

AN EXAMINATION OF STUDENTS' PERCEPTIONS OF THE EFFICACY OF USING GENERATIVE ARTIFICIAL INTELLIGENCE IN STRUCTURAL ENGINEERING EDUCATION

ROSS A. HIGGINS¹, MICHAEL J. QUILLIGAN², DECLAN T. PHILLIPS²,
TERENCE D. RYAN², MICHAEL J. JOHNSON³, AND THOMAS H. COSGROVE²

¹School of Engineering, University of Limerick
Limerick, Ireland
ross.higgins@ul.ie

²School of Engineering, University of Limerick Limerick, Ireland

³Department of Electronic and Computer Engineering, University of Limerick, Limerick, Ireland

Key words: Education, Civil Engineering, Methodology, Learning, Technology.

Abstract. With the rapid advancement of Generative Artificial Intelligence (GenAI) tools like ChatGPT, their integration into education introduces both opportunities and challenges for students and educators. This study examines Gen Z students' perceptions of the efficacy of GenAI in structural engineering education. The integration of GenAI tools has the potential to transform how students approach complex engineering problems, yet understanding their perceived value and limitations remains underexplored. The research adopts a mixed-methods approach, centred on a targeted exercise where students complete a series of structural analysis problems using both traditional hand calculations and GenAI. Data collected through pre- and post-exercise surveys, alongside reflective critiques, provided insights into how students' perceptions evolved throughout the exercise. Students reported GenAI to be effective in solving questions related to basic stability and determinacy but, while they found GenAI helpful in explaining procedures, it generally was unable to accurately solve more complicated deflected shape and beam analysis questions. There was a statistically significant increase in students' perceptions of the efficacy of GenAI to solve stability and determinacy questions following the completion of the exercise, but not in relation deflected shape or beam analysis questions. These findings highlight the importance for students to have a strong foundational structural analysis understanding to effectively evaluate and validate GenAI outputs.

1 INTRODUCTION

The integration of Generative Artificial Intelligence (GenAI) tools into higher education has opened up new pedagogical possibilities while simultaneously raising critical concerns. In structural engineering education, a field that demands both conceptual clarity and procedural precision, understanding the role and efficacy of these tools is particularly important.

1.1 GenAI in Higher and Engineering Education

Students have generally expressed positive perceptions of GenAI tools in higher education,

recognising their usefulness in drafting content, generating ideas, and assisting in research [1]. In engineering education, GenAI has been used to assist students with problem-solving tasks and concept explanations, enabling greater access to learning resources outside traditional classroom hours [2]. Such applications are particularly useful for non-native English speakers and students from underrepresented academic backgrounds. Engineering students have appreciated GenAI's immediacy and responsiveness, which supports self-paced learning [1,3]. The efficiency of GenAI in providing real-time support makes it a useful supplementary learning tool, however concerns have been reported about the accuracy of GenAI outputs in technical domains [4].

1.2 Impact on Learning Performance and Cognitive Development

Meta-analytic research has found that GenAI can significantly improve student learning performance, particularly in tasks requiring procedural understanding and logical reasoning [5]. Other studies affirm that GenAI can enhance higher-order thinking skills, such as problem decomposition and solution synthesis [6], indicating that when used critically, GenAI tools can promote deeper conceptual engagement.

In structural engineering education specifically, where calculations and problem framing are essential, students have reported that using GenAI helped clarify problem structures and highlighted alternative solution paths. However, their reliance on Artificial Intelligence (AI) remained cautious when the answers lacked transparent reasoning steps [2,4].

1.3 Challenges: Accuracy, Ethics, and Overreliance

A recurring issue in the literature is the variable accuracy of GenAI outputs. In complex problem scenarios, especially under-specified or real-world-like problems, GenAI responses can be incorrect or misleading [4]. This reinforces the need for students to retain strong foundational knowledge to evaluate GenAI solutions critically [7].

