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Artificial Intelligence in Engineering Technology: Opportunities, Challenges, and Future Outlook

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Abstract

This systematic study examines how artificial intelligence (AI), particularly generative AI and large language models, is reshaping Engineering Technology (ET) across education, research, laboratory environments, and professional practice. It is motivated by a fragmented literature in which studies of classroom AI adoption, laboratory instrumentation, and industrial deployment rarely reference one another despite drawing on the same underlying technologies. Guided by three research questions, how AI is currently applied across the ET ecosystem, what methodological limitations and contextual biases characterize the existing evidence base, and what structural adaptations are emerging in response, this synthesis draws on a broad corpus of peer-reviewed and conference literature spanning instructional practice, benchmarking and methodological research, intelligent laboratories, and industrial deployment. The analysis finds that AI occupies at least three recurring functional roles, instructional aid, evaluated subject, and embedded decision-support infrastructure, across classrooms, laboratories, and industrial systems. At the same time, the underlying evidence remains predominantly perception-based, short-term, single-site, and unevenly distributed across ET-specific domains such as instrumentation, controls, and manufacturing, limiting confidence in claims about durable learning gains, workforce readiness, or organizational transferability. Despite these limitations, clear structural adaptation is already underway: assessment redesign toward verification and open-ended reasoning, curricular modernization around AI and data literacy, laboratories becoming more connected and data-rich, and professional systems shifting toward predictive, agentic, and human-centered deployment. AI in ET is thus best understood as a coordinated, ecosystem-level transformation rather than an isolated technology adoption, underscoring the need for longitudinal, multi-institutional research connecting educational outcomes to workforce and industrial evidence.

1. Introduction

The rapid diffusion of generative artificial intelligence (GenAI) and large language models (LLMs) since ChatGPT's public release has reshaped Engineering Technology (ET) across education and professional practice, supporting circuit analysis, control-system design, programming, and increasingly autonomous manufacturing and industrial decision-making (Narayan et al. 2024; Ekin 2026). Their use spans classrooms, laboratories, and industrial environments, yet the literature remains fragmented across engineering education, laboratory systems, and industrial automation.

This fragmentation is particularly evident in education. Academic integrity concerns predate GenAI (Narayan et al. 2024), but tools such as ChatGPT intensified these concerns by enabling coherent, technically plausible solutions to assignments with minimal effort (Narayan et al. 2024; Puthumanaillam et al. 2025). Deliberate GenAI integration can nonetheless improve learning outcomes and shift instruction toward critical thinking (Narayan et al. 2024; Honig et al. 2025; Ekin 2026; C. Liu et al. 2026), and engineering education research has expanded accordingly toward AI-assisted learning, evaluation of AI-generated solutions, and responsible student-use frameworks (W. Lu et al. 2024; Talkington et al. 2025; R. Li et al. 2025; C. Liu et al. 2026).

Other documented use cases extend well beyond ChatGPT: one study compared ChatGPT-4, Claude 3.5, and Perplexity AI for evaluating undergraduate engineering assignments (Omwando et al. 2025); another incorporated ChatGPT, Gemini, Claude, and Copilot into senior design activities (Bilgin 2026); and a broader evaluation compared ChatGPT, Gemini, and Copilot across hundreds of questions in mechanical engineering (Akolekar et al. 2025), together indicating heterogeneous LLM adoption. This diversification extends to ET, where Gemini and Copilot support tutoring, programming assistance, and AI-supported design (El-Shahat et al. 2026), aligning with ET's applied, laboratory-centered nature and introducing new requirements for AI literacy and human oversight.

In parallel, ET research increasingly treats AI as both an empirical object and a methodological tool: benchmarking LLM performance against student cohorts (Puthumanaillam et al. 2025), reviewing LLM applications across engineering disciplines (Ma et al. 2025; Nguyen et al. 2025; Gao et al. 2024), evaluating prompt-engineering strategies to reduce hallucination (Freeman et al. 2026), and examining LLMs and control theory (Nosrati et al. 2026). Complementary laboratory research integrates AI with digital twins, cyber-physical systems, and remote laboratories for monitoring and engineering decision-making (Ruppert et al. 2022; Ali et al. 2024; Xia, Dittler, et al. 2024; Vidyalakshmi et al. 2025; Subahi 2024; Huang et al. 2021).

Beyond education and laboratories, AI has moved decisively into professional and industrial practice. Multi-agent LLM systems and industrial copilots have been proposed for adaptive manufacturing and industrial coordination (Shyalika et al. 2025; D. Wen et al. 2025; Wulf et al. 2025), and other studies apply LLMs to fault diagnosis and predictive maintenance, often combining them with retrieval-augmented generation or knowledge graphs to improve reliability (S. Wen et al. 2025; Di Maggio 2025; H. Wang et al. 2024; Zhang et al. 2025; Lin et al. 2025; Boonmee et al. 2024; Chen et al. 2025; P. Wang et al. 2024). These developments reflect the broader transition from Industry 4.0 toward Industry 5.0, encompassing more human-centered, resilient production (Tabim et al. 2024; Rahman et al. 2025; Passalacqua et al. 2025; Tóth et al. 2023; Fazlollahtabar 2025; Barua et al. 2025), while embodied AI and LLM-driven robotics extend this trajectory into autonomous task planning, highlighting persistent limitations in physical and spatial grounding (T. Wang et al. 2025; Xia, Jazdi, et al. 2025; Lim et al. 2024; H. Fan et al. 2025; Xu et al. 2025).

