but conflicting performance metrics exist.	Adopt AI to navigate what might be best for the problem and how to navigate the conflicts.	Not critically think about the AI output and if it actually applies. Accept recommendations that don't match the scenario.

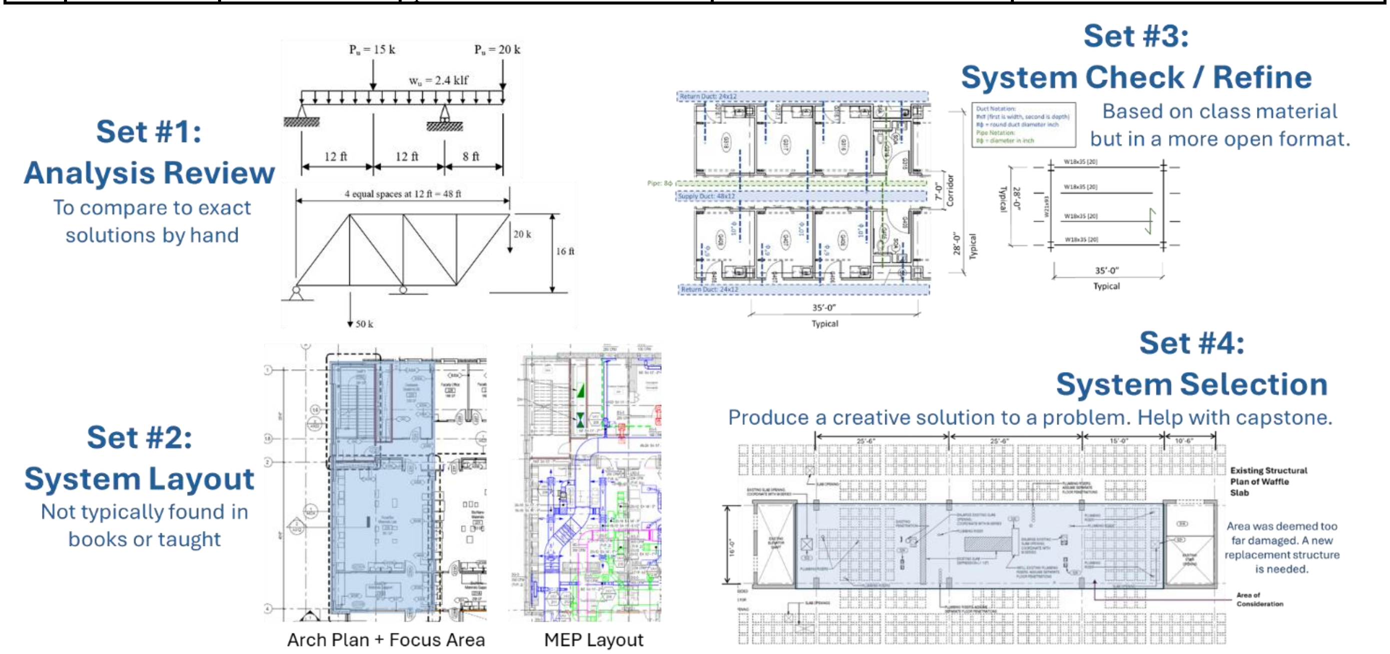


Figure 2: Sample scenario images from assessments

Results and Discussion

This section reports data on student performance (rubric data), adoption mechanics of AI (coded worked), and perceptions towards AI and course topics (pre- post survey). AE 401 had an 87.2% (n=34) participation rate, while AE 404 had a 31.7% (n=19) participation rate. To best help future AI adopters, results are broken into the following sections:

- Student Perceptions on AI Abilities / How AI Enhances their Abilities
- Student Self-Efficacy Perceptions using a Meta AI Literacy Scale
- Student Trends on AI Performance in Assignments
- Student Trends on AI Leveraging in Assignments
- Student Reflections on their AI Work
- Faculty Perceptions on Teaching

Student Perceptions on Leveraging AI and its Results/Abilities

Capturing student perceptions of AI stemmed from questions employed in recent computational thinking surveys [35-36] that are summarized in Figs. 3-5. Questions on learning attitudes toward class and assessment [37-38] and student trust in computers and AI [39] were adopted from vetted literature with minor contextual wording adjustments.

Skepticism was observed regarding AI's ability to fully solve design or analysis problems where it notably increased in AE401 after course completion (Fig. 3). This trend was not uniformly observed in AE404; in some cases, trust increased from pre- to post-survey, such as for solutions to math prompts and recommendations for analysis problems (Fig. 3). Overall, distrust was more common than trust, with the highest level of trust being rarely selected. "Highly Distrust" or "Distrust" accounted for over 50% of responses on many questions. Distrust also appeared in written summaries, where students identified incorrect processes or outright mistakes made by AI. Difficulty obtaining correct answers likely outweighed perceived benefits from a trust perspective.

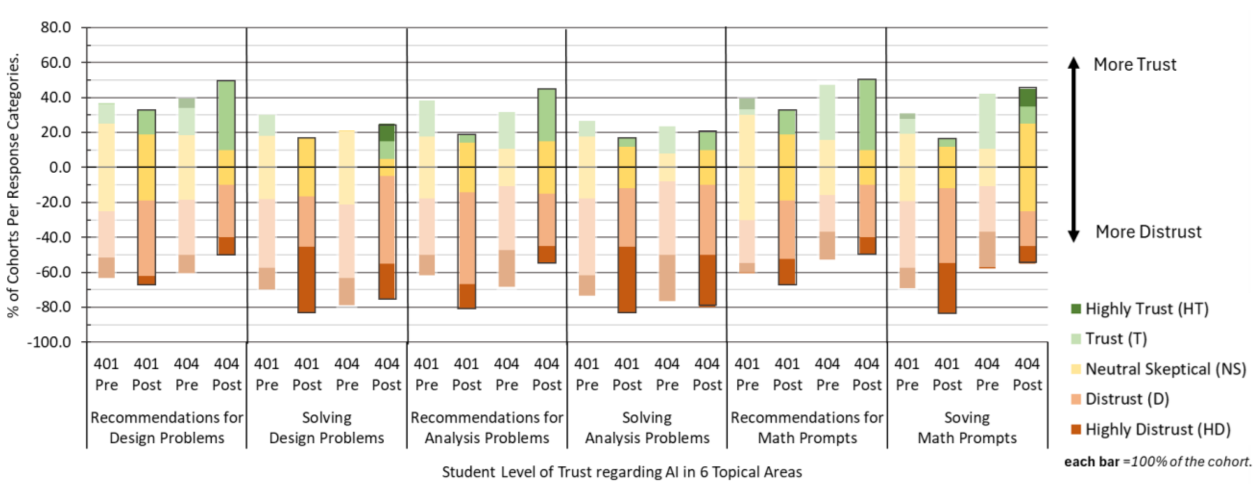


Figure 3: Change in student level of AI trust after course exposure

Note: *Legend order matches bar chart verticality; lighter masked bars are pre-AI perceptions while bars with darkened borders are post-AI perceptions.*

