Student Use of Generative AI in Structural Engineering

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Abstract

The use of generative artificial intelligence (AI) tools has become increasingly common in many fields of work, including engineering. Engineering students are likely aware of these new tools and may be using them to different degrees for their college coursework. In this study, the hypothesis was that engineering students have become familiar with free tools like ChatGPT and Gemini, but they do not fully comprehend how to best use the tools and interpret the results through a technical lens. Therefore, this study was designed to answer two research questions: (i) Can students correctly solve typical structural engineering homework questions with only generative AI tools? (ii) Are students comfortable with and do they have confidence in using these tools to solve structural engineering problems?

Several homework-style technical questions and perception surveys were given to students at two universities in four typical structural engineering courses (statics, mechanics of materials, structural analysis, and reinforced concrete). Students were tasked with solving the homework-style technical questions twice, first by hand and again only using generative AI tools, with approximately one week between attempts. Before and after perception surveys were deployed to collect data related to the students' experiences completing these assignments and the tools they chose to use.

The results indicated that students were aware of AI tools (particularly popular versions such as ChatGPT, Google Gemini, and Microsoft Copilot), but less than 50% currently used them in technical engineering coursework. For students who had experience with the tools, the primary use was as an assistant to learn the material. After completing the exercises in this study, more students were interested in using the tools to check their work, but they still showed a hesitance toward full adoption of generative AI tools to solve technical problems. In this study, on 75% of the technical questions, students arrived at the correct answer using generative AI tools more often than without the tools. The biggest issue encountered by students using the generative AI tools was related to solving problems with visual pictures, like shear and moment diagrams. There was a gap in students' trust in the solutions and ability to use engineering judgement to check the results, particularly among students in second-year courses. Those in fourth-year design courses checked their work often, typically using handwritten work or engineering judgement. Overall, it was determined that there is a need to discuss the uses of AI tools with students, continue having them learn a solid foundation of fundamental concepts, and specifically teach them how to apply engineering judgement in the context of interpreting generative AI output, particularly in lower-division statics and mechanics classes.

Introduction

The use of AI tools has become increasingly common and more widely accepted by society [1] [2]. Reports indicate that AI tools will change the way engineers solve problems and revolutionize the methods used to analyze and design engineering solutions [3]. The exact ramifications of this transformation on the engineering profession are not yet known, but the generative AI landscape is rapidly changing. Engineering students are likely aware of these new tools and may be using them to varying degrees to complete their college coursework. The question is not “are they aware of these tools?” but rather “how are they using the tools and are they doing it effectively?” The purpose of this study was to investigate how students may be using generative AI tools in structural engineering coursework. In addition to using these tools, the study investigated if they use them correctly and trust the technical output.

Background

The exact scope of AI use and direct applications to engineering are under development, but it is reported that AI tools are being used in design, decision making, and optimization problems. These uses include performing repetitive and routine operations and discovering new knowledge hidden in large data sets and systems [4]. AI has also been reported to help write programming code, brainstorm ideas, and summarize literature [5]. At the same time, there have been reports that AI may not be as efficient and accurate in situations that involve reasoning and judgement [6]. The short-term use of AI is still uncertain, but it is very likely AI will be used to generate engineering solutions in some format in the future [7, 8, 9].

Higher education is in flux and still trying to figure out how to address the use of AI tools. Engineering educators aim to develop students into critical thinkers who can apply knowledge to complex problems and use engineering judgement. Accomplishing this requires learning techniques different than simply memorizing text or events, a task that AI tools have become very efficient at performing [6]. The tools may add efficiency to work and possibly the learning process, but AI tools may also prevent students from properly engaging with assessments (like homework) and prevent them from learning core concepts [5]. Homework has traditionally provided an avenue to make significant learning gains and help with the formation of critical thinking skills. Students sometimes view homework as an obstacle that can be more easily overcome by using an outside tool. Using AI to do an entire assignment usurps some of the gains made in the learning process [10]. This is also true when students use an AI tool to research and write a technical paper, which undermines the research and thought process of organizing ideas and putting them together [11]. Professors have also voiced concerns about using AI tools to complete assignments or assessments in the context of academic integrity [12]. Using AI in higher education has been reported as progressing at a varied pace [8]. Part of this is because of the rapid advancement in technology, and professors do not fully grasp the capabilities and limitations of the tools [6].With so much uncertainty associated with such a powerful tool, there is as much concern as there is hope.

Regardless of the feelings of educators, the rapid advancements and notoriety of AI tools demand a response from higher education. In many cases, the AI systems are continuing to improve at solving problems that are traditionally assigned for assessment in an engineering curriculum. This has been shown with the Fundamental Competencies Exam (FCE) used in Latin America. ChatGPT versions 3.5 and 4 scored a 47.4% and 63.1% success rate, respectively, on the FCE test questions on one particular attempt [13]. While these are basic problems, others have noted that AI tools can be used with more advanced design problems; Nasser showed that AI tools can take existing code-based design procedures and follow a data driven approach to perform routine operations such as beam designs in structural engineering [4].

In another study, the professors suggested caution in applying AI because of the ethical concerns, reliability of the outcomes, and the reputation of the profession. At the same time, because students are going to be exposed to the tools, it was recognized that they need a basic understanding and training in how to use AI effectively [7]; there may be a disparity between use in educational versus industry settings. Thus, there is a need to adapt industry expectations for graduates while still providing students knowledge from a comprehensive engineering curriculum [8]. In fields like structural engineering, some understand and value the practical and intuitive skills that are important when using computing tools [14]. One suggestion has been to introduce AI techniques early. Students can verify output in courses such as statics and mechanics of materials and then develop advanced uses of AI in higher-level structural design courses. This could lead to building interactive design procedures driven by AI tools. Ultimately, this could show the efficiencies and proper use of checking output and developing engineering judgement when using any computer tool, including AI [4]. A consensus on when and how to use AI in an engineering class has not been identified and needs additional research [8]. Rather than eliminating AI use entirely, and labeling it as a method of cheating, there are likely compromises that can be reached to use AI effectively in an engineering curriculum [5]. The exact path of doing this is further complicated because implementing AI into a dense engineering curriculum may require removing existing material [4]. Efficiencies may need to be identified, and compromises made, to make this curriculum adjustment.

In 2024, Camarillo et al. indicated that approximately 33% of civil engineering students use AI tools [7]. In addition, the report indicated that students are uncertain about the fairness and safety of the tools; most students did not feel comfortable with the tool or confident they can apply it in the profession. Thus, questions persist—will AI help students personalize the learning process or usurp the learning process and hinder knowledge gains and critical thinking skills [8, 9]? Traditional methods of learning require multiple submission of quizzes, tests, and homework followed by a lag before feedback is provided; throughout this process, students often collaborate to check one another's work and gain confidence in their abilities [15]. If AI tools can provide feedback quicker, then it may make learning more efficient and lead to lasting educational gains. Traditional grading methods are time consuming and not always consistent. AI tools may be developed that provide real-time feedback that helps students understand mistakes, target errors, and encourage continuous improvement [16]. AI may also be able to create additional, tailored practice problems for a student based on feedback from assignments [12]; AI can also quickly show different approaches to solving problems by varying the input prompts and variables [11]. Another impactful use of AI may be to create computer-altered reality platforms, for example, to help students visualize site inspections and structures in civil engineering applications. This has been done effectively in mechanical and aerospace applications, but there continues to be uncertainty across engineering and computer science fields [17, 9].