Taken together, this literature suggests that AI adoption across ET is broad and rapidly evolving, yet remains uneven and incompletely understood, with few studies positioning educational, laboratory, and industrial findings within a common ET framework. The growing use of non-ChatGPT systems also raises a methodological concern, since findings based on a single LLM may not generalize to other models. Addressing these issues requires examining not only where AI is used, but the evidence supporting its use and the structural changes it produces across the ET ecosystem.

To address this fragmentation, the present study is organized around three research questions:

- **RQ1**: How is artificial intelligence currently being applied across ET education, research, laboratories, and professional practice?
- **RQ2**: What methodological limitations and contextual biases characterize current research on artificial intelligence in ET?
- **RQ3**: What structural adaptations are emerging across the ET ecosystem as artificial intelligence becomes embedded in education, research, laboratory environments, and professional practice?

Rather than treating educational and industrial AI applications as separate literatures, this study examines them jointly. Figure 1 categorizes how AI is applied across the ET ecosystem, education, research, laboratories and infrastructure, and professional practice, and Table 1 illustrates each of these categories with named examples of AI best practices from U.S. ET departments. Section 2 reviews related work; Section 3 describes the literature search methodology; Section 4 addresses RQ1 through RQ3; and Section 5 concludes with limitations and future work.

2. Related Work

Prior AI research in ET spans three connected streams: engineering education (learning support, assessment, AI literacy, curriculum design); ET curriculum modernization (laboratories, smart manufacturing, robotics, digital twins); and applied AI in professional systems (predictive maintenance, human–machine collaboration, autonomous manufacturing, Industry 5.0). These streams increasingly converge as ET prepares students for environments where AI is embedded in coursework, equipment, and organizational decision-making. Reviews of AI and LLMs in education identify automated feedback, content generation, and personalized learning while raising ethical and pedagogical concerns (Filippi et al. 2024; Giannakos et al. 2024). Bibliometric reviews show rapid growth in instructional support and learning analytics without distinguishing ET's applied character (N. Liu 2025; Martín Núñez et al. 2020), whereas ET-focused studies directly address curriculum transformation involving generative AI, Industry 4.0, and smart manufacturing (Sarp et al. 2024).

Additional work examines generative AI's effects on student performance and critical thinking (Narayan et al. 2024; W. Lu et al. 2024), and its growing use for writing, coding, and feedback, alongside concerns over assessment integrity (Nikolic et al. 2023; Qadir 2023; Bernabei et al. 2023; Ovi et al. 2025; Rasnayaka et al. 2024). Generative AI can complete conventional assessments, questioning whether homework remains a valid measure of understanding (Nikolic et al. 2023), while other work examines AI-supported grading (Pinto et al. 2023; Jukiewicz 2024); in re-

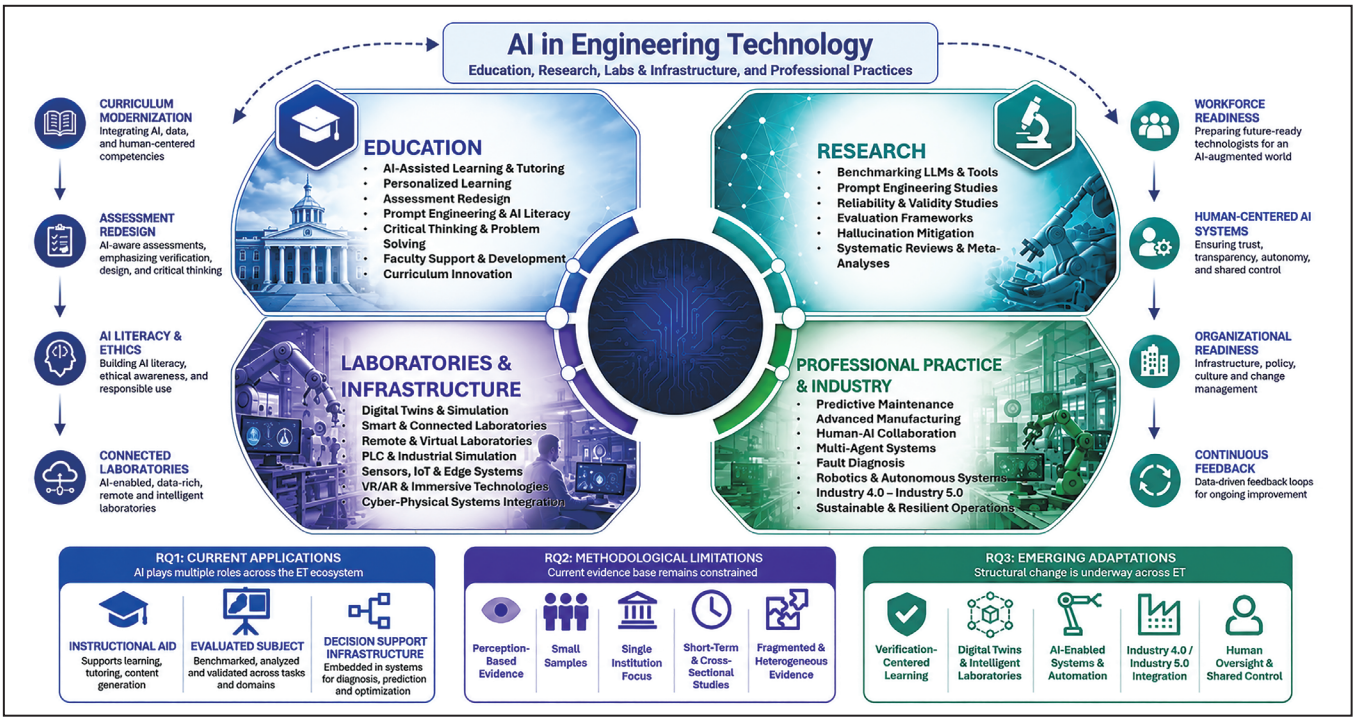


Figure 1. Comprehensive overview of artificial intelligence adoption across the ET ecosystem and its influence on educational, research, laboratory, and professional domains.

