JOURNAL of
ENGINEERING TECHNOLOGY®

A Publication of the Engineering Technology Division of ASEE

FALL 2026

Volume 43 | Number 2

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

A Project-Based Pedagogical Framework for Teaching AI/ML to Mechanical Engineering Technology Students

Affordable Viable Ease-built Electro Hydro Dynamic Machine (AVE-EHDM) for Hands-on Engineering Technology Laboratory Courses

Omni-Directional Wall-Climbing Robot:A Novel Mechatronic System with Propulsion-Based Adhesion

A Hierarchical Framework of the Impact of End-User Machine Learning Tools on Applied Machine Learning Education









MIAMI UNIVERSITY
POLYTECHNIC

BUILD YOUR FUTURE

Information Technology and Engineering Technology

LEARN BY DOING

- **Train** in our **70,000 sq. ft.** Advanced Manufacturing Workforce and Innovation Hub.
- **Learn** through highly applied, industry-connected experiences.
- **Connect** with **100+** industry partners.



POLYTECHNIC PROGRAMS

Engineering Technology

Engineering Technology (A.A.S.): Coming in fall 2027
Mechanical Engineering Technology (A.A.S.)
Electrical and Computer Engineering Technology (A.A.S.)
Mechatronics Engineering Technology (A.A.S.): Coming in fall 2027
Electrical, Computer, and Robotics Engineering Technology (B.S.)
Mechanical and Industrial Engineering Technology (B.S.)
Electromechanical and Automation Engineering Technology (B.S.)
Applied Science in Engineering Technology (B.S.): Degree completion program

Information Technology

Information Technology (B.S.)
Cybersecurity and Networking (B.S.)
Computer and Information Technology (A.A.S.)

WHY CHOOSE A MIAMI POLYTECHNIC PROGRAM?

- **Save** with tuition and fees under $8,500 per year.
- **Thrive** in small class sizes.
- **Gain** experience through Work+, internships, and senior design projects.
- **Choose** from flexible learning and transfer options.
- **Earn** scholarships to help pay for college.
- **Build** on your associate degree with bachelor's completion options.

CAREER READY, DAY ONE.
Miami University Polytechnic

cet@MiamiOH.edu | 513-785-1804
MiamiOH.edu/Regionals/CET

SEE IT FOR YOURSELF. SCAN TO TOUR.

PURDUE™

ENGINEERING TECHNOLOGY

What will your next giant leap make possible?

At the Purdue School of Engineering Technology, faculty research shapes the student experience. From intelligent health technologies to advanced manufacturing, our faculty bring discovery into classrooms, labs and applied research spaces where students learn to solve real problems.

AREAS OF RESEARCH

Human-Centered Intelligent Systems

Sustainable Industrial Systems

Applied Engineering Education

Advanced Manufacturing Technologies

ACADEMIC PROGRAMS

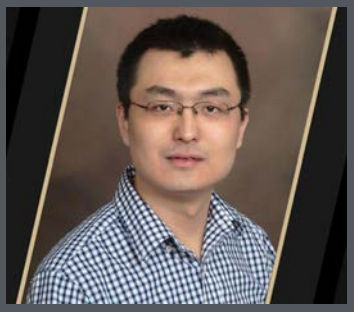
Electrical Engineering Technology

Industrial Engineering Technology

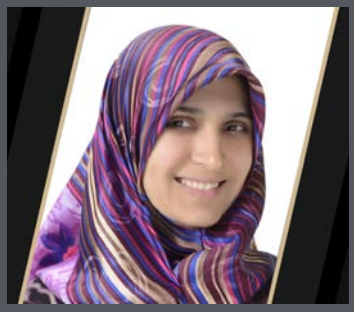
Manufacturing Engineering Technology

Mechanical Engineering Technology

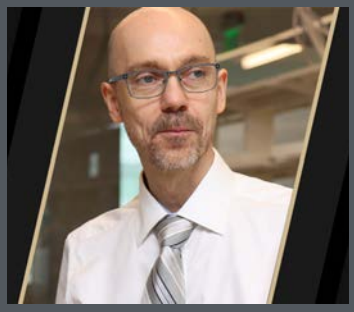
See how Purdue Engineering Technology faculty are shaping what's next.



XIAONAN LU
Associate Professor



MIAD FAEZIPOUR
Associate Professor



ROBERT NAWROCKI
Associate Professor



BRITTNEY NEWELL
Associate Professor

FACULTY POSITIONS COMING SOON RELATED TO SCHOOL OF ENGINEERING TECHNOLOGY.

PURDUE UNIVERSITY
School of Engineering Technology

LEARN MORE ABOUT OUR WORK AND PEOPLE

From the EDITOR

Dear Colleagues:

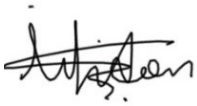
This summer, I began a new chapter at Middle Tennessee State University, leading its engineering and technology programs. I am truly honored to be part of the True Blue family and to work with wonderful faculty who prepare the engineers of the future together.

Another exciting milestone of this summer was the release of the new Journal Impact Factors. The ***Journal of Engineering Technology*** reached an Impact Factor of 3.50. Congratulations, and sincere thanks to our editorial team, reviewers, and authors whose dedication, hard work, and valuable contributions made this achievement possible.

The Fall 2026 issue features five timely articles covering AI in engineering technology, project-based AI/ML education, affordable hands-on laboratory equipment, innovative wall-climbing robotics, and the impact of machine learning tools on applied learning. Together, these articles showcase emerging technologies and innovative approaches that are shaping the future of engineering technology education and practice.

I hope you enjoy this issue and find the articles informative and inspiring. Thank you for being part of our growing ***Journal of Engineering Technology*** community.

All my best,



Ismail Fidan, PhD
Editor-in-Chief
Journal of Engineering Technology®

DOI:10.18260/jet.43.2.editorial
engtech.org/jet
jet.scholasticahq.com



The *Journal of Engineering Technology®* is published in the spring and fall of each year. It is supported by the generosity of the advertisers included herein, paid subscriptions, and author page charges. Authors wishing to contribute papers should submit them through *jet.scholasticahq.com*.

The *Journal of Engineering Technology®* is indexed by Applied Science and Technology Index and Engineering Index.

COVER: The brand-new Applied Engineering Building at Middle Tennessee State University embodies "Engineering the Future Together" through innovation, creativity, and excellence — a vision where innovation and collaboration transform ideas into solutions and learning into tomorrow's technologies.

Image provided courtesy © Middle Tennessee State University, J. Intintoli, MTSU staff photographer

Journal of
ENGINEERING TECHNOLOGY®
A Publication of the Engineering Technology Division

American Society for Engineering Education
1818 N Street NW, Suite 600
Washington, DC 20036
www.asee.org

Editor-in-Chief & Communications Editor — Ismail Fidan, Middle Tennessee State University, 1301 East Main Street, Murfreesboro, TN 37132, *Ismail.Fidan@mtsu.edu*

Manuscript Editor — Mathew Kuttolamadom, Texas A&M University, 3367 TAMU, College Station, TX 77843-3367, *mathew@tamu.edu*

Production Editor — Farid El Breidi, Purdue University, 401 Grant St., West Lafayette, IN 47907, *breidi@purdue.edu*

Advertising Editor — John L Irwin, Michigan Technological University, 1400 Townsend Drive, Houghton, Michigan 49931, *jlirwin@mtu.edu*

Subscription & Financial Editor — Ankit Gupta, California State University, LA, 5151 State University Dr., Los Angeles, CA 90032, *agupta26@calstatela.edu*

Copy Editor — Judy Birchman, Purdue University, West Lafayette, IN 47907, *jabirchman@purdue.edu*

Past Editor — Jyhwen Wang, Texas A&M University, 3367 TAMU, College Station, TX 77843-3367, *jwang@tamu.edu*

THE JOURNAL OF ENGINEERING TECHNOLOGY® (ISSN 0747-9964) is published twice a year by the American Society for Engineering Education, 1818 N Street NW, Suite 600, Washington, DC 20036. ©2026 by the American Society for Engineering Education.

Print ISSN: 0747-9964 Online ISSN: 2998-8969

PERMISSION TO REPRINT: Address requests to Publications & Marketing Services. Individual readers of this magazine and nonprofit libraries acting for them, are freely permitted to make fair use of material in it, such as to make a single copy of an article. Statements and opinions expressed are not necessarily those of the ASEE. The magazine is provided free to dues-paying members of the Engineering Technology Division of ASEE. External subscription rate: $25.00 per year. Foreign subscription rate: $35.00 per year.

POSTMASTER: Send address corrections & undeliverable addresses to Ankit Gupta, California State University, LA, 5151 State University Dr., Los Angeles, CA 90032.

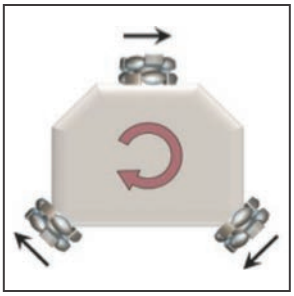
JOURNAL of
ENGINEERING TECHNOLOGY®

FALL 2026 VOL. 43 NO. 2

Table of CONTENTS







DOI: 10.18260/jet.43.2

Features

FEATURED PAPER

Artificial Intelligence in Engineering Technology: Opportunities, Challenges, and Future Outlook 6
by Sabit Ekin, Farid El Breidi, Milad Saadat and Mohammed Metwaly
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.

A Project-Based Pedagogical Framework for Teaching AI/ML to Mechanical Engineering Technology Students 20
by Wenhai Li, Zhou Zhang, Gonca Altuger-Genc and Yue Hung
This study presents a project-based pedagogical framework designed specifically for introducing AI/ML to MET students through an existing senior project course.

Affordable Viable Ease-built Electro Hydro Dynamic Machine (AVE-EHDM) for Hands-on Engineering Technology Laboratory Courses 34
by Srivarshini Vellaisamy and Tazdik Patwary Plateau
This study investigates whether an Affordable, Viable, and Ease-built Electro-Hydro-Dynamic Machine (AVE-EHDM) can provide a multifunctional, low-cost platform suitable for STEM education.

Omni-Directional Wall-Climbing Robot:A Novel Mechatronic System with Propulsion-Based Adhesion 48
by Mahdi Yazdanpour and Boshra Karimi
This paper presents the design, implementation, prototype development, and qualitative evaluation of an omni-directional wall-climbing robot using a propulsion-based adhesion mechanism.

A Hierarchical Framework of the Impact of End-User Machine Learning Tools on Applied Machine Learning Education 58
by Jonathan Niemirowski, David Hall, Krystal Cruse and Mary Fendley
This exploratory study presents an abstraction hierarchy model as a preliminary course design framework for assessing the information and functions associated with applied ML classroom projects from engineering and technology courses.

Announcements

FROM THE EDITOR 4
JOB POSTING 46
NATIONAL HONOR SOCIETY 57
INDEX OF ADVERTISERS 69
CALL FOR SHORT PAPER 69
BACK ISSUES 70
ADVERTISING & SUBSCRIPTIONS 70
MANUSCRIPT REQUIREMENTS 71
STYLE GUIDE FOR AUTHORS 72
CHANGE OF ADDRESS 73

FEATURED PAPER

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

Sabit Ekin, Farid El Breidi, Milad Saadat and Mohammed Metwaly

DOI: 10.18260/jet.43.2.1

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-

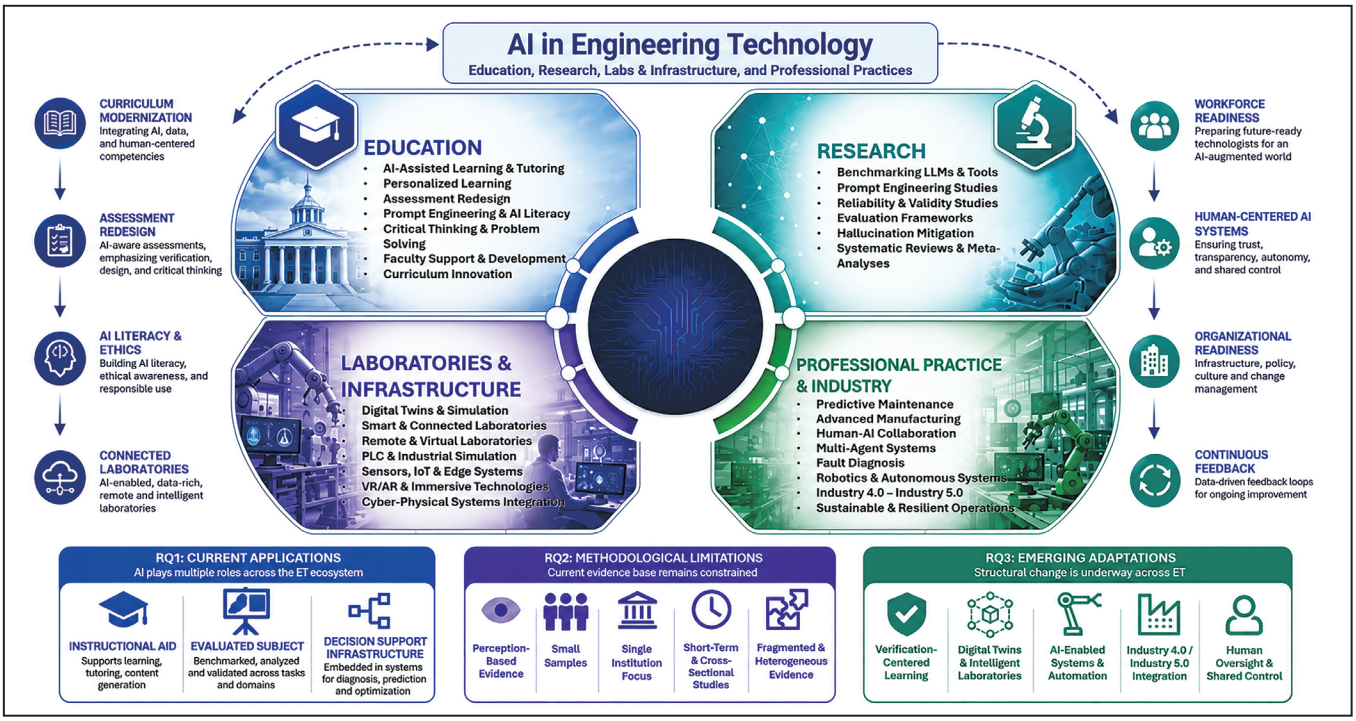


Figure 1. Comprehensive overview of artificial intelligence adoption across the ET ecosystem and its influence on educational, research, laboratory, and professional domains.

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,

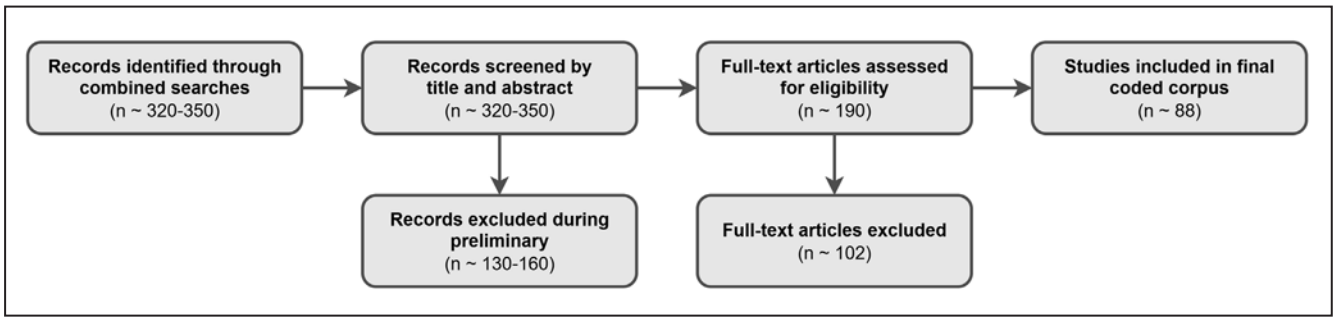


Figure 2. Literature screening and selection process.

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.

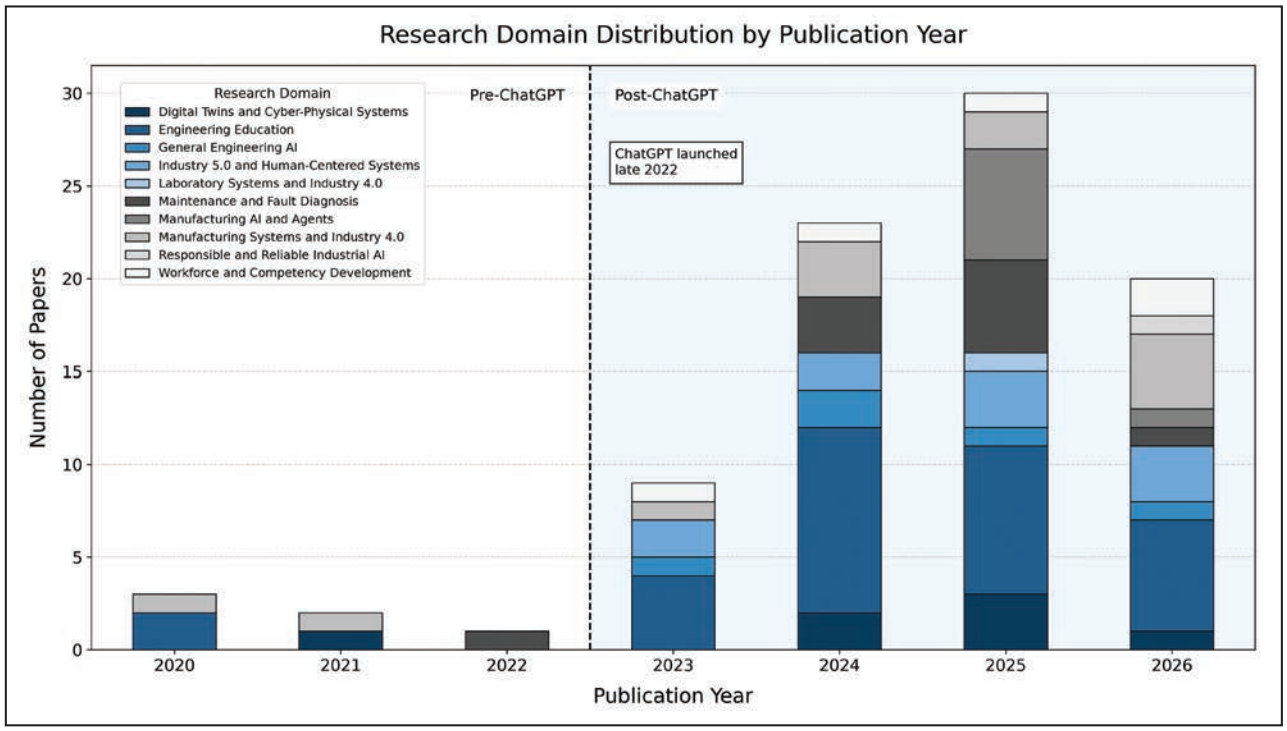


Figure 3. Number of published papers by category since 2020. A marked increase in the volume of publications is evident following the release of ChatGPT-3 in late 2022, reflecting the rapid growth of research on generative AI across the surveyed categories.