Currently, there is pressure to use AI in college classes, but there is not a uniform or specific method of accomplishing this. There is a need to effectively design and study AI use in undergraduate engineering curricula. There is also the possibility that AI will help make a professor's job easier by assisting with the creation of learning objectives, lesson plans, assessments, and grading rubrics. Much of these uses are ongoing and still under development [12]. One of the risks of not keeping up with the new technology is not teaching graduates how to use the AI tools that employers may deem important [8]. At the same time, an overdependence on AI tools may miss an opportunity to teach students judgement skills and techniques needed to check computer output [14]. There also may be lost educational efficiencies that historically have helped students receive a personalized education while also providing better global connectivity among subjects. There is the potential for a symbiotic relationship between AI tools and the development of critical thinking skills in university-level engineering curricula [9]. There is no indication that AI use will abate in the engineering profession in the near future. However, there are many valid concerns and benefits of AI use in engineering education, and AI's exact use in the education process is unclear.

Research Hypothesis and Questions

In this study, it was hypothesized that engineering students have become familiar with free generative AI tools like ChatGPT, Google Gemini, and Microsoft Copilot, but they do not fully comprehend the best ways to use these tools and interpret the results. The following study was designed to answer two research questions:

1. Can students correctly solve typical structural engineering and mechanics homework questions with only generative AI tools?
2. Are students comfortable with and do they have confidence in using these tools to correctly solve structural engineering problems?

Research Methods

Overview

The research questions posed in this study were addressed by implementing the following exercises in required undergraduate civil engineering classes:

I. Homework-style technical questions were completed twice, with approximately one week between attempts: (1) the first attempt was by hand, without any computer tools, and without warning that the same assignment was to be presented again and (2) the second attempt tasked students with solving the same problems using only a generative AI tool of their choosing. The exact nature of the student-AI interaction was not specified, but it was assumed that students were simply feeding questions into generative AI using any method they found intuitive (e.g., file upload, image-to-text features, manual text descriptions, etc.). Numerical answers were submitted to a Google Form.

II. Perception surveys were administered "before" and "after" implementation of the generative AI exercise. The surveys gauged student familiarity with AI tools, use of AI tools in engineering classes and outside the university in professional experiences, motivation and reasons for using generative AI tools, and advantages or drawbacks of the tools.

These research methods were implemented at two universities, in seven different classes, covering four separate structural engineering topics, as shown in Table 1. In all cases, data were collected from students who agreed to participate in the study based on the Institution Review Board (IRB) agreement. There were at least 194 individuals who participated in each phase of the study based on their input of a unique, repeatable, but anonymous identifier (as required by the IRB). Approximately 66% of all students participated in all phases of the study, while the others only participated in part of the study.

Table 1—Classes in which technical homework-style questions and perception surveys were implemented.

Class	University		Technical Question (TQ)	Program year in which the class is taught	No. of students that participated
	A	B			
Statics	✓	✓	1, 2	2	90
Mechanics of Materials		✓	1, 2	2	35
Structural Analysis	✓	✓	3	3	47
Reinforced Concrete		✓	3, 4	4	22
				Total:	194

Students in their second, third, or fourth year of an engineering program were enrolled in the classes listed in Table 1. Most students were civil engineering majors, but some other engineering majors (i.e., mechanical engineering) were enrolled in some classes at University B. A different professor taught each course, but all had previously taught the same course without implementation of the generative AI exercise. University A is a small, public, undergraduate-focused university and University B is a large, public, doctoral degree-granting university.

<u>Homework-style technical questions</u>

Four homework-style technical questions (TQ), covering four different common structural engineering topics, were presented to students enrolled in different classes, as listed in Table 1. The pertinent questions were deployed as an optional extra credit assignment near the end of the semester. Final numerical answers to the questions and scans of handwritten work were submitted via a Google Form. The four technical questions were:

TQ1) Calculation of vertical beam reactions using equilibrium; posed to 125 students in statics and mechanics of materials classes, as shown in Figure 1.

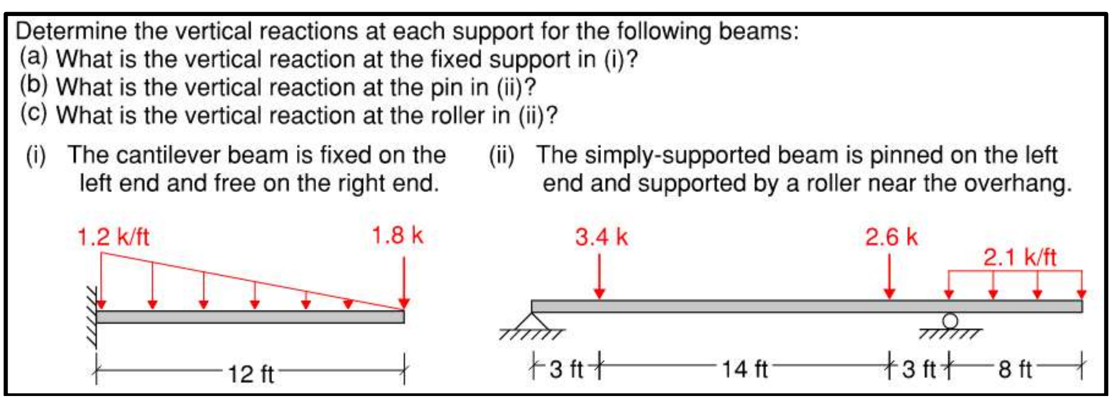


Figure 1—Questions deployed to calculate vertical beam reactions using equilibrium.

TQ2) Calculation of centroid and moment of inertia (MOI); posed to 125 students in statics and mechanics of materials classes, as shown in Figure 2.