Table 1. Examples of AI best practices from U.S. ET Departments, organized by the four ecosystem categories in Figure 1

Category	Institution / Program	Example
Education	Miami University, Robotics Engineering Technology Program	Redesigned assignments so that interrogating and correcting AI-generated solutions, rather than merely producing them, became the graded task; closed-book exams verified comprehension could not be outsourced to GenAI (Narayan et al. 2024).
	Old Dominion University, Frank Batten College of Engineering and Technology	Developed a dedicated data science curriculum for an undergraduate ET program to build AI- and data-literacy competencies alongside traditional ET coursework (Sarp et al. 2024).
Research	Purdue University Northwest, College of Technology	Benchmarked seven machine-learning and AI models, including a convolutional neural network, on their ability to detect steganographically hidden messages in digital images, quantifying detection-accuracy trade-offs across model types (Stefanek et al. 2024).
	Texas A&M University, Department of Engineering Technology and Industrial Distribution	Conducted a case study integrating generative AI into the design of a graduate-level capstone course, documenting how prompt-based tools reshaped project scoping and deliverable quality (W. Lu et al. 2024).
Laboratories & Infrastructure	Kennesaw State University, Department of Mechanical Engineering	Deployed a retrieval-augmented chatbot embedded directly in a Dynamics and Control laboratory, delivering grounded, lab-specific troubleshooting rather than generic responses (Kanala et al. 2026).
	Purdue University, Purdue Polytechnic Institute	Implemented an experiential Industrial IoT laboratory for smart manufacturing through coursework paired with university–industry partnerships (Kim et al. 2023).
Professional Practice / Industry	Trane Technologies (Davidson, NC)	Compared five prompt-engineering strategies for reducing LLM hallucination in industrial engineering-design, ERP, and IoT telemetry workflows in production deployment (Freeman et al. 2026).
	Miami Dade College (with Houston Community College and Maricopa County Community College District), National Applied AI Consortium	Established an NSF ATE-funded, industry-partnered consortium to build technician-level applied-AI courses, certificates, and degree pathways across community and technical colleges nationwide (National Science Foundation 2024).

sponse, researchers emphasize open-ended problems and human oversight (Narayan et al. 2024). Laboratory modernization bridges AI education and ET practice through chatbots, virtual laboratories, and digital twins (Kanala et al. 2026; Gomez et al. 2026), while PLC simulation and industrial robotics transfer industrial technologies into classroom settings (Urrea 2026).

Industry 4.0-driven STEM-lab modernization and Laboratory Information Management System (LIMS) 4.0 research shows laboratories redesigned for flexibility and remote access (Aubel et al. 2024; Yuen et al. 2025). Parallel research examines AI in smart manufacturing and cyber–physical systems (Leitão et al. 2020; Sufian et al. 2021; Barua et al. 2025), and advanced manufacturing research shows ET-relevant AI extending to quality optimization and predictive maintenance (Arinez et al. 2020; Serradilla et al. 2022). Manufacturing AI agents support scheduling and troubleshooting (Witkowski et al. 2026), while digital twins demonstrate coordination between physical and virtual production (Nicoletti et al. 2025; Bhandari et al. 2026).

Predictive maintenance and fault diagnosis are major applied AI themes: Maintenance 4.0/5.0 research shows AI models and operator feedback supporting equipment reliability while retaining personnel in decision-making (Lucantoni et al. 2026), and related work addresses condition monitoring and competency prioritization (Liao et al. 2026). Industry 5.0 and human-centered AI extend the focus to human-AI teams and agentic manufacturing, emphasizing worker trust and shared control (Coronado 2026).

Lights-out factory research highlights full-automation limits, including cybersecurity risks and workforce reskilling (Sivarao Subramonian 2026), underscoring that future ET technologists must supervise and validate AI-enabled systems. Workforce studies identify growing needs for data analytics and human–machine collaboration (Ergunova et al. 2026; Souza et al. 2023), and adoption depends on organizational readiness and strategic alignment (Sabău-Popa et al. 2026; Silva et al. 2025). JET scholarship on Industrial IoT and manufacturing knowledge provides ET-specific evidence that frameworks increasingly incorporate AI and digital twins (Kim et al. 2023; Irwin et al. 2025), framing AI in ET as a transformation rather than merely a classroom technology.

