

Artificial Intelligence in Engineering Education: Opportunities, Risks, and a Human-Centred Framework for Responsible Integration

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ABSTRACT:

Artificial intelligence (AI), and in particular generative AI built on large language models, is reshaping higher education and professional engineering practice. Engineering education is directly affected, because engineers are increasingly expected not only to use AI-enabled tools but also to understand their limitations, failure modes, and ethical implications. This paper presents a narrative review of AI in engineering education, focusing on teaching, learning, assessment, curriculum design, academic integrity, and employability. It does not report new survey or experimental data; instead, it synthesises recent international policy guidance and peer-reviewed scholarship to propose a responsible, human-centred framework for integrating AI into engineering education. The review indicates that AI can support personalised learning, programming assistance, simulation, design exploration, feedback generation, laboratory preparation, and administrative work. Uncritical adoption, however, may amplify risks related to hallucinated outputs, plagiarism, overdependence, skill erosion, algorithmic bias, privacy and data-security exposure, unequal access, and weakened assessment validity. The paper argues that engineering institutions should move from prohibition-based approaches toward transparent, outcome-based, and discipline-specific AI policies. A practical framework is proposed around five pillars: AI literacy, curriculum integration, assessment integrity, ethical governance, and faculty capacity building. The paper concludes that AI should not replace engineering fundamentals, mathematical reasoning, experimentation, design judgement, or teacher guidance; rather, AI should be treated as a powerful but fallible tool that strengthens engineering education when used with verification, transparency, and human responsibility.

Keywords: Artificial intelligence; generative AI; engineering education; large language models; assessment integrity; AI literacy; ethics; curriculum reform.

1. Introduction

Engineering education has always evolved alongside technological change. Computer-aided design, simulation software, numerical computing, online platforms, virtual laboratories, and learning-management systems have already transformed how engineering students learn and practise technical problem-solving. The recent rise of generative AI, including large language models (LLMs), marks a new phase in this transformation. Unlike earlier digital tools that were mostly confined to calculation, modelling, or content delivery, generative AI can produce explanations, code, reports, design suggestions, summaries, images, and conversational feedback. This makes AI relevant to almost every stage of engineering education, from first-year concept learning to final-year project development [6,8].

The significance of AI for engineering education is reinforced by changes in industry. Future engineers will work in environments shaped by automation, data analytics, AI-assisted design, digital twins, robotics, smart manufacturing, sustainable infrastructure, intelligent power systems, and cyber-physical systems. Workforce analyses point to analytical thinking, technological literacy, and AI and big data among the fastest-growing skills, alongside creative thinking, resilience, and curiosity and lifelong learning [5]. Engineering graduates therefore need both technical competence and AI literacy: they must understand how to use AI productively, how to verify AI-generated output, and how to make responsible professional decisions when AI tools are involved.

Integrating AI into engineering education is not straightforward. AI tools can generate plausible but incorrect explanations, fabricate references, produce code with hidden errors, and encourage superficial learning when students use them to bypass thinking [1,8,10]. They also raise serious concerns for academic integrity, because traditional assignments, programming tasks, laboratory reports, and take-home examinations can be completed partly or wholly with AI [7]. Engineering education thus requires a balanced approach: neither uncritically accepting AI as a

solution to every educational problem, nor rejecting it outright.

This paper reviews the role of AI in engineering education and proposes a responsible-integration framework. Because no primary survey or experiment is reported, it is positioned explicitly as a narrative review and conceptual framework paper. Its objective is to provide a practical academic discussion to guide teachers, departments, and institutions in adopting AI without compromising engineering fundamentals, assessment fairness, or professional ethics.

2. Background of AI in Engineering Education

Artificial intelligence refers broadly to computational systems that perform tasks normally requiring human-like capabilities such as reasoning, pattern recognition, prediction, language processing, and decision support. In education, AI has been used in intelligent tutoring systems, adaptive learning platforms, automated grading, learning analytics, recommendation systems, plagiarism detection, and student support [2,10]. Generative AI extends these applications by creating new content in response to prompts.

Engineering education is particularly amenable to AI integration because it involves mathematical modelling, coding, simulation, design, optimization, experimentation, troubleshooting, documentation, and decision-making. AI can support these activities in several ways. A student might ask an LLM to explain Kirchhoff's laws, debug a MATLAB program, compare numerical methods, generate design alternatives, or summarise a technical standard. A teacher might use AI to prepare quizzes, create problem variations, design rubrics, or generate formative feedback [6]. A department might use AI-supported analytics to identify students who need additional academic support.