Fig. 4 shows student trends in AI utilization. Slight increases were observed in using AI to help open-ended design tasks after course completion. Curiously, the percentage of students responding that they "never tried" using AI to solve technical problems increased in the post-survey, particularly in the AE 401 cohort. The only possible explanation (that can be determined) is from mixed success in AI help. Differences between cohorts may reflect instructor, activity, or student characteristics, though many were small, especially within AE 401 from “rarely” to “never.” The largest shifts (23.4%) occurred in the “always” and “often” categories, particularly in AE 404 when asking clarifying questions about topics during in class activities. AE 404 also showed positive changes in asking AI for advice and direct question answering. However, the quality of these requests cannot be determined from response data alone.

When asked why they used AI, students most cited conceptual clarity, lack of topic familiarity, and weaknesses in grammar (Fig. 5), exceeding responses related to time constraints or struggling in the class. AI utilization increased in 3 of 7 categories for both AE 401 and AE 404, with only one shared category: “when students were confused”. This may indicate that AI-integrated activities build confidence in seeking AI assistance. For AE401, using AI to clarify confusion had the highest score (86%) and largest increase (21%). For AE404, grammar showed the highest score (80%) and largest increase (38%). Figure 5 also shows some students used AI when short on time or to generate material under time constraints.

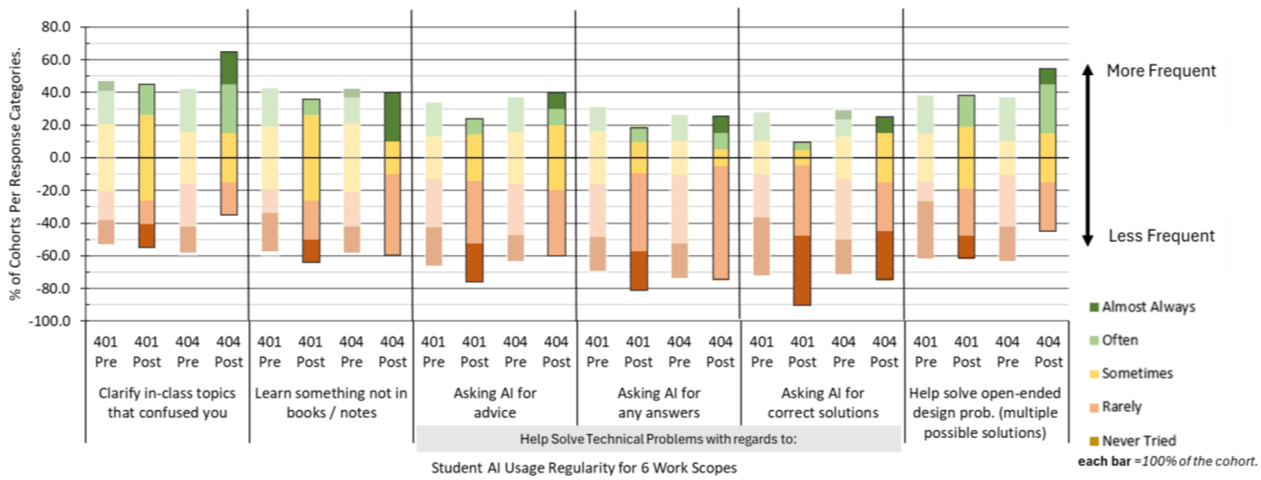


Figure 4: Student trends in types of AI utilization

Note: *Legend order matches bar chart verticality; lighter masked bars are pre-AI perceptions while bars with darkened borders are post-AI perceptions.*

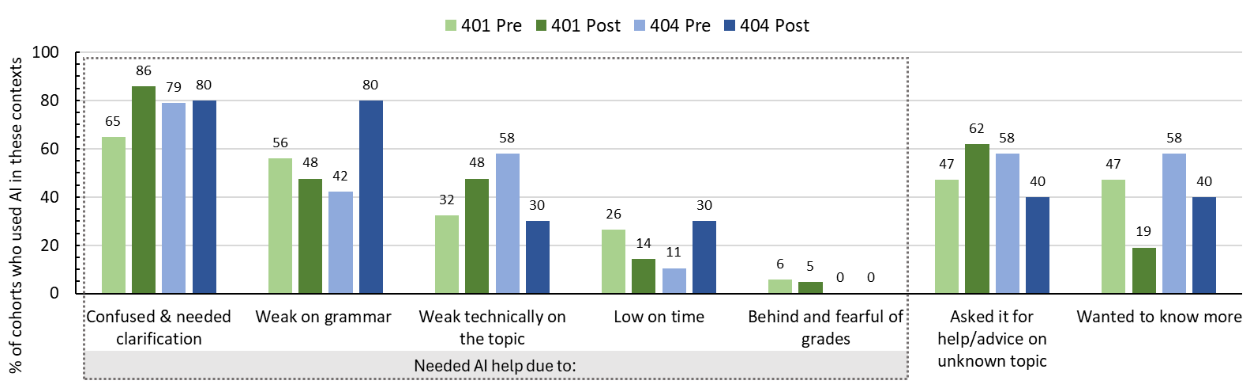


Figure 5: Student Reasons for Using AI in Engineering Contexts.