3. Methodology of Literature Search

This study employs a structured literature review to examine how artificial intelligence is integrated into ET across educational and applied technical contexts, supporting a systematic, transparent, and reproducible process for identifying, screening, coding, and analyzing literature. Because the review treats AI as broader than generative AI or ChatGPT, the search included multiple approaches: machine learning for prediction, classification, and fault diagnosis; deep learning for computer vision, signal processing, and robotics perception; reinforcement learning for control, scheduling, and adaptive decision-making; and generative AI or large language models for tutoring, feedback, and documentation. The search accordingly covered AI-supported instruction, ET curriculum modernization, laboratory transformation, smart manufacturing, digital twins, predictive maintenance, Industry 4.0/5.0, human-machine collaboration, and workforce competencies. Search terms included combinations of the following:

> ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR "generative AI" OR "large language model" OR "ChatGPT")
> AND ("engineering technology" OR "engineering education" OR "technical education" OR "vocational education" OR "laboratory education")
> AND ("curriculum" OR "assessment" OR "learning" OR "smart manufacturing" OR "Industry 4.0" OR "Industry 5.0" OR "digital twin" OR "predictive maintenance" OR "human-machine collaboration" OR "workforce competencies")

Searches were conducted across major citation databases, targeted journals, conference proceedings, and supplementary academic platforms, including Scopus, Web of Science, ASEE, Journal of Engineering Technology (JET), and The American Journal of Engineering and Technology (AJET), with additional targeted searches for smart manufacturing, digital twins, laboratory modernization, and Industry 4.0/5.0, which may not consistently appear in education-focused databases. This multisource approach reduced database-specific bias. The combined searches initially identified approximately 320–350 records. Title and abstract screening removed studies outside scope, weakly connected to ET, or outdated relative to rapid generative AI development; duplicates were also removed. Full-text articles were then assessed for relevance to one or more review themes spanning AI-supported instruction and assessment, ET curriculum modernization, AI-enabled laboratories, smart manufacturing and industrial AI, digital twins, predictive maintenance, Industry 4.0/5.0, human-centered automation, and workforce competencies.

Studies were included if they: (1) examined AI, machine learning, generative AI, or LLMs in engineering or ET education; (2) addressed teaching,

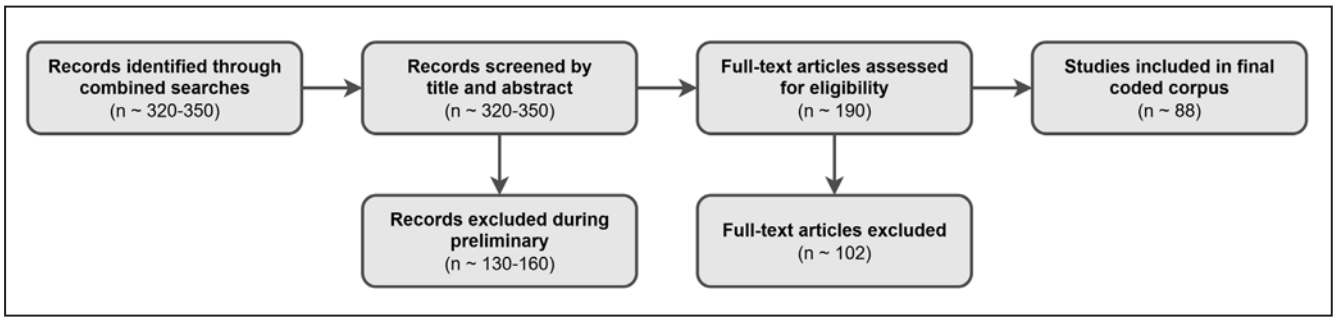


Figure 2. Literature screening and selection process.

curriculum design, assessment, or laboratory instruction; (3) examined applied AI systems relevant to ET practice; or (4) addressed workforce competencies or Industry 4.0/5.0 transformation relevant to ET programs. Studies were excluded if they lacked a meaningful connection to ET or applied technical systems, duplicated included evidence, or addressed AI without relevance to education, workforce preparation, or applied implementation. Recent 2025–2026 studies were retained when directly relevant despite low citation counts, reflecting emerging post-LLM developments, while older studies were retained for foundational context on Industry 4.0 and digital transformation. Figure 2 illustrates the screening workflow: after title/abstract screening, duplicate removal, and full-text eligibility review, 88 papers were retained in the final coded corpus.

Following screening, selected papers were coded using a structured classification aligned with the research questions, recording title, year, study type, ET category, and primary theme. Study types included empirical, review, conceptual, and application or case-based studies; categories included engineering education, manufacturing AI and agents, digital twins and cyber–physical systems, maintenance and fault diagnosis, manufacturing systems and Industry 4.0, Industry 5.0 and human-centered systems, workforce and competency development, laboratory systems, responsible and reliable industrial AI, and general engineering AI.