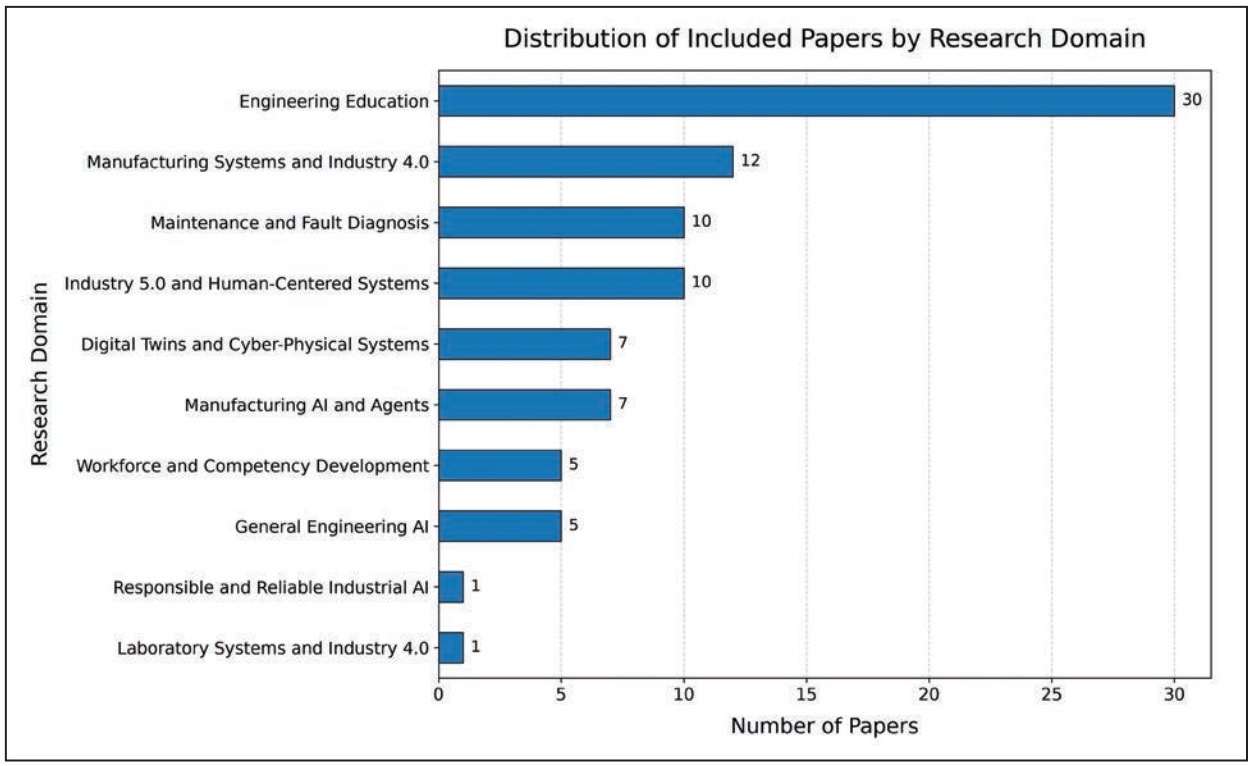


Figure 4. Distribution of the reviewed academic articles by ET category, illustrating the areas in which artificial intelligence has been investigated and implemented across the ET ecosystem.

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

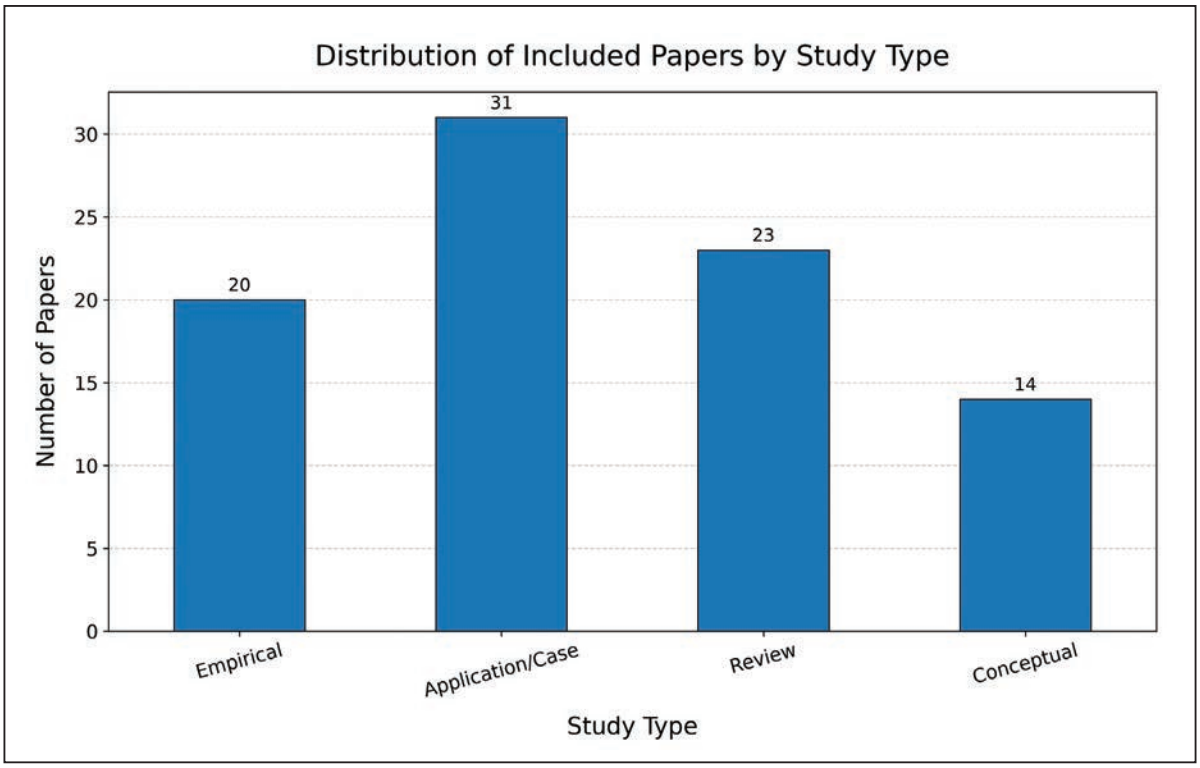


Figure 5. Distribution of the reviewed literature according to study type, providing an overview of the methodological composition of the selected publications.

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.

References

Akolekar, Harshal et al. 2025. "The Role of Generative AI Tools in Shaping Mechanical Engineering Education from an Undergraduate Perspective." https://doi.org/10.1038/s41598-025-93871-z.

Ali, Shaukat, Paolo Arcaini, and Aitor Arrieta. 2024. "Foundation Models for the Digital Twins Creation of Cyber-Physical Systems." https://doi.org/10.1007/978-3-031-75390-9_2.

Arinez, J. et al. 2020. "Artificial Intelligence in Advanced Manufacturing: Current Status and Future Outlook." https://doi.org/10.1115/1.4047855.

Aubel, Ines et al. 2024. "Industry 4.0-Driven STEM-Lab Modernization: Balancing Flexibility and Sustainability." https://doi.org/10.1002/cite.202300236.

Barua, Dhruba Aritra, Samsul Arifeen Sami, and Leon Barua. 2025. "Leveraging Artificial Intelligence for Smart Production Management in Industry 4.0." https://doi.org/10.1038/s41598-025-25413-6.

Bernabei, Margherita et al. 2023. "Students' Use of Large Language Models in Engineering Education: A Case Study on Technology Acceptance, Perceptions, Efficacy, and Detection Chances." https://doi.org/10.1016/j.caeai.2023.100172.

Bhandari, Prakash et al. 2026. "Bridge Health Monitoring and Assessment in Industry 5.0: Lessons Learned from Long-Term Real-Time Field Monitoring of Highway Bridges." https://doi.org/10.3390/infrastructures11020055.

Bilgin, Betul. 2026. "Integrating Generative AI into Senior Design to Cultivate Engineering Judgment and Reflective Learning." https://nemo.asee.org/public/conferences/374/papers/53937/view.

Boonmee, A, K Wongsuwan, and P Sukjai. 2024. "Consultation on Industrial Machine Faults with Large Language Models." https://doi.org/10.48550/arXiv.2410.03223.

Chen, Xuefeng et al. 2025. "Large Models for Machine Monitoring and Fault Diagnostics: Opportunities, Challenges, and Future Direction." https://doi.org/10.37965/jdmd.2025.832.

Coronado, Enrique. 2026. "From Large Language Models to Agentic AI in Industry 5.0 and the Post-ChatGPT Era: A Socio-Technical Framework and Review on Human–Robot Collaboration." https://doi.org/10.3390/robotics15030058.

Di Maggio, Luigi Gianpio. 2025. "Toward Autonomous LLM-Based AI Agents for Predictive Maintenance: State of the Art, Challenges, and Future Perspectives." https://doi.org/10.3390/app152111515.

Ekin, Sabit. 2026. "Prompt Engineering for ChatGPT: A Quick Guide to Techniques, Tips, and Best Practices." https://doi.org/10.18260/jet.43.1.5.

El-Shahat, Adel et al. 2026. "Artificial Intelligence (AI) in Educating Next Generation of Engineering Technology Students." https://nemo.asee.org/public/conferences/374/papers/50429/view.

Ergunova, Olga, Gaini Mukhanova, and Andrei Somov. 2026. "AI-Supported Student Skills Profiling Integrating AI and EdTech into Inclusive and Adaptive Learning." https://doi.org/10.3390/socsci15030209.

Fan, Angela et al. 2023. Large Language Models for Software Engineering: Survey and Open Problems. https://doi.org/10.48550/arXiv.2310.03533.

Fan, Haolin et al. 2025. "Embodied Intelligence in Manufacturing: Leveraging Large Language Models for Autonomous Industrial Robotics." https://doi.org/10.1007/s10845-023-02294-y.

Fazlollahtabar, Hamed. 2025. "Industry 5.0 Paradigm Transformation Adoption in Developing Countries: An Analytical Game Theoretic Model." https://doi.org/10.1038/s41598-025-16089-z.

Filippi, Stefano, and Barbara Motyl. 2024. "Large Language Models (LLMs) in Engineering Education: A Systematic Review and Suggestions for Practical Adoption." https://doi.org/10.3390/info15060345.

Freeman, Brian et al. 2026. "Toward Epistemic Stability: Engineering Consistent Procedures for Industrial LLM Hallucination Reduction." https://doi.org/10.48550/arXiv.2603.10047.

Gao, Robert X et al. 2024. "Artificial Intelligence in Manufacturing: State of the Art, Perspectives, and Future Directions." https://doi.org/10.1016/j.cirp.2024.04.101.

Giannakos, Michail et al. 2024. "The Promise and Challenges of Generative AI in Education." https://doi.org/10.1080/01449290X.2024.2394886.

Gomez, Manuel J. et al. 2026. "Towards the Integration of Remote Laboratories in Massive Open Online Courses: Insights from Usage Logs and Student Feedback." https://doi.org/10.1002/cae.70185.

He, Lijun et al. 2026. "Human-Machine Collaboration in Industry 5.0: An Energy-Efficient Collaborative Approach for Scheduling Intelligent Job Shops Considering Automated Guided Vehicle Transportation and Worker Flexibility." https://doi.org/10.1016/j.tre.2025.104557.

Honig, Christopher, Shannon Rios, and Aditya Desu. 2025. "Generative AI in Engineering Education: Understanding Acceptance and Use of New GPT Teaching Tools within a UTAUT Framework." https://doi.org/10.1080/22054952.2025.2467500.

Huang, Ziqi et al. 2021. "A Survey on AI-Driven Digital Twins in Industry 4.0: Smart Manufacturing and Advanced Robotics." https://doi.org/10.3390/s21196340.

Irwin, John et al. 2025. "The Four Pillars of Manufacturing Knowledge: A Contemporary Perspective on Practical Implementation." https://doi.org/10.18260/jet.42.2.4.

Jukiewicz, Marcin. 2024. "The Future of Grading Programming Assignments in Education: The Role of ChatGPT in Automating the Assessment and Feedback Process." https://doi.org/10.1016/j.tsc.2024.101522.

Kanala, Deekshitha et al. 2026. "An AI-Assisted Framework for Dynamics and Control Laboratory with Chatbot-Supported Multiple Representations of Learning." https://doi.org/10.1109/SoutheastCon63549.2026.11475953.

Kim, Eunseob et al. 2023. "Taking an Experiential Learning Approach to Industrial IoT Implementation for Smart Manufacturing through Course Work and University-Industry Partnerships." https://doi.org/10.18260/1-2--42432.

Leitão, Paulo et al. 2020. "Quo Vadis Industry 4.0? Position, Trends, and Challenges." https://doi.org/10.1109/OJIES.2020.3031660.

Li, Ruimiao, Manli Li, and Weifeng Qiao. 2025. "Engineering Students' Use of Large Language Model Tools: An Empirical Study Based on a Survey of Students from 12 Universities." https://doi.org/10.3390/educsci15030280.

Liao, Chin-Wen, Nguyen Van Thanh, and Yi-Hsin Tai. 2026. "Applying Integrated Delphi–AHP to Maintenance Competency Prioritization in Industry 4.0: A Formally Specified Group Decision Framework with Consistency and Sensitivity Diagnostics." https://doi.org/10.3390/info17050500.

Lim, Jonghan et al. 2024. "Enhancing Human-Robot Collaborative Assembly in Manufacturing Systems Using Large Language Models." https://doi.org/10.1109/CASE59546.2024.10711843.

Lin, Lin et al. 2025. "FD-LLM: Large Language Model for Fault Diagnosis of Complex Equipment." https://doi.org/10.1016/j.aei.2025.103208.

Liu, Chao, and Shengyi Yang. 2026. "Application of Large Language Models in Engineering Education: A Case Study of System Modeling and Simulation Courses." https://doi.org/10.1177/03064190241272728.

Liu, Nannan. 2025. "Exploring the Factors Influencing the Adoption of Artificial Intelligence Technology by University Teachers: The Mediating Role of Confidence and AI Readiness." https://doi.org/10.1186/s40359-025-02620-4.

Lu, Wei, and Behbood Ben Zoghi. 2024. "Using Generative AI for a Graduate Level Capstone Course Design—A Case Study." https://doi.org/10.18260/1-2--48235.

Lucantoni, Laura, Filippo Emanuele Ciarapica, and Maurizio Bevilacqua. 2026. "From Predictive Maintenance 4.0 to 5.0: Bringing Humans Back into the Loop with a Self-Learning Platform and Implementation Roadmap on Automated Production Lines." https://doi.org/10.1108/JQME-12-2025-0147.

Ma, Yunfei et al. 2025. "Leveraging Large Language Models in Next Generation Intelligent Manufacturing: Retrospect and Prospect." https://doi.org/10.1016/j.jmsy.2025.07.019.

Martín Núñez, Jose Luis, and Andres Diaz Lantada. 2020. "Artificial Intelligence Aided Engineering Education: State of the Art, Potentials and Challenges." https://www.ijee.ie/1atestissues/Vol36-6/03_ijee3984.pdf.

Mullett, Gary. 2024. "Modifying Engineering Technology Curriculum to Adapt to the Demands of Industry 4.0." *2023 CIEC Proceedings*. Charleston, South Carolina: ASEE Conferences. https://doi.org/10.18260/1-2-1125-48784.

Narayan, Meenakshi, and Lokesh Saharan. 2024. "Reshaping Engineering Technology Education: Fostering Critical Thinking through Open-Ended Problems in the Era of Generative AI." https://doi.org/10.18260/1-2--47944.

National Science Foundation. 2024. NSF Invests $2.8 Million to Strengthen Technical AI Education at Two-Year Institutions. https://www.nsf.gov/news/nsf-invests-28m-strengthen-technical-ai-education-two-year.

Nguyen, San S, and Javeed Kittur. 2025. "Review of Current and Potential Uses of Large Language Models in Engineering." https://doi.org/10.3389/feduc.2025.1649650.

Nicoletti, Bernardo, and Andrea Appolloni. 2025. "A Digital Twin Framework for Enhancing Human–Agentic AI–Machine Collaboration." https://doi.org/10.1007/s10845-025-02637-x.

Nikolic, Sasha et al. 2023. "ChatGPT Versus Engineering Education Assessment: A Multidisciplinary and Multi-Institutional Benchmarking and Analysis of This Generative Artificial Intelligence Tool to Investigate Assessment Integrity." https://doi.org/10.1080/03043797.2023.2213169.

Nosrati, Komeil et al. 2026. "When Control Meets Large Language Models: From Words to Dynamics." https://doi.org/10.1016/j.engappai.2026.115119.

Omwando, Thomas Aming'a et al. 2025. "Assessing the Impact of the Use of Generative AI in Developing and Using Assessment Grading Rubrics for Engineering Courses." https://doi.org/10.18260/1-2--55482.

Ovi, Jesan Ahammed, Gabriel Fierro, and C. Estelle Smith. 2025. "Assessing Student Adoption of Generative Artificial Intelligence across Engineering Education from 2023 to 2024." https://doi.org/10.48550/arXiv.2503.04696.

Passalacqua, Mario et al. 2025. "Human-Centred AI in Industry 5.0: A Systematic Review." https://doi.org/10.1080/00207543.2024.2406021.

Pinto, Gustavo et al. 2023. "Large Language Models for Education: Grading Open-Ended Questions Using ChatGPT." https://doi.org/10.1145/3613372.3614197.

Puthumanaillam, Gokul, Timothy Bretl, and Melkior Ornik. 2025. "The Lazy Student's Dream: ChatGPT Passing an Engineering Course on Its Own." https://doi.org/10.1016/j.ifacol.2025.08.049.

Qadir, Junaid. 2023. "Engineering Education in the Era of ChatGPT: Promise and Pitfalls of Generative AI for Education." https://doi.org/10.1109/EDUCON54358.2023.10125121.

Rahman, Atiqur et al. 2025. "Industry 5.0, Human–Machine Interface, and Smart Manufacturing in Additive Manufacturing—A Recent Trend." https://doi.org/10.1007/s00170-025-16782-3.

Rasnayaka, Sanka et al. 2024. An Empirical Study on Usage and Perceptions of LLMs in a Software Engineering Project. https://doi.org/10.1145/3643795.3648379.

Ruppert, Tamás et al. 2022. "Demonstration Laboratory of Industry 4.0 Retrofitting and Operator 4.0 Solutions: Education Towards Industry 5.0." https://doi.org/10.3390/s23010283.

Sabău-Popa, Claudia-Diana et al. 2026. "Sustainability-Oriented Digital Transformation Under Industry 4.0: Managerial Perceptions of Digitalization and AI." https://doi.org/10.3390/su18052570.

Sarp, Salih et al. 2024. "Development of a Data Science Curriculum for an Engineering Technology Program." https://doi.org/10.18260/1-2--43109.

Selwyn, Neil. 2019. Should Robots Replace Teachers? AI and the Future of Education. Polity Press. ISBN 9781509528967.

Serradilla, O. et al. 2022. "Deep Learning Models for Predictive Maintenance: A Survey, Comparison, Challenges and Prospects." https://doi.org/10.1007/s10489-021-03004-y.

Shyalika, Chathurangi et al. 2025. "Smartpilot: A Multiagent Copilot for Adaptive and Intelligent Manufacturing." https://doi.org/10.1109/CAI64502.2025.00007.

Silva, Niranga et al. 2025. "Integration of Industry 4.0 Technologies to Overcome Lean Manufacturing Barriers in Sri Lanka's Apparel Sector." https://doi.org/10.1108/IJLSS-09-2025-0257.

Sivarao Subramonian, Kumaran. 2026. "Lights-Out Factory: Advancements, Challenges, and Prospects for Fully Autonomous Manufacturing." https://doi.org/10.14716/ijtech.v17i2.7651.

Souza, Alex Sander Clemente de, and Luciana Debs. 2023. "Identifying Emerging Technologies and Skills Required for Construction 4.0." https://doi.org/10.3390/buildings13102535.

Stefanek, George et al. 2024. "A Comparison of AI Models to Detect Hidden Messages in Images." https://doi.org/10.48009/3_iis_2024_109.

Subahi, Ahmad F. 2024. "Advancing Sustainable Cyber-Physical System Development with a Digital Twins and Language Engineering Approach: Smart Greenhouse Applications." https://doi.org/10.3390/technologies12090147.

Sufian, Amr T. et al. 2021. "Six-Gear Roadmap Towards the Smart Factory." https://doi.org/10.3390/app11083568.