<u>Student Meta AI Literacy Scale Evaluation</u>

AI Literary and psychological competencies, such as problem-solving, understanding students’ attitudes, perceptions, and educational impacts were explored [37]. Carolus et al. [40] developed the Meta AI Literacy Scale (MAILS) to quantitatively measure these traits across AI domains. MAILS was adopted for three sub-scales: Know and Understand AI (KU Scale) [41], Apply and Use AI (AU Scale) [41-42], and Self-Efficacy towards AI Learning (SE Scale) [43-44], which were most relevant here. Wording from Carolus et al. [40] was kept identical where possible, with minor adjustments to the context of structural design. These 21 questions across 3 sub-groups used a 5-point Likert scale of: strongly agree (5) to strongly disagree (1).

For the KU sub-scale, Fig. 6 provides percentage breakdowns for the pre- and post- questions by cohort. Overall, students agreed (SA+A ranged from 41% to 91%) far more than they disagreed (D+SD from 0% to 10%). From a pre-to-post-, SA+A changes ranged from -5% to 34%, while D+SD changes ranged from 1% to -10.5%. Average scores for AE 401 increased from 3.70 to 3.94 and for AE 404 from 3.75 to 4.03, corresponding to shifts of 0.25 and 0.28 (~1/4 of a Likert-scale increment). Both cohorts increased in imagining future AI uses and assessing advantages and disadvantages. AE 404 reported increased ability to assess AI limitations and opportunities, while AE 401 showed a slight decrease. Students were less likely to strongly agree they knew the most important AI topics. Positively, D+SD ratings decreased across all items.

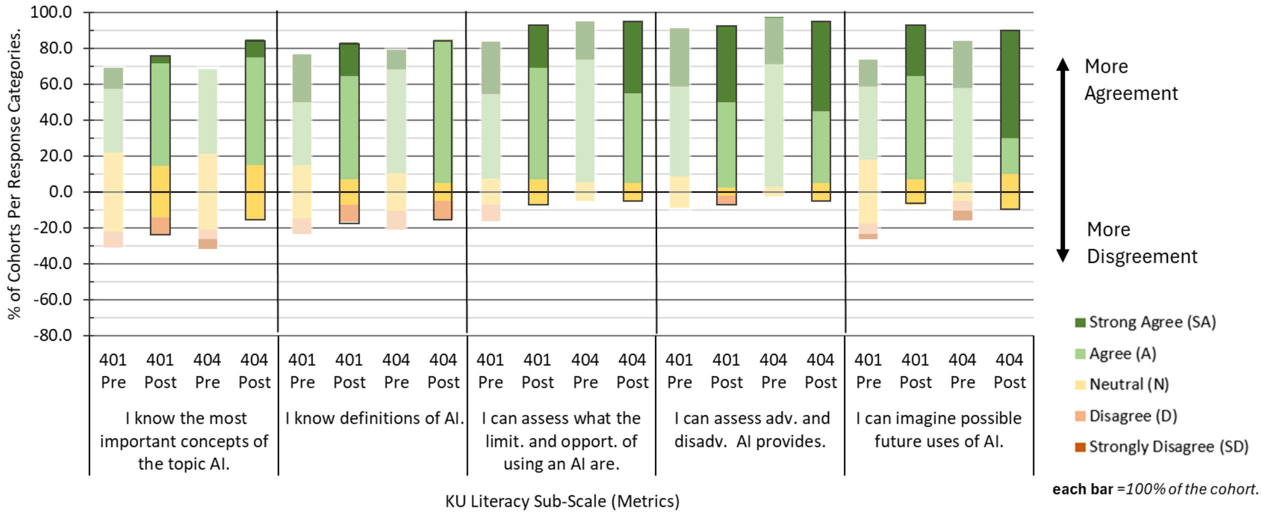


Figure 6: Change in student KU literacy results.

Note: *Legend order matches bar chart verticality; lighter masked bars are pre-AI perceptions while bars with darkened borders are post-AI perceptions.*

For the AU sub-scale, Fig. 7 presents pre- and post- perceptions as cohort percentages. Agreement was slightly weaker overall than in the KU scale with “Agree” and “Neutral” being the most common. Average scores for AE 401 decreased from 3.44 to 3.19, while AE 404 increased from 3.12 to 3.59, reflecting shifts of -0.26 and 0.28 which indicate more positive impacts for AE 404 students; whereas AE 401 yielded more caution. Post averages across items were 22.7% agreement, 20.9% disagreement, and 27.5% neutrality. Pre- to post-SA+A changes ranged from -10% to 24%, and D+SD from -32% to 20%. Both cohorts increased agreement with “I can operate AI applications in the structural domain well,” though other systematic changes were limited. Despite possible mathematical struggles with AI, students maintained positive agreement on AU items, particularly regarding using AI to simplify structural tasks.

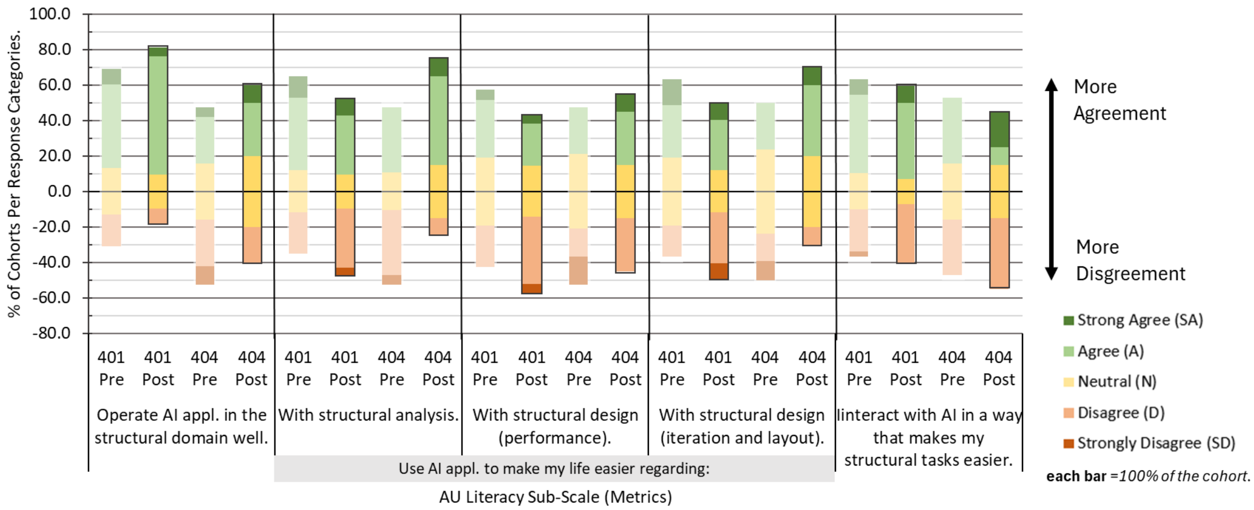


Figure 7: Change in student AU literacy results.

