Ethical Use of Artificial Intelligence in Engineering Education: A Systematic Review

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Abstract

The growing integration of generative artificial intelligence (AI) in engineering education has prompted increased attention to its role in teaching, learning, and assessment. As these tools become more widely adopted, scholarly discourse has shifted from questions of feasibility to concerns about the ethical, responsible, and pedagogically sound use of AI. This study presents a systematic review of the engineering education literature on how ethical guidance concerning AI use is articulated at institutional and instructional levels. Guided by PRISMA 2020 protocols, the review screened 2,158 articles published between 2000 and 2025 across eight databases. Of the 696 articles screened for full-text eligibility, 99 addressed ethical guidance for AI use in the engineering classroom. Inductive analysis of these articles revealed seven recurring themes: transparency and disclosure of AI use; faculty and student accountability and human oversight; student autonomy and agency; confidentiality and student data protection; academic integrity and authorship; fairness, equity, and bias mitigation; and beneficence, safety, and student wellbeing. Across these themes, integrity, accountability, and transparency were the most frequently emphasized aspects of ethical AI use, while beneficence and student autonomy received comparatively limited attention. Furthermore, findings indicate that ethical considerations in AI-enabled engineering education are fragmented and inconsistently articulated. Many guidelines were primarily student-facing and focused on academic integrity, disclosure, and misuse prevention, with less attention to reciprocal faculty accountability, institutional responsibility, and the broader pedagogical conditions needed for responsible AI integration. This imbalance is particularly consequential in engineering education, where instructional practices help prepare future engineers responsible for public safety, infrastructure reliability, and societal wellbeing. Overall, the findings highlight a critical gap between growing ethical awareness of AI risks and the absence of coherent, reciprocal ethical frameworks in engineering education practice. Addressing this gap will require institutions and accrediting bodies to adopt dynamic, human-centered frameworks that integrate ethical principles into pedagogy and assessment, strengthen ethical literacy among faculty and students, and promote shared human-AI accountability to support responsible, socially aligned AI integration in engineering education.

Keywords: Professional Responsibility, Institutional Policy, Classroom Practice, Equity and Access

INTRODUCTION

Educational technologies have long offered promising solutions to persistent challenges in education, including supporting the teaching of abstract concepts, facilitating design thinking, and fostering collaboration. More recently, artificial intelligence (AI) has emerged as a disruptive educational technology with the potential to fundamentally reshape teaching, learning, and assessment. In their review of AI in education, Labadze et al. [1] highlight several educational roles of AI, including assessment support, task automation, information retrieval, personalized learning, use as a study companion, and provision of real-time feedback to both students and educators. These capabilities continue to attract attention from educational stakeholders, researchers, educators, and institutional policymakers alike—as potential avenues for investing in AI integration within classrooms.

Within engineering education, AI has had a similarly disruptive impact, reshaping how knowledge, skills, and competencies are developed and transferred to students. Effective integration of AI into engineering education can enhance students' learning experiences as they acquire core technical knowledge, professional skills, and problem-solving abilities essential to holistic engineering education [2]. Empirical studies have also reported the beneficial role of AI in improving both student learning and instructional practices. For example, in a pilot study examining students' use of ChatGPT for laboratory report writing, Kim et al. [3] highlighted the perceived value of customized feedback in supporting students' development of engineering communication skills. The widespread availability and ease of access to AI tools have further contributed to their adoption across multiple engineering disciplines, moving the conversation from initial concerns about disruption toward questions of effective integration.

As AI becomes more widely used for educational purposes, discussions have shifted from focusing solely on how AI can improve educational processes to considering how ethical governance and policy frameworks shape its responsible use. Ethical considerations, including transparency, accountability, equity, and bias mitigation, have become central to conversations about the adoption of AI in education, with calls for clear frameworks to guide responsible implementation increasingly emphasized as essential rather than optional [4]. These concerns have contributed to the continued development of AI-related policies at national, state, and institutional levels. For instance, [5] identified 112 AI ethics documents published between 2016 and 2019 across 25 distinct ethics topics and recommended further investigation into how such policies are enacted in practice across different sectors.

Ethical concerns surrounding the integration of AI into engineering education include equitable access, data privacy, transparency, and bias. Osunbunmi et al. [6] emphasize the importance of engineering educators being aware of these ethical issues when integrating AI as a pedagogical tool. In this regard, scholars have increasingly examined different aspects of AI ethics across the development and implementation of AI systems, including efforts to translate ethical principles into engineering education contexts.

Martín Núñez and Lantada [7] highlight several ethical considerations associated with the adoption of AI in engineering education, including academic integrity in autonomous and open online learning environments, transparency in data collection, and mechanisms to improve accountability in AI-supported systems. The authors emphasized the importance of preserving human agency in AI implementation, particularly regarding data security and privacy, as increasing volumes of educational data are processed by AI systems. Similarly, Kabashkin et al. [8] identify data privacy as a key ethical risk in the implementation of AI in aviation engineering education and underscore the need for responsible governance frameworks to ensure that professionals can harness AI's benefits without compromising safety or ethical standards.

At the instructional level, Lan and Chen [9] emphasize integrity in the classroom use of AI, calling for faculty-driven strategies to ensure the authenticity of student work and mitigate potential learning harms, such as diminished development of core engineering skills, including problem-solving and critical thinking. Lan further highlights faculty agency in the design and oversight of AI-supported instructional systems, reinforcing the role of AI as a supplemental tool whose use must be guided by transparency and ethical accountability. Across these studies, ethical considerations in AI use within engineering education consistently point to the need for conscious awareness of AI's limitations and boundaries, serving as guardrails to ensure that AI integration supports, rather than impedes, meaningful learning.

Consequently, [10] describes a collaborative initiative to integrate AI ethics into engineering education at the classroom level, with the goal of preparing students to become both technically skilled and socially responsible engineers, given the global impact of engineering practice. Similarly, [11] presents a tool grounded in an AI ethics knowledge base to support engineers' ethical decision-making. Collectively, these efforts reflect growing recognition of the importance of ethical considerations in AI integration within engineering education.

At the same time, early exposure and instructional practice play a critical role in shaping engineers' professional mindsets, underscoring the need to examine how ethical guidance is enacted in educational settings as AI policies continue to be developed and implemented. As AI integration becomes more widely adopted in engineering classrooms, it becomes increasingly important to assess the extent to which ethical considerations are made explicit in instructional practice. Such understanding can inform educators about practical ways to integrate ethical considerations into classroom use of AI, while also providing insight into how institutional AI-related policies are reflected and enacted at the instructional level. Accordingly, the purpose of this systematic review is to examine the current state of the engineering education literature regarding ethical guidance for the responsible use of AI in engineering classrooms. This focus is particularly important within engineering education, where instructional practices contribute to preparing future professionals whose technological decisions directly influence public safety, infrastructure reliability, environmental sustainability, and societal wellbeing. In this sense, ethical AI use in engineering classrooms is not merely a matter of academic policy but of professional formation and societal responsibility. Specifically, this review examines two perspectives: (1) the extent to which explicit institutional ethical policies are provided to guide engineering faculty in their use of AI, and (2) the extent to which engineering faculty offer clear guidance to students regarding acceptable and responsible AI use.