Overreliance on GenAI presents clear pedagogical challenges. While students enjoy the speed and efficiency of GenAI tools, there is a risk that they may bypass critical learning phases, particularly manual calculation and conceptual modelling [8]. In structural engineering, this may compromise their ability to assess real-world constraints or safety considerations.

1.4 Pedagogical Integration and Hybrid Approaches

To mitigate the risks and enhance the benefits, researchers advocate for blended pedagogical approaches, where GenAI is used alongside traditional methods. Studies show that hybrid exercises, where students first attempt problems manually and then compare with GenAI outputs, can help foster critical evaluation skills and reflective thinking [2,9].

Understanding the capabilities, limitations, and ethical dimensions of GenAI tools can empower students to use them more responsibly and effectively, with comprehensive artificial intelligence literacy education requiring not only technical skills but also critical evaluation and ethical awareness, enabling learners to responsibly interpret and apply GenAI outputs [10].

2 METHODOLOGY

This paper outlines the integration of GenAI into part of the Structural Analysis module (6

ECTS credits) in Year 2 of the Civil Engineering programme at the University of Limerick. The programme was established in 2008 with the aim of cultivating professionals with a lifelong orientation toward research, capable of addressing complex challenges in the built environment through rational yet creative problem-solving and effective team collaboration [11,12]. A total of 41 students participated in the study. Participation was voluntary, and ethical approval was obtained through the university's research ethics committee.

The study employs a mixed-methods research design to explore students' perceptions and experiences of the role and efficacy of GenAI tools in structural engineering education. The methodology integrates both quantitative and qualitative data collection techniques to capture a comprehensive understanding of student experiences and reflections.

The core of the study involved a targeted classroom exercise designed to compare traditional and AI-assisted approaches to solving structural engineering problems. The exercise was divided into two sequential phases:

- **Traditional Method Phase:** Students individually solved a series of structural analysis problems using conventional hand calculation techniques. These problems were aligned with curriculum outcomes and required application of equilibrium, bending moment, and deflection principles;

- **GenAI-Assisted Phase:** The same problems were then approached using a GenAI tool where students were encouraged to input problem statements and compare AI-generated solutions with their own. Instructions were provided on responsible and critical use of the tool.

Three primary sources of data were used:

- **Pre-exercise survey ($n = 41$):** Captured baseline attitudes towards GenAI, prior experience with AI tools, and self-assessed proficiency in structural analysis;

- **Reflective survey ($n = 33$):** Students were asked to submit reflective commentary discussing the strengths, weaknesses, and implications of using GenAI in solving the problems. These reflections provided rich qualitative insights into their evolving perceptions;

- **Post-exercise survey ($n = 22$):** Assessed students' perceptions of GenAI's accuracy, efficiency, and educational value after completing both phases. Likert-scale and open-ended questions were included to gather both quantitative and narrative responses.

Quantitative data from the surveys were analysed using descriptive statistics and independent sample t-tests to identify shifts in perceptions before and after the exercise. The following coding was used: Strongly Disagree: 1, Disagree: 2, Neutral: 3, Agree: 4 and Strong Agree: 5 to allow means and mean differences to be calculated. Qualitative data from open-ended survey responses and reflective critiques were analysed using thematic coding to identify recurring themes such as perceived reliability, trust, engagement, and learning depth.

To ensure methodological rigour, surveys were piloted with a small group of students to confirm clarity and relevance. Triangulation of data sources, quantitative surveys and qualitative reflections, was employed to enhance the credibility and validity of the findings. Researcher bias was mitigated through independent coding and inter-rater reliability checks during qualitative analysis.

3 RESULTS & DISCUSSION

3.1 Pre-Exercise GenAI Experience

The survey results indicate that the majority of respondents (58.5%) have used GenAI a few times, including for some of their coursework. A smaller portion (24.4%) reported limited use of GenAI, but not for any academic work. Regular use of AI tools for coursework was noted by 14.6% of participants, suggesting a growing comfort and integration of these technologies in academic settings. Only one respondent (2.4%) stated they had never used GenAI, indicating near-universal exposure to or experimentation with the technology among those surveyed (Table 1).