Tabim, Verônica M et al. 2024. "Implementing Manufacturing Execution Systems (MES) for Industry 4.0: Overcoming Buyer-Provider Information Asymmetries through Knowledge

Sharing Dynamics." https://doi.org/10.1016/j.cie.2024.110483.
Talkington, Samuel, and Daniel K Molzahn. 2025. "VArsity: Can Large Language Models Keep Power Engineering Students in Phase?" https://doi.org/10.1109/NAPS66256.2025.11272354.
Tóth, Attila et al. 2023. "The Human-Centric Industry 5.0 Collaboration Architecture." https://doi.org/10.1016/j.mex.2023.102260.
Uddin, Md et al. 2024. "ChatGPT as an Educational Resource for Civil Engineering Students." https://doi.org/10.1002/cae.22747.
Urrea, Claudio. 2026. "Industrial Robotics and Adaptive Control Systems in STEM Education: Systematic Review of Technology Transfer from Industry to Classroom and Competency Development Framework." https://doi.org/10.3390/app16042026.
Vidyalakshmi, G et al. 2025. "Digital Twins and Cyber-Physical Systems: A New Frontier in Computer Modeling." https://doi.org/10.32604/cmes.2025.057788.
Vieriu, Aniella Mihaela, and Gabriel Petrea. 2025. "The Impact of Artificial Intelligence (AI) on Students' Academic Development." https://doi.org/10.3390/educsci15030343.
Walter, Yoshija. 2024. "Embracing the Future of Artificial Intelligence in the Classroom: The Relevance of AI Literacy, Prompt Engineering, and Critical Thinking in Modern Education." https://doi.org/10.1186/s41239-024-00448-3.
Wang, Huan et al. 2024. "An Intelligent Industrial Visual Monitoring and Maintenance Framework Empowered by Large-Scale Visual and Language Models." https://doi.org/10.1109/TICPS.2024.3414292.
Wang, Peng, John Karigiannis, and Robert X Gao. 2024. "Ontology-Integrated Tuning of Large Language Model for Intelligent Maintenance." https://doi.org/10.1016/j.cirp.2024.04.012.
Wang, Tianyu et al. 2025. "A Multimodal Large Language Model Framework for Intelligent Perception and Decision-Making in Smart Manufacturing." https://doi.org/10.3390/s25103072.
Wen, Di et al. 2025. "Mica: Multi-Agent Industrial Coordination Assistant." https://doi.org/10.48550/arXiv.2509.15237.
Wen, Sijie et al. 2025. "Leveraging Large Language Models for Human-Machine Collaborative Troubleshooting of Complex Industrial Equipment Faults." https://doi.org/10.1016/j.aei.2025.103235.
Witkowski, Aron, and Andrzej Wodecki. 2026. "A Prescriptive Generative AI Maturity Model for New Product Development Processes." https://doi.org/10.1108/JMTM-09-2025-0884.
Wulf, Jochen, and Juerg Meierhofer. 2025. "The Impact of Large Language Models on Task Automation in Manufacturing Services." https://doi.org/10.1016/j.procir.2025.03.071.
Xia, Yuchen, Daniel Dittler, et al. 2024. "LLM Experiments with Simulation: Large Language Model Multi-Agent System for Simulation Model Parametrization in Digital Twins." https://doi.org/10.1109/ETFA61755.2024.10710900.
Xia, Yuchen, Nasser Jazdi, et al. 2025. "Control Industrial Automation System with Large Language Model Agents." https://doi.org/10.1109/ETFA65518.2025.11205539.
Xu, Jing et al. 2025. "When Embodied AI Meets Industry 5.0: Human-Centered Smart Manufacturing." https://doi.org/10.1109/JAS.2025.125327.
Yuen, Norton et al. 2025. "Laboratory Information Management System (LIMS) 4.0: A Model to Solve the Current Pain Points for Commercial Electrical and Electronic Laboratories." https://doi.org/10.1177/18479790251385743.
Zhang, Qi et al. 2025. "LLM-TSFD: An Industrial Time Series Human-in-the-Loop Fault Diagnosis Method Based on a Large Language Model." https://doi.org/10.1016/j.eswa.2024.125861.

Sabit Ekin

Dr. Sabit Ekin is an Associate Professor in the Engineering Technology and Industrial Distribution Department at Texas A&M University. His research focuses on wireless communications, and AI/ML-enabled wireless systems. He is a recipient of the U.S. Department of Energy Early Career Award and leads initiatives in Generative AI Literacy Initiative at TAMU.

Farid El Breidi

Dr. Farid El Breidi is an Associate Professor in Purdue University's School of Engineering Technology. His research focuses on extended reality and smart manufacturing. He is the Production Editor of Journal of Engineering Technology, a Purdue Faculty and Impact Fellow, and the Associate Program Chair of the ASEE Manufacturing Division.

Milad Saadat

Milad Saadat is a Ph.D. student in the Department of Electrical and Computer Engineering at Texas A&M University. His research focuses on wireless communications and applied artificial intelligence, with an emphasis on AI-enabled wireless systems and intelligent communication technologies. His work explores the application of artificial intelligence to emerging wireless communication challenges.

Mohammed Metwaly

Mohammed Metwaly is a Ph.D. student in Mechanical Engineering Technology at Purdue University. His research focuses on immersive telepresence, extended reality, computer vision, and task-aware video optimization for engineering and infrastructure applications. He has experience in VR systems, data analysis, and applied transportation research.

CADCIM Technologies

www.cadcim.com sales@cadcim.com

VIDEO COURSES

CADCIM offers video courses in CAD, CAE Simulation, BIM, Civil/GIS, and Animation domains on various e-Learning/Video platforms. For more information about the video courses, visit https://www.cadcim.com/video-courses

CAD/CAM/CAE

Autodesk Fusion 360
AutoCAD Electrical 2027*
AutoCAD: 2D and 3D
Learning SOLIDWORKS
Autodesk Inventor Professional
Solid Edge 2026*
Plant 3D 2027*
Siemens NX 2026*
Creo 12.4*

Civil/BIM/GIS

Civil 3D
Revit Architecture
Staad Pro
Navisworks
Revit Structure
ArcGIS Pro

Animation/VFX

Adobe Photoshop CC
Adobe Illustrator CC
Autodesk Maya 2027*
CINEMA 4D 2024
Autodesk 3ds Max 2027*

Latest eBOOKS/PUBLICATIONS

CAD/CAM/CAE

AutoCAD 2027 with Videos: A Problem-Solving Approach, Basic and Intermediate
SOLIDWORKS 2026 with Videos for Designers
Autodesk Inventor Professional 2027 for Designers with Videos
Creo Parametric 13.4 for Designers with Videos*
AutoCAD Plant 3D 2027 for Designers with Videos
CATIA V5-6R 2025 with Videos for Designers
Solid Edge 2026 with Videos for Designers
AutoCAD Electrical 2027 with Videos for Electrical Control Designers

Animation/VFX

Autodesk 3ds Max 2027 with Videos: A Comprehensive Guide
Autodesk Maya 2027: A Comprehensive Guide
Autodesk Maya 2027 with Videos: A Tutorial Approach
MAXON ZBrush 2026: A Comprehensive Guide*
MAXON CINEMA 4D 2026: A Tutorial Approach

Civil/GIS

Exploring Autodesk Revit 2027 for Architecture with Videos
Exploring Autodesk Revit 2027 for Structure with Videos
Exploring AutoCAD Civil 3D 2027 with Videos*
Exploring Autodesk Revit 2027 for MEP with Videos*

CONSULTING SERVICES & ONLINE TRAINING

CADCIM provides consulting services and online training on various software packages related to CAD/CAM/CAE, Animation/VFX, Architecture, Civil, GIS, and Computer Programming.

** Upcoming titles/courses, available by December 2026*

525 St. Andrews Drive Schererville, IN 46375, USA
Tel: (219) 228-4908 Fax: (270) 717- 0185



Build on your background

Ph.D. in
Technology
Management

Consider our online* Ph.D. program if either your bachelor's or master's degree is in the following areas:

- Engineering/Technology Management
- Engineering/Engineering Technology
- Electronics and Computer
- Construction
- Quality
- Human Resource Development & Training
- Manufacturing
- Other Aligned Fields



Ph.D. in Technology Management Consortium Institutions

A. Bowling Green State University
B. University of Central Missouri
C. East Carolina University
D. Indiana State University

We offer specializations in Construction Management, Digital Communication, Human Resource Development and Industrial Training, Manufacturing, Quality as well as a custom specialization.

*For detailed information, please visit the website below.

INDIANA STATE UNIVERSITY

https://indianastate.edu/academics/academic-program-finder/technology-management-phd

A Project-Based Pedagogical Framework for Teaching AI/ML to Mechanical Engineering Technology Students

Wenhai Li, Zhou Zhang, Gonca Altuger-Genc and Yue Hung

DOI: 10.18260/jet.43.2.2

Abstract

Artificial Intelligence (AI), including Machine Learning (ML) as a major subfield, is becoming increasingly important in engineering practice, but many Mechanical Engineering Technology (MET) students have limited formal preparation in advanced mathematics, programming, and computer science. This study presents a project-based pedagogical framework designed specifically for introducing AI/ML to MET students through an existing senior project course. The framework includes three connected components: scaffolded AI/ML instruction, accessible AI tools as instructional supports, and project-based reinforcement through AI/ML-focused capstone projects. This structure was designed to match the applied, hands-on learning style of engineering technology education. It introduces essential AI/ML concepts at an accessible level, uses no-code tools, instructor-provided examples, and LLM-assisted support to reduce learning barriers, and reinforces learning through practical engineering projects. The pedagogical innovation of this work is not simply adding AI/ML topics to a course, but creating a guided pathway that helps MET students move from basic conceptual understanding to practical AI-enabled engineering implementation. Assessment results, including quizzes, student self-evaluations, reflection responses, and capstone project outcomes, suggest that students improved their foundational AI/ML literacy and were able to connect AI/ML concepts with practical engineering systems. This framework provides a practical model for making AI/ML learning accessible, scaffolded, and application-driven for engineering technology students.

1. Introduction

Artificial Intelligence (AI), particularly Machine Learning (ML), is rapidly transforming engineering practice across areas such as manufacturing, automation, robotics, predictive maintenance, quality control, system optimization, and more. As AI technologies become increasingly integrated into modern engineering applications, there is a growing expectation that engineering graduates possess not only technical expertise in their disciplines but also the ability to understand, evaluate, and apply AI-enabled tools to solve engineering problems. Recent studies have highlighted the importance of AI literacy and related competencies as essential skills for students in an increasingly AI-driven higher education environment (Ng et al. 2021, Zawacki-Richter et al. 2019). At the same time, industry and government reports have identified a growing demand for engineers who can effectively work with AI-assisted technologies and data-driven engineering workflows (Ellingrud et al. 2023, Boggs et al. 2023).

The rapid adoption of AI technologies has created new challenges for engineering education. While many institutions have begun exploring the integration of AI and ML into undergraduate education, most existing approaches have primarily been developed within computer science and data science programs (Zawacki-Richter et al. 2019). Comparatively less attention has been given to how AI/ML can be effectively taught to students in applied engineering and engineering technology programs, whose educational backgrounds, learning objectives, and career pathways differ substantially from those of computer science students. As a result, there remains a need for instructional approaches that can introduce AI/ML concepts in a manner that is both accessible and directly relevant to engineering technology students. Recent studies in engineering technology education have also emphasized the importance of application-oriented and industry-relevant instructional approaches that bridge theoretical knowledge with hands-on implementation and workforce preparation (Khan et al. 2026).

Recent studies have also examined different approaches for integrating AI and ML into engineering education. Hao et al. (2025) reviewed current efforts to incorporate AI into engineering curricula and emphasized that AI education in engineering programs requires careful consideration of both

technical content and pedagogical design. Vargas et al. (2020) further demonstrated that project-based learning can be used to teach AI to undergraduate engineering students by connecting AI concepts with real-world computer vision problems, teamwork, and applied problem solving. These studies suggest that AI/ML education in engineering should not only focus on technical knowledge, but also on how students learn, apply, and transfer AI concepts to engineering practice.

However, teaching AI/ML to students outside computer science remains challenging. Machine learning topics often require background knowledge in programming, statistics, linear algebra, and algorithmic thinking, which many non-CS students may not have fully developed. Mike and Hazzan (2022) noted that learners without sufficient mathematical preparation may struggle to understand ML algorithms if they are taught only through traditional theoretical approaches. Similarly, recent work on no-code AI education suggests that students with diverse academic backgrounds can benefit from tools that reduce programming barriers while still allowing them to engage with data collection, model training, and model evaluation (Sundberg et al. 2024). These findings are especially relevant to engineering technology students, whose preparation is often more focused on applied engineering practice than advanced mathematics or computer science.

Project-based and experiential learning provide a strong pedagogical foundation for addressing these challenges. Recent engineering technology studies have similarly shown that hands-on and implementation-centered learning environments improve student engagement and technical understanding in engineering applications (Oni et al. 2026). In engineering education, project-based learning has long been recognized as an effective way to connect technical knowledge with practical problem solving (Mills et al. 2003). Active learning research also shows that students often learn more effectively when they are actively engaged in applying concepts rather than only receiving information through traditional lectures (Prince 2004). Problem-based learning further emphasizes collaborative inquiry, self-directed learning, and reflection, with instructors serving more as facilitators than as the sole source of knowledge (Hmelo-Silver 2004). These ideas are consistent with experiential learning theory, which views learning as a process built through concrete experience, reflection, conceptual understanding, and active experimentation (Kolb 1984). Table 1 summarizes the major literature areas that informed the design of the proposed framework.

Taken together, the literature suggests that AI/ML education for engineering technology students should be designed differently from traditional computer science instruction. Prior studies have examined AI/ML integration in engineering education, project-based AI instruction, ML learning for non-CS students, and no-code AI tools. However, these areas are often treated as separate instructional strategies. Comparatively less work has focused on how these elements can be combined into a practical pedagogical framework specifically designed for MET students. In particular, there remains a need for an approach that integrates scaffolded AI/ML instruction, accessible AI tools, and capstone-based

Table 1. Summary of literature related to the framework design.

Literature Area	Representative References	Main Focus
AI literacy and workforce needs	Ng et al. 2021; Zawacki-Richter et al. 2019; Ellingrud et al. 2023; Boggs et al. 2023	AI literacy, AI use in higher education, and workforce demand
AI/ML in engineering and non-CS education	Hao et al. 2025; Vargas et al. 2020; Mike and Hazzan 2022; Sundberg et al. 2024	AI curriculum design in engineering education; use of no-code AI tools
Project-based learning and scaffolding	Mills and Treagust 2003; Bell 2010; Prince 2004; Hmelo-Silver 2004; Kolb 1984; Wood et al. 1976; Hmelo-Silver et al. 2007	Active, project-based, and experiential learning approaches
Engineering technology education	Khan et al. 2026; Oni et al. 2026; Turner et al. 2026; Jin and Zahraee 2026	Hands-on, implementation-centered, and industry-relevant education

engineering projects to reduce learning barriers while helping students develop meaningful AI/ML literacy and practical implementation skills.

To address this gap, this study proposes and evaluates a project-based pedagogical framework for teaching AI/ML to MET students. The framework uses the existing senior project structure as an applied learning environment where AI/ML concepts are introduced through scaffolded weekly instruction and reinforced through AI/ML-focused capstone projects. Instead of emphasizing advanced mathematical derivations or algorithm development, the approach focuses on application-driven instruction, guided implementation, and accessible AI tools that reduce programming and learning barriers. This paper expands preliminary conference work (Li et al. 2025) by incorporating additional implementation data and a more complete analysis of the pedagogical framework.

The main contribution of this paper is the development and evaluation of a project-based pedagogical framework specifically designed for teaching AI/ML to MET students. Rather than simply adding AI/ML topics to an existing course, the framework combines scaffolded AI/ML instruction, accessible AI tools as instructional supports, and capstone-based engineering projects into one connected learning pathway. The framework is evaluated using multiple forms of evidence, including pre- and post-course assessments, topic-specific quizzes, student self-evaluations, reflection responses, and capstone project outcomes. Through this approach, the study provides a practical model for helping engineering technology students develop foundational AI/ML literacy and apply AI-enabled tools in real engineering contexts.

2. Pedagogical Framework and Instructional Design

The proposed framework was designed to help MET students learn AI/ML through a structured, application-oriented process within the senior project experience. Rather than treating AI/ML as a standalone theoretical subject, the framework connects basic AI/ML instruction, accessible tools, and capstone project work. This structure supports students in developing AI/ML literacy and implementation skills while maintaining the hands-on focus of engineering technology education.

2.1 Scaffolded AI/ML Instruction

The weekly AI/ML instruction was designed as the first layer of the pedagogical framework. Its purpose was not to train MET students to become AI/ML specialists, but to provide the conceptual foundation needed for them to understand and apply AI-enabled tools in their senior projects. Since many students had limited prior exposure to AI/ML, the lectures were structured to gradually move from basic awareness to practical implementation. The instructional sequence began with fundamental AI/ML concepts and common engineering applications, then moved into supervised learning, dataset preparation, model evaluation, neural networks, computer vision, natural language processing, and reinforcement learning. This progression helped students build a working understanding of the AI/ML process before applying these ideas in their capstone projects. Table 2 summarizes the weekly AI/ML lecture topics, the main content covered, and their connection to the senior projects.

A key feature of the instructional design was the use of scaffolding, which has long been used to describe instructional support that helps learners complete tasks they could not complete independently at the early stage of learning (Wood et al. 1976, Hmelo-Silver et al. 2007). Each topic was introduced at a level appropriate for MET students, with emphasis placed on conceptual understanding, engineering relevance, and practical use rather than advanced mathematical derivations. For example, supervised learning was introduced through classification problems and simple models before students encountered more advanced tools. Engineering technology education research has also highlighted the importance of gradually connecting conceptual understanding with applied implementation experiences through structured instructional activities (Turner et al. 2026). Dataset preparation and model evaluation were taught as essential steps in the AI/ML workflow, helping students understand the importance of data quality, training and testing, and performance metrics. More advanced topics, such as neural networks, convolutional neural networks, natural language processing, and reinforcement learning, were introduced through simplified explanations and application examples so that students could understand their purpose and potential engineering uses without being overwhelmed by theoretical complexity.

The lectures were also intentionally aligned with the senior project topics. Concepts related to image classification, computer vision, and object detection supported projects involving automated sorting, defect detection, and quality control. Topics related to natural language processing and large language models supported the voice-controlled robotic arm project. Reinforcement learning was introduced at a conceptual level to expose students to its potential applications in robotics and autonomous systems,

Table 2. Scaffolded AI/ML instruction sequence.

Topic	Core Concepts	Instructional Purpose	Connection to Projects
Introduction to Machine Learning	ML concepts; supervised, unsupervised, and reinforcement learning; engineering examples	Help students understand what ML is and how it can be used in engineering	Help students identify where AI/ML fits in their project ideas
Supervised Learning and Classification	Classification problems; perceptron model; basic training process; simple Python example	Introduce how a model learns from labeled data	Support image classification tasks in the automated sorting project
Dataset Preparation and Model Evaluation	Data types; encoding; preprocessing; train/test split; accuracy, precision, recall, and confusion matrix	Help students understand why data quality and model evaluation matter	Guide students in collecting, labeling, testing, and improving project datasets
Regression and Unsupervised Learning	Linear regression; classification vs. regression; K-means clustering; Python examples	Introduce prediction and grouping methods beyond classification	Help students think about other possible engineering uses of ML, such as sensor data or system behavior analysis
Deep Learning and Neural Networks	Artificial neurons; layers; activation functions; forward propagation; TensorFlow example	Give students a basic understanding of deep learning models	Prepare students to understand the models behind image recognition and NLP tools
CNNs and Computer Vision	CNN structure; convolution; pooling; image classification; OpenCV and TensorFlow examples	Connect deep learning with image-based engineering applications	Support camera-based sorting and wind turbine blade defect detection
Natural Language Processing	RNN/LSTM concepts; transformers; LLMs; OpenAI API; prompt design	Show how language can be processed and converted into useful information	Support the voice-controlled robotic arm project using spoken commands and ChatGPT interpretation
Reinforcement Learning	Agent, environment, reward, Q-table, Bellman equation, epsilon-greedy policy; maze example	Introduce the basic idea of learning through rewards	Provide background for future robotics and autonomous control applications

even though it was not the central focus of all projects. This alignment helped students see the immediate connection between lecture content and project implementation, which strengthened motivation and reinforced learning through application.

To keep the instruction manageable within the existing senior project course, the lecture series was delivered in a seminar-like format with limited additional workload. Each session focused on essential concepts, practical examples, and connections to project work. Short topic-specific quizzes were used to encourage engagement and provide feedback on student understanding. In this way, the weekly instruction served as a scaffold that prepared students to use accessible AI tools and apply AI/ML concepts in practical engineering contexts.

2.2 Accessible AI Tools as Instructional Supports

Accessible AI tools were used as an important instructional support in this framework. Since many MET students had limited programming experience and limited background in advanced mathematics, requiring them to build AI/ML algorithms from scratch would likely create unnecessary barriers at the early stage of learning. Therefore, the course intentionally introduced a combination of no-code tools, established AI/ML libraries, AI APIs, instructor-provided sample code, and AI-assisted programming support. Tools such as Google Teachable Machine, Roboflow, scikit-learn, TensorFlow, PyTorch, OpenCV, and the OpenAI API allowed students to use existing models, training functions, computer vision routines, and language-processing capabilities without having to develop the underlying algorithms independently (Pedregosa et al. 2011, Abadi et al. 2016, Paszke et al. 2019, Bradski 2000). These supports helped students experience the major steps of an AI/ML workflow while focusing on the engineering problem, data quality, model behavior, and interpretation of results.