Significance and Contribution of this Study

The novelty of this study lies in its contribution to the growing literature on artificial intelligence in engineering education by moving beyond conceptual discussions of AI ethics to examine how ethical guidance is enacted in instructional practice. While prior reviews of AI ethics in education often synthesize policy documents, conceptual frameworks [12], literacy interventions [13], [14], or cross-disciplinary perspectives, this systematic review focuses specifically on empirical studies of AI utilization in higher education engineering classrooms. By combining deductive coding of core ethical principles with inductive thematic analysis, this study identifies seven recurring forms of ethical guidance provided in engineering education contexts: transparency and disclosure of AI use; faculty–student accountability and human oversight; designing for student independence and agency; privacy and data protection; academic integrity and authorship; fairness, equity, and bias mitigation; and beneficence.

Most importantly, this review reveals a consistent pattern across the literature: ethical AI guidance in engineering education is predominantly student-facing and compliance-oriented, often centered on academic integrity and disclosure requirements, while reciprocal accountability for faculty AI use and institutional responsibility remains comparatively underdeveloped. By documenting this imbalance and synthesizing how ethical guidance is operationalized in engineering classrooms, this study provides a practice-oriented evidence base to inform future instructional design, faculty development, and institutional policy related to responsible AI integration in engineering education.

METHODS

Inclusion and Exclusion Criteria

We conducted a systematic literature review to identify published research on the use of artificial intelligence (AI) in engineering education, following the PRISMA 2020 guidelines [15]. Rather than restricting the search to studies explicitly focused on ethics, we adopted a broader search strategy centered on AI applications in engineering education. This approach enabled an in-depth examination of how ethical considerations are addressed, both explicitly and implicitly, in the use of AI within engineering classrooms. By focusing on broader applications of AI, we identified how ethical guidance is articulated, operationalized, or omitted in the existing literature on AI in engineering education.

Studies were included if they met the following criteria: (1) artificial intelligence (AI) was implemented to support or enhance learning; (2) the study was peer-reviewed; (3) the educational context was undergraduate engineering education; (4) the study was an empirical study examining AI use in curriculum design or instructional practice, including studies that did not directly measure student learning outcomes; (5) the study addressed ethical considerations related to AI use for faculty or students, either explicitly or implicitly through related concepts such as bias, privacy, transparency, or accountability; (6) the publication was written in English; and (7) the study was published between 2000 and 2025.

Studies were excluded if (1) the full text was not accessible; (2) the publication was a conceptual paper, opinion piece, or review article; (3) the study did not address ethical considerations or provide any discussion relevant to ethical guidance in AI use; or (4) the study was written in a language other than English.

Search Strategy

After establishing the inclusion and exclusion criteria, we iteratively developed the search strategy through multiple discussions within the research team and consultations with a university librarian. Several combinations of search terms relating to learning and AI were tested before finalizing the search strings and selecting databases that aligned with the study objectives. In total, eight databases were searched: APA PsycInfo; ProQuest Dissertations & Theses (gray literature); ERIC via EBSCO; Engineering Village; Education Research Complete; ScienceDirect; Scopus; and Web of Science. The selection of databases followed best practices for engineering education research reviews [16].

For our search terms we used the search string **, ** (("generative artificial intelligence" OR "generative AI" OR "Gen AI") OR (chatbots OR ChatGPT OR "Microsoft Copilot" OR Gemini or LLaMA) OR (LLM OR “Large Language Model”) OR (“Artificial Intelligence” OR AI) AND (Engineer*) AND (learning OR performance OR achievement OR “learning outcome”) AND (Undergraduate OR Graduate OR college OR university OR “Higher Education” OR “Tertiary Institution”) AND (Student* OR learner* OR Education)). For databases that required fewer Boolean operators or search terms, the search string was modified to align with database-specific requirements. In Figure 1, we present an overview of the search, screening, and full-text review process. The database search yielded 2,158 records, which were imported into Rayyan AI for duplicate identification and removal prior to screening. Following the deletion of 696 identified duplicate records, 1,462 articles remained for title and abstract screening (See Figure 1).

Data Extraction and Screening

Using Rayyan AI, title and abstract screening were conducted for the 1,462 articles, applying predefined inclusion and exclusion criteria. Screening was distributed evenly among the three authors, and coding was conducted blind, so they could not view others’ decisions until the screening phase was completed. To establish inter-coder agreement, a fourth author independently screened forty randomly selected articles from each group of articles screened by the three primary coders. Upon independent completion of title and abstract screening, multiple research team meetings were held to resolve discrepancies. Discussions continued until consensus was reached on all contested articles. This process resulted in 696 articles being retained for full-text review.

Full-text screening was conducted by four authors, with 696 articles evenly distributed, and an additional coder reviewed a subset of articles to assess inter-coder agreement. Upon completion of full-text screening, discrepancies were addressed through recurring team discussions, during which articles were recoded or information updated based on collective consensus. These meetings included additional authors who were not directly involved in the coding process, providing an unbiased perspective on coding discrepancies.

Data was extracted using a Qualtrics-based survey instrument developed collaboratively by the research team and aligned with the study objectives. The coding metrics included disciplinary context, research methodology, type of AI application, nature of ethical considerations, and the presence or absence of ethical guidance for faculty and students. Both generative AI tools and other AI applications were considered during the screening process. This process yielded 184 articles in total that used AI in engineering education. An additional screening of the 184 articles resulted in 99 articles being included for analysis based on their implicit or explicit ethical considerations or objectives. Another team member coded independently 20% of these 99 articles, and meetings were held until resolution and agreement were reached.

Given the diversity of pedagogical approaches and the study's focus on ethical guidance rather than instructional effectiveness, no quality scoring or study weighting was applied. Throughout the screening and coding process, team members consulted full-text articles as needed to clarify interpretations and ensure consistency. Following data extraction, a research team member who was not involved in the coding process analyzed the synthesized dataset, providing an additional independent perspective during results interpretation.