At the same time, engineering learning is not only about obtaining answers. It requires conceptual clarity, mathematical derivation, physical interpretation, laboratory skills, design

judgement, safety awareness, teamwork, communication, and ethical responsibility. If AI use reduces students' engagement with these core processes, it may harm learning. The central question, therefore, is not whether AI should be used, but how it should be used responsibly [1,11].

3. Methodological Position of the Paper

This paper follows a narrative review approach. It synthesises recent international policy guidance and published literature on AI, generative AI, higher education, and engineering education. It is not a systematic literature review with database search strings, inclusion criteria, and bibliometric analysis; rather, it offers a structured conceptual discussion intended for engineering educators and academic decision-makers. Where systematic evidence is cited, it is drawn from existing peer-reviewed reviews rather than generated here [6,10].

The review draws on three types of sources: policy and governance documents on AI in

education; scholarly studies on generative AI and engineering education; and broader workforce reports on AI-driven skill change. It is organised around four questions:

1. What opportunities does AI create for engineering teaching and learning?
2. What risks does AI introduce in assessment, academic integrity, and skill development?
3. What changes are required in engineering curriculum and pedagogy?
4. How can institutions develop a responsible framework for AI integration?

Table 1 summarises the scope and positioning of the review, making explicit what the paper does and does not claim. Table 6 (Section 11) summarises the principal sources that inform the discussion.

Table 1. Scope and positioning of the review.

Element	This paper
Review type	Narrative / conceptual review with a proposed framework; not a systematic review or meta-analysis.
Claims made	Synthesis of existing policy guidance and peer-reviewed literature; a conceptual five-pillar framework for responsible integration.
Claims not made	No primary survey, interview, or experimental data; no quantitative performance results; no claims of measured learning gains.
Guiding questions	Opportunities; risks to integrity and skills; curriculum and pedagogy changes; institutional framework.
Intended audience	Engineering teachers, departments, programme coordinators, and institutional decision-makers.

Table 1 clarifies the evidentiary basis of the paper so that conceptual recommendations are not mistaken for empirical findings.

4. Opportunities of AI in Engineering Education

This section outlines where AI can plausibly add value. Table 2 maps common AI capabilities to engineering education activities and pairs each with the human safeguard that responsible use requires.

4.1 Personalised and Adaptive Learning

Engineering cohorts vary widely in preparation across mathematics, programming, physics, communication, and domain knowledge. AI tools can offer individualised explanations, practice questions, hints, and step-by-step feedback, and can give students who hesitate to

ask questions in class a low-pressure environment for revision and self-study [6]. In subjects such as circuit theory, control systems, thermodynamics, data structures, power systems, and mechanics, students may request alternative explanations or worked examples. AI-generated explanations should not, however, be treated as automatically correct; students must learn to compare them against textbooks, lecture notes, simulations, and experimental results [8].

4.2 Programming and Computational Support

Programming is now essential across engineering disciplines, spanning MATLAB, Python, C, simulation packages, finite-element tools, optimization libraries, and data-analysis platforms. AI can help students interpret syntax errors, generate starter code, explain algorithms, and compare implementation approaches, which is useful in numerical methods, machine learning, signal processing, embedded systems, power-system analysis, optimization, and computer-aided design [6]. Coding support, however, carries a major educational risk: students who submit AI-generated code without understanding it may pass assignments while failing to develop computational thinking. Programming assessment should therefore include oral explanation, code tracing, debugging tasks, version history, live coding, and reflection on design choices [7].

4.3 Design and Project-Based Learning

Engineering design involves open-ended problem formulation, trade-off analysis, creativity, constraints, prototyping, and evaluation. AI can support brainstorming, literature mapping, requirement analysis, risk

identification, and early-stage concept generation, and can help final-year students prepare project plans, compare technologies, and improve technical writing. Design responsibility must nonetheless remain with students and teachers: AI-generated suggestions may ignore safety factors, standards, manufacturability, local constraints, cost, environmental effects, or ethical issues. AI should function as a design assistant, not a design authority [11].