Note: *Legend order matches bar chart verticality; lighter masked bars are pre-AI perceptions while bars with darkened borders are post-AI perceptions.*

Lasty, Fig. 8 presents SE sub-scale results. Students predominantly "strongly agree" that they are aware of AI influence and can resist it if necessary. AE 401 averages increased from 4.03 to 4.10, and AE 404 from 3.65 to 3.87 (shifts <0.22), indicating limited intervention impact. Overall, students appear comfortable interacting with, trusting, and self-regulating AI. They reported relying on prior learned technical skills when encountering suspicious or "out-of-place" AI output and agreed they can recognize when AI influences their final work, suggesting metacognitive awareness via critical thinking.

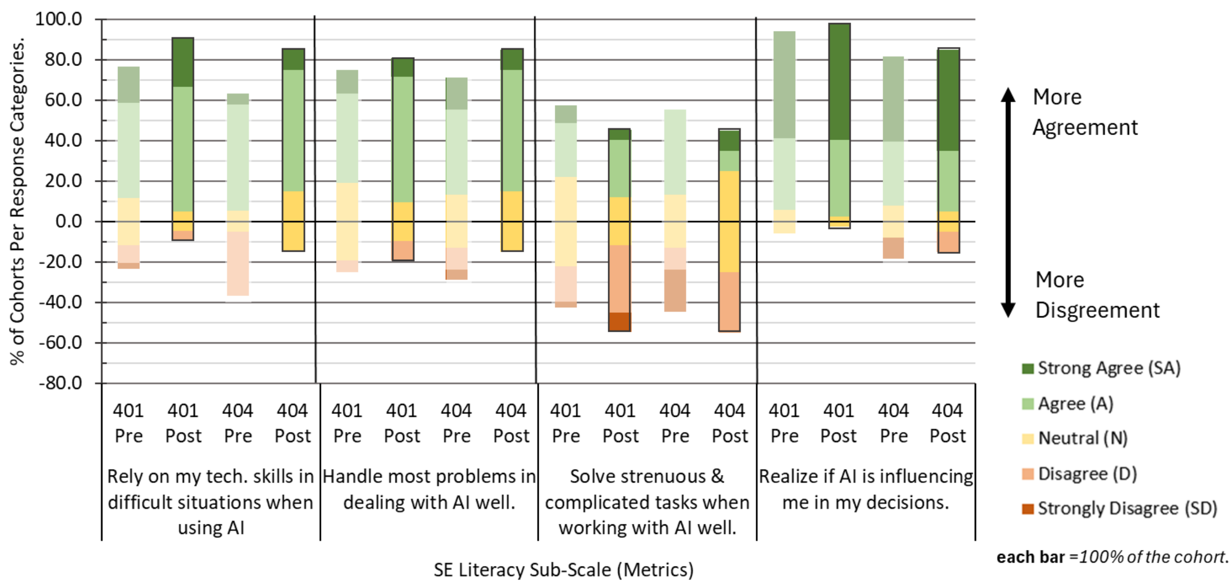


Figure 8: Change in student SE literacy results.

Note: *Legend order matches bar chart verticality; lighter masked bars are pre-AI perceptions while bars with darkened borders are post-AI perceptions.*

<u>Student Trends in Assignments on AI Performance</u>

While four assignment sets were completed, Sets 1 and 4 had the greatest overlap between courses. This paper focuses on these overlaps due to nearly identical language and required methods. Set 1 was homework in both classes. Set 4 used identical language but was assigned as an out-of-class activity in AE

401 (≤2 hours) and as Quiz 3 in AE 404. A consistent rubric was applied for all assignments with these ratings: Comprehensive (100%), Sufficient (90%), Adequate (80%), Lacking (70%), Marginal (60%), and Unacceptable (0%) for each major component.

Table 4 summarizes descriptive statistics for Set 1 (structural analysis) and performance (%) by category across three problems: (1) calculating the shear and moment (V&M) diagram; (2) determining truss forces (T vs. C) and zero-force members; and (3) cross-sectional stress calculations with stress-reduction recommendations. AE 404 outperformed AE 401 on trusses and cross-sections, especially the cross-section stress problem. A likely contributor was a review session in AE 404 that was not provided in AE 401. AE 404 had the highest comprehensive scores on cross-section stress, whereas AE 401's performance was very low. Results suggest AE 404 students more effectively leveraged AI to revise cross-sections to reduce stress. Notably, AE 401 had fewer math errors but more conceptual errors than AE 404.

Table 5 presents descriptive statistics for Set 4 (open-ended conceptual design) and performance (%) by category for: (1) generating new structural concepts to replace a deficient system(s); (2) conducting a pro–con evaluation of ideas; and (3) selecting a concept and outlining required processes and checks to complete. AE 401 performed lower than expected on Conceptual Sketches and Design Process where the task involved replacing part of an ineffective waffle slab. Many responses were rated sufficient or adequate due to limited detail, missing framing elements, or insufficient system integration. Parts 2 and 3 were also unexpectedly low. For the pro–con evaluation, weaknesses included missing logical detail, insufficient specificity, or focusing only on structural aspects (contrary to instructions). Design process responses frequently lacked sufficient detail or a complete process. All components could be developed correctly and in greater depth using AI when generating the assignment.

Table 4: Set 1 Student Performance.