Separately, 28 (93%) indicated that they do not pay a subscription for GenAI, with the remaining 3 (7%) confirming some subscription.

Table 1: Pre-exercise levels of experience with GenAI

Response	No. Responses	%
I have never used it	1	2.4%
I have used it a few times but not for any coursework	10	24.4%
I have used it a few times including for some coursework	24	58.5%
I use it regularly including for coursework.	6	14.6%
Total	41	100.0%

3.2 GenAI Tool

The results in Table 2 indicate that the vast majority of participants (84.8%) used the free version of ChatGPT for the exercise, making it by far the most used GenAI tool among respondents. A smaller proportion (12.1%) used ChatGPT Plus, while only one participant (3.0%) reported using an alternative GenAI tool.

Table 2: GenAI tools used during the exercise

Tool	Number	%
ChatGPT (Free)	28	84.8%
ChatGPT Plus	4	12.1%
Other	1	3.0%
Total	33	100.0%

3.3 Question interpretation

The survey results show that GenAI's ability to interpret questions varied across different structural analysis topics. For the Beam Stability/Determinacy question, 78.8% of students

reported that GenAI correctly interpreted the question. In relation to the Deflected Shape question, only 54.5% felt GenAI understood the question accurately and for the Beam Analysis question, 60.6% of students believed the question was interpreted correctly (Table 3). Overall, students perceived GenAI as more effective in interpreting questions related to fundamental concepts like beam stability/determinacy, with reduced clarity in more visual or complex topics such as beam deflection and analysis.

Table 3: Proportions of students who indicated that GenAI could interpret various questions (n = 33)

Was GenAI able to interpret the question?	Beam Stability / Determinacy		Deflected Shape		Beam Analysis	
	n	%	n	%	n	%
Yes	26	78.8%	18	54.5%	20	60.6%
No	5	15.2%	10	30.3%	10	30.3%
I don't know	2	6.1%	5	15.2%	3	9.1%
Total	33	100%	33	100.0%	33	100.0%

3.4 Insights Provided by GenAI

3.4.1 Beam Stability / Determinacy Analysis Insights

A summary of insights in relation to the beam stability / determinacy question is shown in Table 4. Student responses to the beam stability and determinacy problem indicated that GenAI generally provided helpful procedural support. Many noted that it offered step-by-step explanations, identified key elements such as supports and degrees of freedom, and used standard methods like equilibrium checks to evaluate determinacy and stability.

Table 4: Reported insights that GenAI tool provided for the beam stability and determinacy question

Theme	Description	Example Responses	Frequency
Step-by-step explanation	Provided a structured approach to solving the problem	"Step by step explanation", "simple step by step process", "It broke down the structure..."	7
Conceptual clarity	Helped explain key concepts (e.g., determinacy, supports, reactions)	"Explained why it was determinate", "identified supports", "what indeterminacy is"	6
Not helpful / issues interpreting	Found output unhelpful or incorrect	"Not helpful", "keeps reading the picture incorrectly", "none", "nothing new"	6
Correct and complete solution	Fully solved and explained the problem correctly	"Gave me the correct solution", "complete insight", "fully solve some problems on its own"	5

Some appreciated that it articulated the logic behind classification, including appropriate formulas and reasoning. A few responses indicated that GenAI was able to fully solve problems or offer complete solutions. However, others reported issues such as incorrect interpretation of diagrams, mathematical errors, or a lack of new insight which aligns with the findings of Wang et al. (2023).

3.4.2 Deflected Shape Insights

The student responses reflect a wide range of experiences regarding GenAI's ability to provide insight into deflected shape problems in structural analysis. Several students noted that GenAI was helpful in highlighting key points, offering written explanations, or sketching deflected shapes, sometimes even correctly identifying support conditions, symmetry, and locations of maximum deflection. A few mentioned that it described the general behaviour or gave guidance on steps needed to solve the problem. However, others found the output confusing, inaccurate, or too vague, with comments pointing out incorrect sketches, minimal insight, or a failure to produce usable diagrams (Table 5).