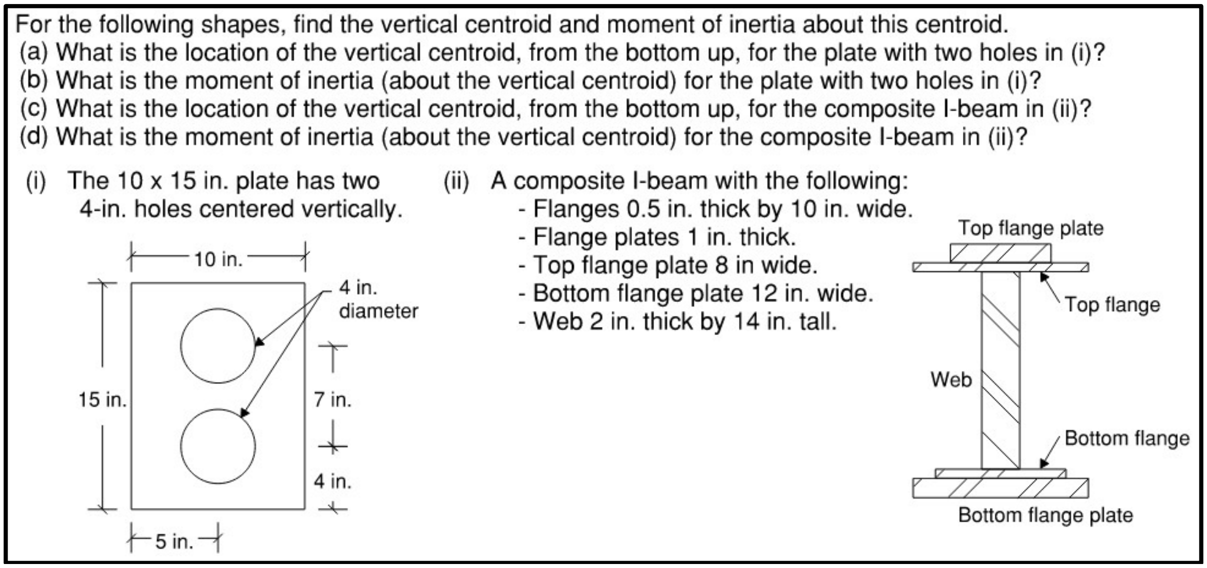


Figure 2—Centroid and moment of inertia questions.

TQ3) Determination of maximum shear and moment (values and location) using visual diagrams; posed to 69 students in structural analysis and reinforced concrete classes, as shown in Figure 3.

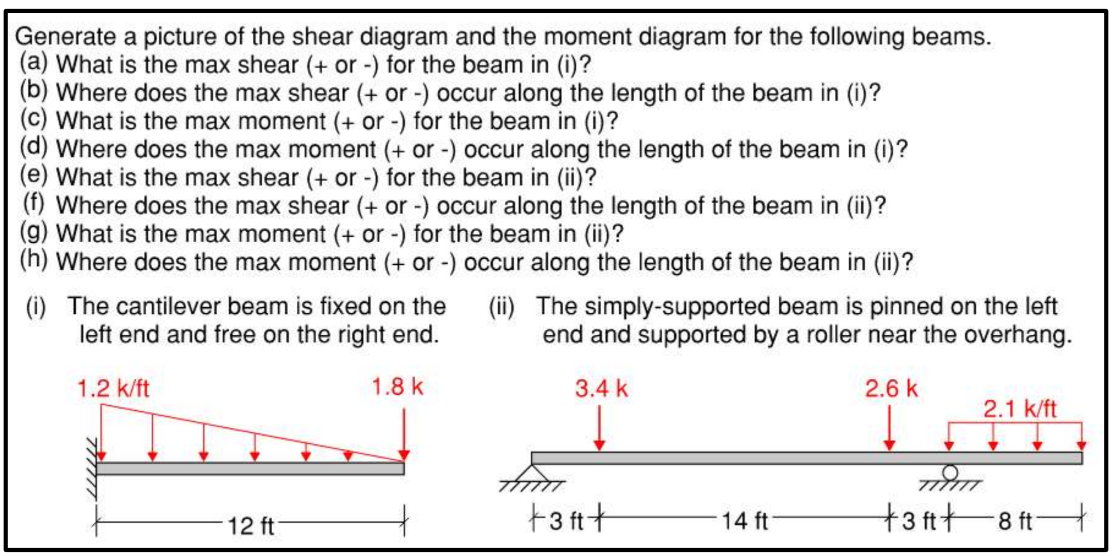
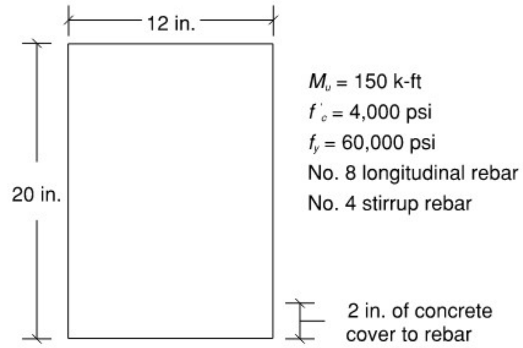


Figure 3—Shear and moment diagram questions.

TQ4) Rectangular concrete beam design; posed to 22 students in reinforced concrete class, as shown in Figure 4.

Consider the following reinforced concrete cross-sectional details:



Using the ACI 318 Building Code Requirements for Structural Concrete and determine the following:
(a) Compute the effective depth, *d*, based on the given dimensions and bar sizes.
(b) Determine the required nominal moment capacity, M_n.
(c) Use equilibrium and compatibility to calculate the required steel area, A_s, to resist M_u.
(d) Check if the section is tension-controlled (use strain limits per ACI 318).
(e) Specify a reasonable bar arrangement (number and size) that meets or exceeds the required A_s.

Figure 4—Concrete beam design questions.

Student perception survey

Student perception data were collected from surveys administered “before” and “after” implementation of the generative AI exercise, about one week apart. A total of 16 survey questions (SQ) were presented to students via a Google Form, as listed in Table 2; six of the survey questions were presented to students before they were tasked with completing the technical questions using generative AI tools, and 10 of the survey questions were presented to students after they were tasked with completing the technical questions using generative AI tools. Survey questions SQ1, SQ2, and SQ 11 contained a long list of generative AI tools from which the students could select multiple answers (presented as footnotes in Table 2).

Table 2—Survey questions implemented before and after deployment of the generative AI exercise to gather student perceptions.

Survey Question (SQ)		Before	After
1[*]	Overall, in all your experiences, select the generative AI tool(s) that you have used for any application. Mark all that apply. Listed in alphabetical order.	✓	
2[†]	In which context(s) do you currently use a generative AI tool? Mark all that apply.	✓	
3	Have you used generative AI for technical analysis or design in engineering classes? (yes or no). If yes, how? What were the advantages or drawbacks?	✓	
4	Have you used generative AI tools for technical analysis or design outside of the University, for example during an internship or other professional experience? (yes or no). If yes, how? What were the advantages or drawbacks?	✓	
5	Do you use generative AI tools to be efficient and solve the problem, or do you use it to learn the material? (a) be efficient and solve the problem, (b) learn the material, (c) other	✓	

	Survey Question (SQ)	Before	After
6	Briefly list your motivation or reasons for using generative AI tools. (open-ended).	✓	
7	Briefly describe how you determined that the generative AI tool arrived at the correct solution, which then stopped your prompting? (open-ended).		✓
8	How many prompts did you enter into the generative AI tool to arrive at the correct solution? (individual numerical answers of 1 to 10, including an option of 10+).		✓
9	On a scale of 1 to 5, rate your confidence level in the solution provided by the generative AI tool. (1) No confidence, (2) Below average confidence, (3) Average confidence, (4) Above average confidence, (5) Very high confidence		✓
10	Compared to your hand-worked homework solution for this problem, list the issues you noticed in the solution from the generative AI tool. (open-ended). Enter N/A if no issues exist.		✓
11*	Select the generative AI tool(s) that you found most effective for use while solving problems as part of this study. Mark all that apply. Listed in alphabetical order.		✓
12	List any major ***limitations*** you encountered using generative AI to solve problems as part of this study. (open-ended).		✓
13	List any major ***benefits*** you encountered using generative AI to solve problems as part of this study. (open-ended).		✓
14	On a scale of 1 to 5, how likely are you to use generative AI to answer technical engineering questions moving forward in your ***university career***? (1) Definitely not, (2) Probably not, (3) Neutral, (4) Probably, (5) Definitely		✓
15	On a scale of 1 to 5, how likely are you to use generative AI to answer technical engineering questions moving forward in your ***professional career***? (1) Definitely not, (2) Probably not, (3) Neutral, (4) Probably, (5) Definitely		✓
16	Briefly list your motivation or reasons for using generative AI tools. (open-ended).		✓