No-code and low-code platforms played a particularly important role in helping students understand the AI/ML workflow at the early stage of the projects. For computer vision applications,

Google Teachable Machine and Roboflow were used to support image classification and object detection tasks. These platforms allowed students to collect images, label data, train models, test performance, and deploy trained models with a much lower programming burden. For example, Google Teachable Machine provided a simple way for students to experience supervised image classification in the automated sorting project, while Roboflow supported defect annotation and object detection in the wind turbine blade inspection project. In both cases, the tools were not used simply for convenience. They served as instructional scaffolds that made key AI/ML steps, including data preparation, model training, testing, and deployment, more visible and manageable for students.

At the same time, coding was not avoided completely. Python-based tools were introduced where they were needed for implementation and integration. During the lectures, the instructor provided sample Python code for tasks such as model training, webcam image capture, OpenCV processing, use of pre-trained models, and API-based communication. These examples served as starting templates that students could study, modify, and adapt for their own projects when appropriate. This approach allowed students to gain practical coding experience while avoiding the frustration of developing every component from the beginning. It also helped them understand how AI/ML tools can be connected with engineering systems such as cameras, robotic arms, and external APIs. Large language models were also used as learning supports for coding and problem solving, consistent with recent work suggesting that LLMs can support explanation, feedback, and programming-related learning tasks when used with appropriate guidance (Kasneci et al. 2023, Ekin 2026). Students were encouraged to use tools such as ChatGPT to help interpret error messages, understand unfamiliar code, revise Python scripts, and generate possible implementation ideas. In the voice-controlled robotic arm project, an LLM API was also used as part of the technical implementation, where natural language commands were interpreted and converted into structured robot actions. In this way, LLMs served two roles: they supported students during the learning and development process, and they also became part of one project's AI-enabled engineering solution.

Overall, accessible tools, instructor-provided sample code, and LLM-assisted support helped students move from concept understanding to working prototypes. These supports lowered the initial technical barrier while still allowing students to engage with meaningful AI/ML workflows, including data preparation, model testing, system integration, troubleshooting, and application to real engineering problems.

2.3 Project-Based Reinforcement Through Capstone Projects

The capstone projects served as the main project-based reinforcement component of the pedagogical framework. This design is consistent with project-based learning approaches that emphasize applying knowledge through extended, practical, and student-centered work (Mills et al. 2003, Bell 2010). While the weekly lectures introduced AI/ML concepts and accessible tools, the senior projects required students to apply these ideas to practical engineering problems. This was important because many AI/ML concepts, such as supervised learning, dataset preparation, model evaluation, computer vision, and natural language processing, can remain abstract if they are only taught through lectures or small examples. By embedding AI/ML learning into capstone projects, students were able to connect these concepts with physical systems, testing procedures, hardware integration, and engineering decision-making.

The projects were intentionally designed to provide different contexts for applying AI/ML in engineering technology. Instead of assigning the same AI/ML task to all students, each team applied related concepts to a different engineering problem, such as robotic sorting, quality inspection, defect detection, computer vision, or human-robot interaction. In most projects, AI/ML was not the entire project, but one component within a broader engineering design and problem-solving process. Students had to combine AI/ML tools with mechanical design, sensor or camera setup, robotic control, hardware integration, testing, and troubleshooting. This project variety helped students see that AI/ML is not a single tool or isolated technique, but a set of methods that can be integrated into different engineering systems. Figure 1 shows representative examples of the AI/ML-focused capstone projects implemented in this framework. Table 3 summarizes the AI/ML-focused capstone projects and their role in reinforcing student learning.

These projects supported AI/ML learning in several ways. First, students had to move beyond simply learning definitions and concepts. They needed to collect or prepare data, train models, test model outputs, interpret prediction confidence, and revise their approach when performance was weak. Second, students had to connect AI/ML tools with physical engineering systems, including webcams, robotic arms, grippers, Arduino controllers, relays, and Python-based communication packages. This integration helped students understand that AI/ML perfor-

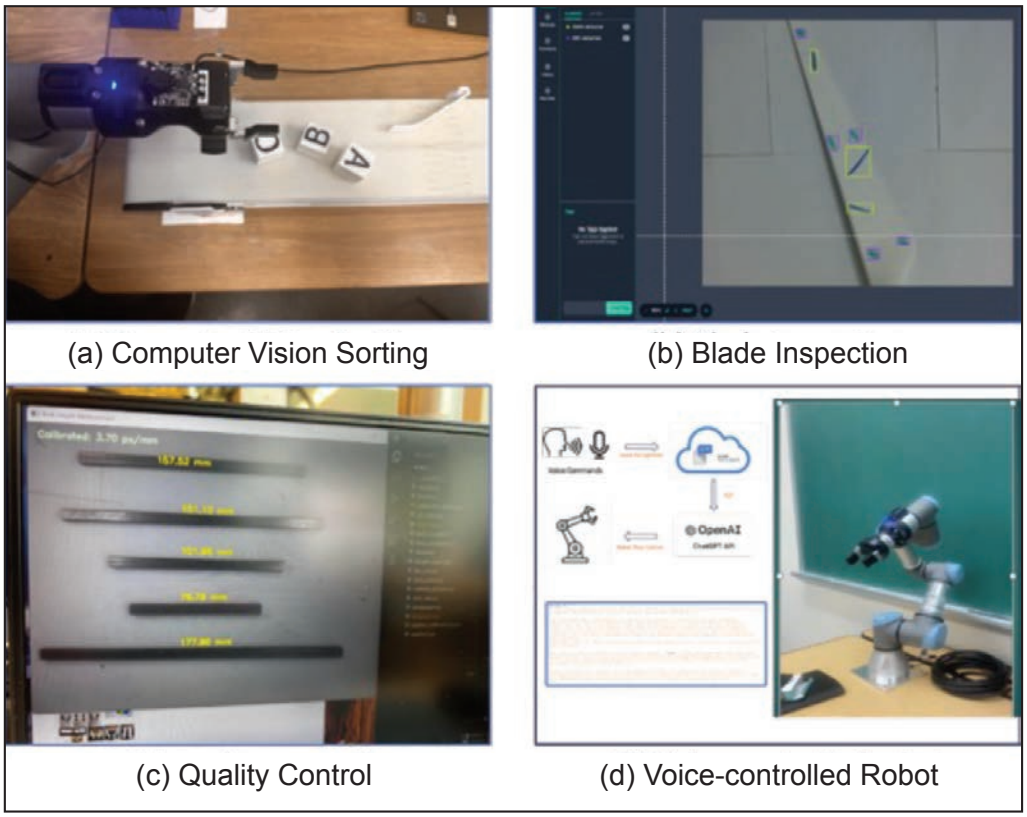


Figure 1. Representative AI/ML-focused capstone projects implemented in the proposed framework: (a) intelligent sorting system based on computer vision, (b) automated wind turbine blade inspection simulation, (c) assessment of an automated quality control system, and (d) voice-controlled robotic arm using NLP.

mance in engineering applications depends not only on the model itself, but also on lighting, calibration, part positioning, mechanical design, data quality, and system timing.

The projects also helped students understand the limitations of AI/ML tools in real applications. Several teams encountered issues such as inconsistent detection accuracy, misclassification, lighting sensitivity, limited training data, hardware communication problems, and the need for repeated calibration. These challenges were pedagogically valuable because they required students to troubleshoot the complete engineering system rather than treating AI/ML as a black-box solution. For example, in the quality-control project, students identified challenges related to detection accuracy, false readings, environmental sensitivity, calibration, and limited training data, and then proposed improvements such as expanding the dataset, improving lighting, adding fixtures, and improving calibration routines.

Overall, the capstone projects provided a practical setting for students to apply AI/ML concepts, test their ideas, explain their results, and develop practical experience with AI-enabled engineering problem solving. In this framework, the senior project served as the main bridge between classroom instruction and engineering implementation, allowing students to turn AI/ML concepts into working systems.

3. Assessment Design, Data Collection, and Results

The pedagogical framework was implemented in the Senior Projects course in the MET program at Farmingdale State College. The course is a required capstone experience in which students work in teams to solve practical engineering problems through design, implementation, testing, documentation, and presentation. Because of its applied and project-based structure, the course provided a suitable setting for integrating AI/ML learning without creating a separate standalone AI/ML course.

To evaluate the effectiveness of the proposed pedagogical framework, multiple forms of assessment were used to examine both conceptual learning and practical application. The assessment design included pre- and post-course quizzes to measure overall learning gains, topic-specific quizzes to evaluate understanding of individual AI/ML topics, student self-evaluation and reflection surveys to capture learning experiences and perceived challenges, and capstone

Table 3. AI/ML-Focused capstone projects and pedagogical reinforcement.

Project	Engineering Application	AI/ML Component	Key Project Outcome	Pedagogical Reinforcement
Automated sorting system using computer vision	Robotics and automation	Image classification using Google Teachable Machine	Students trained an image classification model and used the model output to control the robotic arm and conveyor for automated sorting tasks.	Supervised learning, image data collection, model testing, and robot integration
Automated wind turbine blade inspection	Defect detection and inspection	Object detection using Roboflow	Students annotated blade defect images, trained a defect detection model, and integrated the model with a robotic arm to simulate the blade inspection process.	Data annotation, defect classification, model confidence, and real-time inspection
Voice-controlled robotic arm with NLP	Human-robot interaction	Speech recognition and OpenAI API	Students developed a voice-command system that converted spoken commands into text, interpreted the intended robot action, and changed the robotic arm pose accordingly.	Speech-to-text processing, NLP, prompt design, API use, and AI-assisted robotic control
Automated quality control using computer vision	Manufacturing quality inspection	Computer vision-based measurement and inspection	Students used computer vision to measure different part features and evaluate how lighting, training images, and setup conditions affected inspection accuracy.	Computer vision measurement, inspection accuracy, calibration, lighting effects, training data quality, and automated quality-control evaluation
Automated sorting with custom grippers and ML	Robotic sorting and end-effector design	Image classification, custom gripper design, and robotic arm control	Students designed custom finger, vacuum, and magnetic grippers, trained an image classification model, and used the model output to activate the proper gripper for sorting tasks.	Image classification, gripper design, robot integration, hardware/software control, and automated sorting

project evaluations to assess students' ability to apply AI/ML tools in engineering contexts. This mixed assessment approach was selected because the framework aimed not only to improve students' knowledge of AI/ML concepts, but also to support their ability to use these concepts in real engineering projects.

Across two semesters, the framework was implemented in AI/ML-focused senior projects with a total of 17 students, and the course and assessments were conducted by the same instructor. Response counts included 17 paired pre/post quiz responses, 14–17 responses per topic-specific quiz, 17 student surveys, and 17 capstone project evaluations. All 17 respondents provided valid responses to the closed-ended survey items presented in Figures 4 and 5. The project-challenge question presented in Figure 6 allowed students to select more than one response; therefore, the category counts could exceed the number of respondents. Because the topic-specific quizzes and student surveys were voluntary, voluntary-response bias is possible. The following subsections present the assessment methods and results.

3.1 Pre- and Post-Course Learning Gains

To measure overall learning gains, students completed the same multiple-choice quiz at the beginning of the first class and again during the final class meeting. The quiz was intentionally designed to assess basic AI/ML literacy rather than advanced mathematical derivations or algorithm development. Questions focused on core ideas such as types of machine learning, supervised learning, dataset preparation, model evaluation, neural networks, computer vision, natural language processing, and reinforcement learning. Because the quiz measured foundational concepts, it was expected that some students could answer a portion of the questions correctly before the course based on general exposure to AI/ML, informal learning, or prior technology experience. The quiz was instructor-developed and aligned directly with the instructional topics presented in Table 2. It was not a standardized measure of general AI literacy. Formal pilot validation, independent expert validation, and item-level reliability analysis were not conducted for this implementation. The scores are therefore interpreted as performance on a course-aligned assessment of foundational AI/ML concepts.

The results showed a clear improvement in student performance. As shown in Figure 2, the average pre-

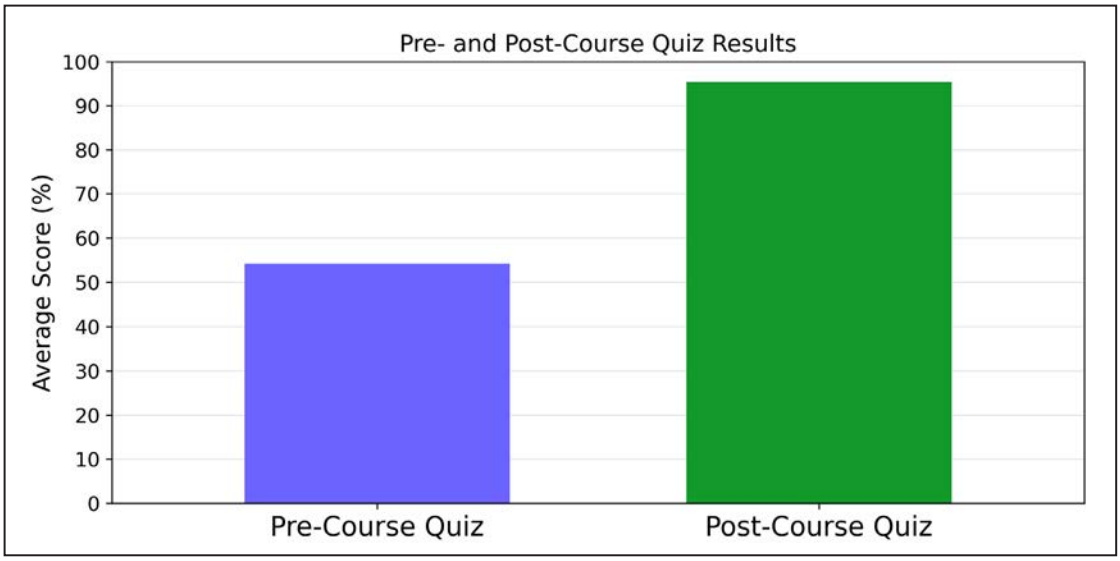


Figure 2. Comparison of average pre-course and post-course quiz scores.

course quiz score was 27.1 out of 50, indicating that students had some awareness of basic AI/ML ideas but still lacked a complete understanding of the concepts. After completing the scaffolded instruction and applying AI/ML tools in their senior projects, the average post-course score increased to 47.7 out of 50. The post-course mean of 47.7 out of 50, or 95.3%, indicates strong performance on the foundational concepts assessed. However, it also suggests a ceiling effect because the instrument provided limited ability to distinguish among students near the upper end of performance. Note that possible testing effects may have been introduced since the same quiz was used twice.

Figure 3(a) shows the individual pre- and post-course quiz scores for all students. Each student showed improvement from the pre-course quiz to the post-course quiz, suggesting that the learning gain was consistent across the group rather than being driven by only a small number of students. Figure 3(b) shows the distribution of individual learning gains, which were generally clustered around the average improvement. This indicates that the observed gain was broadly shared across the cohort.

To further examine whether the improvement was statistically significant, a paired-sample t-test was conducted using the 17 paired pre- and post-course quiz scores. As summarized in Table 4, the average

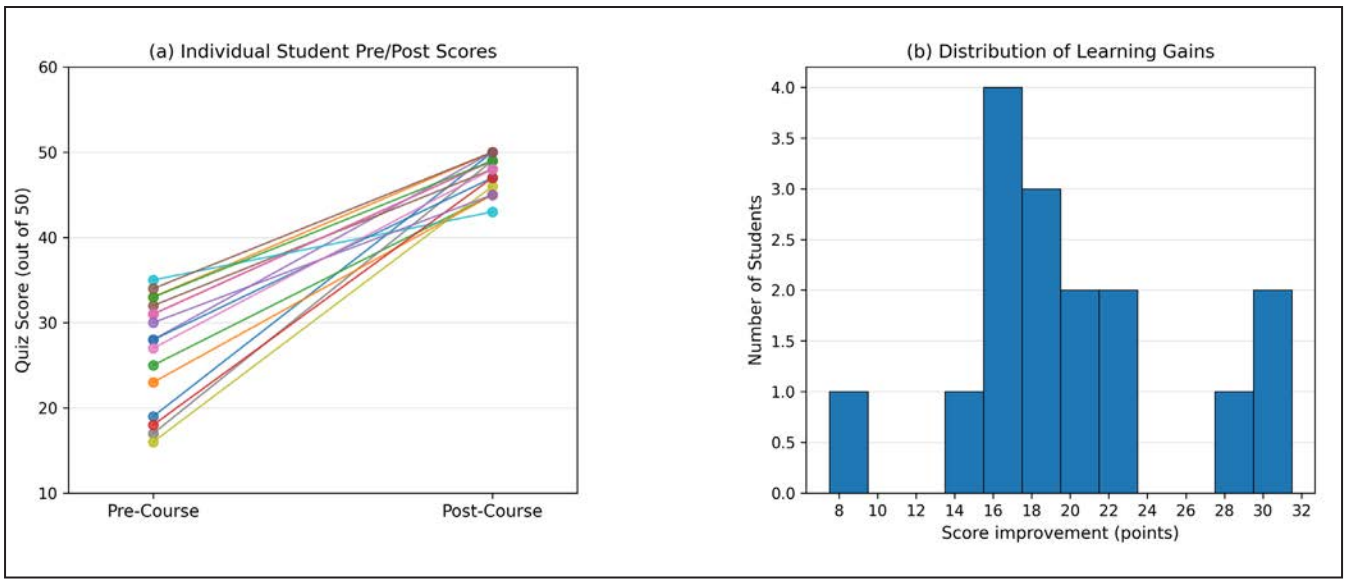


Figure 3. Analysis of individual learning gains: (a) pre- and post-course quiz scores for each student, where each color represents a different student; and (b) distribution of score improvements, calculated as post-course score minus pre-course score.

Table 4. Summary of pre- and post-course quiz results.

Metric	Value
Number of students	16
Mean pre-course score	27.06/50
Mean post-course score	47.65/50
Mean improvement	20.59 points
Pre-course percentage	54.1%
Post-course percentage	95.3%
Paired t-test	t(16)=12.98
p-value	p < 0.001

improvement was 20.59 points, and the paired t-test showed that the improvement was statistically significant, t(16)=12.98, p<0.001. This result provides quantitative evidence of improved foundational AI/ML literacy within this cohort. It does not isolate the causal effect of the framework because the study did not include a comparison group and used the same assessment at both measurement points.

3.2 Topic-Specific Quiz Results

In addition to the pre- and post-course quiz, topic-specific quizzes were used to evaluate students' understanding of individual AI/ML topics. These quizzes were given after each major lecture topic and included short multiple-choice questions focused on the concepts covered in that topic. Unlike the pre- and post-course quiz, which focused on broad and fundamental AI/ML literacy, the topic-specific quizzes were more closely connected to the detailed content of each lecture and required students to engage with the material at a deeper and more challenging level. Therefore, they provided a more direct measure of how well students understood specific concepts during the instructional sequence.

The results of the topic-specific quizzes are summarized in Table 5. The average scores ranged from 62.4% to 89.7% across the eight topics. Lower scores appeared in the earlier and more technical topics, especially the topic focused on dataset preparation and model evaluation. This result is reasonable because these topics involved more abstract concepts, such as data preprocessing, training and testing, model performance metrics, overfitting, and underfitting, which can be difficult for students who are new to AI/ML. Higher scores were observed in later applied topics, including deep learning, computer vision, natural language processing, and reinforcement learning. This may be partly because these topics were introduced through ready-to-use tools, application examples, and project connections rather than extensive theoretical treatment. Several of these topics were also closely connected to project tasks, including automated sorting, defect inspection, and voice-controlled robotic systems.

Overall, the topic-specific quiz results show that MET students were able to follow the AI/ML lectures designed within this framework, which made foundational AI/ML topics accessible at an appropriate level. Because the study did not include a control group, these results should be interpreted as evidence of the framework's feasibility rather than as direct proof of its effectiveness alone.

3.3 Student Self-Evaluation and Reflection

Student self-evaluation and reflection were used to complement the quiz results and provide insight into students' perceived learning, confidence, and project experience. The survey asked students to evaluate their understanding of AI/ML topics covered in the lectures and reflect on how the capstone projects helped them apply these concepts in engineering contexts. For the lecture-related self-evaluation, students rated their confidence using a four-point scale: Excellent = 4, Good = 3, Average = 2, and Poor = 1. Figure 4 shows the student self-evaluation scores for AI/ML topic understanding.