Table 5: Reported insights that GenAI tool provided for the deflected shape question

Theme	Description	Example Responses	Frequency
Written descriptions of shape	Provided a verbal or textual explanation of expected deflected shape	"Written explanation of what the deflected shape would look like", "described general deflected shape"	6
Attempted sketch (accurate or not)	GenAI generated a sketch, whether correct or flawed	"Drew a deflected shape", "attempted deflected shape but was wrong", "diagram bending heavily"	6
Conceptual explanation	Explained beam behaviour or related theory (e.g., tension/compression)	"Where max deflection would occur", "explained behaviour", "conditions where curves are smooth/continuous"	4
Incorrect or confusing output	Output included errors or unclear representations	"Confusing code", "wrong sketch", "not fully accurate"	4

3.4.3 Beam Analysis Insights

As shown in Table 6, student responses to the beam analysis question revealed that GenAI offered a range of useful insights, particularly in applying correct structural analysis methods. Many students noted that it employed standard procedures such as equilibrium equations, integration for shear force and bending moment diagrams (SFD and BMD), and step-by-step breakdowns to guide problem-solving. Some also appreciated its ability to identify key loads

and reaction forces. However, while the methodology was generally sound, several students observed that GenAI often struggled with accurate calculations and diagram generation, as found in other research [2, 3].

3.5 GenAI Accuracy

For the Beam Stability/Determinacy questions, the majority of students (67.7%) reported that GenAI was able to accurately solve the problems. This suggests a relatively strong performance by the AI in handling questions related to structural stability and determinacy, which are often more rule-based and procedural.

Table 6: Reported insights that GenAI tool provided for the beam stability and determinacy question

Theme	Description	Example Responses	Frequency
Step-by-step guidance	Provided structured steps or walkthroughs for problem-solving	"Step by step guide", "Showed the steps required", "steps", "gave a step-by-step guide"	6
Correct method but incorrect math	GenAI applied the correct approach or structure but produced calculation errors	"Correct method but couldn't follow the numbers", "similar methods but incorrect math"	5
Partial accuracy	Some elements (e.g. reactions) were correct, but diagrams or values were wrong	"Correct reactions but incorrect diagrams", "values but not the calculations", "wrong shear and BMDs"	5

In contrast, student responses were notably less favourable when it came to Deflected Shape problems. Only 28.1% found GenAI provided accurate solutions, while a significant majority (62.5%) said it did not. This indicates that GenAI struggled with the more conceptual and visual reasoning required to predict deflected shapes.

A similar pattern emerged for Beam Analysis problems, where only 28.1% of students felt GenAI solved the problems correctly. These results suggest that while GenAI may be somewhat helpful, its capabilities in performing detailed structural analysis – especially when calculations, boundary conditions, and distributed loads are involved – remain limited (Table 7).

Table 7: Reported insights that GenAI tool provided for the beam stability and determinacy question

Was GenAI able to accurately solve the problem?	Beam Stability / Determinacy		Deflected Shape		Beam Analysis	
	n	%	n	%	n	%
Yes	21	67.7%	9	28.1%	9	28.1%
No	7	22.6%	20	62.5%	19	59.4%
I don't know	3	9.7%	3	9.4%	4	12.5%
Total	31	100.0%	32	100.0%	32	100.0%

3.6 GenAI Solution Commentary

Student feedback on the use of GenAI in structural analysis tasks revealed differing levels of confidence in its accuracy across three topics: beam stability/determinacy, deflected shape, and beam analysis. Overall, while some students found the AI helpful in explaining concepts, many raised concerns about reliability and precision.