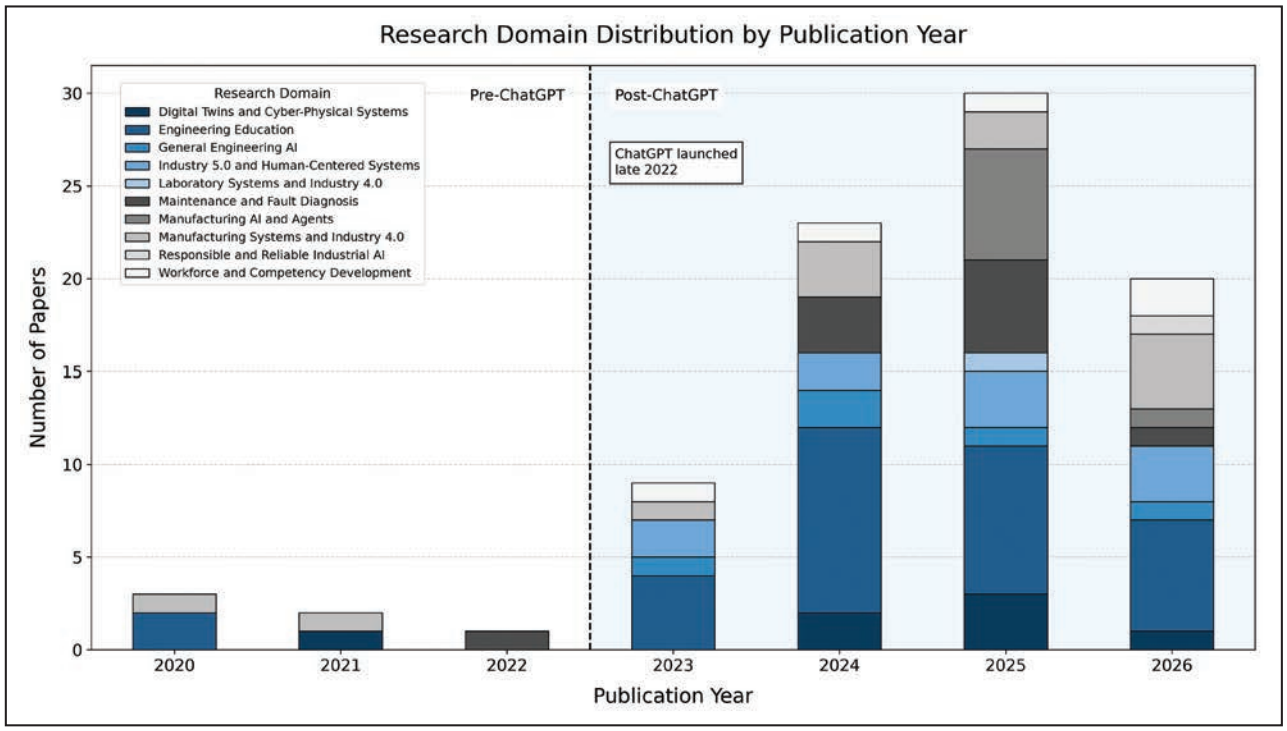


Figure 3. Number of published papers by category since 2020. A marked increase in the volume of publications is evident following the release of ChatGPT-3 in late 2022, reflecting the rapid growth of research on generative AI across the surveyed categories.

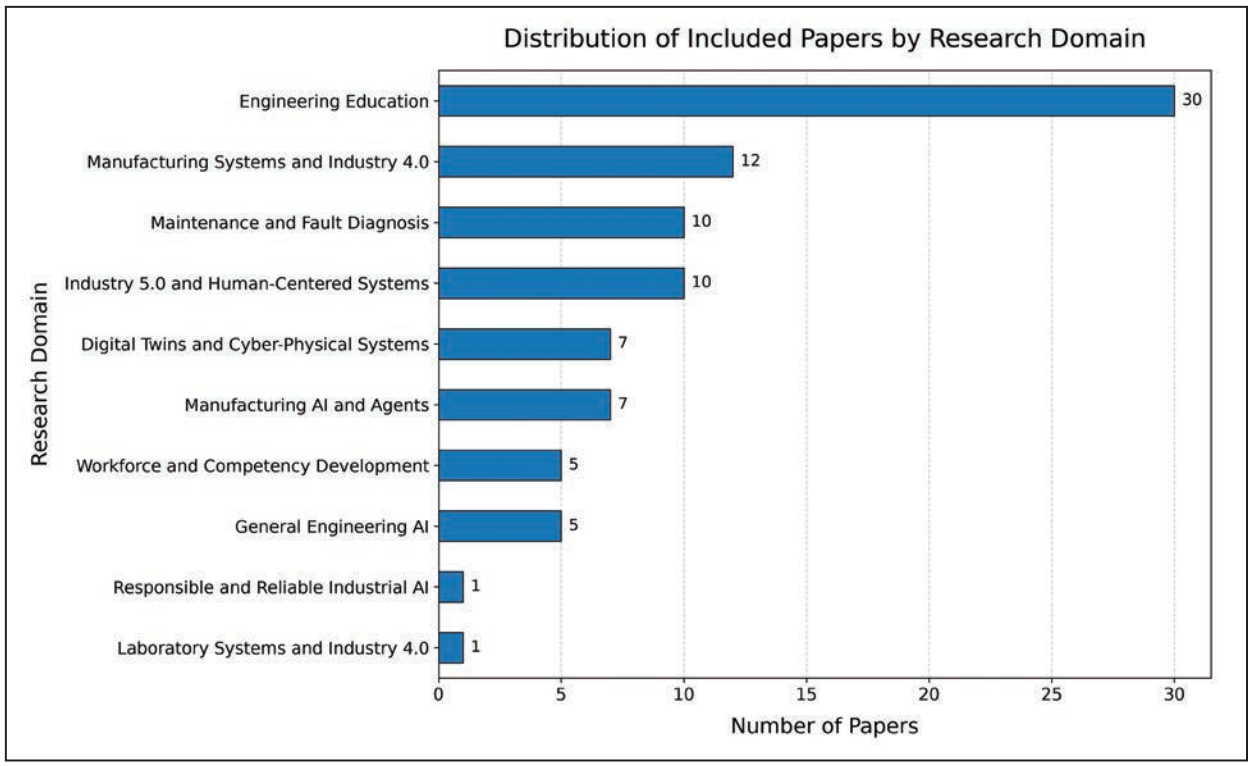


Figure 4. Distribution of the reviewed academic articles by ET category, illustrating the areas in which artificial intelligence has been investigated and implemented across the ET ecosystem.

The final coded corpus was summarized visually in Figures 3–5 to characterize publication trends, topical distribution, and methodological composition.