The average scores for the 16 AI/ML topic questions ranged from 2.88 to 3.82, indicating that students generally rated their understanding between "Good" and "Excellent." Students reported stronger confidence in topics closely connected to project implementation, such as practical ML applications, supervised learning, model evaluation, CNNs, and AI/ML tools. Lower scores were observed for more abstract topics, including model-based versus model-free reinforcement learning (2.88) and Q-learning (3.06). This result is reasonable because reinforcement learning was introduced mainly as an introductory topic and was not required in most capstone projects.

Table 5. Average scores for topic-specific quizzes.

Topic-Specific Quizzes	Average Score	Valid n
#1	76.2%	17
#2	66.5%	16
#3	62.4%	14
#4	72.1%	15
#5	82.8%	17
#6	86.5%	16
#7	87.1%	16
#8	89.7%	15

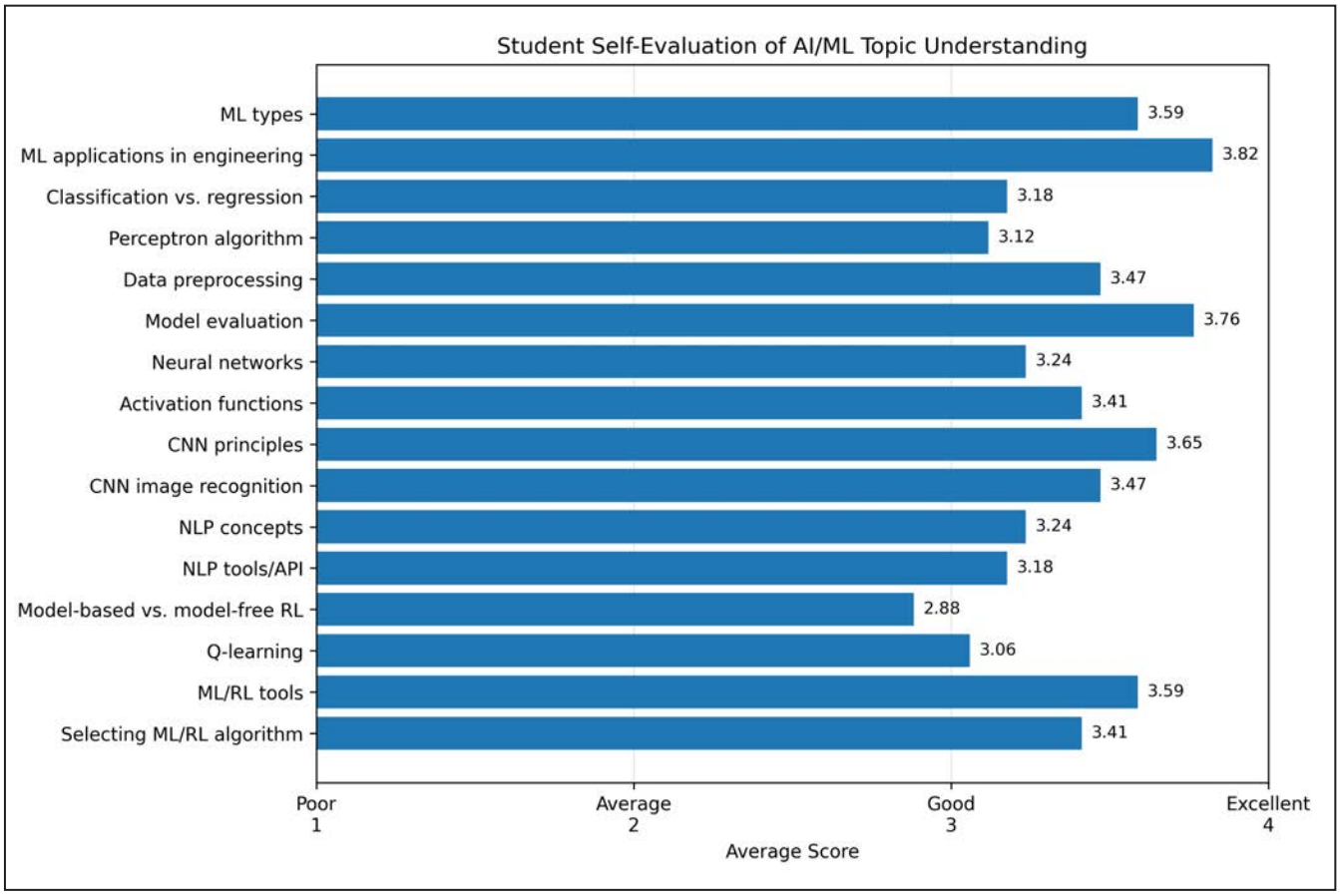


Figure 4. Student self-evaluation scores for AI/ML topic understanding.

As shown in Figure 5, the project-related self-evaluation results were also positive. Students rated their understanding of technical concepts involved in the project at 3.53, the effectiveness of the project in understanding real-world AI/ML applications at 3.71, and their confidence in explaining the project to others at 4.0. Reflection responses further showed that students viewed the senior project as the practical part of their AI/ML learning experience. Many students noted that the projects helped them connect AI/ML concepts with Python programming, robotics, computer vision, data processing, and engineering problem solving.

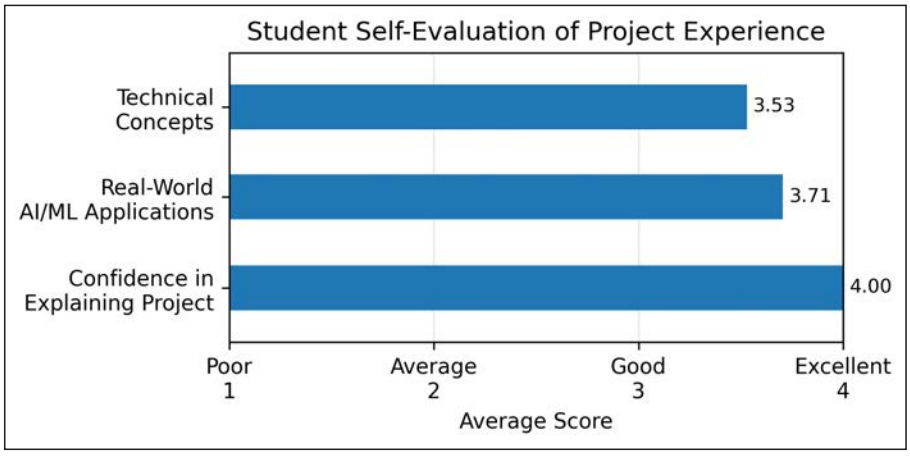


Figure 5. Student self-evaluation scores for capstone project experience.

At the same time, Figure 6 shows that students still faced several challenges during project implementation. The most frequently reported challenges were writing code for implementation and debugging/troubleshooting, followed by time management, tool use, team collaboration, and other issues. These results are consistent with the background of many MET students, who had limited prior experience with programming and AI/ML tools. The findings suggest that future implementations could benefit from earlier

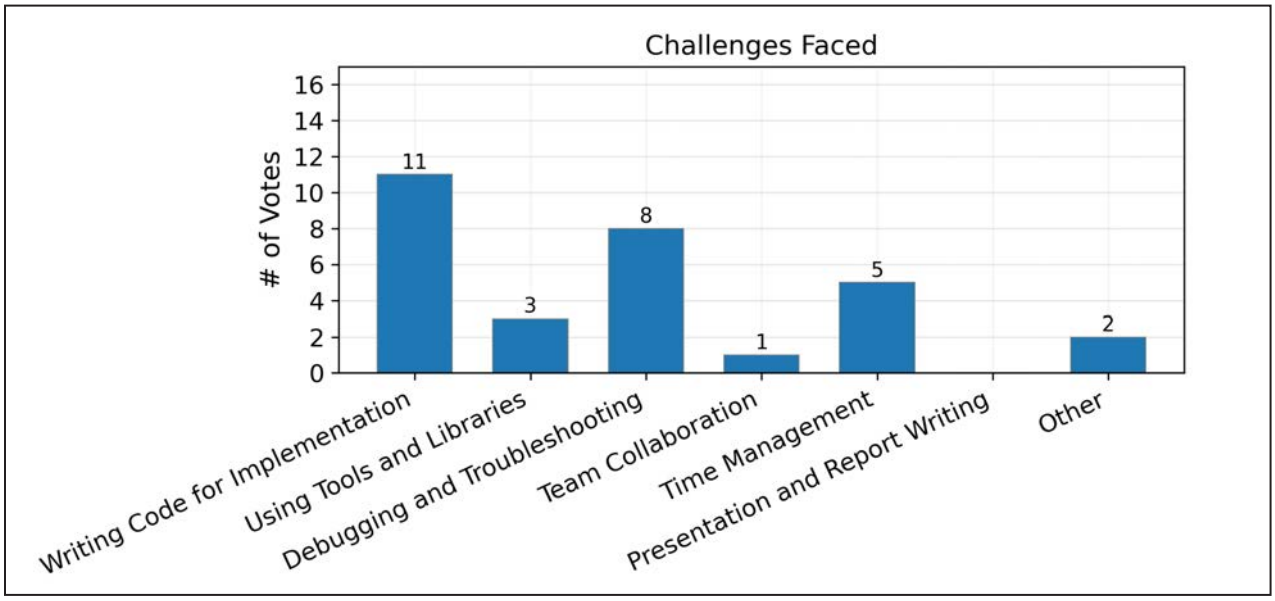


Figure 6. Student-reported challenges during AI/ML-focused capstone projects. Students could select more than one response.

preparation in Python programming, robot control, and basic AI/ML tools.

3.4 Capstone Project Evaluation

Capstone project evaluation was used to assess students' ability to apply AI/ML concepts in practical engineering contexts. Unlike quizzes and self-evaluations, the project evaluation focused on whether students could integrate AI/ML tools into broader engineering systems involving hardware, software, testing, and troubleshooting. The five capstone projects were completed in teams, while the assessment dataset contained 17 student-level course scores. Students were therefore nested within project teams. The scores are summarized descriptively and are not treated as 17 independent project replications.

The projects were evaluated using the existing capstone assessment structure, which included project design and implementation (50%), presentation (20%), and report writing (30%). The evaluation considered technical content, system complexity, implementation quality, use of resources, communication of results, documentation, and the ability to respond to questions. Any small bonus points related to quiz participation were excluded from this analysis.

The project scores ranged from 75% to 94.3%, with an average score of 86.16%. These results indicate that students were generally able to complete functional AI/ML-related engineering projects and communicate their work effectively. While the scores should not be interpreted as a direct measure of AI/ML knowledge alone, they show that students could incorporate AI/ML tools into broader engineering design tasks. This finding supports the central goal of the framework, which was to help MET students use AI/ML as part of applied engineering problem solving rather than as an isolated computational topic.

4. Discussion

The goal of the proposed framework was to make AI/ML learning accessible to MET students and help them understand how AI/ML can be used to solve real engineering problems. The assessment results suggest that the framework achieved its intended purpose. The pre- and post-course quiz results showed improvement in foundational AI/ML literacy, while the topic-specific quizzes, self-evaluations, reflection responses, and capstone project outcomes showed that students were able to connect AI/ML concepts with practical engineering applications. Taken together, these results support the value of the framework as an accessible and application-driven approach for MET students.

One important finding is that the senior project format made AI/ML learning more meaningful for MET students. Similar findings have been reported in engineering technology education, where experiential and application-driven learning environments help students connect technical concepts with practical engineering implementation and workforce-oriented skills (Jin et al. 2026). In most projects, AI/ML was not the entire project, but one part of a broader engineering system involving hardware, cameras, robot control, grippers, Python scripts, testing, and troubleshooting. This helped students see AI/ML as an engineering tool rather than an isolated computer

science topic. The project work required students to consider practical issues such as data quality, lighting, calibration, part positioning, model confidence, and hardware/software integration. These issues are difficult to fully understand through lectures alone.

The results also show that accessible tools were useful but did not eliminate all barriers. Tools such as Google Teachable Machine, Roboflow, instructor-provided code examples, and LLM-assisted coding support helped students start their projects and build working prototypes. At the same time, student feedback showed that coding, debugging, tool use, and hardware/software troubleshooting remained major challenges. This suggests that accessible tools should be viewed as scaffolding, not as a complete replacement for programming and system-integration preparation (Wood et al. 1976, Hmelo-Silver et al. 2007).

The assessment results also show that students benefited most when AI/ML concepts were directly connected to project tasks. This was especially clear because most current projects focused on computer vision, classification, object detection, and NLP-based robot control. Students were more confident when they could immediately see how a concept or tool supported their own project work. In contrast, topics that were less directly tied to project implementation, such as reinforcement learning, were harder for students to internalize because they had fewer opportunities to apply them in the project. This suggests that future implementations should align AI/ML instruction more closely with project needs and avoid adding too many topics only for broad coverage.

The implementation also revealed that coding and debugging were the biggest challenges for many MET students. The difficulties were not mainly caused by the AI/ML concepts themselves, but by the need to translate those concepts into working code and connect them with hardware, cameras, robot control, APIs, and other tools. In other words, students could often understand what the AI/ML tool was supposed to do, but still struggled when they had to make the full system work reliably. Future versions of the framework should therefore provide more structured support early in the project, such as short preparation activities, starter code, tool demonstrations, and checkpoints for data quality and system functionality. In the longer term, a dedicated programming course or programming module for MET students, especially one focused on Python, hardware communication, and engineering automation, may further reduce these barriers. These changes would keep the project-based nature of the framework while reducing unnecessary barriers during implementation.

Several limitations should be noted. First, the study included only 17 students. This is partly due to the nature of senior projects, since not all students choose AI/ML-related projects and one instructor can only supervise a limited number of teams. Second, the study did not include a control group. Since AI/ML senior projects require instructional support, it was not appropriate to ask students to complete similar projects without guidance. Therefore, the assessment results should be interpreted mainly as evidence of the feasibility of the proposed framework, which is an important first step toward integrating AI/ML instruction into MET education. Future work will further refine the instructional content, accumulate more assessment data over time, and share instructional materials as OER to support adoption by other programs.

5. Conclusion

This study presented a project-based pedagogical framework for teaching AI/ML to MET students through three connected components: scaffolded AI/ML instruction, accessible AI tools as instructional supports, and project-based reinforcement through AI/ML-focused senior projects. The framework was designed not to train students as AI/ML experts, but to help them understand basic AI/ML concepts, become familiar with common AI/ML workflows, and apply AI-enabled tools to real engineering problems.

The findings provide preliminary evidence that the framework is feasible and that student participation was associated with substantial gains on a course-aligned assessment of foundational AI/ML concepts. These results suggest that the framework matched the applied and hands-on nature of engineering technology education. Scaffolded instruction gave students an accessible conceptual foundation. No-code tools, instructor-provided examples, and LLM-assisted support reduced the initial learning barrier. Senior projects then allowed students to connect AI/ML concepts with physical systems, testing, troubleshooting, and engineering implementation.

The main contribution of this work is the development and evaluation of a practical pedagogical pathway for introducing AI/ML into engineering technology education. Rather than simply adding AI/ML topics to an existing course, the framework shows how AI/ML learning can be organized, supported, and reinforced through practical engineering projects. Overall, this study provides a practical model for making AI/ML learning accessible, scaffolded, and application-driven for engineering technology students.

References

Abadi, Martín, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, et al. 2016. "TensorFlow: A System for Large-Scale Machine Learning." In *Proceedings of the 12th USENIX Symposium on Operating Systems Design and Implementation*, 265–283.

Bell, Stephanie. 2010. "Project-Based Learning for the 21st Century: Skills for the Future." *The Clearing House: A Journal of Educational Strategies, Issues and Ideas* 83 (2): 39–43.

Boggs, A. S., K. Buchanan, H. Evans, D. Griffith, D. Meritis, L. Ng, A. Sberegaeva, and M. Stephens. 2023. "National Institute of Standards and Technology Environmental Scan 2023: Societal and Technology Landscape to Inform Science and Technology Research." NIST Internal Report 8482. National Institute of Standards and Technology.

Bradski, Gary. 2000. "The OpenCV Library." *Dr. Dobb's Journal of Software Tools* 25 (11): 120–125.

Ekin, Sabit. 2026. "Prompt Engineering for ChatGPT: A Quick Guide to Techniques, Tips, and Best Practices." *Journal of Engineering Technology* 43 (1): 52–68. doi:10.18260/jet.43.1.5.

Ellingrud, Kweilin, Saurabh Sanghvi, Anu Madgavkar, Gurneet Singh Dandona, Michael Chui, Olivia White, and Paige Hasebe. 2023. "Generative AI and the Future of Work in America." McKinsey Global Institute.

Hao, Yijia, Yushi Liu, Bo Liu, George Amarantidis, and Rami Ghannam. 2025. "Integrating AI in Engineering Education: A Comprehensive Review and Student-Informed Module Design for UK Students." *IEEE Transactions on Education*. doi:10.1109/TE.2025.3536105.

Hmelo-Silver, Cindy E. 2004. "Problem-Based Learning: What and How Do Students Learn?" *Educational Psychology Review* 16 (3): 235–266. doi:10.1023/B.0000034022.16470.f3.

Hmelo-Silver, Cindy E., Ravit Golan Duncan, and Clark A. Chinn. 2007. "Scaffolding and Achievement in Problem-Based and Inquiry Learning: A Response to Kirschner, Sweller, and Clark (2006)." *Educational Psychologist* 42 (2): 99–107. doi:10.1080/00461520701263368.

Jin, Ge, and Mohammad A. Zahraee. 2026. "Evolutional Roadmap from BS Degree to Doctoral Degree in Technology." *Journal of Engineering Technology* 43 (1): 6–16.

Kasneci, Enkelejda, Kathrin Sessler, Stefan Küchemann, Maria Bannert, Daryna Dementieva, Frank Fischer, Urs Gasser, et al. 2023. "ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education." *Learning and Individual Differences* 103: 102274. doi:10.1016/j.lindif.2023.102274.

Khan, Muhammad S., Anis Fatima, and John Irwin. 2026. "In Teaching Lean Manufacturing with Digital Twin: A Modern Approach to Engineering Education." *Journal of Engineering Technology* 43 (1): 28–38. doi:10.18260/jet.43.1.3.

Kolb, David A. 1984. *Experiential Learning: Experience as the Source of Learning and Development.* Englewood Cliffs, NJ: Prentice Hall.

Li, W., Altuger-Genc, G., Hung, Y., Zhang, Z., and Tatoglu, A. 2025. "Integrating AI/ML Learning in Senior Projects for Mechanical Engineering Technology Students." *Proceedings of the 2025 ASEE Annual Conference & Exposition*, Montreal, Canada.

Mike, Koby, and Orit Hazzan. 2022. "Machine Learning for Non-Major Data Science Students: A White Box Approach." *Statistics Education Research Journal* 21 (2): Article 10.

Mills, Julie E., and David F. Treagust. 2003. "Engineering Education—Is Problem-Based or Project-Based Learning the Answer?" *Australasian Journal of Engineering Education* 3 (2): 2–16.

Ng, Davy Tsz Kit, Jac Ka Lok Leung, Samuel Kai Wah Chu, and Maggie Shen Qiao. 2021. "Conceptualizing AI Literacy: An Exploratory Review." *Computers and Education: Artificial Intelligence 2*: 100041. doi:10.1016/j.caeai.2021.100041.

Oni, Oluwasola S., Chloé Dydasco, James N. Onukwu, Oluyemisi Oloniyo, Yetunde Adaramola, Pearl Oladele, Olusola Adesope, Bernie VanWie, Jacqueline Gartner, and Prashanta Dutta. 2026. "Low-Cost Desktop Learning Modules: Effect of Implementation Types on Student's Learning Performance." *Journal of Engineering Technology* 43 (1): 40–51. doi:10.18260/jet.43.1.4.

Paszke, Adam, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, et al. 2019. "PyTorch: An Imperative Style, High-Performance Deep Learning Library." *Advances in Neural Information Processing Systems* 32.

Pedregosa, Fabian, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, et al. 2011. "Scikit-Learn: Machine Learning in Python." *Journal of Machine Learning Research* 12: 2825–2830.

Prince, Michael. 2004. "Does Active Learning Work? A Review of the Research." *Journal of Engineering Education* 93 (3): 223–231. doi:10.1002/j.2168-9830.2004.tb00809.x.

Sundberg, Leif, and Jonny Holmström. 2024. "Teaching Tip: Using No-Code AI to Teach Machine Learning in Higher Education." *Journal of Information Systems Education* 35 (1): 56–66. doi:10.62273/CYPL2902.

Turner, Matthew, Joseph Dues Jr., Thomas Lucas, Damon Sisk, and Andy Schaffer. 2026. "Using Product Archeology to Increase High School Student Interest in Engineering Technology Majors." *Journal of Engineering Technology* 43 (1): 18–26. doi:10.18260/jet.43.1.2.