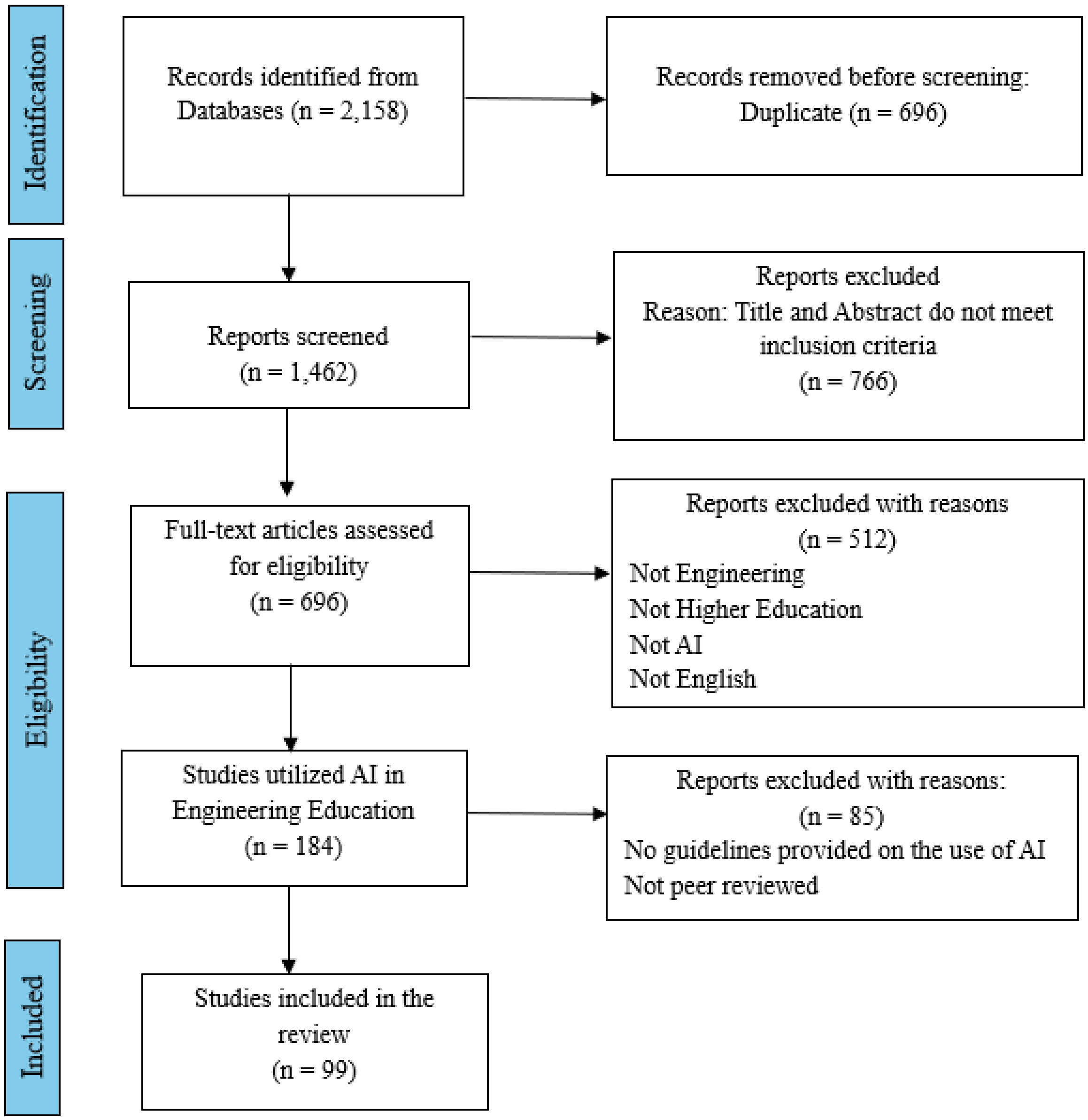

Figure 1: PRISMA flowchart for systematic review process

RESULTS AND DISCUSSION

To provide a structure for theming and synthesizing the findings of this review, we drew upon the conceptual and philosophical operationalization of the core aspects of AI ethics as articulated by a range of authors and organizations, and systematically compared by [17]. In addition to using this framework, we also let our data speak for itself [18].

The results of our coding for all core aspects of ethical AI use in engineering education, either implemented by the instructor or provided to students, are presented below. In total, 99 studies either explicitly or implicitly provided ethical guidance for faculty AI adoption in the classroom, student use of AI, or institution-facing AI policies (See Appendix A1 for article metadata, including methodology, discipline, degree focus, and authors' in-text citations). Our findings indicate that accountability (n = 47) and transparency in AI use (n = 34) are the most highly emphasized core aspects of ethical use, while autonomy (n = 12) and beneficence (n = 10) are the least emphasized in the literature (See Figure 2). Furthermore, many authors provided guidelines on integrity (n = 49), leading to its inclusion as a distinct theme.

Table 1 presents representative examples of stakeholder-facing guidelines: student-facing, faculty-facing, and institution-facing ethical guidelines for the use of AI across the core aspects identified in this systematic review. Readers should note that individual studies often address multiple core aspects of ethical guidelines and may also include multiple categories of stakeholder-facing guidelines.

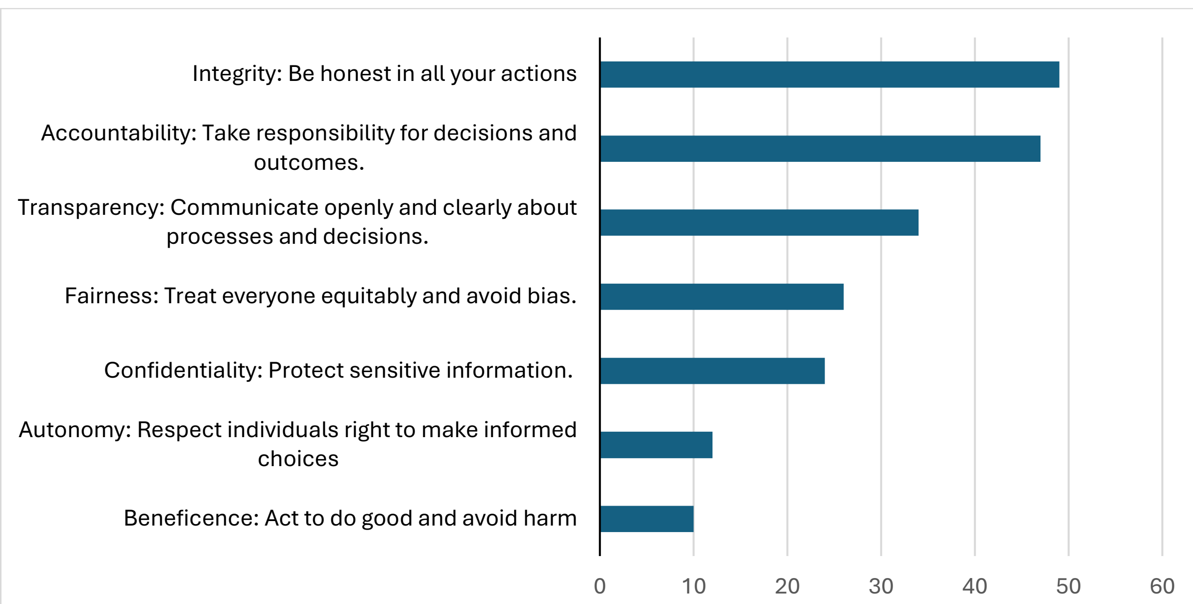

Figure 2: Core aspects of ethical guidelines followed or provided

Thematic Analysis of AI Ethical Guidelines in Engineering Education

Themes were generated using inductive coding from identified empirical studies that stated the AI ethical guidelines that were followed by engineering faculty or provided to engineering students [18]. This approach allowed for the systematic identification and categorization of AI ethical principles emphasized in the literature. The analysis focused on explicit and implicit guidance on the ethical use of AI in engineering educational settings. The following themes emerged from the inductive coding exercise: Transparency, Accountability, Autonomy, Confidentiality, Integrity, Fairness, and Beneficence.