4.4 Laboratory and Simulation Support

AI can help students prepare for laboratory work by explaining procedures, anticipating expected results, and identifying common sources of error, and can assist in interpreting plots, debugging models, and comparing theoretical with simulated outcomes. Used before and after experiments, this can make laboratory learning more reflective. AI must not, however, substitute for actual observation, measurement, instrumentation, and uncertainty analysis; laboratories develop practical judgement that text-based explanations cannot replace.

4.5 Teacher Support and Academic Productivity

Faculty can use AI to prepare teaching materials, generate question banks, draft rubrics, simplify explanations, translate technical content, and produce formative feedback, reducing routine workload and freeing time for mentoring, discussion, and higher-order learning [6]. Teacher use must remain transparent and accountable: AI-generated teaching content should be checked for correctness, bias, and alignment with course outcomes, and should not be relied upon without verification [4].

Table 2. Mapping of AI capabilities to engineering education activities, with the human safeguard each requires.

Educational activity	How AI can assist	Required human safeguard
Concept learning	Alternative explanations, worked examples, practice questions, hints	Cross-check against textbooks, lectures, and first principles
Programming / computation	Explain errors, draft starter code, compare algorithms	Code tracing, debugging, oral explanation, live coding

Educational activity	How AI can assist	Required human safeguard
Design & projects	Brainstorming, literature mapping, requirement and risk analysis	Student/teacher ownership of safety, standards, cost, ethics
Laboratory & simulation	Procedure preparation, plot interpretation, model debugging	Real observation, measurement, and uncertainty analysis
Teacher productivity	Question banks, rubrics, formative feedback, translation	Check correctness, bias, and alignment with outcomes

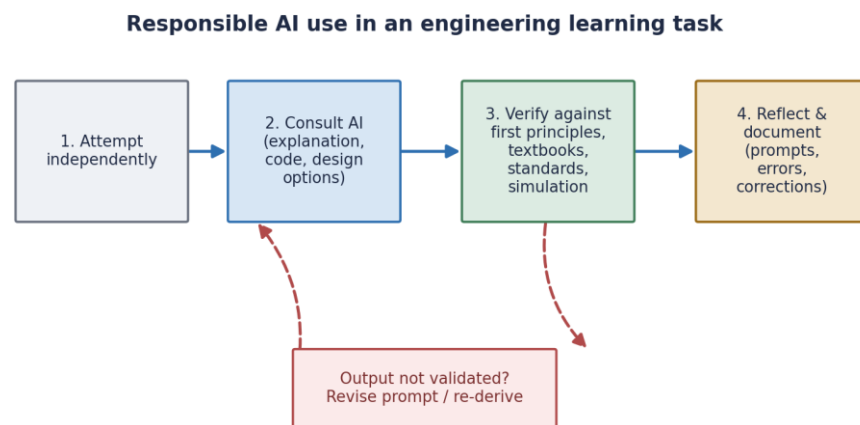
Table 2 frames AI as an assistant whose output is always subject to human verification.

5. Risks and Challenges

5.1 Hallucination and Technical Inaccuracy

A central risk of generative AI is hallucination: the system produces confident but incorrect information. In engineering this can take the form of wrong formulas, unsafe design recommendations, faulty code, fabricated citations, or misleading explanations, and because output is often fluent and authoritative, students

may accept it without checking [8,10]. Engineering education must therefore emphasise verification: students should validate AI-generated results using first principles, textbooks, standards, simulations, experiments, or peer-reviewed sources. The guiding rule is simple — AI may suggest, but the engineer must verify. Figure 1 expresses this as a workflow for a single learning task.



Guiding rule: AI may suggest, but the engineer must verify.

Figure 1. A verification-first workflow for responsible AI use in an engineering learning task.

5.2 Academic Integrity

AI challenges the validity of traditional assessment. Homework, laboratory reports, essays, design documentation, and coding assignments can be generated or heavily assisted by AI, and detection tools are unreliable and may produce false accusations [7]. Assessment design should therefore shift from policing alone toward making evidence of learning more authentic. Useful strategies include oral viva, in-class problem solving, handwritten derivations, staged

submissions, project logs, reflective statements, live demonstrations, and individual questioning, together with disclosure of AI use where permitted. Section 7 develops this into an assessment model.