Vargas, Manuel, Tabita Nuñez, Miguel Alfaro, Guillermo Fuertes, Sebastián Gutierrez, Rodrigo Ternero, Jaime Sabattin, L. Banguera, C. Duran, and M. A. Peralta. 2020. "A Project Based Learning Approach for Teaching Artificial Intelligence to Undergraduate Students." *International Journal of Engineering Education* 36 (6): 1773–1782.

Wood, David, Jerome S. Bruner, and Gail Ross. 1976. "The Role of Tutoring in Problem Solving." *Journal of Child Psychology and Psychiatry* 17 (2): 89–100. doi:10.1111/j.1469-7610.1976.tb00381.x.

Zawacki-Richter, Olaf, Victoria I. Marín, Melissa Bond, and Franziska Gouverneur. 2019. "Systematic Review of Research on Artificial Intelligence Applications in Higher Education—Where Are the Educators?" *International Journal of Educational Technology in Higher Education* 16: Article 39. doi:10.1186/s41239-019-0171-0.

Wenhai Li

Dr. Wenhai Li is an Assistant Professor in the Department of Mechanical Engineering Technology at Farmingdale State College. His teaching and research interests include AI/ML applications in engineering technology, thermal-fluid systems, CFD, engineering software development, and applied engineering education.

Zhou Zhang

Dr. Zhou (Joe) Zhang is an Assistant Professor of Mechanical Engineering Technology at SUNY Farmingdale State College. His research focuses on artificial intelligence, robotics, computer vision, digital twins, virtual and augmented reality, and engineering education. He has extensive academic and industrial experience and has authored numerous peer-reviewed publications and patents.

Yue Hung

Dr. Yue (Jeff) Hung obtained his Ph.D. in Materials Science and Engineering at Stony Brook University. He also holds a M.S. degree in Mechanical Engineering and B.S. degree in Manufacturing Engineering Technology. Currently, he is the Chair and professor of the Mechanical Engineering Technology department at Farmingdale State College.

Gonca Altuger-Genc

Dr. Gonca Altuger-Genc is a Professor of Mechanical Engineering Technology at Farmingdale State College. Her research interests are incorporating AI and developing machine learning systems to support engineering courses, developing discrete event simulation models for production line optimization. Dr. Altuger-Genc received her PhD degree from Stevens Institute of Technology.

Consider submitting a short paper to

The Journal of Engineering Technology.

See page 69 for details.

Affordable Viable Ease-built Electro Hydro Dynamic Machine (AVE-EHDM) for Hands-on Engineering Technology Laboratory Courses

Srivarshini Vellaisamy and Tazdik Patwary Plateau

DOI: 10.18260/jet.43.2.3

Abstract

The primary goal of Engineering Technology (ET) programs is to emphasize practical, hands-on experiential learning that prepares technologists for applied and industry-focused careers. Rapid advances in micro- and nanotechnologies continue reshaping healthcare, electronics, and advanced manufacturing, industries increasingly demand graduates with practical experience in these emerging methods. This underscores the need for ET students to learn techniques like electrospinning, electrospraying, and near-field-electrospinning. However, integrating such techniques into ET education is limited by the prohibitively expensive, technically complex, and single-functional nature of most commercial systems. This study investigates whether an Affordable, Viable, and Ease-built Electro-Hydro-Dynamic Machine (AVE-EHDM) can provide a multifunctional, low-cost platform suitable for STEM education. The purpose of this study is to support laboratory classes with developing low-cost and simple operational devices.

The AVE-EHDM was designed as an educational device incorporating a high-voltage power supply, interchangeable syringe pumps, and a customizable gantry system adapted from a modified FDM 3D printer. Prototyping, performance tests, and comparative evaluations against commercial and literature-reported devices were conducted to assess functionality and cost-efficiency.

Testing demonstrated that the AVE-EHDM successfully performs the nanofibers fabrication method, offering broader functionality than most commercial educational systems at significantly low-cost. A cost reduction of approximately 90% was achieved compared to the literature value and more than 95% reduction compared to the commercial devices. The AVE-EHDM provides an accessible, multifunctional platform that enhances ET laboratory capabilities. Its integration can improve student engagement, support experiential learning, and better prepare future technologists for emerging micro- and nanomanufacturing fields.

1. Introduction

Engineering Technology (ET) education focuses on applying scientific and engineering principles through hands-on practical experiences that prepare students for real-world challenges. Most of the students in ET are working technicians who have the urge to learn new technologies and gain experiential knowledge (Shull 2009; Carlson et al., n.d.). These students are keen to learn modern methodologies and experience hands-on utilization of the manufacturing technologies. A key area within the modern manufacturing technologies is Micro-and-Nano Manufacturing techniques, which equip students with the skills to design and fabricate structures at extremely small scales. These technologies play a critical role in advancing industries such as healthcare, electronics, energy, and environmental engineering (Plateau 2025; Irwin et al. 2025; Dimov et al. 2012).

Micro-Nano Manufacturing technology involves a variety of additive techniques to fabricate nanoparticles, nano-wires, nanofibers, nanotubes spanning to micro-level structures (Plateau 2025; Plateau et al. 2025; Prasad et al. 2024). Among the additive techniques, widely used techniques involve Electrohydrodynamic (EHD) processes due to their ability to harness electric fields and fluid flow to precisely manipulate materials at extremely small scales (Cong et al. 2022). The popular EHD techniques are electrospinning (ES) for nanofiber fabrication and electro-spraying (ESpray) for fabricating nanoparticles (Mawazi and Alfatama 2025; Alkhatib et al. 2025). A modern version of ES process has emerged to enable highly controlled fiber deposition and patterned micro-nano structures which is named as Near-Field Electrospinning (NFES) (Bharath and Subramanian 2025).

1.1 Applications in Various Engineering Fields

Introducing students to ES, ESpray, and NFES provides hands-on experience with advanced manufacturing methods that are directly applicable to a wide range of engineering disciplines. Through guided exploration and experimentation, students gain

experiential knowledge of how these techniques are used in Engineering. For instance, environmental engineers utilize the ES technique to fabricate nanofiber membranes for air and water filtration, learning the impact of fiber morphology and porosity on performance (Song et al. 2023). In the energy sector, they explore how ES nanofibers are essential for improving performance metrics of battery components (Plateau et al. 2021; Cavaliere et al. 2011; Plateau et al. 2022), supercapacitors (Bhattacharya et al. 2020), solar cell (López-Covarrubias et al. 2019; Plateau 2019) and fuel cell membranes (Sarkar et al. 2025), gaining insight into the relationship between nanostructure and energy efficiency. Working with NFES introduces students to precision deposition techniques relevant to electronics and sensor engineering, helping them understand how micro-patterned circuits and flexible sensors would be fabricated (He et al. 2017). These experiences enhance their skills in spatial control, materials handling, and process optimization. Exposure to advanced textile applications teaches students how to play with functional nanofibers to improve fabric breathability, insulation, and environmental responsiveness (Rożek et al. 2008). In bioengineering, students learn how electrospun scaffolds mimic extracellular matrices for tissue engineering (Dahlin et al. 2011) and controlled drug delivery (Singh et al. 2021; Hiwrale et al. 2023), reinforcing principles of biocompatibility and cellular interaction. In agricultural engineering, students would explore sustainable practices by studying nano-formulated delivery systems for fertilizers and biodegradable fiber mats (Badgar et al. 2021; Meraz-Dávila et al. 2021; Plateau 2019). Similarly, applications in materials and manufacturing engineering provide insight into how nanofibers can be tailored for specific mechanical, electrical, or chemical functionalities, giving students valuable experience in designing and characterizing multifunctional materials. By engaging in these interdisciplinary applications, students develop technical competence, design thinking, and a deeper understanding of real-world problem-solving using micro-nanomanufacturing techniques. This experiential learning approach bridges theory and practice, preparing them for careers in emerging technology sectors and empowering them to innovate across disciplines.

1.2. Need for ES, NFES, and ESpray in ET Education

ET focuses on the practical application of scientific and engineering principles to solve real-world problems. Unlike traditional engineering programs that often emphasize deep theoretical understanding, ET curricula are built around applied learning, hands-on experimentation, and skill development aligned with industry practices. ET graduates work alongside technicians, engineers, and scientists in multidisciplinary teams, contributing to rapid technological innovation across sectors. A significant portion of ET students transfer from community colleges or enroll after completing associate degrees in applied science. Many are non-traditional students working-professionals returning to school part-time to advance their careers or transition into high-demand technical fields. For these students, hands-on, project-based courses are especially valuable, as they prioritize practical skills over abstract theory.

1.3. Limitations to Use in Laboratories

Despite the growing relevance of micro–nano fabrication methods, students' hands-on access to these technologies remains severely limited in educational environments due to the high cost of commercial equipment ("Electrospinning Machine High-Speed Drum 200¨C4500 Rpm -30kV | StonyLab," n.d.; MicroNano Tools, n.d.-a; mic1453ro, n.d.; Bioinicia 2018). Acquiring separate ES, ESpraying, and NFES systems typically requires an investment exceeding $50,000, making it difficult for institutions to support only one lab. Beyond affordability, ensuring reliable operation across all three modes presents an additional challenge, as each technique requires precise control of voltage, fluid delivery, environmental conditions, and motion systems. Attempts to reduce costs by building these systems from scratch introduce yet another hurdle: constructing a multifunctional EHD setup requires advanced proficiency in electrical engineering, mechanical design, safety integration, and software programming. Although a few studies describe low-cost ES devices (Bioinicia 2018; Owida et al. 2022; Velasco Barraza et al. 2016; Switz et al. 2024), they still involve complex circuit-designs, specialized components, and custom programming code, offering no straightforward path to replicate. Consequently, there is a pressing need for an affordable, easily assembled, and versatile system capable of performing all three EHD techniques for effective STEM laboratory instruction.

1.4. Solution: AVE-EHDM

With a view to solving these problems, this paper introduces a multifunctional machine which is affordable, easy to build, and can be easily modified to pursue these three setups of ES, ESpray and NFES. This device is named – "Affordable Viable Ease-built Electro Hydro Dynamic Machine (AVE-EHDM)". We also demonstrated a huge cost reduction of the device by preparing and modifying different home-built sub-devices including modified Gantry System, handmade syringe pump, and custom-fabricated

nozzle holders. In developing this AVE-EHDM device, a key focus was on flexibility of building it, as it should be easily built by an engineer or student interested in hands-on fabrication and experimentation. In addition to its technical innovations, this paper highlights the educational framework behind the development of the device. The AVE-EHDM integrates three EHD processes into a single compact, user-friendly platform tailored for lab-based learning. By using this system, ET students gain direct, experiential exposure to advanced micro-nano fabrication techniques, enhancing their understanding through guided experimentation, process optimization, and hands-on engagement with modern manufacturing technologies.

2. Working Principle of the Three Techniques

2.1 Electrospinning (ES)

ES employs electrostatic forces to produce continuous polymer nanofibers from a liquid solution or melt. The process is governed by the interplay between fluid dynamics, electrostatics, and mass transfer. In a typical ES setup, a polymer solution is loaded into a syringe fitted with a metallic nozzle, connected to a high-voltage power supply (10 to 30 kV). A collector plate positioned at a fixed distance serves as the grounded counter-electrode. When a high voltage is applied, the electrostatic field accumulates charges on the surface of the droplet at the nozzle tip. As electrostatic forces overcome surface tension, the droplet forms a conical shape known as Taylor cone. From the apex of this cone, a fine liquid jet is ejected once the electrostatic force exceeds the surface tension. The jet undergoes shear-thinning behavior of the polymer solution. The jet then travels toward the collector plate, following a whipping or spiral path due to bending instabilities and further elongation. During this flight, the solvent rapidly evaporates, and solid nanofibers form in the air. These fibers are deposited onto the collector in a nonwoven mat-like structure.

A schematic diagram in Figure 1(a) illustrates the ES process, where the Taylor cone forms at the nozzle tip and a charged polymer jet is ejected. The jet undergoes bending instabilities and a whipping trajectory before depositing as nanofibers on the collector at a tip-to-collector distance of 10–15 cm under an applied voltage of 10–20 kV.

2.2 Electro-spraying (ESpray)

ESpraying is a technique closely related to ES; both utilize a high-voltage electric field to manipulate a liquid. Unlike ES, ESpraying aims to generate nano- to microscale droplets that can solidify into nanoparticles or uniform thin films upon solvent evaporation. In this process, a low-viscosity solution is typically used to facilitate droplet formation rather than filament stretching. In ESpraying, due to the low viscosity and surface tension of the solution, instead of forming a continuous jet, the solution becomes unstable and breaks up into a fine spray of charged droplets. These nano- to microscale droplets are ejected from the cone and travel through the electric field toward the collector. During their flight, the solvent in each droplet evaporates rapidly, leading to the formation of solid nanoparticles, depending on the substrate and operating conditions. Interestingly, this process can be performed by enhancing the voltage, increasing the nozzle tip to collector distance too (Gaskell 1997; Plateau et al. 2026).

A schematic diagram in Figure 1(b) illustrates the ESpraying process, showing the formation of a Taylor cone at the nozzle tip, which breaks up into fine, charged droplets. These droplets travel toward the collector across a distance of 10–15 cm under an applied voltage of 5–20 kV.

2.3 Near-field Electrospinning (NFES)

A key limitation of the ES method is the random deposition of fibers on the collector surface. Due to the long jet travel distance and inherent bending instabilities, electrospun fibers form in a chaotic, nonaligned manner, which makes it difficult to control fiber orientation, porosity, and spatial patterning. This randomness is a significant drawback in applications where precise micro/nanostructures, anisotropic properties, or architected materials are required. To address this limitation, NFES has emerged as a powerful alternative that offers significantly improved spatial control (He et al. 2017). In NFES, the key modification lies in the drastic reduction of the distance between nozzle tip and collector; typically to less than a few millimeters. By shortening this distance, the jet is collected before the onset of whipping instabilities forming spiral path, allowing it to travel in a straight and stable trajectory. This direct, controlled deposition enables patterning of fibers with precision. A computer-controlled gantry system is typically integrated into the NFES setup to maneuver either the nozzle or the collector substrate. In this way, NFES combines the material versatility of ES with the positional precision of additive manufacturing or 3D printing (He et al. 2017).

However, operating at such a proximity introduces several technical constraints. The high-voltage range (10 to 30 kV) used in ES cannot be applied in NFES, as the short distance may cause dielectric breakdown or spark formation between the electrodes. As a result, NFES systems typically operate at much lower voltages (<4 kV) (He et al. 2017). Additionally,

because the jet travels a very short distance, it does not have sufficient time to undergo adequate thinning, often resulting in fibers with larger diameters compared to ES. Due to less flight time, the polymer solution typically needs to be more viscous and concentrated. Despite these challenges, NFES offers a major advantage: the ability to fabricate structures with highly controlled porosity, precise fiber alignment, and specific aspect ratios, promising for applications where architectural fidelity and functional integration are critical (Cisquella-Serra et al. 2019).

A schematic diagram in Figure 1(c) illustrates the NFES process, where a stable jet emerges from the Taylor cone at the nozzle tip and travels in a straight path over a very short gap of 0.5–3 mm under a low voltage of 0.5–3 kV, enabling precise fiber deposition on the substrate.

2.4 AVE-EHDM Setup

The AVE-EHDM system allows seamless switching between modes by adjusting key parameters such as solution viscosity, applied voltage, flow rate, and nozzle-to-collector distance. In ES mode, a high-voltage field and longer working distance produce randomly deposited nanofibers from viscous polymer solutions. In ESpraying, a low-viscosity solution and similar voltage range lead to the formation of nanoscale droplets that solidify into nanoparticles upon solvent evaporation. NFES operates with a drastically reduced nozzle-to-collector distance and lower voltage, allowing the stable deposition of straight jets without bending instability, which are precisely patterned using a motorized motion stage. This mode enables controlled fiber alignment and 3D structure fabrication. The shared hardware comprising a high-voltage supply, syringe pump, collector, and programmable gantry makes the system modular, cost-effective, and adaptable for any lab-based course. Such a multifunctional setup not only supports experiential learning by demonstrating electrohydrodynamic principles in real-time but also enables rapid prototyping and cross-disciplinary exploration of advanced materials and manufacturing technologies for Engineering Technologists.

3. Device Setup

3.1 Device Design and Components

The AVE-EHDM educational device consists of a high-voltage power supply (Acopian P030HP2), interchangeable syringe pumps, a grounded collector platform (304 Stainless Steel), and a customizable motion-controlled stage that enables precise adjustment of the nozzle-to-collector distance. The high-voltage unit provides the necessary electric field strength for operating in ES, ESpraying, and NFES modes. The focus was on developing a modular, accessible system that allows students to explore the applied tasks of EHD fabrication in a hands-on learning environment.

3.2 Modification of 3D Printer

A modified FDM 3D printer serves as the gantry platform, allowing for XYZ-axis movement and programmable deposition paths, particularly for NFES applications. In this configuration, the original print head is replaced with a securely mounted

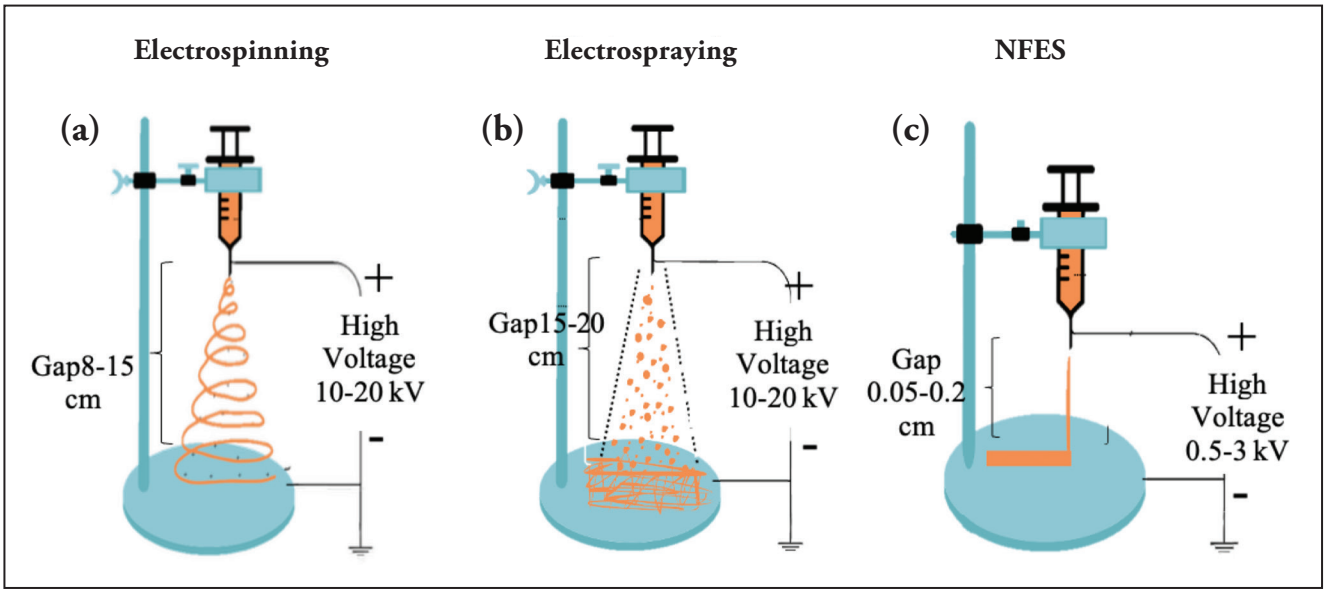


Figure 1. Schematic Diagram of (a) ES setup, (b) ESpray Setup, and (c) NFES setup.

syringe nozzle, enabling controlled jet placement instead of filament extrusion. The printer's build plate is redesigned to serve as the grounded collector, accommodating various substrates such as metal foils, conductive films, or coated slides. Motion control is achieved through standard G-code commands, allowing users to generate custom patterns, adjust deposition speeds, and execute complex trajectories with high repeatability.

3.3 Design and fabrication of Nozzle Holder

The nozzle holder was designed to securely support the syringe and needle while ensuring proper alignment with the collector. It was fabricated using a durable polymer material and was structured to allow easy integration with the syringe pump system. The assembly provides stability for the needle during operation and includes a dedicated connection point at the syringe end for integration with the high-voltage power supply. Its modular structure facilitates quick needle replacement and easy cleaning after use. Figure 2 illustrates both the CAD model and the 3D-printed holder. The dimensions were selected based on the gantry base length and the outer diameter of standard commercial syringes. More details of the nozzle holder can be found in Supplemental Document (Appendix A: Nozzle Holder CAD Design and Figure S1).