Notes:

*Answer options included: None, Adobe Firefly, AIVA, AlphaCode, Amazon Q Developer, Anyword, Beautiful.ai, Beatoven.ai, Boomy, Canva AI Image Generator, Canva AI Video Generator, CapCut, ChatGPT, Claude, Copy.ai, DALL-E, DeepL, ElevenLabs, Elicit, Fathom, Fireflies.ai, Framer, GitHub Copilot, Google Gemini, Grammarly, Ideogram, Jasper, Luma AI (Genie), Lumen5, Mem, Meshy, Microsoft Copilot, Midjourney, Mubert, NCSEA SE GPT, None, NotebookLM, Notion AI, OpenAI Codex, Otter.ai, Perplexity AI, Pika, QuillBot, Recraft, Replit AI, Runway, Rytr, Sora, Soundraw, Spline, Stable Diffusion, StarCoder2, Sudowrite, Suno AI, Synthesia, Tabnine, Udio, Wondershare Filmora, Writesonic.

†Answer options included: None, Art and graphic design, Writing and storytelling, Music and audio creation, Personalized learning and tutoring, Marketing and advertising, Software development, Customer service, Internal operations and knowledge management, Design and manufacturing, Educational material generation, Research and data analysis, Academic support.

Results

Homework-style technical questions

Results from the four homework-style technical questions (TQ) are shown in Figure 5 through Figure 8. In three of the four questions (75%), the use of generative AI tools to solve the problems resulted in more correct answers (TQ1, TQ2, TQ4); the one case where generative AI tools yielded mixed results compared to student work was for the shear and moment diagram question (TQ3), which required pictures. This indicated that students were likely better at creating visual learning tools, such as shear and moment diagrams, than generative AI. For TQ1 (reactions), results from using the generative AI tools were more correct; for the simpler cantilevered beam problem, AI results were correct 95% of the time, and AI results were correct 63-78% of the time for the more complicated simply-supported beam with multiple types of loading. For TQ2 (centroid and moment of inertia), students calculated the correct centroid by-hand more than 66% of the time and more than 84% of the time when using generative AI tools; however, students calculated the correct moment of inertia only 20-29% of the time by-hand and more than 50% of the time when using generative AI tools. Student results, both by-hand and using generative AI tools, were mixed for TQ3 (shear and moment). For TQ4 (reinforced concrete beam design), results from using the generative AI tools were nearly 90% correct for all subproblems, except for calculating the effective depth *d*; it is unknown why only 9% successfully calculated the effective depth *d*. The result may be linked to incorrect assumptions by students. Generally, students correctly answered the questions 61-83% of the time by-hand.

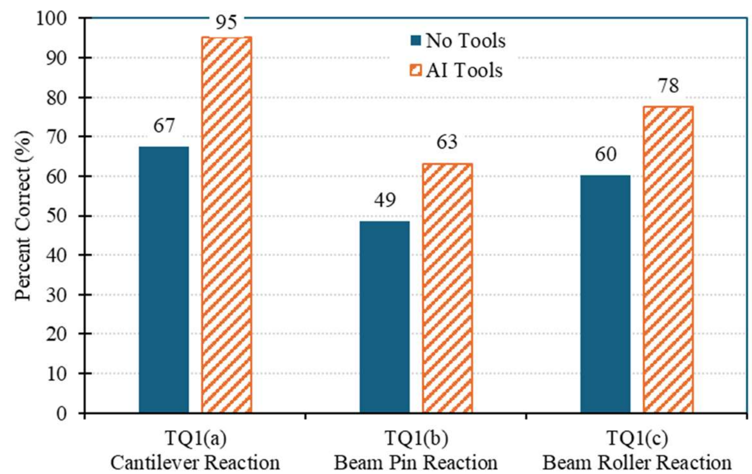


Figure 5—Results from TQ1 deployed in the statics and mechanics of materials classes to calculate vertical beam reactions using equilibrium.

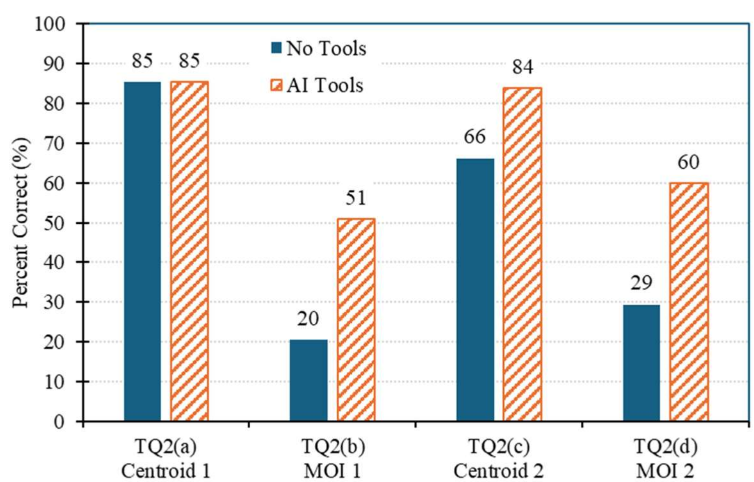


Figure 6—Results from TQ2 deployed in the statics and mechanics of materials classes to calculate the centroid and moment of inertia (MOI).

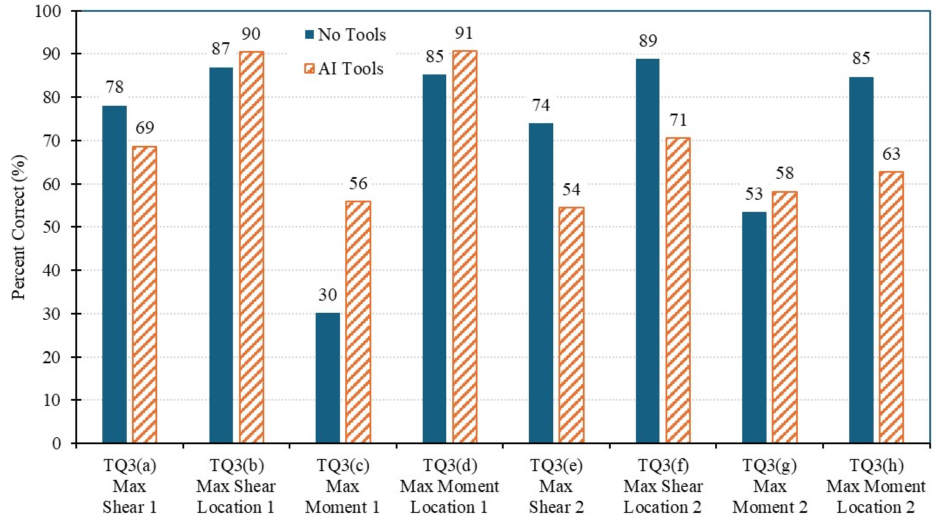


Figure 7—Results from TQ3 deployed in the structural analysis and reinforced concrete classes to determine maximum shear and moment (values and location) using visual diagrams.