5.3 Overdependence and Skill Erosion

If students turn to AI for every explanation, calculation, and writing task, they may lose confidence in independent problem-solving. Engineering competence depends on sustained engagement with concepts, equations, diagrams,

and experiments, and immediate AI-generated answers can reduce productive effort and weaken deep learning [8]. AI use should therefore be restricted or structured in early learning stages where foundational skills are formed — for example, students might first attempt a problem independently, then use AI for feedback, and finally submit a short reflection on what they corrected and why.

5.4 Bias, Fairness, and Unequal Access

AI systems may reflect biases in their training data and perform unevenly across languages, regions, disciplines, and student backgrounds. Students with paid access to advanced tools may gain advantages over those using free or limited ones, raising equity concerns [3,4]. Institutions should consider common access, clear rules, and alternative arrangements, and AI policy should

avoid creating hidden advantages for students who can afford better tools or who happen to know more advanced prompting techniques.

5.5 Privacy and Data Security

Students and teachers may upload assignments, project data, unpublished research, industrial problems, or personal information into AI systems, creating privacy, intellectual-property, and confidentiality risks. Because engineering projects often involve industry collaboration, patents, or sensitive data, students must be taught not to upload confidential or personal data into public AI platforms unless explicitly permitted [1,3].

Table 3 pairs the principal opportunities of Section 4 with their associated risks and the safeguards that keep AI use responsible.

Table 3. Paired opportunities, risks, and safeguards across key domains.

Domain	Opportunity	Principal risk	Safeguard
Personalised learning	Tailored explanations and practice	Acceptance of incorrect output	Verify against first principles and texts
Programming	Faster debugging and code drafting	Submission without understanding	Code tracing, oral defence, live coding
Design & projects	Concept generation and literature mapping	Ignored safety, standards, ethics	Human ownership of design decisions
Assessment	Item generation and feedback	Weakened integrity and validity	Authentic, process-based, oral evidence
Equity & access	Low-pressure self-study support	Tool-based advantage gaps	Common access and clear rules
Privacy & security	Productivity and drafting support	Exposure of confidential data	No upload of sensitive data to public tools

Table 3 is a synthesis of Sections 4 and 5; each opportunity is matched to the safeguard that makes it educationally sound.

6. Curriculum Implications

AI should enter engineering education at two levels: education about AI and education with AI. Education about AI means teaching the fundamentals of AI, machine learning, data, algorithms, ethics, and limitations. Education with AI means using AI tools to support learning

in existing subjects [11]. A responsible curriculum should include:

5. Basic AI literacy for all engineering students.
6. Discipline-specific AI applications — for example in power systems, manufacturing, civil infrastructure,

- electronics, robotics, biomedical engineering, or software systems.
- 7. Prompting and verification skills.
- 8. Ethical and legal issues, including bias, privacy, safety, accountability, and intellectual property.
- 9. AI-assisted design and simulation activities.
- 10. Assessment tasks that require students to critique AI-generated output.

Treated this way, AI becomes a cross-cutting professional competence rather than a separate, fashionable topic.

7. Assessment Redesign for the AI Era

Assessment is the area most disrupted by generative AI. Traditional take-home assignments are no longer sufficient evidence of individual learning unless carefully designed [7]. Engineering assessment should be rebuilt around authenticity, process visibility, and higher-order thinking, combining elements such as:

- Closed-book or supervised assessment for core fundamentals.

- Open-AI assignments in which students may use AI but must disclose prompts, outputs, corrections, and verification.
- Viva voce examinations to confirm individual understanding.
- Design reviews in which students justify assumptions, constraints, and trade-offs.
- Debugging and error-detection tasks based on AI-generated faulty solutions.
- Reflective reports explaining how AI was used and what limitations were identified.
- Laboratory performance and observation-based assessment.

In this model, AI use is neither fully banned nor left uncontrolled; assessment instead makes AI use visible, accountable, and educationally meaningful. Table 4 sets out three permitted modes and the evidence of learning each requires.

Table 4. Modes of permitted AI use in assessment.

Mode	Description	Suitable for	Evidence of learning required
Prohibited	AI use not allowed for the task	Core fundamentals; foundational skills	Supervised performance; handwritten work
Permitted with disclosure	AI allowed; prompts and edits disclosed	Higher-level analysis, design, writing	Disclosed prompts, corrections, verification
Actively required	Task built around using and critiquing AI	Critique, debugging, error detection	Reflection on limitations and corrections

Table 4 lets each assignment specify its AI policy explicitly rather than leaving it to assumption.