Transparency

When ethical guidelines for AI use are provided, transparency is commonly emphasized through expectations that users disclose which AI tools were used and how they were applied in teaching, learning, and assessment in engineering education [3], [19], [20], [21]. By asking engineering students to reflect on their use of AI, such documentation can assist them in their metacognitive process of developing AI literacy as they pursue their engineering degrees. Also, the reflection artifact can become a collection of what worked and what did not when using AI, which they may go back to in the future, potentially increasing their AI literacy. This documentation can also help delineate which aspects of learning were human and which were AI-supported, and how that translated into the overall internalization of the material presented in the classroom. The authors' review of literature suggests that the most explicit requirement of disclosures of AI use has been from faculty to students. For example, [19] embedded transparency practices within a first-year engineering course by requiring disclosure of prompts and outputs and providing structured instruction on ethical AI risks such as bias, misinformation, and data privacy.

Also, faculty mostly provided guidelines when they adopted AI for assessment [22], [23], [24]. Based on this review, we suggest that faculty increase transparency regarding how they use AI in their classrooms and document these practices in syllabi, teaching processes, and educational materials. We also recommend that AI-generated outcomes be verified and that users explain how and why they use AI tools.

Accountability

The outcome of this review suggests that AI use in the engineering classroom requires a balanced approach that holds both faculty and students accountable while ensuring sufficient oversight [3], [19], [25]. Accountability in this context varies between faculty and students. For engineering faculty, accountability primarily involves ongoing supervision and monitoring of AI systems and student learning, ensuring their use aligns with educational objectives and ethical standards. For engineering students, accountability should be demonstrated through taking responsibility for all submitted work when AI tools are utilized. Such guidelines on human oversight will provide verification of work that may mitigate the occurrence of hallucinations, errors, and made-up references. For example, [26] emphasized instructor supervision and assessment design that prioritizes critical thinking when integrating AI chatbots into civil engineering education, requiring students to verify AI-generated outputs to prevent misinformation and academic misconduct.

Furthermore, the reviewed literature suggests that AI should serve as a supportive tool in teaching, assessment, and learning. This emerging technological tool should complement rather than replace human judgment and faculty roles. In line with this perspective, a recurring recommendation is to adopt a “human-in-the-loop” guideline for any academic task. The synthesis of literature indicates the need for faculty to actively supervise and monitor AI use, rather than allowing students to use AI tools independently without clear guidance. This approach helps preserve the value of human expertise and judgment throughout the educational experience.

Also, adopting this approach will mitigate the concerns that engineering educators have that AI implementation at the institutional or system level could shift toward productivity gains, with less human involvement (cutting back on faculty and staff) to reduce costs, rather than an inclination toward supporting student-centered learning by personalizing the learning experience. Another concern is that students’ critical thinking skills may decline due to overreliance on AI tools. However, other studies suggest that AI may improve students’ problem-solving skills when integrated using sound pedagogical principles.

Autonomy

The need to design for independence and student agency cannot be overemphasized. As artificial intelligence becomes more prevalent in educational settings, engineering educators have recognized the importance of establishing guidelines to encourage students to engage thoughtfully with AI tools rather than become overly dependent on them. Studies highlight concerns that the introduction of AI into the classroom may inadvertently encourage students to rely on these technologies at the expense of their own analytical abilities [25], [27]. To address this, it is essential that engineering educators intentionally design AI integration within the learning process. The aim should be to ensure that the use of AI supports and enhances students’ critical thinking and independence, rather than diminishing these essential skills. By doing so, instructors can foster an environment where engineering students continue to develop their problem-solving abilities and maintain agency in their learning, while using AI as a complementary resource rather than a crutch. For example, engineering faculty could develop AI agents or custom GPT-based chatbots with retrieval-augmented generation (RAG) systems that use guided questioning rather than simply providing solutions to students.

Furthermore, most AI tools are designed for broad, generalizable use rather than context-specific learning needs. When used for feedback and assessment, these tools may disadvantage students whose responses are innovative, unconventional, or otherwise differ from expected solution patterns. Therefore, guidelines are needed to ensure that AI-supported feedback and assessment remain context-sensitive, equitable, and subject to faculty review.

Confidentiality: Student Data Protection

Generative AI systems typically operate by analyzing past datasets that include student learning outcomes and experiences. To safeguard engineering students' identities, studies have emphasized the need for explicit guidelines centered on confidentiality and privacy. These guidelines advocate anonymizing and de-identifying student data whenever AI tools are employed. Any use of student datasets for AI integration must adhere to the established frameworks to ensure compliance with ethical standards and institutional policies [25]. In addition to privacy concerns, the deployment of AI for feedback and assessment raises questions about permissible practices. Whenever AI use involves accessing students' current or future data, it is essential to inform students about such usage. Further recommendations include refraining from using actual student or faculty data and opting instead for simulated AI datasets whenever possible. In instances where the use of real student data is necessary or valuable, measures must be implemented to minimize potential harm by adhering to the Family Educational Rights and Privacy Act (FERPA) and Institutional Review Board (IRB) protocols. Together, these guidelines help foster a secure and ethical environment for AI integration in engineering education, with confidentiality and the protection of student information prioritized at every stage.

Integrity

Academic integrity and authorship were extensively discussed under this theme. Faculty have established clear guidelines defining ethical and unethical use of AI within the classroom. These guidelines serve as essential guardrails for appropriate AI engagement. Violating such guidance may constitute an academic integrity violation, including but not limited to plagiarism, cheating, academic misconduct, and actions that circumvent learning objectives. These violations can undermine student skill development and threaten the overall integrity of higher education institutions [22], [25], [28], [29]. To address these concerns, it is recommended that policies clearly delineate the boundaries between legitimate AI use for academic tasks and misconduct. This involves redesigning assessments to account for responsible AI use and facilitating classroom discussions that clarify responsible and ethical engagement with AI tools. One key guideline is that any use of AI in coursework should be fully disclosed. Regardless of the extent to which AI tools are used, students remain responsible for the originality and integrity of their submitted work.

There is also a conflict over what constitutes student work and AI work when AI is being used in the classroom. There may be a need for clarity and reaching consensus on what this will look like. Hence, it is important that students take ownership of and carefully review AI-supported work. For example, an ethical use of AI is using it to gain a deeper understanding by asking it conceptual questions and procedures for approaching a problem. Writing out a solution from an AI without reviewing or understanding the concept is unacceptable and may also lead to shallow learning. It is recommended that faculty provide examples of what ethical and unethical use of AI is when ethical guidelines are discussed in the classroom. Studies also warned against both students' unethical use of AI and institutions' unethical responses to AI use.

These considerations underscore the importance of reassessing what constitutes genuine student understanding and developing effective methods to evaluate depth of learning, especially as AI tools become more prevalent. While much emphasis is placed on student integrity, there is limited guidance on what this looks like for faculty when they use AI for teaching and assessment. More explicit institutional guidelines for faculty are therefore needed. Additionally, locally run AI models may offer advantages over cloud-based large language models (LLMs) by providing institutions with greater control over data privacy, system oversight, and academic integrity.