		Avg.	% of Cohort in a Rubric Performance Category					
			Comprehensive	Sufficient	Adequate	Lacking	Marginal	Unacceptable
V&M Diagrams	AE 401	92.4	42.4	6.8	8.5	10.2	0.0	0.0
	AE 404	92.4	66.1	11.9	15.3	3.4	1.7	1.7
Truss	AE 401	81.6	15.3	11.9	22.0	15.3	0.0	3.4
	AE 404	91.0	64.4	13.6	8.5	5.1	6.8	1.7
Cross-section Stress	AE 401	72.4	6.8	11.9	11.9	30.5	0.0	6.8
	AE 404	82.5	28.8	18.6	28.8	6.8	15.3	1.7

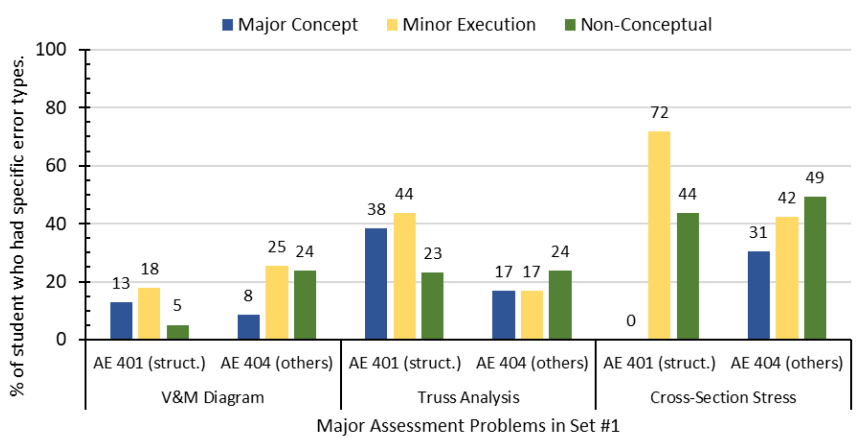
Table 5: Set 4 Student Performance

		Avg.	% of Cohort in a Rubric Performance Category					
			Comprehensive	Sufficient	Adequate	Lacking	Marginal	Unacceptable
Concepts/ Sketches	AE 401	80.6	14.3	37.1	20.0	14.3	11.4	2.9
	AE 404	83.7	17.5	31.6	26.3	19.3	5.3	0.0
Pros/Cons	AE 401	56.1	40.0	40.0	17.1	0.0	0.0	2.9
	AE 404	53.9	38.6	10.5	29.8	17.5	3.5	0.0
Design Process	AE 401	49.8	35.3	32.4	8.8	8.8	2.9	11.8
	AE 404	53.5	35.1	19.3	26.3	15.8	1.8	1.8

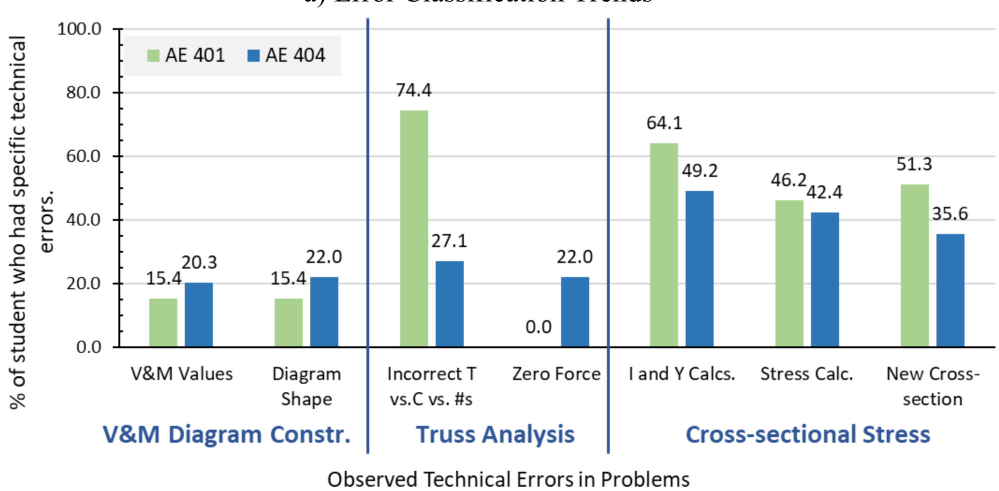
To better understand student performance (Tables 4 and 5), a coded collection of common errors and error classifications was developed, inspired by Bruhl et al [45]. Identifying engineering problem types—such as preconceived misunderstandings or incomplete grasp of basic concepts [46]—helps determine whether AI contributed to errors or whether fundamental understanding gaps existed. For Sets 1 and 4, mistakes were categorized as: 1) non-conceptualization errors [47] (e.g., calculation, representation, or expression errors); 2) minor execution errors [48] (math, signs, labeling, directions, missing steps); and/or 3) major conceptual errors [49] (incomplete or incorrect application of knowledge, or total topic failure) [45]. While specific errors differed by part and set (as observed by Bruhl), only high-level trends are discussed here.

For Set 1 (analysis), Fig. 9 compares error types between cohorts. Notably, none of the recorded errors were directly attributed to AI, suggesting no overreliance. Results do reveal gaps in fundamental analysis, potentially from earlier coursework in some cases. No students relied solely on AI when their own calculations differed. AE 404 had substantially fewer incorrect tension/compression identifications and slightly fewer I/Y, stress, and cross-section fixing errors. The reverse was true for shear and moment diagrams. Both courses showed more truss errors than beams. The higher error rate in AE 401 was unexpected, it may reflect the lack of review lectures and lower attention to detail (they "knew it already"), whereas AE 404 students appeared more cautious.

For Set 4 (open-ended conceptual design), Fig. 10 compares cohort error types. Minor execution errors were most common in both courses, followed by major conceptual errors. AE 401 struggled with missing multidisciplinary review, improper holistic context, and non-creative solutions, while AE 404 most often showed poor system layout and incomplete pro–con lists. In these cases, AI was used more as a guidance tool than a direct solver. The most frequent AI-related adoption errors were in pro–con list generation (Fig. 10), where students accepted illogical or disconnected answers. These findings align with performance in Table 5.



a) Error Classification Trends



b) Incorrect Work Error Trends

Fig 9: Coded Set 1 error type and frequency trends across student work.