8. A Human-Centred Framework for AI Integration

Drawing the preceding sections together, the paper proposes a five-pillar framework for responsible AI integration in engineering

education, summarised in Figure 2 and Table 5. The framework rests on a foundation of engineering fundamentals and human judgement, and is oriented toward the goal of responsible, verification-driven AI use.

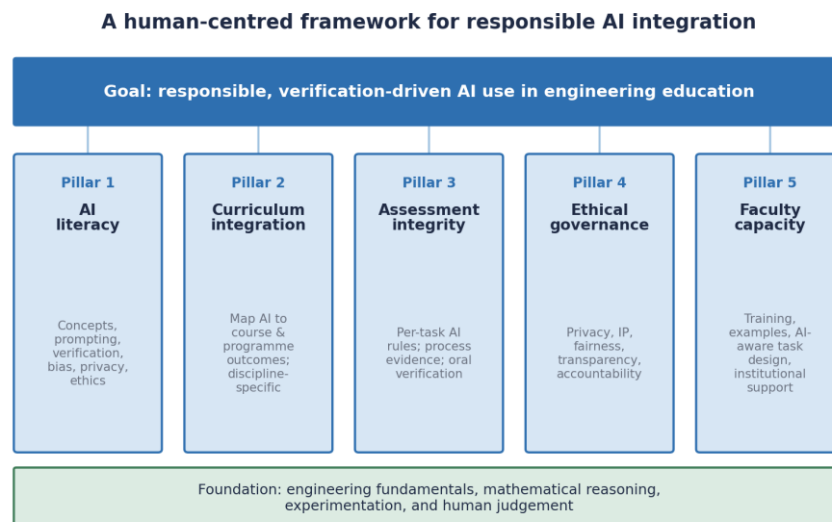


Figure 2. The proposed five-pillar human-centred framework, resting on engineering fundamentals and human judgement.

Pillar 1 — AI Literacy

All students and faculty should understand what AI can and cannot do, including basic concepts, prompt design, verification, hallucination, bias, data privacy, and ethical responsibility [1,5].

Pillar 2 — Curriculum Integration

AI should be mapped to programme and course outcomes. Each department should identify where AI tools support learning and where they may weaken foundational competence, keeping activities discipline-specific rather than generic [6,11].

Pillar 3 — Assessment Integrity

Institutions should set clear rules for AI use in assessment. Every assignment should state whether AI use is prohibited, permitted with

disclosure, or actively required, and should include process evidence and oral verification where needed [7].

Pillar 4 — Ethical Governance

AI policy should address privacy, intellectual property, bias, transparency, fairness, and accountability, and should make clear that professional engineers remain responsible for final decisions even when AI tools are used [1,3,10].

Pillar 5 — Faculty Capacity Building

Faculty need training, examples, and institutional support to design AI-aware assignments, evaluate AI-assisted work, guide students in verification, and use AI responsibly for teaching [4].

Table 5. Summary of the five-pillar human-centred framework.

Pillar	Focus	Key actions
1. AI literacy	What AI can and cannot do	Teach prompting, verification, bias, privacy, and ethics to students and staff
2. Curriculum integration	Outcome-aligned, discipline-specific use	Map AI to course/programme outcomes; identify where it helps or harms
3. Assessment integrity	Authentic, accountable evidence	State per-task AI rules; use process evidence and oral verification

Pillar	Focus	Key actions
4. Ethical governance	Privacy, IP, fairness, accountability	Set policy; keep human responsibility for final decisions
5. Faculty capacity	Teacher readiness and support	Provide training, examples, and AI-aware task design support

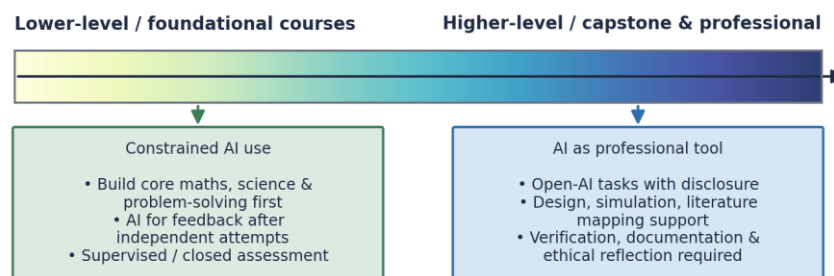
Table 5 operationalises Figure 2 into concrete institutional actions.