Fairness

Ethical guidelines on what will be fair, equitable, and bias-mitigating in the use of AI have been proposed. Studies cautioned that AI systems can reproduce or amplify biases embedded in training data, potentially leading to skewed outputs, reinforcing stereotypes, and contributing to unequal treatment. These concerns are relevant as AI tools are increasingly adopted for assessment, feedback, programming support, and personalized learning experiences in engineering education [28], [30], [31]. For example, to mitigate gender, racial, cultural, and other biases when AI is used for feedback in the first-year engineering course, [31] removed engineering students' names, pronouns, races, and other identifiable information that may increase bias in outputs. Another key consideration is equitable access to AI resources. Disparities in resource availability can result in some groups having greater access to advanced AI tools, while others may be left behind. This discrepancy has the potential to widen the gap between well-resourced and under-resourced populations [19], [25].

Despite these challenges, AI, when governed by appropriate guidelines, can also promote fairness in assessment. For example, AI tools can help standardize grading and reduce inconsistencies and subjectivity in evaluation. This consistency may contribute to narrowing the achievement gap, as a broader range of students can benefit from more objective and accessible assessment practices. To uphold fairness in tests and examinations, it is important to ensure that only versions of AI tools accessible to all students are permitted. Additionally, there is the need for ongoing bias mitigation efforts throughout AI model development, particularly to address algorithmic bias and ensure equitable outcomes for all learners.

Beneficence: Promoting Good and Avoiding Harm

The principles of beneficence and nonmaleficence require that the use of AI in engineering education provide clear benefits while minimizing potential harm. When AI use involves student data, institutional practices should ensure that such data are used in ways that benefit students and do not cause harm. If there is any risk of negative outcomes, students should be informed of the potential risks.

Ensuring the safe use of AI in educational environments involves prioritizing students' psychological wellbeing. Instructors are advised to implement AI in ways that actively reduce potential harm, safeguard student confidentiality, and address any biases when processing peer-evaluation data [32]. To achieve this, student information should be anonymized prior to any AI processing. Additionally, instructors should consider filtering out inappropriate or harmful peer comments before sharing feedback with students [31]. When carefully reviewed by instructors, AI-generated summaries of peer feedback may help reduce students' exposure to harmful or inappropriate comments and support psychological safety.

Student safety also entails protecting them from exposure to harmful content, misinformation, inaccurate educational materials, and any content that could cause emotional distress or negatively impact their mental health during AI use. These precautions are essential for fostering a safe and supportive learning environment.

Faculty safety, on the other hand, must also be considered when integrating AI tools. Rather than replacing engineering instructors and threatening their employment, AI should be used to enhance faculty workflows and responsibilities. By supporting, rather than replacing, faculty roles, AI can contribute to more effective and efficient educational practices.

Table 1: Ethical Principles Across Stakeholders with Representative Evidence

Ethical Principle	**Student-Facing (n = 58)**	**Faculty-Facing (n = 81)**	**Institution-Facing (n = 42)**
		Representative Evidence with Citations	
Integrity: Be honest in all your actions (n = 49)	[33] framed ChatGPT's role as part of a supervised and intentionally structured learning activity. The authors cautioned that ChatGPT should not serve as a primary or authoritative source. Instead, students should use it to spark ideas and guide further inquiry. [34] emphasized that students should first attempt problems independently before consulting ChatGPT, using the tool as a point of comparison rather than a shortcut. The authors emphasize that responsible and ethical use of AI requires students to critically evaluate ChatGPT's outputs and verify them using academic sources, as this combination is essential to maintaining the integrity of the learning process [35].	[36] encouraged educators to focus on teaching responsible AI use rather than banning AI, framing ethical AI use as a pedagogical responsibility. The authors argue that responsible ChatGPT integration requires carefully designed instructional activities, clear learning objectives, instructor guidance, and use of ChatGPT as a complementary tool rather than a replacement for traditional teaching. They also caution against open and unguided use, noting that misuse may occur when students submit ChatGPT-generated responses without revising or critically evaluating them [37]. [34] argued that AI may not necessarily threaten academic integrity, especially when faculty design AI-resilient assignments that are not easily solvable using AI. They encourage explicitly teaching students the strengths, weaknesses, and limitations of these tools.	The authors recommend that institutions adopt a balanced approach to AI integration that prioritizes equity and mitigates potential biases. The authors further advise institutions to embrace thoughtful integration strategies and establish clearly articulated policies and guidelines to govern AI usage throughout the learning journey [38]. The authors recommend that institutions establish policies and norms, strengthen teacher training, and address privacy and security challenges to ensure the responsible and ethical integration of AI technologies. These actions support an integrity lens by promoting honest use of AI in educational settings [39].
Accountability: Take responsibility for decisions and outcomes. (n = 47)	The authors indicate that students must engage deeply with the material, critically assess ChatGPT's responses, and avoid simply relying on confident-sounding outputs. They emphasize that ChatGPT can produce	The author argue that AI should be used to reinforce students' learning rather than replace it, since AI models can give inaccurate results or incorrect methods, and students often need to check the correctness of the answers themselves [40].	The authors note that educators and institutions need a structured approach when introducing AI into curricula. They emphasize that clear guidelines for the ethical and efficient use of AI tools are

	plausible but inaccurate answers, making it essential for students to use their own contextual and domain knowledge to evaluate and refine AI-generated content rather than accepting it at face value [36]. The author argues that students must use their own mathematical understanding and judgment when working with AI, since AI models can give inaccurate results or incorrect methods [40]. The authors argue that human judgment must remain central in design work, noting that LLMs can support generative brainstorming but still require people to evaluate options and make decisions [41]. The authors argue that students must understand the difference between natural language processing and genuine language understanding. They emphasize that learners need to remain aware of ChatGPT's capabilities and limitations rather than accepting its outputs uncritically [42].	The authors argue that educators need to teach students how to use LLMs effectively, including understanding their flaws, biases, and limitations, so that students can critically evaluate the information that these tools provide [41]. The authors suggest that teachers need to learn new skills and adapt their teaching to make good use of AI tools, and that faculty engagement and behavior play a major role in how effectively AI is used in higher education [43].	essential and that these tools should function as supplementary resources that support, rather than replace, students' learning and problem-solving [44].
Transparency: Communicate openly and clearly about processes and decisions.	Ambikairajah et al. [45] provided a student-facing transparency example by allowing students to use ChatGPT openly as a learning aid while requiring them to produce original work. Students used ChatGPT to	Pesovski et al. [46] explained that the AI-generated learning materials were produced, checked, and approved by the professor immediately after each class, rather than being generated on demand. They argued that this workflow created a controlled	The authors noted that "Many people believe that universities should regulate the use of artificial intelligence, but currently, it is not clear how to do it" [48].