4. Research Questions and Analysis

4.1 RQ1: How is artificial intelligence currently being applied across ET education, research, laboratories, and professional practice?

Across the reviewed literature, AI assumes at least three recurring functional roles in ET, often within the same study: an instructional aid that scaffolds student learning, an evaluated system benchmarked against human performance, and an operational infrastructure component embedded in shop-floor decision-making. Understanding adoption therefore requires focusing less on which tool is used than on its role in context, since the pedagogical, methodological, and organizational implications differ substantially.

In the instructional role, the literature shows a shift from treating generative AI as a plagiarism risk toward viewing it as a curricular design constraint. Rather than prohibiting AI, instructors in circuits, robotics, power systems, and simulation courses have redesigned assignments to make capable models part of the learning task: students interrogate AI-generated solutions for errors and demonstrate understanding under conditions such as closed-book exams where external models cannot substitute for comprehension (Narayan et al. 2024; Talkington et al. 2025; C. Liu et al. 2026). A parallel use positions AI as an instructional collaborator for faculty, assisting with rubrics and course structure while remaining subject to human judgment (W. Lu et al. 2024). Engagement depends not only on access but also on perceived reliability and institutional support (Honig et al. 2025; R. Li et al. 2025), and AI's instructional role is being actively engineered by educators rather than passively absorbed by students, though its durability remains uncertain as newer model versions close the gap with earlier ones (Talkington et al. 2025).

The evaluative role is most visible when researchers treat the model itself as an experimental subject. Benchmarking an LLM across an entire semester-long course shifts the question from whether AI can solve engineering problems to how it performs against a human cohort, revealing a competence ceiling in structured tasks and persistent weakness in open-ended design (Talkington et al. 2025), echoed by literature syntheses consolidating fragmenting evidence on LLM applications across engineering and manufacturing (Ma et al. 2025; Nguyen et al. 2025; Gao et al. 2024). Related work treats LLM reliability as an engineering problem requiring repeatable procedures, with prompt-engineering strategies tested to reduce output variance and hallucination (Freeman

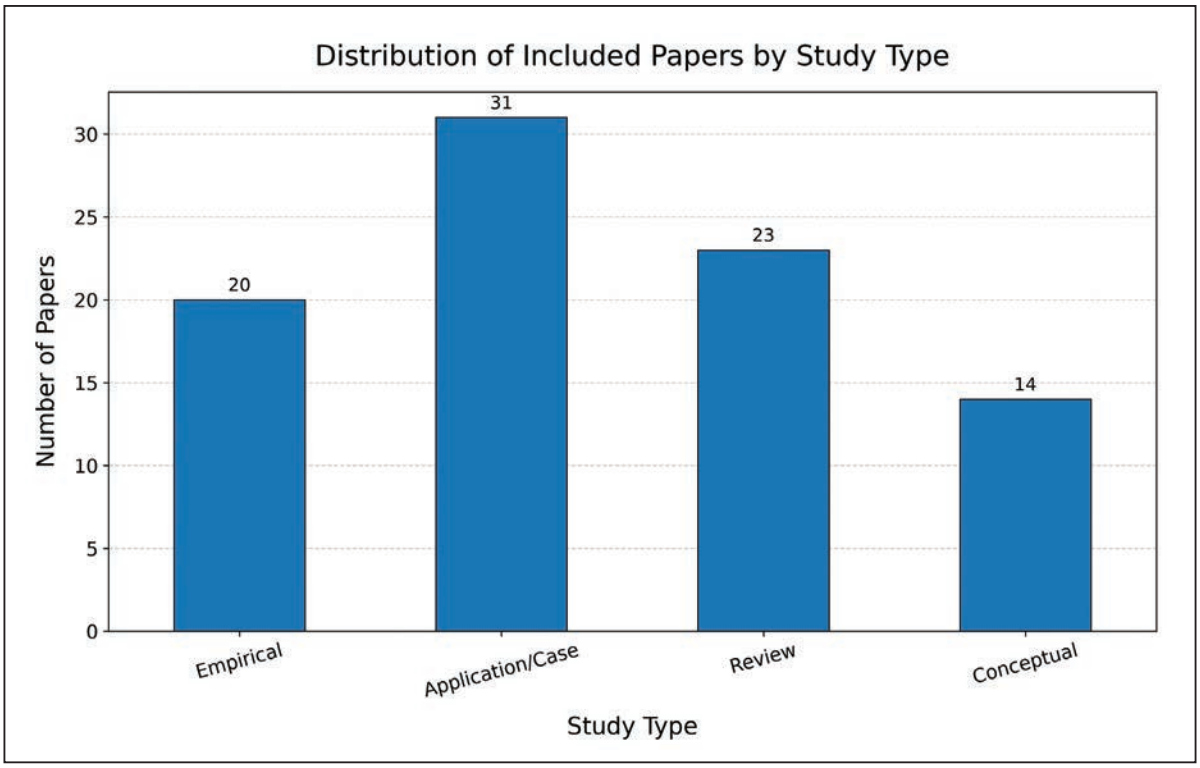


Figure 5. Distribution of the reviewed literature according to study type, providing an overview of the methodological composition of the selected publications.

et al. 2026), showing researchers constructing benchmarks and reliability procedures to hold AI systems to engineering-grade evidence standards.