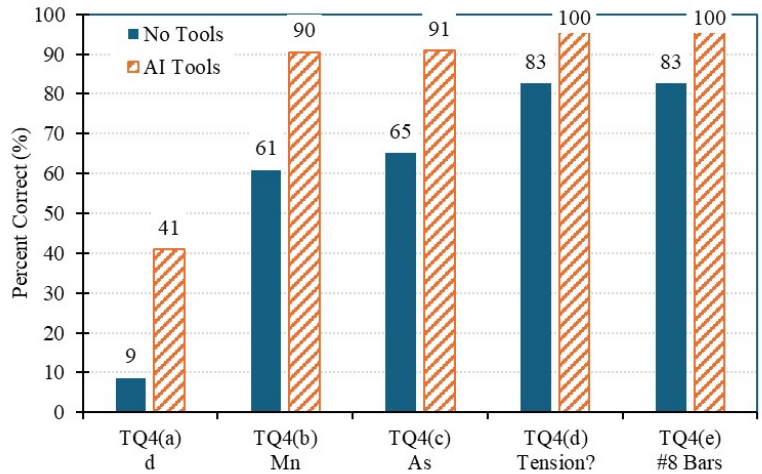


Figure 8—Results from TQ4 deployed in the reinforced concrete class to complete beam design.

Student perception survey

Results from the 16 student perception survey questions (SQ) are shown in Figure 9 through Figure 20; the total number of students who replied to the survey questions was at least 194 each time. At the beginning of this study, Figure 9 indicates that students have used a wide range of generative AI tools, but the most common tools were ChatGPT (used by 33% of students), Google Gemini (20%), Grammarly (11%), and Microsoft Copilot (9%). Overall, the trend is that students have used the popular, mass-market versions of generative AI tools. However, after completing the generative AI exercises in this study, results from SQ11 in Figure 10 indicated that students primarily used ChatGPT (51%), Google Gemini (21%), and Microsoft Copilot (7%). This means that nearly 80% of students completing this study relied on the largest and most "name brand" generative AI products to complete their technical tasks.

Data in Figure 11 indicated that students' primary use of generative AI tools (≥10%) was for:

(i) personalized learning and tutoring (22%),
(ii) academic support (21%),
(iii) educational material generation (13%),
(iv) research and data analysis (12%), and
(v) writing and storytelling (10%).

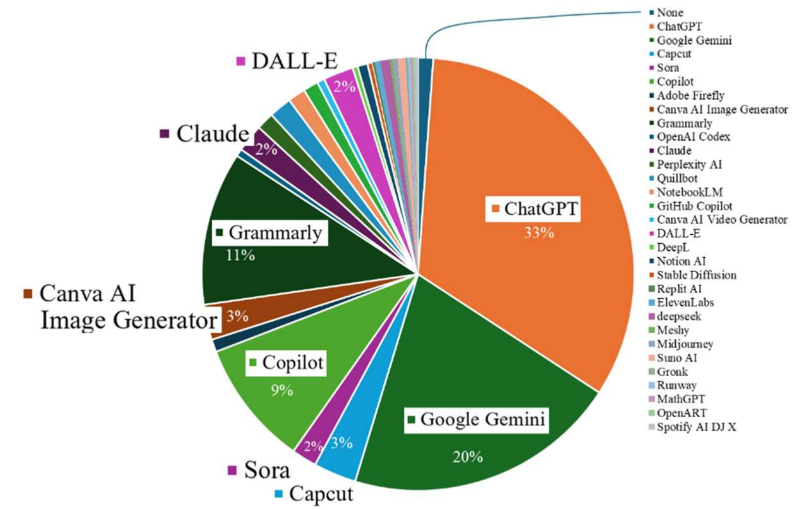


Figure 9—Results from SQ1: Overall, in all your experiences, select the generative AI tool(s) that you have used for any application.

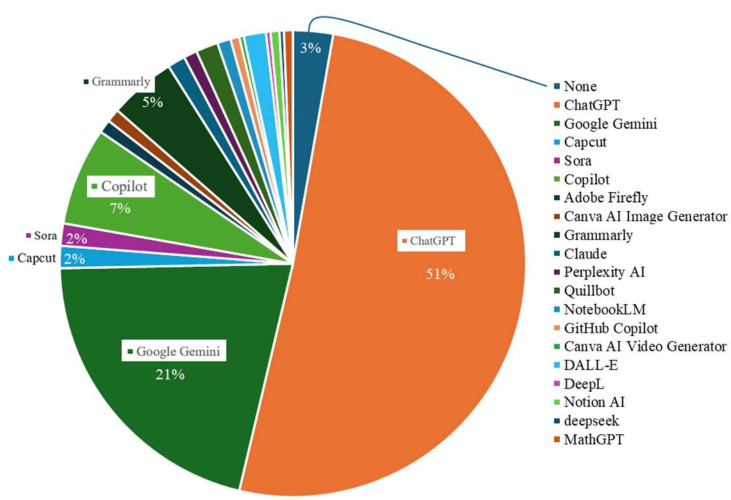


Figure 10—Results from SQ11: Select the generative AI tool(s) that you found most effective for use while solving problems as part of this study.

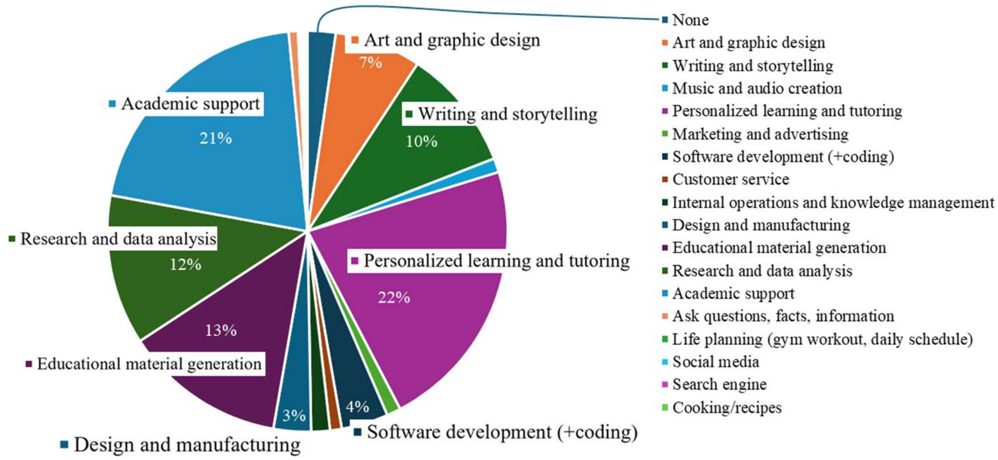


Figure 11—Results from SQ2: In which context(s) do you currently use a generative AI tool?