(n =34)	support debugging, resource discovery, MATLAB learning, idea generation, and quick searches, positioning the tool as a quasi-tutor rather than a substitute for student effort [45].	generative environment and allowed final proof-checking by the professor, thereby helping to mitigate ethical challenges associated with generative AI. The authors stated, “As educators, we find ourselves in a position where we cannot control the presence or usage of ChatGPT, but we can play a vital role in educating students on its responsible and effective utilization.” [47]	Qureshi suggested that universities can address concerns about AI tools such as ChatGPT by adopting a proactive and ethical approach to their implementation [21].
Fairness: Treat everyone equitably and avoid bias. (n = 26)		Žáková et al. [49] noted that the use of AI tools raises fairness concerns in assessment because not all students may use these tools. To address concerns related to academic integrity and fairness, they recommended that AI-based activities be used primarily in formative assessments rather than high-stakes summative assessments [49]. The author mentioned that “the training and validation of the AI model may introduce biases in the data and the predictions, affecting the accuracy and fairness of the assessments. Continuous efforts will be made to mitigate biases in the data collection, annotation, and augmentation processes, as well as in the model training, optimization, and evaluation processes and various metrics and methods will be used to measure and monitor the model’s performance and ensure its alignment with human observations.” [50]	The authors argued that “ethical and bias considerations are integral to re-training.” They further explained that “using balanced and representative datasets can help identify and mitigate the inherent biases in the pre-trained model, leading to more equitable outputs” [51].
Confidentiality: Protect	[48] noted that “11 students (8%) highlighted privacy and data security issues and expressed concerns about	Sajja et al. [53] stated that future work should “investigate the ethical implications of using AI in education, addressing	The author emphasized the need to ensure students’ privacy and anonymity, protect sensitive

sensitive information. (n = 24)	unauthorized access to personal information by AI systems and data misuse." The authors noted that participants expressed concerns about privacy risks, including potential breaches and leaks of sensitive information in AI-generated code [52].	concerns related to data privacy, algorithmic bias, and the potential impact on the human role in education."	information, and comply with data protection regulations. They also note that transparency about the use of NLP and the purpose of student sentiment analysis is essential to maintain trust within the university community [23].
Autonomy: Respect individuals right to make informed choices. (n = 12)	The paper argued that ethical use of AI requires human responsibility. Hence, students must retain decision-making authority [54]. The authors illustrate how students' autonomy can be preserved in AI-supported learning by designing an activity in which students remain responsible for planning, conducting the audit, asking well-reasoned questions, requesting documentation, evaluating compliance, and developing an action plan [55].	The authors suggest that ethical AI education should prepare students to identify, address, and mitigate ethical risks associated with AI technologies [56]. Mahande et al. [57] stated that "ChatGPT use should be balanced with strategies that promote self-efficacy, reduce anxiety, and foster engagement."	
Beneficence: Act to do good and avoid harm (n = 10)	The authors caution that generative AI can harm student skill development and threaten the integrity of higher education. To address these concerns, they recommend students learn the ethical challenges of AI, clarifying boundaries between legitimate assistance and misconduct [22].	[32] stated that "Another important consideration was the intentional filtering of inappropriate comments within peer feedback. To prevent this, we edited the prompt to add language to exclude comments that would be inappropriate for the workplace. We found this to be effective in removing comments that were derogatory, disrespectful, or used profanity."	The authors caution that AI use in education must be carefully managed because misuse, bias, hallucinations, and flawed explanations of course concepts can interfere with learning [27] Ding et al. [58] mitigated privacy and hallucination risks by favoring locally run models over cloud-based LLMs and requiring human verification of LLM-generated analyses.

RECOMMENDATIONS

This systematic review synthesizes empirical evidence from engineering classrooms to examine how ethical AI guidance is enacted in instructional practice. The recommendations below are grounded in the recurring ethical themes identified across the reviewed studies and highlight engineering-education-specific gaps, including the predominance of student-facing ethical guidance, limited attention to faculty accountability, and the absence of continuous evaluation of AI-supported teaching and assessment practices.

Transparency: Engineering educators should normalize transparent disclosure of AI use in teaching, learning, and assessment. Faculty should model ethical AI engagement by documenting how AI tools are used in instructional design, feedback generation, and evaluation processes. Students should also be required to disclose and reflect on their AI use in coursework to support metacognitive awareness and AI literacy development [20], [22], [25], [59]. Strengthening transparency at both faculty and student levels addresses the imbalance in ethical guidance identified in this review.

Accountability: Institutions should promote reciprocal accountability for AI use between faculty and students. Faculty should maintain active human oversight in AI-supported instruction and assessment, while students remain responsible for the originality and integrity of submitted work [3], [54]. Establishing "human-in-the-loop" practices ensures that AI tools augment rather than replace professional judgment and student learning.

Autonomy: Designing for Student Independence and Agency. AI integration in engineering education should be intentionally designed to preserve student autonomy, critical thinking, and problem-solving development. Instructional activities should encourage students to use AI for conceptual exploration, feedback, and reflection rather than solution substitution. Scaffolded AI-use activities and guided interactions can help maintain student agency and support independent learning [25], [27]. Although autonomy is frequently discussed in student- and faculty-facing contexts, the reviewed articles did not explicitly address institutional autonomy as an ethical concern.

Privacy, Confidentiality, and Student Data Protection: Institutions should establish clear policies governing the use of student data in AI-supported educational systems. These policies should prioritize anonymization, FERPA compliance, and IRB oversight when AI tools process student information [32], [60]. Students should be informed whenever AI systems use their data for feedback, assessment, or instructional purposes.

Integrity: Universities should update academic integrity policies to reflect evolving distinctions between AI-assisted learning and academic misconduct [22], [28]. Faculty development initiatives should support instructors in redesigning assessments that evaluate reasoning, conceptual understanding, and engineering problem-solving rather than product completion alone.

Fairness, Equity, Bias Mitigation, and Student Wellbeing: Engineering programs need to ensure equitable access to AI tools used in coursework and assessment while monitoring AI-supported systems for bias and unintended harm [19], [28], [61]. Ethical AI integration should prioritize fairness in assessment practices and student psychological safety, both of which remain underrepresented in existing classroom guidance.

Continuous Evaluation and Ethical Review: Ethical AI integration should be supported through periodic ethical audits and continuous evaluation of AI-supported teaching, assessment, and data governance practices. Ongoing review mechanisms help identify unintended consequences such as bias, over-reliance, or inequitable access while supporting dynamic validity as ethical guidance evolves alongside technological and pedagogical change.

Finally, ethical AI integration in engineering education requires coordinated action across instructional design, faculty development, institutional governance, and accreditation expectations. Institutions should align classroom guidance, professional development initiatives, and policy frameworks to support consistent and responsible AI use across teaching, learning, and assessment. Such coordination can address the fragmented ethical guidance identified in this review while reinforcing shared accountability among faculty, students, and institutional leadership. Together, these recommendations translate empirical findings from engineering education research into actionable guidance that supports sustainable, human-centered AI integration in both classroom practice and institutional policy.