3.4 Integration of Nozzle holder and High-voltage Power Supply

The nozzle holder was integrated with the syringe system to provide stable and strong support for the dispensing needle. The high-voltage connection was established at the syringe end (shown in Figure 3), ensuring that the applied potential was effectively transferred to the needle while keeping the rest of the structure electrically isolated. The insulating body of the holder prevented and minimized the risk of unintended discharge. Strain-relieved cabling and protective insulation were employed to maintain a safe and reliable connection during operation. This integration allowed precise control of the ES process while maintaining operator's safety and ease of maintenance.

3.5 Integration of Syringe pump in AVE-EHDM

In this AVE-EHDM setup, the syringe is mounted onto the 3D printer's gantry system, allowing synchronized motion with the printer head. Details of the syringe pump can be found in the Supplementary Materials (Appendix B: Syringe Pump and Figure S2). This integration combines the programmable flow-rate control of the syringe pump with the spatial precision of the 3D printer. By connecting the syringe pump to the 3D printer, the device can deliver polymer solutions accurately while simultaneously enabling controlled deposition paths for ES, ESpraying, or NFES. The modular design further allows syringes of different volumes to be interchanged, expanding the range of experimental possibilities and enhancing the adaptability of the system for educational purposes. The details about Arduino code for syringe pump operation can be found in Supplemental Document (Appendix C: Arduino Code).

4. Results

The functionality and performance of the AVE-EHDM system are demonstrated in Figure 4 through the fabrication of polyvinyl alcohol (PVA) nanofibers using the ES mode. To prepare the ES solution, 12.5 wt% PVA powders (Sigma-Aldrich) were dissolved in distilled water. The mixture was initially stirred at 300 RPM while being heated to 60 °C for 20 min-

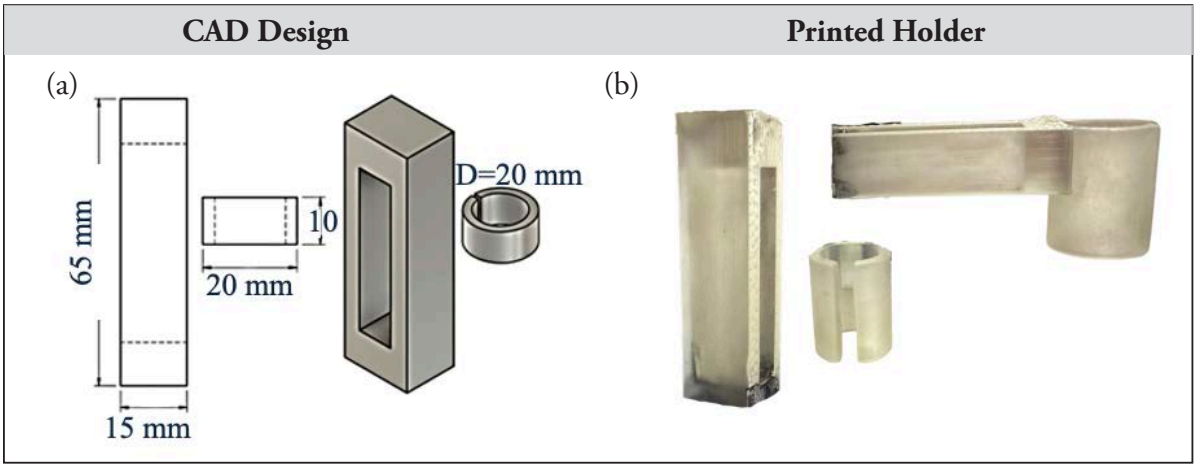


Figure 2. 2D and 3D CAD representations of the holder, with all dimensions provided in millimeters (a), alongside digital images of the completed holder components (b).

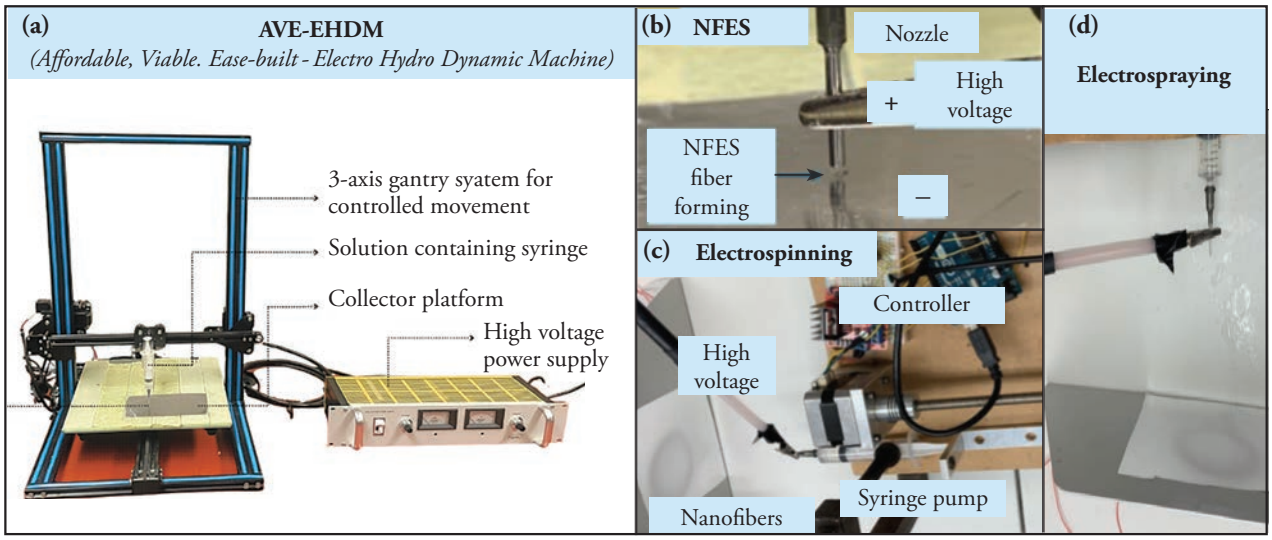


Figure 3. Digital image of the AVE-EHDM setup (a), zoomed-in image showing NFES (b), image of ES nanofibers (c), and image of continuous ESpraying for making a thin film layer (d).

utes to facilitate polymer dissolution and reduce solution viscosity. Following this, the solution was further homogenized using a high-speed stirrer (ISTOYO) operating at 1200 RPM to obtain homogeneous solution. Once a uniform and bubble-free solution was obtained, it was transferred into a 10 ml syringe with a 16G nozzle.

During ES, the AVE-EHDM's high-voltage power supply was used to apply an electric potential of 16 kV between the nozzle tip and the grounded collec-

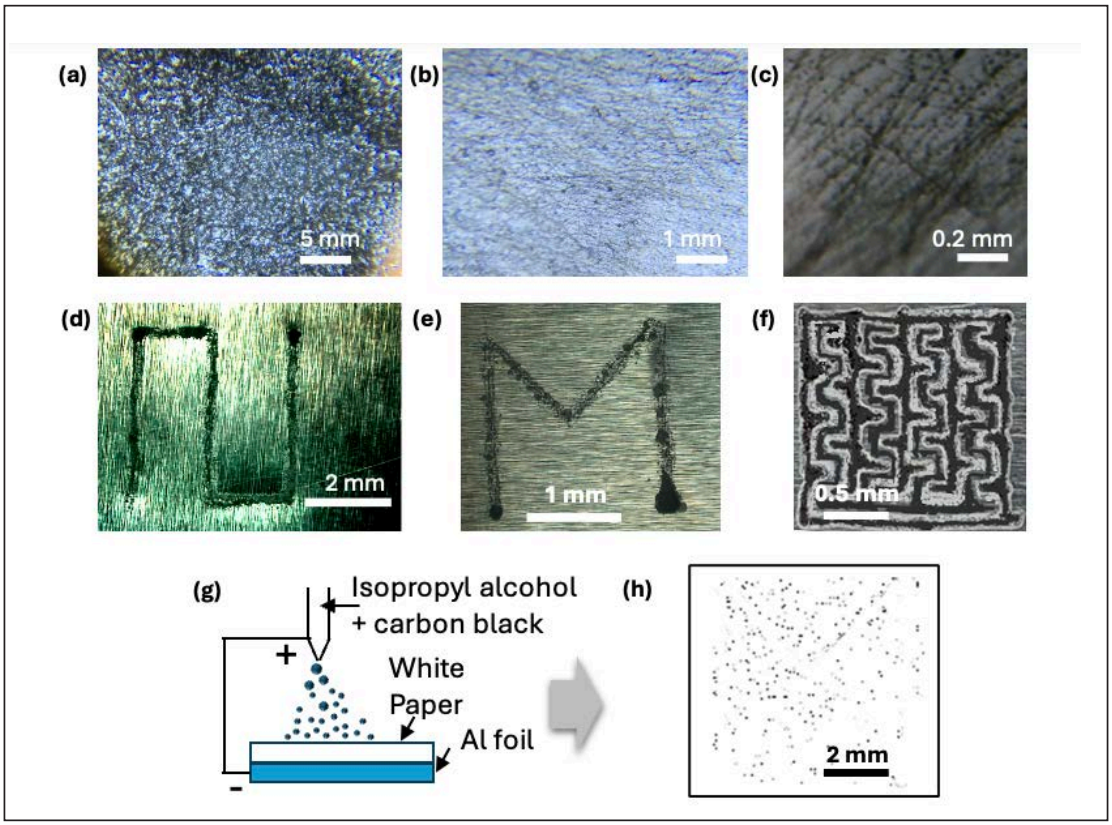


Figure 4. Microscopic images of PVA nanofibers at different magnifications 10X (a), 40X (b) and 100X (c). Digital image of printed layer structure via NFES functionality of the AVE-EHD system with 19 G (d), 23 G (e), and 26 G (f) needle. (g) shows the experimental setup, while Figure 4(h) presents the deposited carbon black pattern on the filter paper, illustrating the functionality of ESpraying.

tor. The nozzle-to-collector distance was set to 12 cm, a parameter chosen to allow sufficient jet elongation and solvent evaporation while maintaining stable Taylor cone formation. The syringe pump, integrated into the AVE-EHDM system, was programmed to deliver the polymer solution at a controlled flow rate of 3 mL/hour to achieve uniform fiber deposition. Aluminum foil was placed on the collector surface, providing both a conductive substrate for stable fiber collection and an easily removable layer for post-processing.

After ES was completed, the resulting nanofiber mat was carefully peeled from the foil and left to dry at room temperature overnight to ensure complete solvent evaporation. The morphology of the fabricated nanofibers was examined using a Zeiss optical microscope (Model MC 100), capturing micrographs at three different magnifications. These images, presented in Figure 4(a-c) clearly demonstrate the ability of the AVE-EHDM system to generate continuous, uniform PVA nanofibers suitable for instructional use.

Furthermore, to demonstrate the capability of the AVE-EHD system to operate as a NFES device, three different patterns were fabricated with varying line widths. The variation in line width was achieved by changing the needle diameter from 19 G to 26 G. The NFES printing was performed at an applied voltage of 1000 V where the needle tip to substrate distance was maintained at 1 mm distance. The corresponding results are presented in Figure 4(d-f). For the NFES experiments, a composite solution consisting of 20 wt% carbon black and 80 wt% PVDF dissolved in NMP was used. Aluminum foil was employed as the substrate to facilitate the electric field during structure formation.

Additionally, ESpraying tests were conducted to further validate the multifunctionality of the AVE-EHD system. In this case, a white filter paper was placed on top of an aluminum foil substrate, with the foil ensuring effective electric field required for ESpraying. A solution containing 1.2 wt% carbon black dispersed in isopropyl alcohol was ESprayed at an applied voltage of 18 kV, with a nozzle-to-collector distance of 8 cm. Figure 4(g) shows the experimental setup, while Figure 4(h) presents the deposited carbon black pattern on the filter paper. These results confirm that the AVE-EHD system can also operate effectively in ESpraying functionality.

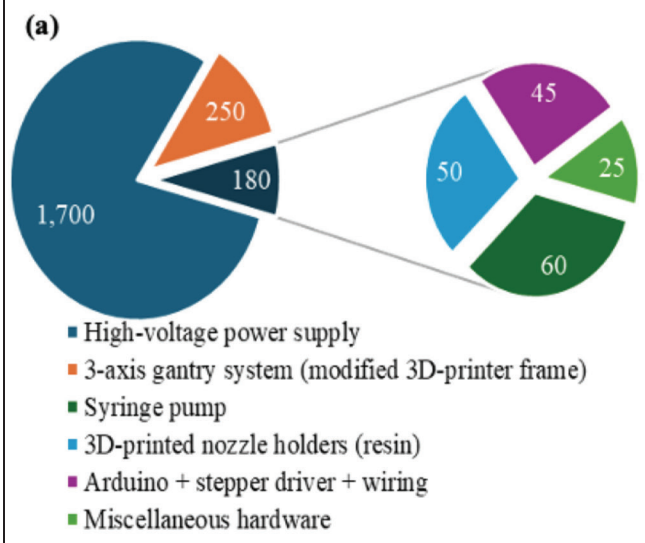
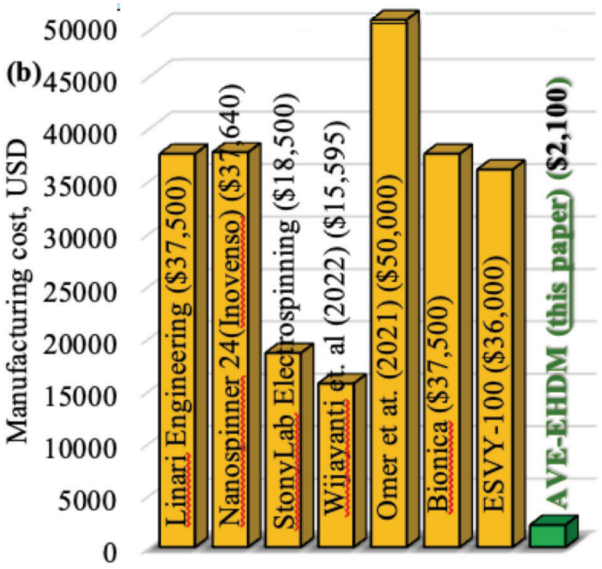
5. Cost Analysis Results

5.1 AVE-EHDM Manufacturing Cost

The AVE-EHDM device is composed of several integrated components, including a high-voltage power supply, a three-axis gantry system, a custom-built syringe pump, and 3D-printed nozzle holders. Because constructing a reliable high-voltage power supply requires advanced electrical engineering expertise and involves significant safety considerations, a commercial unit was selected for this project. We utilized an Acopian high-voltage supply (Model P030HP2) to ensure stable and safe operation. Similarly, fabricating a gantry system from scratch would present substantial challenges for non-specialists; therefore, instead of designing one, we modified a commercial 3D printer which is inexpensive and capable of controlled motion along the X, Y, and Z axes. We removed the extruder assembly from a Geetech A10 printer. A new nozzle holder was designed and fabricated using a 3D printer to interface the syringe nozzle securely with the gantry. To regulate the flow rate of the ES solution, a DC motor–driven mechanism was developed to function as a syringe pump. For precise control over the motor speed and flow delivery, an Arduino microcontroller was incorporated into the system, and the full code is provided in the supplementary materials. Although several components were sourced from commercial vendors, the total cost of the AVE-EHDM system remained exceptionally low at approximately $2,100, with the high-voltage power supply accounting for the majority of the expense (about $1,700). A detailed cost distribution is presented in the pie chart shown in Figure 5a. In addition, AVE-EHDM was designed with maintainability and long-term educational use in mind. Most components are commercially available and can be replaced individually if required. Routine maintenance primarily involves cleaning the nozzle, replacing consumable syringes and needles, and periodically inspecting electrical connections. The modular architecture of the system allows individual components to be repaired or replaced without reconstructing the entire setup, thereby reducing long-term operational costs and supporting durability for repeated laboratory use. These features make the AVE-EHDM particularly suitable for instructional laboratories.

5.2 Cost Comparison with Literature Values

A detailed cost comparison of eight devices, including commercial systems, literature-reported units, and our multifunctional platform, is presented in Figure 5b. Commercial ES units, such as those from Inovenso (mic1453ro, n.d.), Linari Engineering (Linari Nanotech, n.d.), and Bioinicia (Bioinicia 2018), remain relatively expensive, with typical prices around $37,500. The Nanospinner 24 (Inovenso) model shows comparable pricing at $37,640, while advanced systems like the NanoFiber ES and Vortex Yarning Machine ESVY-100 reach approximately

AVE-EHDM manufacturing cost (USD)	Manufacturing cost comparison
	

(c) Functionality	Electrospinning	Electrospraying	NFES
Linari Engineering	☑		
Nanospinner 24 (Inovenso)	☑		
StonyLab High-Speed Electrospinning Machine	☑		
Wijayanti et. al (2022)	☑		
Omer et at. (2021)	☑	☑	
Bioinicia	☑	☑	
Electrospinning & Vortex Yarning Machine ESVY-100	☑		
AVE-EHDM (This paper)	☑	☑	☑

Figure 5. Cost breakdown of AVE-EHDM (this paper) in USD where each component's price is shown in the pie-chart (a). A cost comparison among the commercial electrospinning devices, literature manufacturing cost and AVE-EHDM is showed in bar chart (b). The operational functionalities offered by these machines are illustrated in chart (c).

$36,000 (MicroNano Tools, n.d.-b). Other laboratory-grade devices, including the StonyLab high-speed ES machine, are priced at $18,500 ("Electrospinning Machine High-Speed Drum 200¨C4500 Rpm -30kV | StonyLab," n.d.). Literature reports reflect similar trends across academic settings: Wijayanti et al (Wijayanti et al. 2022) documented a system costing $15,595, whereas Omer et al (Omer et al. 2021) noted equipment exceeding $50,000 for high-capacity or specialized configurations. In contrast, our AVE-EHDM device developed in this study can be assembled for approximately $2,100. This represents a cost reduction of more than 90% when compared to commercial alternatives and enables low-cost solution for instructional laboratories in ET programs.

5.3 Operational Functionalities Comparison

Although the cost of commercially available devices is significantly higher than that of AVE-EHDM, their operational capabilities are comparatively limited. Figure 5c showed a comparison between the functionalities and operational modes of these systems. Most existing machines were originally designed for ES only. Among the reviewed systems, only one commercial device (Bioinicia) and a single design reported in the literature offer both ES and ESpraying functionalities; however, neither of these solutions support NFES. In contrast, our AVE-EHDM platform is uniquely versatile, enabling all three advanced micro-nano-fabrication techniques within a single integrated system.

6. Educational Implementation and Assessment Framework

While this study focuses on the design and low-cost fabrication of an EHD system intended for educational integration, formal educational assessment has not yet been conducted. The developed device is scheduled for implementation in two laboratory-intensive courses within the Division of Engineering Technology at Wayne State University in Fall 2026: ET 5400 Micro-Nanomanufacturing and MCT 3410 Kinematics and Dynamics of Machines. As these courses have not yet been delivered using the proposed system, no student performance data, survey results, or learning outcome measurements are currently available.

It is important to note that the primary objective of this study is not to evaluate students' epistemic gains, but rather to develop and demonstrate a scalable and affordable experimental platform that facilitates experiential learning. In many existing engineering curricula, instruction related to advanced manufacturing and electrohydrodynamic phenomena remains predominantly theoretical and lecture-based, largely due to the high cost and limited accessibility of specialized laboratory equipment. The EHD system developed in this work directly addresses this limitation by offering a low-cost, reproducible experimental setup that is suitable for instructional use in laboratory environments.

To support future classroom integration, comprehensive laboratory modules, task descriptions, and clearly defined learning objectives have been developed for both courses and are provided in the Supplementary Materials. These instructional components are designed to reinforce theoretical concepts through hands-on experimentation, enhance student engagement with micro- and nano-manufacturing processes, and provide exposure to multidisciplinary applications relevant to modern engineering practice.

In anticipation of future deployment, a structured educational assessment framework has also been outlined. This framework includes pre- and post-course conceptual understanding surveys, student feedback on the effectiveness of experiential learning, and performance-based evaluation of laboratory tasks. However, due to the absence of prior laboratory-based instructional platforms involving EHD systems, there is currently no established baseline for direct comparative analysis, such as pre/post or control group studies. The planned implementation in Fall 2026 is expected to establish such benchmarks and enable rigorous educational assessment in future work.