Even though most students reported using generative AI for academics, education, and learning (in the list of (i)-(v) above, associated with Figure 11), students surveyed in this study indicated that they did not use generative AI specifically for technical analysis/design in engineering classes (56%) or outside of the University in a professional setting (77%), such as during an internship or other professional experience, as shown in Figure 12 for SQ3. Of those that said yes for SQ3, over 72% said they used it to learn, study, or clarify a concept and about 39% mentioned checking, comparing, or starting a class problem. However, 33% of the responses mentioned concerns over the accuracy of the information provided, even though they still used the tool. For those that said yes for SQ4, nearly 48% said they used it in an internship, over 45% used it for technical calculations, coding, or math, and 44% used it for some form of writing or obtaining ideas. For SQ4, only 14% of students said they thought AI output had errors or should not be trusted.

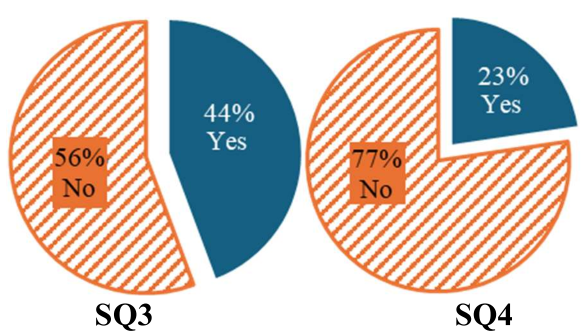


Figure 12—Results from SQ3: Have you used generative AI for technical analysis or design in engineering classes? and SQ4: Have you used generative AI tools for technical analysis or design outside of the University, for example during an internship or other professional experience?

Overall, 69% of students surveyed in this project used generative AI to learn material better, as indicated in Figure 13, and 25% of students reported using generative AI to be efficient and solve problems. Within that dataset, 6% of students reported doing both, which means 75% of students used generative AI to learn material better. Furthermore, results from SQ6 in Figure 14 (left), which asked for free response answers associated with students' motivation or reasons for using generative AI tools, indicated that students seek to understand, help(s), learn, solve, step, time, and ask, which aligns closely with results from SQ5. After completing the generative AI exercise in this study, students' responses changed little to understand, learn, time, tool, and using (Figure 14 right). This aligns with continuing to use it as a learning tool, but also as a calculation tool.

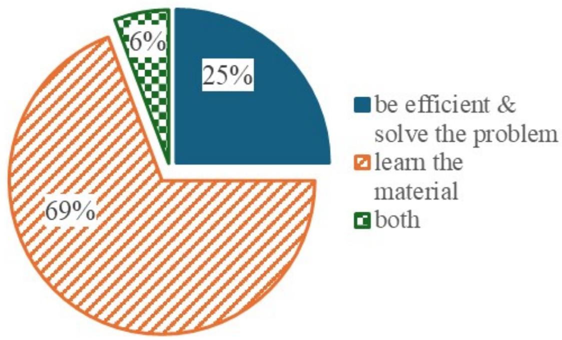


Figure 13—Results from SQ5: Do you use generative AI tools to be efficient and solve the problem, or do you use it to learn the material?

SQ6 (*before* AI exercise) SQ16 (*after* AI exercise)

Figure 14—Results from SQ6 and SQ16: Briefly list your motivation or reasons for using generative AI tools. Word clouds include the 25 most frequent single words.

When using the generative AI tools for this study's exercise, students were required to arrive at what they perceived as a correct solution. The stop-prompting mechanisms for this decision, as reported by students' responses, were binned into four main categories: (1) trust/faith, (2) checked other resource(s), (3) handwritten checks, and (4) logic/judgement (SQ7). Overall, students reported stopping AI prompts frequently when they trusted/had faith in the solutions. This could be attributed to the way this study was conducted, as extra credit rather than as an assessment carrying a large portion of the course grade, or it could also be attributed to the novelty of being asked by faculty to specifically use generative AI on technical work. Results in Figure 15 indicate that second-year students in statics and mechanics relied most on trust/faith (40%) and not as much on their own handwritten work (<33%) or logic/judgement (<25%). Fewer fourth-year students relied on trust/faith (27%) but relied more on handwritten checks (46%) and logic/judgement (27%). Students tended to use handwritten checks or logic/judgement if they were more experienced and solving design problems.

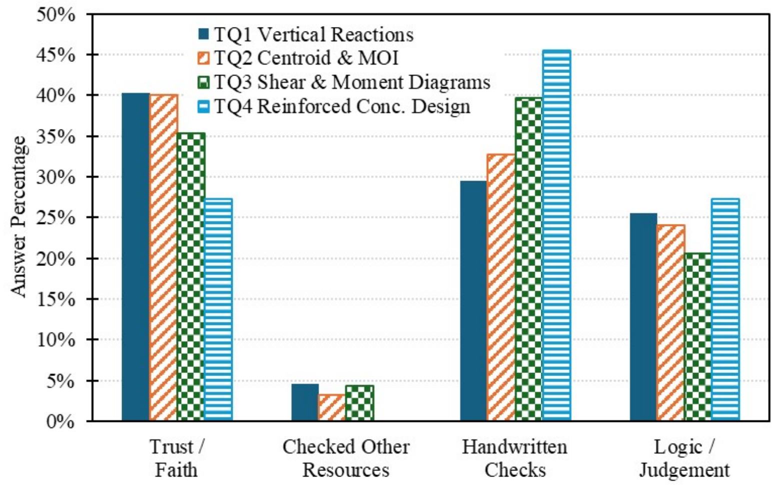


Figure 15—Results from SQ7: Briefly describe how you determined that the generative AI tool arrived at the correct solution, which then stopped your prompting.

Furthermore, results in Figure 16 generally indicated that the number of prompts required for students to arrive at the correct generative AI solution increased with the difficulty of the question. For example, on average, 1.82 prompts were required to generate vertical reactions using equilibrium, 2.34 prompts were required to generate centroid and moment of inertia values, and 3.35 prompts were required to generate shear and moment diagrams, which were used to select numerical answers. However, in the most advanced structures course in this study (reinforced concrete), posing a question at an advanced Blooms taxonomy level (design), an average of 1.41 prompts were required to generate the correct solution, as perceived by students. This distinct difference may be due to the specificity of TQ4, which tasked students with basic reinforced concrete beam design steps explicitly using *ACI 318 Building Code Requirements for Structural Concrete*; this design code could be considered prescriptive, which may have led to correct generative AI results quicker than a design involving more engineering judgement.