IMPLICATIONS

Although Table 1 presents representative evidence of ethical principles across stakeholder groups, a cross-stakeholder synthesis reveals some gaps. Although students are frequently mentioned, they are rarely positioned as active ethical agents with clearly articulated roles in AI governance, decision-making, or accountability structures. Furthermore, recommendations from stakeholders tend to remain high-level and lack operational specificity, including mechanisms for implementation, enforcement strategies, and evaluative benchmarks. This imbalance suggests the need for integrated, multi-stakeholder ethical models that move beyond principle identification toward actionable, participatory governance frameworks.

The findings of this systematic review reveal that ethical engagement with AI in engineering education remains fragmented and underdeveloped. Although some institutional and classroom-level guidelines exist, many recommendations concerning students appear reactive, focusing on limiting misuse rather than fostering reciprocal accountability or shared ethical literacy between faculty and students. This imbalance reflects a broader challenge within AI-augmented education: the tendency to treat ethical governance as an afterthought to innovation rather than as a foundational design principle. Taken together, these findings suggest a necessary shift from rule-based ethical compliance toward participatory governance models in engineering education, where ethical responsibility is collaboratively enacted by students, faculty, and institutions.

In this context, as students and faculty continue to engage with AI ethically and productively, it is important to position AI tools appropriately within educational contexts. AI should be treated as a technological support tool, used only when it meaningfully advances learning objectives and strengthens assessment quality [62].

Taken together, these findings suggest that engineering ethics education should more explicitly incorporate AI-related data literacy, participatory governance, and reflective evaluation of AI use. Also, institutional frameworks should not only guide how AI is used but also continually evaluate the rationale and effect of use. Dynamic validity, understood as continuous monitoring and updating of AI-related ethical and pedagogical practices, should be embedded as a standard educational norm.

CONCLUSION

The ethical integration of AI in engineering education is at a pivotal stage. This systematic review demonstrates that ethical AI guidance remains fragmented and predominantly compliance-oriented. While integrity, accountability, and transparency were frequently emphasized, ethical dimensions central to professional engineering responsibility, including autonomy, beneficence, and student wellbeing, remained comparatively underrepresented. These gaps highlight the need to move beyond reactive misuse prevention toward proactive ethical design embedded within instructional practice and institutional policy.

Ethical AI integration in engineering education should be grounded in shared human and AI accountability. Faculty and students should engage in transparent relationships with AI, where ethical reflection accompanies teaching, learning, and assessment. Institutions that adopt this reciprocal approach can preserve academic integrity while cultivating engineers capable of designing fair, explainable, and human-centered AI systems.

Engineering education occupies a uniquely consequential position because it prepares professionals whose decisions shape the reliability of infrastructure, public safety, environmental sustainability, and societal trust in technological systems. As AI becomes increasingly embedded within engineering practice, the ethical norms developed in classrooms may influence how intelligent systems are designed, deployed, and governed in real-world contexts. Ethical governance should remain inseparable from pedagogical innovation, as engineering education evolves alongside rapidly advancing artificial intelligence technologies [36]. The future of engineering education will not be defined by how quickly AI is adopted, but by whether ethical responsibility, human oversight, and societal accountability evolve alongside technological capability.

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Artificial Intelligence was used as a grammar editing tool.

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APPENDIX A1: Article Metadata

SN	Citation	Source	Study Degree	Engineering Discipline	Methodology
1	Abril et al. (2024)	Conference	Undergraduate	Civil engineering	Qualitative
2	Adeika et al. (2024)	Conference	Undergraduate	Civil engineering, Computer engineering, Computer science	Non-empirical
3	Ai et al. (2024)	Conference	Undergraduate	Computer engineering/Computer science	Multi-Method
4	Ambikairajah et al. (2024)	Conference	Graduate	Electrical engineering	Multi-Method
5	Anderson et al. (2024)	Conference	Undergraduate		Non-empirical
6	Aucoin et al. (2024)	Conference	Undergraduate	Engineering (broadly)	Multi-Method
7	Ayre et al. (2023)	Conference	Other	Engineering (broadly)	Multi-Method
8	Baalsrud and Jeong (2024)		Graduate		Qualitative
9	Babo et al. (2024)	Conference	Undergraduate Graduate	Engineering (broadly), Other	Quantitative
10	Banavar et al. (2023)	Conference	Undergraduate Graduate	Computer engineering, Computer science	Multi-Method
11	Bego (2023)	Conference	Undergraduate	Engineering (broadly)	Quantitative
12	Bernabei et al. (2023)	Journal	Graduate	Mechanical engineering	Mixed-Method
13	Bhardwaj & Bedi (2024)	Journal	Undergraduate	Engineering (broadly)	Non-empirical
14	Blake et al. (2021)	Conference	Undergraduate	Civil engineering, Electrical engineering, Mechanical engineering	Quantitative
15	Borges et al. (2024)	Journal	Undergraduate Graduate	Engineering (broadly), Chemical engineering, Computer engineering, Computer science, Electrical engineering, Mechanical engineering, Other	Quantitative
16	Bravo & Cruz (2024)	Journal	Undergraduate	Electrical engineering, Other	Qualitative
17	Caccavale et al. (2024)	Journal	Graduate		Mixed-Method
18	Caccavale et al. (2025)	Journal	Undergraduate Graduate	Chemical engineering	Quantitative
19	Camacho-Zuñiga et al. (2025)	Conference	Undergraduate	Engineering (broadly)	Multi-Method
20	Chaikovska et al. (2024)	Journal	Graduate	Electrical engineering	Quantitative
21	Cubillos et al. (2025)	Journal	Undergraduate Graduate	Computer engineering/Computer science	Quantitative
22	Darvishi et al. (2024)	Journal	Undergraduate	Engineering (broadly), Other	Quantitative
23	de León López (2024)	Conference	Undergraduate	Biomedical engineering, Civil engineering, Computer engineering/Computer science, Mechanical engineering, Industrial engineering, Other STEM focus	Qualitative
24	Ding et al. (2024)	Conference	Undergraduate	Engineering (broadly)	Mixed-Method
25	Dirin & Laine (2024)	Journal	Undergraduate	Other STEM focus	Mixed-Method
26	Divasón et al. (2023)	Journal	Undergraduate	Engineering (broadly),Computer engineering/Computer science	Quantitative
27	Ely & Rad (2024)	Conference	Undergraduate	Engineering (broadly)	Quantitative
28	Fong et al. (2022)	Conference	Undergraduate Graduate	Civil engineering, Computer engineering/Computer science, Mechanical engineering. Other	Quantitative
29	Gambhir et al. (2024)		Undergraduate	Engineering (broadly)	Qualitative
30	Giray & Aquino (2024)	Journal	Undergraduate	Engineering (broadly)	Qualitative