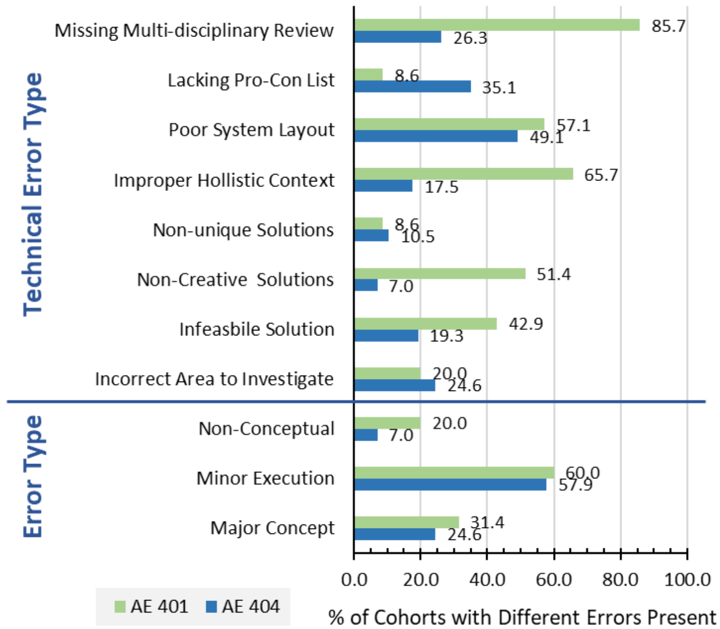
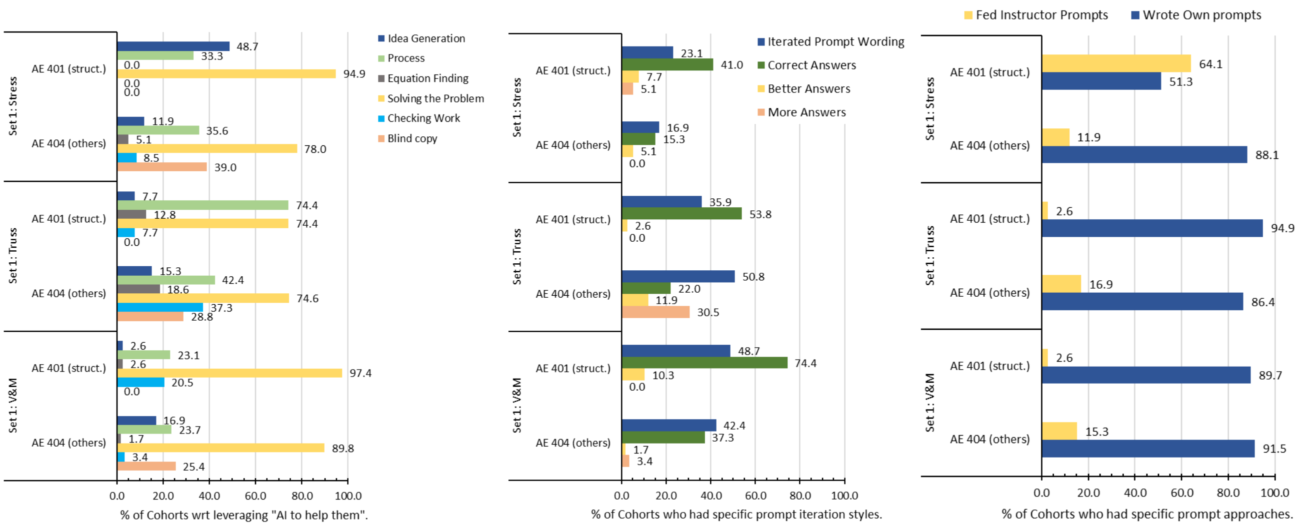


Figure 10: Coded Set 4 error type and frequency trends across student work.

<u>Student Trends on How AI was Leveraged in Assignments</u>

Figs. 11 and 12 show how AI was used across three categories for each major problem in Set 1 and 4: 1) What was AI Leveraged for (Group A: 6 domains), 2) What was the intent during prompt iteration (Group B: 3 domains), and 3) Types of prompt engineering (Group C: 2 domains). In the Group A (Fig. 11a and Fig. 12), six AI leverages were tracked: 1) blind copying results (partial to totality) [50], 2) solve the problem as required where they use AI as a reference solver [51], 3) generate ideas to start the problem or to overcome specific stumbling points [52], 4) obtain the process to solve the question(s) [53], 5) checking their work [54], and lastly 6) find the right equations to use [55].

In Set 1, all problems recorded leveraging AI to solve the problem as bar far the largest 74-94%. with other interactions <23% for V&M diagrams. For trusses, the most common was AI aiding in learning the process (42–74%). For cross-section stresses, AE 401 used AI 49% for idea generation, while AE 404 used it 39% for blind copying and 36% for processes. In Set 4, AE 401 and AE 404 primarily used AI to solve problems (89% and 56%). AE 401 also heavily leveraged AI for idea generation (71%), whereas AE 404's second-most common use was 23% for idea generation. By Set 4, structural students were more likely to use AI in multiple problem-solving approaches, while other students relied on a single method.



a) Group A Trends b) Group B Trends c) Group C Trends

Figure 11: Coded AI usage (leveraged) by students regarding Set 1 problems.

Note: *Legend order matches bar charts.*

As part of the short training sessions (Table 2), prompt engineering basics were taught to help students obtain meaningful AI answers. Student prompt iterations, including the "why," were recorded for Group B (Figs. 11b and 12). For Set 1, 23–49% of AE 401 and 17–51% of AE 404 students iterated prompts across the three problems; for Set 4, 26% of both cohorts iterated. Students gathering more information occurred least often, while obtaining better or correct information—requiring metacognitive recognition of AI errors—was most frequent.

Within Set 1, AE 401 largely iterated for correct answers (41-74%) across problems, indicating sufficient problem knowledge to adjust AI mistakes via prompts. AE 404 showed similar pattern, albiet at a much lower rate. Low percentage rate for more or better answers is posivitve as student began asking for more information shows a shift leveraging their fundamental technical skills. In Set 4, iteration reasons were more varied. Few students refined AI results specifically for correctness (lowest in AE 401); instead, many sought better answers (41% AE 404) or more answers (28% AE 401), indicating awareness that results were not wrong but could be more complete or better described.

Group C examined general prompting approaches. Students either wrote tailored prompts or copied assignment content directly into AI. A common challenge was AI's limited image interpretation, requiring detailed text descriptions across both Sets. AE 401 used both approaches more frequently (21% Set 1, 55% Set 4) than AE 404 (9% Set 1, 15% Set 4), showing lecture-taught prompt tips were applied by most students. AE 401 used both approaches more frequently (21% Set 1, 55% Set 4) than AE 404 (9% Set 1, 15% Set 4). This adoption shows lecture-taught prompt tips were applied. Those who used instructor wording often needed more iterations than those who customized prompts, as AI misinterpreted assignment requirements without added context.