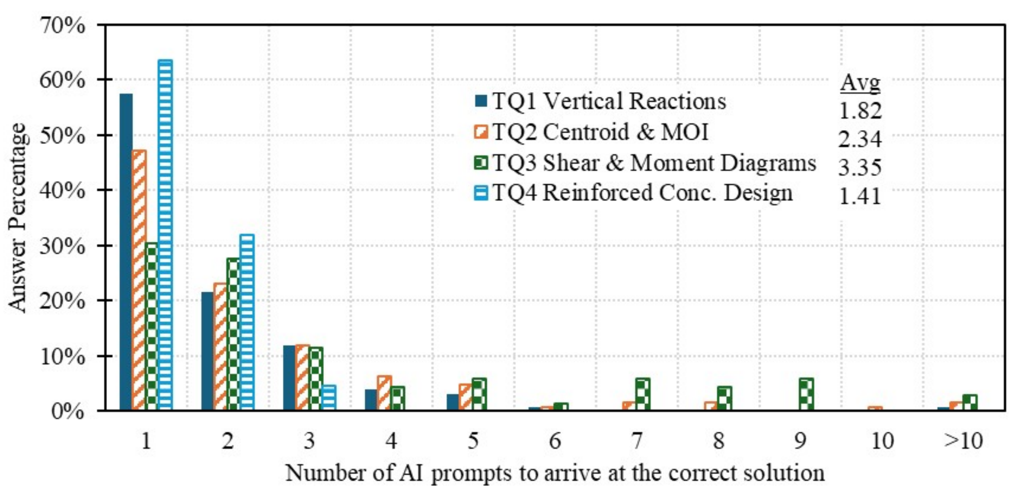


Figure 16—Results from SQ8: How many prompts did you enter into the generative AI tool to arrive at the correct solution?

Overwhelmingly, data in Figure 17 indicated that perceived student confidence in generative AI tools was average (numerically, 3.0). For TQ1 (reactions) and TQ4 (reinforced concrete design), the level of confidence was slightly above average, ranging from 3.2-3.3. For TQ2 (centroid & MOI) and TQ3 (shear & moment diagrams), the level of confidence was slightly below average, ranging from 2.8-2.9. When comparing handwritten and generative AI TQ solutions, students were asked to identify issues with the generative AI solutions, which were binned into seven main categories: (1) no issues, (2) lack of explanations, (3) skipped steps, (4) wrong calculation or problem interpretation, (5) wrong answer, (6) no work shown, and (7) caught my own mistake. Overall, results in Figure 18 indicated that students often encountered no issues with the generative AI solutions for reaction and reinforced concrete solutions. However, the most prevalent issue reported for shear, moment, and reinforced concrete design problems was "wrong calculation or problem interpretation," which may be associated with the graphical nature of shear and moment diagrams and the technical nature of design problems.

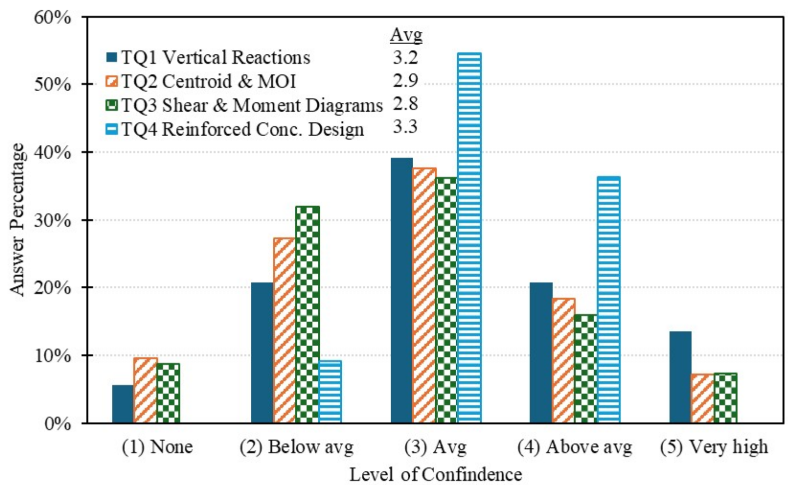


Figure 17—Results from SQ9: On a scale of 1 to 5, rate your confidence level in the solution provided by the generative AI tool.

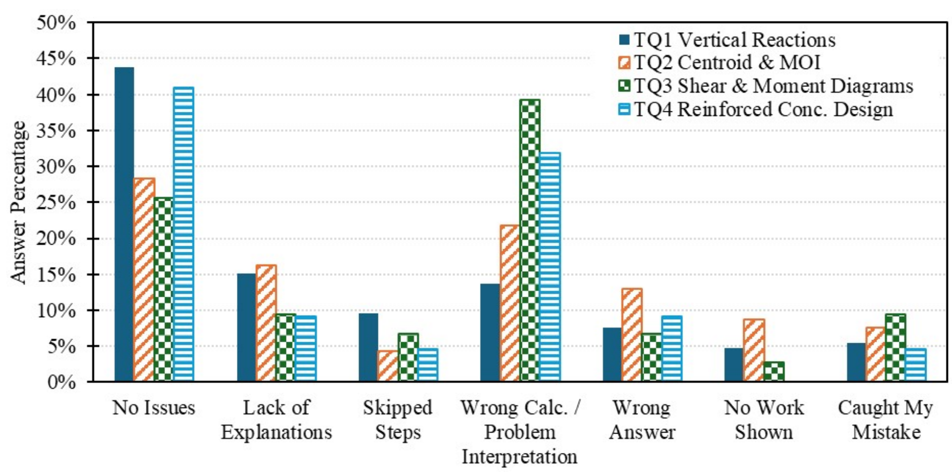
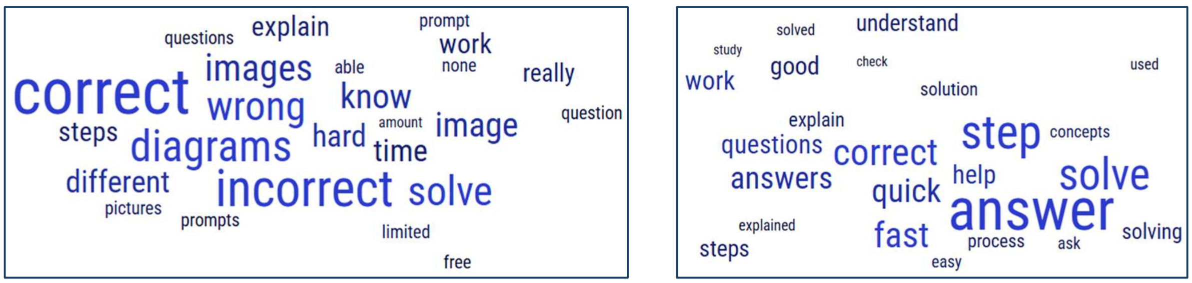


Figure 18—Results from SQ10: Compared to your hand-worked homework solution for this problem, list the ***issues*** you noticed in the solution from the generative AI tool.

After completing the homework-style technical questions in this study, students were asked to characterize what major limitations and benefits they perceived to be associated with using generative AI to solve technical problems. Word cloud results in Figure 19 show both the limitations (left) and benefits (right) perceived by students. The words most used to describe the major *limitations* included correct, incorrect, wrong, solve, diagrams, and image(s), which correspond with the themes of "knowing what is correct versus incorrect" and "issues with images/diagrams in technical problems." The words most used to describe the major *benefits* included answer(s), correct, step, solve, quick, and fast, which correspond with the themes of "fast and quick reference as it relates to time" and "ability to solve problems with correct problem steps or answers."



SQ12 Generative AI *Limitations* SQ13 Generative AI *Benefits*

Figure 19—Results from SQ12: List any major *limitations* you encountered using generative AI to solve problems as part of this study and SQ12: List any major *benefits* you encountered using generative AI to solve problems as part of this study.