SN	Citation	Source	Study Degree	Engineering Discipline	Methodology
31	Gouia-Zarrad & Gunn (2024)	Journal	Undergraduate	Engineering (broadly)	Mixed-Method
32	Groothuijsen et al. (2024)	Journal	Graduate	Mechanical engineering	Multi-Method
33	Günzel et al. (2022)	Conference	Undergraduate	Engineering (broadly)	Mixed-Method
34	Haderer & Ciolacu (2022)	Journal	Undergraduate	Other	Non-empirical
35	Hammer et al. (2024)	Conference	Undergraduate	Computer engineering/Computer science	Mixed-Method
36	Hashimoto (2024)	Conference	Undergraduate/Graduate	Biomedical engineering	Quantitative
37	Hodgkinson & Whittenburg (2024)	Conference	Undergraduate	Aerospace engineering	Quantitative
38	Honig et al. (2025)	Journal	Undergraduate	Engineering (broadly), Chemical engineering	Mixed-Method
39	Huesca et al. (2024)	Journal	Undergraduate	Engineering (broadly), basic programming courses	Quantitative
40	Inoferio et al. (2024)	Journal	Undergraduate	Different math-related programs (i.e., engineering, statistics/mathematics, computer science, education (math major))	Qualitative
41	Insuasti et al. (2023)	Journal	Undergraduate	Engineering (broadly), System Engineering	Mixed-Method
42	Jamieson et al. (2023)	Conference	Undergraduate	Computer engineering/Computer science (cybersecurity program)	Non-empirical
43	Jiang & Dong (2020)	Journal	Undergraduate/graduate	Education	Quantitative
44	Jiao et al. (2022)	Journal	Graduate	Ocean engineering: Smart Marine Metastructures	Quantitative
45	Kabashkin et al. (2023)	Journal	Undergraduate	Aviation engineering	Qualitative
46	Keith et al. (2024)	Conference		Engineering and Computer science	Non-empirical
47	Keith et al. (2025)	Journal	Undergraduate	Chemical engineering	Multi-Method
48	Kieser et al. (2023)	Journal	Undergraduate	Engineering (broadly)	Quantitative
49	Kim et al. (2024)	Journal	Undergraduate	Engineering (broadly), Electrical engineering and Mechanical engineering	Qualitative
50	Kofahi & Husain (2025)	Journal	Undergraduate	Information Technology (Operating systems course)	Quantitative
51	Kong et al. (2023)	Journal	Undergraduate	Chemical engineering	Non-empirical
52	Kosar et al. (2024)	Journal	Undergraduate	Computer engineering/Computer science, Electrical engineering	Quantitative
53	Kumar et al. (2024)	Conference	Undergraduate	Computer science	Mixed-Method
54	Lai et al. (2021)	Conference	Undergraduate	Civil Aviation Vocational and Technical	Quantitative
55	Lauren & Watta (2023)	Conference	Undergraduate	Computer engineering/Computer science; Engineering Education	Qualitative
56	Li et al. (2024)	Journal	Undergraduate	Engineering science	Quantitative
57	Lyons et al. (2024)	Conference	Undergraduate	Computer engineering/Computer science	Quantitative
58	Mahande et al. (2025)	Journal	Undergraduate	Science and Engineering (broadly)	Quantitative
59	Mehrabi et al. (2024)	Journal	Undergraduate Graduate	Engineering (broadly)	Quantitative
60	Mekić et al. (2024)	Journal	Undergraduate	Engineering (broadly), Computer engineering/Computer science	Non-empirical
61	Nikolic et al. (2024)	Journal		Engineering (broadly)	Descriptive-comparative
62	Onal & Kulavuz-Onal (2024)	Journal		Industrial engineering, Other	Qualitative
63	Ortega et al. (2024)	Conference	Undergraduate	Aerospace engineering, Mechanical engineering	Quantitative

SN	Citation	Source	Study Degree	Engineering Discipline	Methodology
64	Ouyang et al. (2023)	Journal	Graduate	Ocean Engineering (Smart Marine Structure)	Mixed-Method
65	Pesovski et al. (2024)	Journal	Undergraduate	Software engineering	Quantitative
66	Peuker (2024)	Conference	Undergraduate	Mechanical engineering	Mixed-Method
67	Pham et al. (2023)	Journal	Undergraduate	Engineering (broadly)	Qualitative
68	Pillai et al. (2024)	Journal	Graduate Undergraduate	Higher Education	Mixed-Method
69	Popovici (2024)	Journal	Undergraduate	Computer engineering and science	Multi-Method
70	Prohofsky & Lande (2024)	Conference	Other		Qualitative
71	Pyae et al. (2023)	Journal	Undergraduate	Engineering (broadly), Computer engineering/Computer science	Mixed-Method
72	Qureshi (2023)	Conference	Undergraduate	Computer engineering/Computer science, Other STEM focus	Quantitative
73	Remoto (2024)	Journal	Undergraduate		Qualitative
74	Rincón-Flores et al. (2019)	Conference	Undergraduate	Engineering (broadly)	Mixed-Method
75	Rincón-Flores et al. (2020)	Conference	Undergraduate	Other STEM focus	Mixed-Method
76	Sajadi et al. (2023)	Conference	Undergraduate	Engineering (broadly)	Qualitative
77	Sajja et al. (2024a)	Journal	Undergraduate Graduate	Computer engineering Computer science	Quantitative
78	Sajja et al. (2024b)	Journal	Undergraduate Graduate	Engineering (broadly)	Non-empirical
79	Shabunina et al. (2023)	Conference	Undergraduate	Electrical engineering	Qualitative
80	Sinkus & Ozola (2024)	Journal	Undergraduate	Engineering (broadly), Computer engineering/Computer science	Quantitative
81	Stairs et al. (2021)	Conference	Undergraduate	Engineering (broadly)	Multi-Method
82	Subirats et al. (2023)	Journal	Undergraduate	Chemical engineering	Quantitative
83	Talha Junaid et al. (2024)	Journal	Undergraduate	Civil engineering	Non-empirical
84	Tomić (2022)	Journal	Undergraduate	Engineering (broadly)	Quantitative
85	Tossell et al. (2024)	Journal	Undergraduate	Other STEM focus	Mixed-Method
86	Tsai et al. (2023)	Journal	Undergraduate	Chemical engineering	Non-empirical
87	Ubowska & Królikowski (2023)	Conference	Graduate	Engineering (broadly)	Quantitative
88	Uddin et al. (2024)	Journal	Undergraduate	Civil engineering	Mixed-Method
89	Usher & Barak (2024)	Journal	Graduate	Other	Mixed-Method
90	Wang et al. (2023)	Journal	Undergraduate	Computer engineering and science	Quantitative
91	Waseem et al. (2024)	Conference	Undergraduate	Other STEM focus	Multi-Method
92	Whitman et al. (2024)	Conference	Undergraduate	Other STEM focus	Mixed-Method
93	Wu et al. (2024)	Journal	Undergraduate	Engineering (broadly), Computer engineering/Computer science	Quantitative
94	Xu et al. (2024)	Conference	Undergraduate	Engineering (broadly)	Qualitative
95	Xu et al. (2025)	Journal	Undergraduate	Other STEM focus	Quantitative
96	Yabaku & Ouhbi (2024)	Conference	Undergraduate Graduate	Computer engineering/Computer science	Multi-Method
97	Žáková et al. (2025)	Journal	Undergraduate Graduate	Computer engineering/Computer science, Industrial engineering	Mixed-Method
98	Zhang & Xu (2025)	Book chapter	Undergraduate	Other STEM focus	Quantitative
99	Zhang (2023)	Journal	Undergraduate	Other	Quantitative