9. Discussion

Integration should be guided by educational purpose rather than technological excitement. AI can widen access to explanations, support programming, enrich project learning, and reduce routine workload; it can also produce inaccurate information, weaken academic integrity, and encourage shallow learning [8,10]. The most defensible posture is controlled integration. In

lower-level courses, AI use should be carefully limited so that students develop core mathematical, scientific, and engineering reasoning; in higher-level courses, students can be encouraged to use AI as a professional tool under explicit requirements for verification, documentation, and ethical reflection. Figure 3 represents this as a continuum across course levels.

Controlled integration of AI across course levels



Degree of permitted AI autonomy increases as foundational competence is secured.

Figure 3. Controlled integration: permitted AI autonomy increases as foundational competence is secured.

Engineering education should also shift from answer-based learning to judgement-based learning. Because AI can produce answers quickly, the value of engineering education increasingly lies in asking the right questions, identifying assumptions, checking validity, interpreting results, considering safety, and making responsible decisions — human-centred skills that AI cannot replace [11].

10. Recommendations

11. Engineering institutions should create clear AI-use policies for teaching, learning, and assessment.

12. Every course should specify acceptable and unacceptable AI use.
13. Students should be trained to verify AI-generated technical content.
14. Faculty should redesign assessments to include oral, practical, reflective, and process-based components.
15. AI literacy should be introduced as a common component across engineering programmes.
16. Departments should develop discipline-specific AI examples and case studies.

17. Institutions should address equity by ensuring fair access and avoiding hidden tool-based advantages.
18. Confidential data, unpublished research, and industry project information should not be uploaded to public AI tools without permission.
19. Teachers should use AI to support, not replace, academic judgement.
20. Future research should include empirical studies measuring the effect of AI use on engineering learning outcomes, creativity, problem-solving ability, and professional readiness.

11. Conclusion

Artificial intelligence is becoming an important part of engineering education and engineering practice, visible in learning support, programming, design, simulation, assessment, and academic administration. Used responsibly,

AI can help students learn more actively, support teachers, and prepare graduates for AI-enabled professional environments; used carelessly, it can damage academic integrity, weaken foundational skills, and increase dependence on unverified output. The future of engineering education should therefore be human-centred, AI-aware, and verification-driven. Students should learn not merely how to obtain answers from AI but how to question, test, validate, and responsibly apply AI-generated suggestions. The role of engineering educators remains essential, because teachers provide context, judgement, ethics, mentorship, and disciplinary depth. AI should be integrated as a powerful assistant, not as a replacement for engineering thinking.

Note on sources: Table 6 summarises the principal policy and scholarly sources that ground this review. All cited references were verified against their publishers or indexing databases; the paper reports no primary or fabricated data.

Table 6. Principal policy and scholarly sources informing the review.

Source (Ref.)	Type	Relevant position drawn on
UNESCO — Miao & Holmes, 2023 [1]	Policy guidance	Human-centred vision; regulation outpaced by GenAI; data privacy and ethical validation
UNESCO, 2021 [2]	Policy guidance	Earlier guidance for policy-makers on AI in education
OECD, 2023 [3]	Policy / governance	Risks of bias, inaccuracy, plagiarism, copyright, access, and privacy; mitigation strategies
OECD–Education International, 2023 [4]	Policy guidance	Equity, teacher AI literacy, and guardrails for effective use
WEF Future of Jobs, 2025 [5]	Workforce report	Analytical thinking, technological literacy, AI and big data among fastest-growing skills
Filippi & Motyl, 2024 [6]	Systematic review	LLMs as tutors, feedback, and material generation in engineering education
Nikolic et al., 2023 [7]	Empirical study	ChatGPT benchmarked against engineering assessments across seven universities; integrity concerns
Qadir, 2023 [8]	Conference review	Promise and pitfalls of generative AI for engineering education
Honig, Rios & Desu, 2025 [9]	Empirical study	Acceptance and use of GPT teaching tools in undergraduate chemical engineering
Yan et al., 2024 [10]	Scoping review	Use cases and ethical/practical challenges of LLMs in education
Johri, 2023 [11]	Perspective	Implications of generative AI for engineering education and the educator's role

Table 6 lists the verified sources underpinning the discussion; it is not a substitute for the full reference list below.

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