Laboratory contexts illustrate a third role in which AI functions less as tutor or subject and more as embedded infrastructure mediating between physical equipment and learners. AI and digital twins help bridge abstract instruction with legacy equipment and brownfield retrofitting (Ruppert et al. 2022), and foundation models automate digital twin parametrization, treating the twin as a semi-autonomous simulation collaborator (Ali et al. 2024; Xia, Dittler, et al. 2024). Spanning machining, additive manufacturing, human-robot interaction, and smart agriculture, this work suggests laboratories increasingly prototype AI decision-support infrastructure at scales prohibitive on active production lines (Vidyalakshmi et al. 2025; Subahi 2024; Huang et al. 2021).

That infrastructural role is fully operationalized in professional practice, where LLMs are embedded in multi-agent systems combining natural-language reasoning with structured retrieval and sensor data to support rather than replace human decision-makers (Shyalika et al. 2025; D. Wen et al. 2025; Wulf et al. 2025). This is especially pronounced in fault diagnosis and predictive maintenance, where studies ground language models in causal knowledge graphs and ontologies because unconstrained LLM reasoning is insufficiently reliable for high-consequence decisions (S. Wen et al. 2025; Di Maggio 2025; H. Wang et al. 2024; Zhang et al. 2025; Lin et al. 2025; Boonmee et al. 2024; Chen et al. 2025; P. Wang et al. 2024). This finding, that fluency does not ensure diagnostic trustworthiness, extends to LLM agents for automation control and embodied robotics, where symbolic reasoning does not yet reliably extend to spatial reasoning or physical manipulation (Xia, Jazdi, et al. 2025; Lim et al. 2024; H. Fan et al. 2025). Industry 4.0/5.0 studies further emphasize that organizational readiness and worker trust remain as consequential as model capability (Tabim et al. 2024; Rahman et al. 2025; Passalacqua et al. 2025; Tóth et al. 2023; Fazlollahtabar 2025; Barua et al. 2025; Xu et al. 2025).

4.2 RQ2: What methodological limitations and contextual biases characterize current research on artificial intelligence in ET?

Research on AI in ET is expanding rapidly, but the evidence remains exploratory, localized, and methodologically uneven. Educational studies often rely on self-reported perceptions, surveys, and technology-acceptance measures that capture usefulness or confidence rather than durable learning or technical competence (Ovi et al. 2025; Bernabei et al. 2023; Rasnayaka et al. 2024; Vieriu et al. 2025), and rigorous experimental or longitudinal designs remain scarce, with many studies based on single courses or short-term comparisons (Narayan et al. 2024; Filippi

et al. 2024). Reported gains may therefore reflect novelty or course-specific conditions rather than stable AI-attributable improvements.

A second limitation is contextual narrowness. Studies often emphasize programming, writing, feedback, and general classroom tasks, where AI use is easier to observe (Pinto et al. 2023; Jukiewicz 2024; Uddin et al. 2024), while ET domains such as laboratories, instrumentation, manufacturing systems, and controls remain comparatively underexamined despite growing ET-specific work (Sarp et al. 2024), biasing the literature toward viewing AI as a classroom tool rather than part of the applied technical systems ET graduates must operate and maintain.

Laboratory and applied industrial studies broaden technical relevance but introduce transferability constraints. AI-assisted laboratory research often evaluates prototypes or single instructional modules using accuracy, latency, or student perception, with limited evidence of learning transfer or institutional sustainability (Kanala et al. 2026; Gomez et al. 2026), compounded by infrastructure demands: Industry 4.0 laboratories, digital twins, PLC simulation, and LIMS 4.0 platforms require specialized equipment and institutional resources that vary across ET programs (Aubel et al. 2024; Yuen et al. 2025), with cost and scalability rarely reported alongside feasibility. ML and DL studies face different limitations: advanced-manufacturing and predictive-maintenance models often encounter heterogeneous data, scarce failure data, and a persistent gap between benchmark architectures and industrial deployment (Arinez et al. 2020; Serradilla et al. 2022).

The broader industrial and organizational literature offers stronger technical evaluation but limited transferability to ET education. Studies of predictive maintenance, digital twins, and human–robot collaboration often rely on simulations or single case sites, making performance dependent on specific production settings (He et al. 2026; Nicoletti et al. 2025; Lucantoni et al. 2026), and research on human-centered AI perception and skills demand often uses specialized samples of uneven representativeness (Liao et al. 2026; Ergunova et al. 2026), while adoption studies tied to specific national or firm contexts should not be assumed universally transferable (Sabău-Popa et al. 2026; Silva et al. 2025).

Across education and industry, the literature remains more tool-centric than pedagogy- or practice-driven (Pinto et al. 2023; Jukiewicz 2024; Uddin et al. 2024), with industrial studies emphasizing technical performance over how workers interpret or challenge AI recommendations (He et al. 2026; Sivarao Subramonian 2026), and inconsistent evaluation metrics, satisfaction and grades versus latency, downtime, or scheduling, impede synthesis across courses, laboratories, and organizations (Ergunova et al. 2026). Additional validity concerns arise from AI systems themselves: generative AI can produce hallucinated or unverifiable outputs affecting both student work and industrial decision support (Qadir 2023; Nikolic et al. 2023; A. Fan et al. 2023), and transparency and human oversight remain unresolved when AI is embedded in safety-relevant environments (Coronado 2026; Witkowski et al. 2026). Ethical and workforce concerns are widely acknowledged but inconsistently measured, spanning plagiarism and overreliance in education (Selwyn 2019; Narayan et al. 2024; Ovi et al. 2025) to displacement and deskilling in industry, often in conceptual rather than empirical terms (Coronado 2026; Sivarao Subramonian 2026).