In beam stability and determinacy, several students reported that the AI produced accurate solutions and found its step-by-step explanations useful. A few described the outputs as “perfect” or highly effective. However, others noted that the AI’s accuracy was inconsistent and that incorrect answers were common when the user lacked foundational knowledge or the prompt was unclear.

For deflected shape problems, responses were largely negative. Students consistently reported that the AI failed to generate accurate or useful sketches. Some noted that while the AI could explain how to approach the task, it struggled to interpret beam geometry, boundary conditions, or produce meaningful diagrams. Many found the diagrams incorrect or missing altogether, even after follow-up prompts.

In beam analysis, students again highlighted significant limitations. While a few found the AI helpful for estimating maximum values or explaining procedures, many reported errors in basic support reactions, load interpretation, and diagram continuity. Several students mentioned that, although the general methodology was sound, the execution—particularly in generating shear and moment diagrams—was often flawed.

These reflections suggest that while GenAI can aid conceptual understanding in structural analysis, as found by [6], it lacks the reliability needed for detailed problem-solving aligning with the findings of [4].

3.7 Comparing Pre- and Post-Exercise Perceptions

The Likert scale results reveal statistically significant changes, between the pre- and post-exercise, in students’ perceptions of GenAI’s capabilities for certain structural analysis tasks. Notably, participants showed significantly increased agreement post-exercise that GenAI can assess whether a structure is stable or unstable ($t(59.68) = -4.198$, $p < .001$, mean difference = -0.696) and whether it is statically determinate or indeterminate ($t(44.03) = -2.966$, $p = .005$, mean difference = -0.654).

Table 8: T-test results comparing means of Likert scale responses pre- and post-exercise

Statement	t-test for Equality of Means				
	t	df	p	Mean Difference	Std. Error Difference
GenAI can assess whether a structure is stable or unstable.	- 3.657	61	0.001	-0.696	0.190
GenAI can assess whether a structure is statically determinate or indeterminate.	- 2.943	61	0.005	-0.654	0.222

GenAI can analyse a determinate beam and return the principal shear force and bending moment values.	0.754	60	0.454	0.196	0.260
GenAI can calculate deflections on a loaded beam.	- 1.108	61	0.272	-0.259	0.234
GenAI can sketch the deflected shape of a loaded beam.	0.004	61	0.997	0.001	0.278

t: calculated t-statistic, df: degrees of freedom, p: significance. Significant difference shown in bold.

However, for more complex analytical tasks such as analysing beams for shear force and bending moments, calculating deflections, or sketching deflected shapes, there were no statistically significant changes in perceived usefulness ($p > .05$). See Table 8. These findings suggest that while the intervention improved confidence in GenAI’s conceptual diagnostic abilities, its perceived value for detailed structural computations and visualisations remained unchanged.

4 CONCLUSIONS

- The integration of GenAI tools like ChatGPT into third-level coursework is no longer a theoretical possibility, it is a present reality, with 73% of students already engaging with these tools in their studies. Among the available technologies, ChatGPT has emerged as the primary resource used by students. Our experience highlights both the potential and the limitations of such tools in the context of structural engineering education.
- GenAI demonstrates competence in handling foundational concepts such as basic stability and determinacy. However, it is significantly less effective when dealing with more complex or nuanced tasks, such as deflected shape predictions or analytical problem-solving. While GenAI can support students by guiding them through the steps of problem-solving processes, it frequently struggles to deliver accurate numerical solutions on its own.
- Importantly, this exercise has helped students develop a critical understanding of GenAI’s capabilities and limitations. When faced with under-specified or real-world-inspired scenarios, they observed firsthand that AI-generated responses can be misleading or incorrect. This has reinforced the value of maintaining strong foundational knowledge in order to critically assess and verify AI outputs.
- By introducing GenAI early in structural engineering education, we aim to equip students with not only technical proficiency but also the judgment to navigate the evolving digital landscape responsibly. This approach ensures they can leverage AI effectively while remaining aware of its potential pitfalls.

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