The most forward-thinking question asked how likely students are to use generative AI to answer technical engineering questions in their future university or professional careers. Average results (Figure 20) indicated that students were generally neutral in their response. The average student response associated with using generative AI in their professional career was lower (2.8) compared to the response associated with their university career (3.0). In both cases, average student responses trended toward "probably not," but both distributions were normal. This indicated that <33% of students were convinced they are likely to use AI tools for technical engineering questions in the near future.

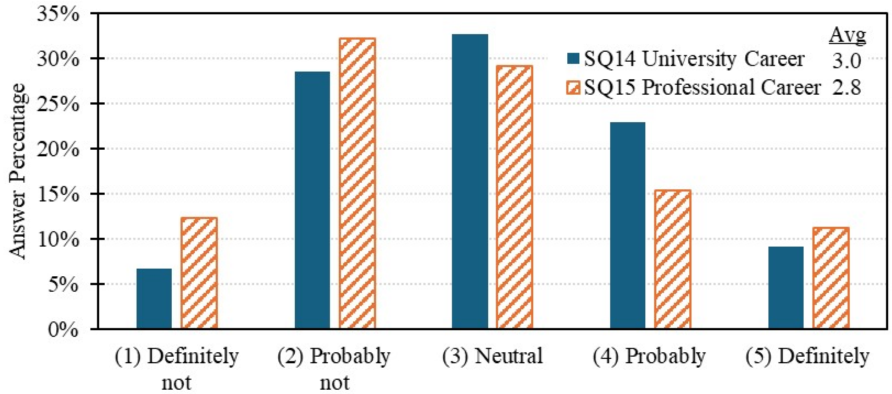


Figure 20—Results from SQ14: On a scale of 1 to 5, how likely are you to use generative AI to answer technical engineering questions moving forward in your *university career*? and SQ15: On a scale of 1 to 5, how likely are you to use generative AI to answer technical engineering questions moving forward in your *professional career*?

Discussion

Two research questions drove the scope of the study:

1. Can students correctly solve typical structural engineering and mechanics of materials homework questions with only generative AI tools?

Overall, quantitative results indicated that students submitted more correct answers using generative AI tools than using handwritten work for the same problems. This occurred 75% of the time, or on three of the four homework-style technical questions (those related to reactions, centroid, moment of inertia, and reinforced concrete beam design). The level of the class (second-, third-, or fourth-year) did not make a difference. The fourth-year questions on reinforced concrete design were solved correctly as often as the questions on basic mechanics.

The one technical question where generative AI tools yielded mixed results was associated with shear and moment diagrams. Of the eight shear and moment subproblems, 50% of the questions were answered correctly more often with handwritten work. These problems were unique because both the problem statements and results required images. The results indicated that students' have not developed abilities to use generative AI tools to solve visual diagram-based problems comparable to their ability to solve the problems with handwritten work.

One limitation within this study design could be addressed in future research. Namely, students may have gained some level of mastery-building by seeing the same homework-style technical question twice rather than simply having access to a new AI tool. In a future study, modification to the groups could include one group seeing the same technical question again and attempting to resolve it by hand, while the variable group sees the same technical question again but is tasked with using generative AI tools; this difference could lead to a more nuanced understanding of the impact of using generative AI tools to solve homework-style technical questions.

2. Are students comfortable with and do they have confidence in using these tools to correctly solve structural engineering problems?

Nearly 80% of students in this study reported using the most widely recognized and "name brand" generative AI products to complete their technical tasks, such as ChatGPT, Google Gemini, and Microsoft Copilot. Almost every student had used a generative AI product, and results ranged among 29 different products.

Before completion of the generative AI exercise in this study, most students reported that they did not use generative AI specifically for technical analysis/design in engineering classes (56%) or in a professional setting outside the university (77%). Most who had used AI tools viewed them as a method to learn, study, or clarify concepts (72%) while a smaller number used them to help them solve problems (39%). These values were nearly identical to the responses to the question asking why they use AI tools in class. Free-response results displayed a similar pattern in that students reported that they use AI tools to understand the concepts, get help, and learn the material before these exercises; after doing these exercises, students added that AI tools help them use their time effectively and solve class problems.

After completing the generative AI exercise in this study, most students reported that they were neutral (average response of 3 on a scale from 1 to 5) toward using generative AI to answer technical engineering questions moving forward in their university or professional careers. Less than 33% were sure they would use the tools again in a technical, engineering setting. Overall, qualitative student perception survey results indicated that student confidence in generative AI tools to calculate the correct answers to technical engineering questions was average (response of 3 on a scale from 1 to 5). This aligned with the original survey results that said 33% of students were concerned with the accuracy of the AI results. However, more than 33% of the students in second-year courses trusted the answers without checking the results, while over 40% of students with more experience (third- and fourth-year students) confirmed their answers with handwritten checks or used logic/judgment. Interestingly, only 23% of students had used a generative AI tool professionally in an internship or job, but of those, only 14% were concerned with the accuracy of the results. The overall trend is that most students are not experienced and do not trust the results, but that changes with more experience either in school or the workplace.

Students indicated that the most prevalent issue they noticed when obtaining a solution from a generative AI tool was either "wrong calculation or problem interpretation" or "a lack of explanation." The words most used by students to describe the major *limitations* associated with their use of generative AI to solve technical questions included correct, incorrect, wrong, solve, diagrams and images, which correspond with the themes of "knowing what is correct versus incorrect" and "issues with images/diagrams in technical problems." The words most used to describe the major *benefits* included answer, step, solve, quick and fast, which correspond with the themes of "fast and quick reference as it relates to time" and "ability to solve problems with correct problems steps or answers."

Summary and Conclusion

This study sought to determine if undergraduate engineering students could correctly solve homework-style technical questions with only generative AI tools and gauge if the students were comfortable with and confident in the use of the tools. Students completed homework-style technical questions twice, once by hand and once using generative AI, and completed surveys to characterize their perceptions and experience of the process. These research methods were implemented at two universities, in seven different classes, covering four separate structural engineering topics (statics, mechanics of materials, structural analysis, and reinforced concrete).

The results indicated that students were very aware of many generative AI tools and used them outside of technical engineering settings. However, they did not use them extensively or have a uniform method of implementation on structural engineering problems. The students' confidence in and planned future use of generative AI tools on engineering problems was average. There was a hesitancy in using generative AI tools, which indicates that there is a need to discuss the limitations of AI tools with students and provide them with experience using generative AI tools effectively.

While many fourth-year students in a design class understood the importance of checking AI output, most students in this study did not understand how to apply engineering judgement in the context of interpreting generative AI results. Most students did not check the output of generative AI tools or use judgement to review the results indicating a need to provide students, especially during their second and third year of study, with a solid foundation on the fundamental concepts. Evidence supports this conclusion because many students became more familiar with generative AI tools during the study and reported an increased likelihood to use the tools to solve problems and learn engineering concepts after this study was complete. This same pattern was confirmed by the students who had used generative AI tools in the workplace or during an internship. Furthermore, generative AI capabilities are evolving rapidly and technical hurdles encountered when collecting data for this study during Fall 2025 (e.g., lower success solving visual diagram-based problems) may already be obsolete by the Summer 2026 publication date.

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