Overall, current evidence supports the claim that AI can be introduced into engineering courses, laboratories, and manufacturing platforms, but offers weaker support for claims about durability, scalability, and human-centered impact, requiring longitudinal, multi-institutional research that clearly defines ET populations.

4.3 RQ3: What structural adaptations are emerging across the ET ecosystem as artificial intelligence becomes embedded in education, research, laboratory environments, and professional practice?

AI integration into ET is producing structural adaptation rather than simple tool addition, reshaping the technical judgment and systems thinking expected of students and graduates. At the course level, AI increasingly serves as a learning assistant, shifting student workflows toward prompting and verification (Uddin et al. 2024; Rasnayaka et al. 2024; Bernabei et al. 2023), and instructors are redesigning tasks around reasoning, AI literacy, and critical evaluation rather than passive tool use (Narayan et al. 2024; Qadir 2023; Walter 2024). Automated grading is also reshaping course structure, though its value depends on human oversight and assessments that demonstrate independent understanding (Pinto et al. 2023; Jukiewicz 2024; Vieriu et al. 2025; Uddin et al. 2024).

At the program level, AI literacy is becoming a core competency, with ET curricula modernizing around data science, smart manufacturing, and digital twins aligned with Industry 4.0 (Sarp et al. 2024; Mullett 2024). This extends beyond chatbot use: machine learning supports analytics and predictive maintenance; deep learning supports computer vision and inspection; reinforcement learning supports control and adaptive manufacturing; and generative AI or LLMs support design ideation, documentation, and troubleshooting. AI is thus increasingly embedded across programming, automation, robotics, and data analytics rather than taught as a standalone

topic, aligning with workforce studies showing rising demand for intelligent maintenance and human-machine collaboration (W. Lu et al. 2024; Ergunova et al. 2026; Souza et al. 2023; Liao et al. 2026; Irwin et al. 2025).

Laboratory environments are shifting from isolated equipment demonstrations toward connected, data-rich systems integrating sensors, digital twins, and AI-supported feedback. AI-assisted troubleshooting, condition-monitoring, and remote laboratories enable system-level learning when equipment is costly or inaccessible (Kanala et al. 2026; Gomez et al. 2026), though modernization depends on institutional capacity and faculty expertise (Aubel et al. 2024). Advanced mechatronic and LIMS 4.0 platforms further suggest that ET laboratories increasingly resemble industrial environments, requiring students to understand data flow and system-level coordination (Yuen et al. 2025).

Professional practice is undergoing similar restructuring. Predictive maintenance is shifting toward data-driven, human-in-the-loop decision-making (Lucantoni et al. 2026; Liao et al. 2026); digital twins extend AI-enabled monitoring across manufacturing and infrastructure (Nicoletti et al. 2025; Bhandari et al. 2026); and manufacturing systems are moving toward agentic coordination among LLM-based agents and human workers (He et al. 2026). Industry 5.0 scholarship emphasizes keeping these systems human-centered through worker empowerment and shared control (Coronado 2026; Sivarao Subramonian 2026), and organizational readiness remains a structural bottleneck, as integration depends on culture and governance rather than technology alone (Sabău-Popa et al. 2026; Witkowski et al. 2026).

RQ3 indicates a shift toward integrated AI structures across ET: courses becoming more verification-centered, curricula more data-oriented, laboratories more connected, and professional systems more predictive and human-centered. The emerging ET professional is expected not merely to use AI, but to validate its outputs and preserve meaningful human oversight.

5. Conclusion, Limitations, and Future Work

This research set out to characterize how AI is currently applied across ET, what limitations constrain the evidence for that adoption, and what structural changes are emerging in response. RQ1 through RQ3 together describe an ecosystem in motion rather than a settled adoption: AI functions simultaneously as instructional aid, evaluated subject, and embedded decision-support infrastructure, as at Kennesaw State University's lab-embedded troubleshooting chatbot and Trane Technologies' production-scale evaluation of prompt-engineering strategies (RQ1; Table 1); the supporting evidence remains largely perception-based, short-term, and unevenly distributed across ET-specific domains such as instrumentation and controls (RQ2); and assessment practices, curricula, laboratories, and professional systems are already restructuring around verification, data literacy, and human-centered oversight, as at Miami University's redesigned closed-book assessments and Old Dominion University's dedicated data-science curriculum (RQ3; Table 1). AI's impact on ET is thus propagating across education, research, and practice in a mutually reinforcing way, grounded in named institutional practice rather than abstraction alone.

This synthesis carries its own limitations. The literature search prioritized recent, English-language, peer-reviewed publications; while Table 1 highlights practice at four-year programs such as Purdue University and Texas A&M alongside two-year and community-college contexts including Miami Dade College, the broader corpus still skews toward research-intensive institutions, and non-English scholarship likely remains underrepresented. A recency bias is also inherent, since most cited work is only two to three years old, leaving little basis for judging whether reported gains will persist as tools mature. Finally, because education, laboratory, and industrial literatures use incompatible metrics, higher-level claims about AI's aggregate impact should be read as directional rather than precisely comparable.

These limitations identify concrete priorities: longitudinal, multi-institutional studies following ET students from AI-integrated coursework into early careers are needed to distinguish durable gains from novelty effects, alongside standardized frameworks linking classroom, laboratory, and industrial outcomes and further examination of AI adoption in under-resourced, non-research-intensive ET programs. Worker trust, autonomy, and equitable infrastructure access remain more conceptual than empirical, particularly in Industry 5.0 scholarship, requiring sustained study of whether its human-centered aspirations are realized in practice.

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