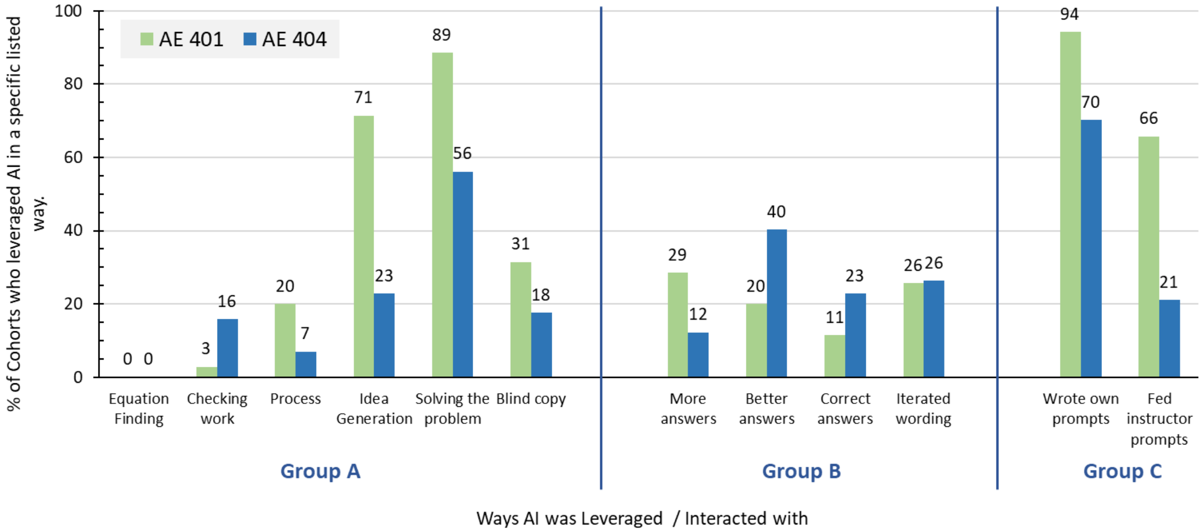


Figure 12: Coded AI usage (leveraged) by students regarding Set 4 problems.

Student Reflections on their AI Assignment Work

As AI is new to structural engineering and literature highlights its barrier and challenges [56], it was important for the instructors to have an AI reflection within each Set to engage students' metacognition [57]. Common to both Sets 1 and 4 were four areas (Fig. 12): (1) whether AI results made sense, (2) ethical considerations and connections, (3) perceived helpfulness with the assignment, and (4) feasibility of AI in structural practice. Furthermore, Set 1 also asked whether AI could make an engineer better or worse and its industry impact, while Set 4 asked if AI provided new discovery knowledge (Fig. 12). Professional ethics and implications were not commonly discussed (<16% in Set 1, < 18% in Set 4), which suggests more time could likely be used to address ethics into the "lectures" by connecting it towards pro-practice competency, liability, and licensure.

For Set 1, AE 404 showed higher metacognitive engagement, with larger percentages in 5 of 6 tracked items, especially AI's impact on the industry (Fig. 12). AE 404 students were more vocal about AI's helpfulness in the scenarios, aligning with performance trends (Tables 4 and 5). For Set 4, AE 401 showed higher metacognition across all items except ethics, suggesting these structural students grasped the concepts quicker long-term.

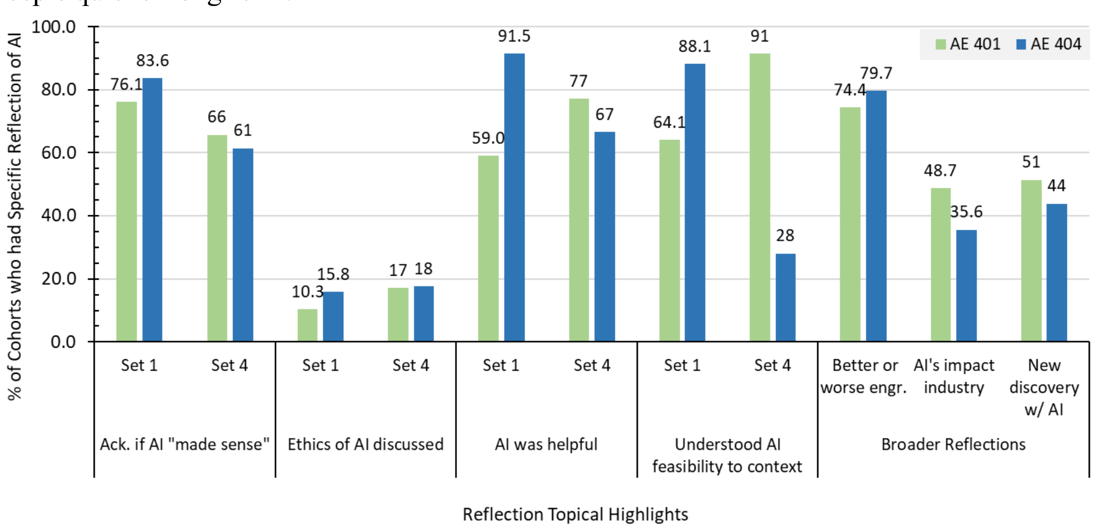


Figure 12: Coded student AI reflection trends across Set 1 and Set 4.

Beyond these tracked metrics, students were quick to become skeptical of AI's ability to solve problems automatically, though ~45% expected improvement as AI continues to advance. A recurring theme was that expertise is needed to validate AI outputs (especially Set 1 calculations), while Set 4 students were disappointed by lack of detail in AI-generated answers. Across cohorts equally, about 30% felt AI was better suited for "office-type work" (reports, memos, summarizing, grammar), reflecting prior use and AI's current maturity. This aligns with Structures Magazine documented possibilities for firm adoption in practice [58].

Faculty Perceptions from Teaching

To complement student perceptions, the instructors summarized their experiences. Broadly, faculty observed similar trends to the presented data, though rubric-based numerical performance was lower than expected, suggesting a potential need for rubric. Several AI-related patterns were notable.

In AE 401, structural students quickly became skeptical of AI's numerical results after the first demo (revealing AI "math guessing"), viewing AI as "extra work" since they could perform the calculations themselves. Concurrent AI and hand-calculation tasks were often seen as excessive especially "when other work was due". Positively, AI supported process-oriented aspects in open-ended design. Many students initially fed assignments directly into AI or relied on AI when frustrated (a surprise to the instructors). Some accepted AI-generated content (e.g., pro–con lists) without filtering out off-topic items, though in open-ended tasks, AI provided useful starting points for creative solutions.

In AE 404, students showed initial resistance to using AI for assignments, perceiving AI as added workload. Skepticism increased after demos showing mixed accuracy in following processes and calculating "correct answers". However, in the more open-ended activities, AI was accepted as a resource for finding information and helping with concepts, sometimes after an initial surprise that AI was "allowed." Some students exhibited anxiety about learning AI in an engineering context, possibly due to uncertainty about how AI might impact their future careers. AI is likely to change their jobs in the future compared to what engineers have done before, but in a way that could not be fully anticipated and prepared for while still in school.

In both cohorts, AI was rarely seen to speed up work. This may change as multimodal AI is more capable of reading detailed engineering images and correctly extracting vital information. Additionally, neither cohort consistently considered the document versions of AI they were using or what versions of reference documents AI pulled from (ex: IBC 2018 or 2024, or ASCE 7-16 or 7-22) which instructors should emphasize in future exercises.

Implications and Lessons Learned

This pilot leveraged AI in two structural design courses with two unique cohorts to support future AI integration efforts. From this experience, the authors/instructors report lessons learned regarding the teaching and assignment side of AI. Takeaway recommendations are three-fold grouped: 1) to help construct the classroom experience (CE), 2) to have better student buy-in (BI), and 3) to better connect topics to AI (CT).

Approaching Teaching

- **CE & CT**: Spend time emphasizing careful prompt engineering and, more importantly, iterating to get better or "correct" answers. This could include giving reference images.
- **CE**: Use live demos in class, which can have pre-built supplemental screenshot results (to save time and to give to them out later).
- **CE**: Showcase by comparing outputs across platforms and model versions.

- **CE** & **CT**: Demonstrate applications across multiple structural engineering topics and result types.
    - Structural topics: analysis: (V&M, stress, deflections, trusses, load path, etc.), design: (generating systems and section / system selection), code interpretation and application, and material specific capacity checks.
    - Result type: solving questions with math, asking for procedural guidance, and identification of governing equations.
- **CE** & **CT**: Guide students through AI answers that contain both correct and incorrect answers (where it brings in non-relevant topics due to certain word associations or items with dual meanings.)
- **CE** & **CT**: Highlight the importance of verifying cited standards and code versions (e.g., ASCE 7-16 vs. 7-22).
- **CE** & **BI**: Emphasize analytical accuracy over aesthetic output (e.g., visually appealing graphics).
- **CE** & **BI**: Utilize freely available platform versions when feasible to maintain accessibility.
- **CE**: Update and adapt teaching approaches frequently.
    - For example, multimodal AI tools that are better at interpreting images might have yielded different results in our study.
    - AI tools (with RAG capabilities) that can retrieve and cite relevant information are already a significant improvement for these applications than earlier generation AI tools.
    - Rapid tool development necessitates a dynamic approach to instruction.
- **CE** & **BI**: Be thoughtful on when to introduce AI in relation to foundational engineering concepts.
    - Many fields are grappling with how experts performing AI-assisted tasks can become less engaged or less effective over time, depending on the abilities of the AI and whether the human still feels needed.
    - Premature integration may reduce motivation to master core concepts.

Approaching Assignments

- **CT** & **BI**: Include exploratory activities requiring student comparisons across multiple AI platforms to examine variation in outputs.
- **BI**: Require submissions to have representative prompts and AI output as supplemental documentation to support transparency and gauge effort.
- **CE** & **CT**: Careful construct assignments to make students check/verify the output (never just AI answers). This helps build critical thinking, problem solving, and model validation habits/ skills.
- **BI**: Limit the scope and duration of AI-intensive activities (shorter is better), particularly those requiring iteration.
- **BI:** Incorporate brief reflective components to support metacognitive development.
- **BI**: Integrate AI into selective homework problems or as distinct activities (rather than both) to manage workload.

Conclusions

This paper investigated embedding text-based generative AI activities into structural design courses, focusing on how students adopt AI, how AI affects student performance, and evolving perceptions of AI across design tasks of increasing complexity. By integrating commercial "off-the-shelf" AI tools into steel design activities, this study contributes empirical evidence to a growing body of engineering education research that moves beyond generalized AI use cases such as writing or coding. A comparative analysis across two distinct cohorts—future structural engineers and non-structural architectural engineering students—highlights that AI adoption is neither uniformly beneficial nor uniformly detrimental, but instead dependents on task type, student background, and instructional framing.

Students in both AE 401 and AE 404 demonstrated an ability to engage critically with AI when encouraged to do so, particularly in scenarios that required result checking, refining prompts, or using AI to clarify process rather than directly solve problems. Persistent challenges were observed: students frequently over trusted AI outputs beyond what would be expected of professional engineers, or accepted illogical recommendations in open-ended contexts, or disengaged when AI failed to be helpful. Structural students often perceived AI as inefficient for tasks involving calculations, while non-structural students appeared more willing to rely on AI for conceptual guidance and idea generation. These mixed outcomes indicate that AI does not inherently improve learning but presents opportunities for thoughtful integration.

Several limitations should be considered when interpreting these findings. First, the study examined only two cohorts at a single institution, which limits the generalizability of the results to other programs and other student populations. Second, while care was taken to align activities, some differences in assignments, delivery format, and reviews existed between courses, which may have influenced performance and perceptions. Third, the investigation focused on a single domain (structural steel design) within engineering, limiting conclusions about how AI adoption may differ across other materials, disciplines, or instructional contexts.

Despite these limitations, this work offers practical insights for thoughtful integrations of text-based AI into engineering design education and identifying where caution is needed. As AI tools continue to evolve, especially with improvements in multimodality, reliability, and domain-specific training, their role in engineering will likely expand. Future research should explore longitudinal impacts, additional materials and design domains, and multi-institutional studies to better understand how AI can support learning without undermining foundational engineering judgment. The ultimate goal is not to replace engineering thinking with AI, but to prepare students to critically, ethically, and effectively engage with AI as it becomes an increasingly common component of professional engineering practice.

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