7. Conclusions

This study presents a multifunctional micro-nano manufacturing device, called AVE-EHDM, capable of performing ES, ESpraying, and NFES within a single, compact platform. By integrating a modified gantry system, syringe pump, nozzle holders, and a high-voltage power supply, the device delivers the core functionalities of commercial systems while remaining accessible for instructional use. With an estimated total cost of approximately $2,100, the system offers a reduction of more than 90% compared to commercial equipment. The multifunctional nature of the AVE-EHDM device broadens its relevance across numerous engineering fields, including environmental engineering, energy storage, electronics, biomedical engineering, materials science, and smart textiles. Through hands-on experiments, students can investigate nanofiber fabrication, nanoparticle formation, and precision fiber patterning. This experiential learning approach enhances technical skills, supports design thinking, and bridges theoretical concepts with real-world applications.

Overall, the AVE-EHDM device provides a practical and scalable platform for integrating advanced EHD fabrication techniques into STEM laboratory education, particularly within ET programs. By offering a cost-effective, simple manufacturing method and multifunctional operations substantially expand its educational access to advanced fabrication techniques. Enabling three major EHD processes, the system provides a scalable and impactful model for enhancing ET curricula and preparing students for emerging technology-driven industries. Future work will include formal educational assessment through student feedback, surveys, and performance analysis following implementation in Fall 2026.

Supplemental Material

For those who are interested, supporting materials can be found at— Supporting Materials

Acknowledgements

We extend our sincere gratitude to the Division of Engineering Technology at Wayne State University, where the AVE-EHDM system was developed. We are especially thankful to Prof. Dr. Ece Yaprak, Chair of the Engineering Technology Division, for her continuous inspiration and unwavering support in advancing educational research initiatives.

References

Alkhatib, Hamzeh, Okba Al Rahal, Md Sanower Hossain, and Saeid Mezail Mawazi. 2025. "Recent Advances in Electrospraying and Electrospinning Technologies." *Electrospraying and Electrospinning in Drug Delivery*, 224–56.

Badgar, Khandsuren, Joe Prokisch, and Hassan El-Ramady. 2021. "Nanofibers for Sustainable Agriculture: A Short Communication." *Egyptian Journal of Soil Science* 61 (3): 373–80. https://doi.org/10.21608/ejss.2021.105877.1477.

Bharath, and K. R. V. Subramanian. 2025. "A Review on Scalable Printing Techniques for Conductive and Composite Polymer Nanoinks." *Advances in Natural Sciences: Nanoscience and Nanotechnology* 16 (1): 013002. https://doi.org/10.1088/2043-6262/ad9ff5.

Bhattacharya, Somdatta, Indroneil Roy, Aaron Tice, et al. 2020. "High-Conductivity and High-Capacitance Electrospun Fibers for Supercapacitor Applications." *ACS Applied Materials & Interfaces* 12 (17): 19369–76. https://doi.org/10.1021/acsami.9b21696.

Bioinicia. 2018. "Electrospinning equipment products." Bioinicia, April 27. https://bioinicia.com/electrospinning-equipment-products/.

Carlson, Lawrence E., Jacquelyn F. Sullivan, and Benjamin Franklin. n.d. *Hands-on Engineering: Learning by Doing in the Integrated Teaching and Learning Program.*

Cavaliere, Sara, Surya Subianto, Iuliia Savych, Deborah J. Jones, and Jacques Rozière. 2011. "Electrospinning: Designed Architectures for *Energy Conversion and Storage Devices." Energy & Environmental Science* 4 (12): 4761–85. https://doi.org/10.1039/c1ee02201f.

Cisquella-Serra, Albert, Marco Magnani, Álvaro Gual-Mosegui, Sunshine Holmberg, Marc Madou, and Manuel Gamero-Castaño. 2019. "Study of the Electrostatic Jet Initiation in Near-Field Electrospinning." *Journal of Colloid and Interface Science* 543: 106–13. https://doi.org/10.1016/j.jcis.2019.02.041.

Cong, Chenhao, Xinlin Li, Wei Xiao, et al. 2022. "Electrohydrodynamic Printing for Demanding Devices: A Review of Processing and Applications." *Nanotechnology Reviews* 11 (1): 3305–34. https://doi.org/10.1515/ntrev-2022-0498.

Dahlin, Rebecca L., F. Kurtis Kasper, and Antonios G. Mikos. 2011. "Polymeric Nanofibers in *Tissue Engineering." Tissue Engineering Part B: Reviews* 17 (5): 349–64. https://doi.org/10.1089/ten.teb.2011.0238.

Dimov, S., E. Brousseau, R. Minev, and S. Bigot. 2012. "Micro- and Nano-Manufacturing: Challenges and Opportunities." *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science* 226 (1): 3–15. https://doi.org/10.1177/0954406211422972.

"Electrospinning Machine High-Speed Drum 200¨C4500 Rpm -30kV | StonyLab." n.d. https://stonylab.com/products/840371315798-electrospinning-ps4?srsltid=AfmBOooYnl08dPKzMvV16Q0fhD0kWCJ6UjwkO5OQw_4lhWuKWaGfBSHe.

Gaskell, Simon J. 1997. "Electrospray: Principles and Practice." Journal of Mass Spectrometry 32 (7): 677–88. https://doi.org/10.1002/(SICI)1096-9888(199707)32:7%3C677::AID-JMS536%3E3.0.CO;2-G.

He, Xiao-Xiao, Jie Zheng, Gui-Feng Yu, et al. 2017. "Near-Field Electrospinning: Progress and Applications." *The Journal of Physical Chemistry C* 121 (16): 8663–78. https://doi.org/10.1021/acs.jpcc.6b12783.

Hiwrale, Abhijeet, Swati Bharati, Prashant Pingale, and Amarjitsing Rajput. 2023. "Nanofibers: A Current Era in Drug Delivery System." *Heliyon* 9 (9). https://doi.org/10.1016/j.heliyon.2023.e18917.

Irwin, John, Ismail Fidan, Neil Littell, et al. 2025. "The Four Pillars of Manufacturing Knowledge: A Contemporary Perspective on Practical Implementation." *Journal of Engineering Technology* 42 (2): 38–51. https://doi.org/10.18260/jet.42.2.4.

Linari Nanotech (Linari Nanotech). n.d. "Compact Electrospinning Unit for Nanofibers." https://www.linarinanotech.com/products/compact-electrospinning-unit.

López-Covarrubias, Jesse Gerardo, Laura Soto-Muñoz, Ana Leticia Iglesias, and Luis Jesús Villarreal-Gómez. 2019. "Electrospun Nanofibers Applied to Dye Solar Sensitive Cells: A Review." *Materials* 12 (19): 3190. https://doi.org/10.3390/ma12193190.

Mawazi, Saeid Mezail, and Mulham Alfatama. 2025. "4 Preparation Methods Used in Electrospinning and Electrospraying." *Electrospraying and Electrospinning in Drug Delivery: Principles, Methods, and Applications*, 117. https://doi.org/10.1201/9781003583691-4.

Meraz-Dávila, S., C. E. Pérez-García, and Ana A. Feregrino-Perez. 2021. "Challenges and Advantages of Electrospun Nanofibers in Agriculture: A Review." *Materials Research Express* 8 (4): 042001. https://doi.org/10.1088/2053-1591/abee55.

mic1453ro. n.d. Nanospinner24 Advanced Electrospinning Machine. Accessed August 9, 2026.

https://www.inovenso.com/portfolio-view/nanospinner24-electrospinning-machine-2/.

MicroNano Tools (MicroNano Tools). n.d.-a. "NanoFiber Electrospinning and Yarning Machine - ESVY-100." Accessed August 9, 2026. https://www.micronanotools.com/products/nanofiber-electrospinning-and-vortex-yarning-machine-esvy-100.

MicroNano Tools (MicroNano Tools). n.d.-b. "NanoFiber Electrospinning and Yarning Machine - ESVY-100." Accessed August 9, 2026. https://www.micronanotools.com/products/nanofiber-electrospinning-and-vortex-yarning-machine-esvy-100.

Omer, Safaa, László Forgách, Romána Zelkó, and István Sebe. 2021. "Scale-up of Electrospinning: Market Overview of Products and Devices for Pharmaceutical and Biomedical Purposes." *Pharmaceutics* 13 (2): 286. https://doi.org/10.3390/pharmaceutics13020286.

Owida, Hamza Abu, Bashar Al-haj Moh'd, and Mohammad Al Takrouri. 2022. "Designing an Integrated Low-Cost Electrospinning Device for Nanofibrous Scaffold Fabrication." *HardwareX* 11: e00250. https://doi.org/10.1016/j.ohx.2021.e00250.

Plateau, Tazdik Patwary. 2019. "Potentiostat Electro-Deposited Cuprous Oxide and Cupric Oxide Thin Films for Photovoltaic Use." *International Journal of Automotive and Mechanical Engineering*, ahead of print. https://doi.org/10.15282/ijame.16.2.2019.11.0498.

Plateau, Tazdik Patwary. 2025. "Nano-Micro Engineering for Advanced Energy Devices." Doctoral Dissertations, ahead of print, January 1. https://doi.org/scholarsmine.mst.edu/doctoral_dissertations/3396.

Plateau, Tazdik Patwary, Gracie Boyer, and Jonghyun Park. 2025. "Hyper-Thick Electrodes for Lithium-Ion Batteries Enabled by Micro-Electric-Field Process." *Advanced Science* 12 (7): 2413444. https://doi.org/10.1002/advs.202413444.

Plateau, Tazdik Patwary, Hiep Pham, and Jonghyun Park. 2026. "Atomized Oxidative Polymerization as a 3D Printing Platform for Binder-Free, Bulk Conductive Polymer Architectures." *Advanced Functional Materials* 36 (55): e76488. https://doi.org/10.1002/adfm.76488.

Plateau, Tazdik Patwary, Hiep Pham, Susmita Sarkar, and Jonghyun Park. 2021. "Inter-Bonded Carbon Nanofibers Based Anode for High Areal Capacity Lithium-Ion Battery." *Electrochemical Society Meeting Abstracts 239*, no. 9: 493–493. https://doi.org/10.1149/MA2021-019493mtgabs.

Plateau, Tazdik Patwary, Hiep Pham, Yaqi Zhu, Ming Leu, and Jonghyun Park. 2022. "Enabling Ultrathick Electrodes via a Microcasting Process for High Energy and Power Density Lithium-Ion Batteries." *Advanced Energy Materials* 12 (38): 2201353. https://doi.org/10.1002/aenm.202201353.

Prasad, Rai Dhirendra, P. D. Sarvalkar, Nagina Prasad, et al. 2024. "Emerging Trends of Bioactive Nano-Materials in Modern Veterinary Science and Animal Husbandry." *ES Food and Agroforestry* 18: 1144. https://doi.org/10.30919/esfaf1144.

Rożek, Z., W. Kaczorowski, D. Lukáš, P. Louda, and S. Mitura. 2008. "Potential Applications of Nanofiber Textile Covered by Carbon Coatings." *Journal of Achievements in Materials and Manufacturing Engineering* 27 (1): 35–38.

Sarkar, Antara, Jerome Michael Bidu, Jagannath Panda, et al. 2025. "Applications of Electrospinning for Fuel Cell and Electrolysis Cell Applications in Hydrogen Technologies." *Energy Reviews* 4 (1): 100119. https://doi.org/10.1016/j.enrev.2024.100119.

Shull, P. J. 2009. *Improved Learning of Engineering Mathematics through Hands-on, Real-World Laboratory Experiments*. 10 (2009).

Singh, Baljinder, Kibeom Kim, and Myoung-Hwan Park. 2021. "On-Demand Drug Delivery Systems Using Nanofibers." *Nanomaterials* 11 (12): 3411. https://doi.org/10.3390/nano11123411.

Song, Jialing, Xuanhao Lin, Liang Ying Ee, Sam Fong Yau Li, and Manhong Huang. 2023. "A Review on Electrospinning as Versatile Supports for Diverse Nanofibers and Their Applications in Environmental Sensing." *Advanced Fiber Materials* 5 (2): 429–60. https://doi.org/10.1007/s42765-022-00237-5.

Switz, Alexi, Aditi Mishra, Katrina Jabech, and Anamika Prasad. 2024. "Affordable Lab-Scale Electrospinning Setup with Interchangeable Collectors for Targeted Fiber Formation." *HardwareX* 17: e00501.https://doi.org/10.1016/j.ohx.2023.e00501.

Velasco Barraza, R. D., A. S. Álvarez Suarez, L. J. Villarreal Gómez, J. A. Paz González, A. L. Igle-

sias, and R. Vera Graziano. 2016. "Designing a Low Cost Electrospinning Device for Practical Learning in a Bioengineering Biomaterials Course." *Revista Mexicana de Ingeniería Biomédica* 37 (1): 7–16. https://doi.org/10.17488/RMIB.37.1.1.

Wijayanti, Ika Dewi, Ari Kurniawan Saputra, Faris Ibrahim, Amaliya Rasyida, Putu Suwarta, and Indra Sidharta. 2022. "An Ultra-Low-Cost and Adjustable in-House Electrospinning Machine to Produce PVA Nanofiber." *HardwareX* 11: e00315. https://doi.org/10.1016/j.ohx.2022.e00315.

Appendix A: Nozzle Holder CAD Design

The nozzle (syringe) holder was designed as a two-part modular component (Figure A1) to enable flexible mounting on the gantry system. By fastening Section B of the holder to the mounting interface, the syringe orientation can be adjusted to accommodate different gantry layouts and experimental configurations. This design allows the syringe and nozzle to be positioned in multiple orientations without requiring redesign of the holder, thereby supporting flexible integration with the modified 3D printer platform used in the AVE-EHDM system.

The holder incorporates a stepped internal diameter that provides clearance for syringe bodies with slight dimensional variations, enabling compatibility with multiple syringe sizes. This feature ensures secure mechanical support while maintaining proper alignment and stability of the syringe during operation.

Appendix B: Syringe Pump

The syringe pump (Figure A2) was developed as a low-cost, motor-driven mechanism to provide controlled and continuous delivery of polymer solution during electrospinning, electrospraying, and near-field electrospinning operations. The system consists of a DC geared motor coupled to a lead screw, which converts rotational motion into linear displacement of the plunger carriage. This linear motion enables precise advancement and retraction of the syringe plunger, allowing stable and repeatable solution flow.

Motor operation is controlled using an Arduino microcontroller in combination with a motor driver module, which regulates both the direction and speed of rotation. Flow rate is adjusted by varying the motor speed through pulse-width modulation (PWM) signals generated by the Arduino. This approach provides flexible control of solution delivery while maintaining a simple and easily replicable electronic design suitable for instructional laboratory use.

The syringe pump assembly is mechanically integrated with the nozzle holder mounted on the gantry system, allowing synchronized movement during NFES operation while maintaining stable fluid delivery. The modular design of the pump enables easy maintenance, syringe replacement, and component modification, supporting the overall goal of the AVE-EHDM system to provide a flexible, low-cost, and easy-to-assemble educational platform.

Appendix C: Arduino Code

The syringe pump is controlled using an Arduino microcontroller that drives a stepper motor through four digital output pins connected to the motor driver module. The code generates a fixed stepping sequence by switching the logic states of the four control pins in a predefined order, which

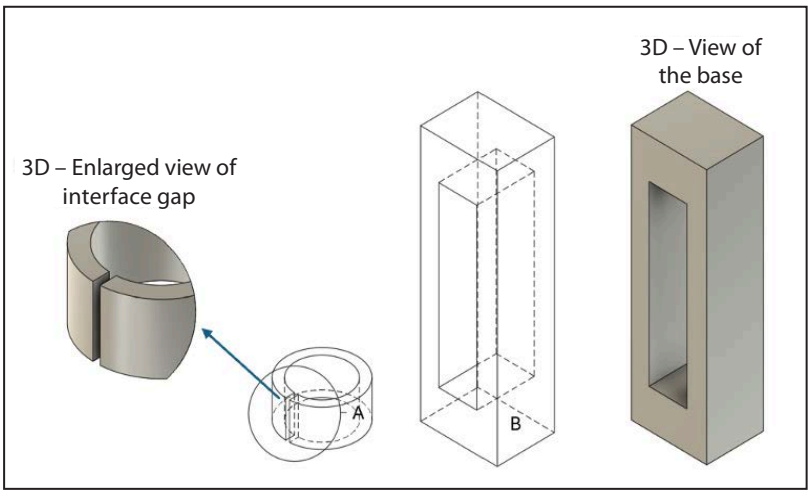


Figure A1. CAD views of the two-part nozzle (syringe) holder showing the interface gap and base mounting section.

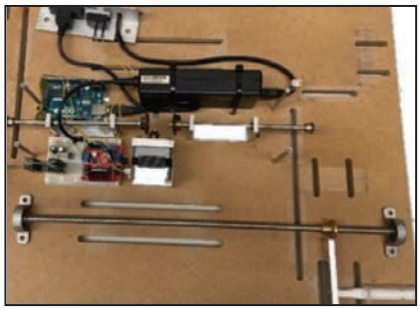


Figure A2. Assembled syringe pump system showing the motor, lead screw mechanism, and mounted syringe.

produces continuous forward rotation of the stepper motor.

The stepping speed is controlled by adjusting the delay time between each step sequence. By modifying this delay value, the rotational speed of the motor and the linear motion of the plunger driven by the lead screw can be regulated. This provides indirect control of the volumetric flow rate delivered by the syringe pump.

The program continuously executes the forward stepping routine, enabling uninterrupted infusion of the polymer solution during electrospinning, electrospraying, and near field electrospinning operations. This simple open loop control strategy was selected to maintain low system complexity while providing stable and repeatable solution delivery suitable for instructional laboratory use. The code will be available upon reasonable request.

Srivarshini Vellaisamy

Srivarshini Vellaisamy is a graduate student in Robotics and Industrial Automation at Wayne State University. Her research interests include robotics, industrial automation, control systems, and engineering education. Her work focuses on applying emerging technologies to practical engineering challenges while exploring innovative approaches to hands-on learning, automation, and robotics education.

Tazdik Patwary Plateau

Dr. Tazdik Patwary Plateau is a tenure-track Assistant Professor of Engineering Technology at Wayne State University with a PhD in Mechanical Engineering. His research focuses on AI in Education, AI-enabled advanced manufacturing, micro-nano manufacturing, and sustainable materials. He has secured NSF and industry grants and served on NSF review panels.

TEXAS A&M UNIVERSITY
Department of Engineering
Technology & Industrial Distribution

Applications are invited for faculty positions at Texas A&M University.

- **Manufacturing and Mechanical Engineering Technology program**
  Tenure-Track: Assistant Professor
  Academic Professional Track: Open Rank & Title
- **Multidisciplinary Engineering Technology program**
  Tenure-Track: Assistant Professor
- **Industrial Distribution program**
  Academic Professional Track: Open Rank & Title

View details & apply:
tx.ag/ETIDFacultyApply

Does your institution have a chapter of

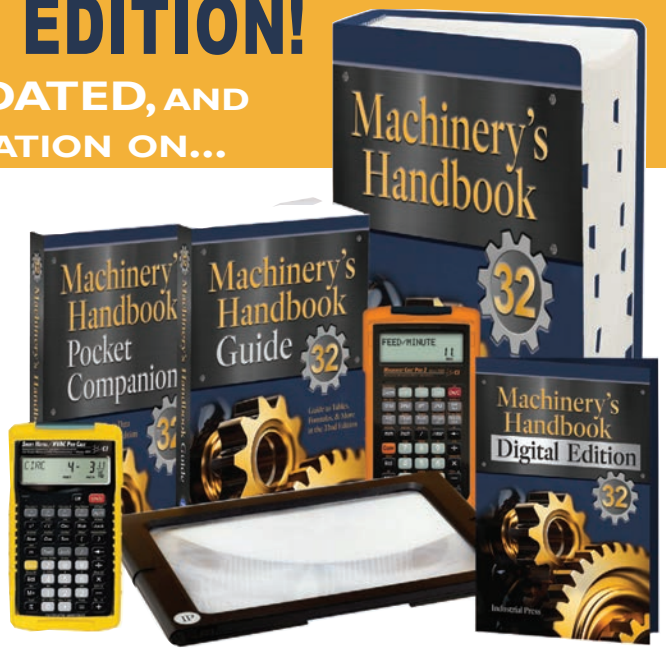
Tau Alpha Pi National Honor Society?

See page 57 for how to get involved.

NOW IN ITS 32ND EDITION!

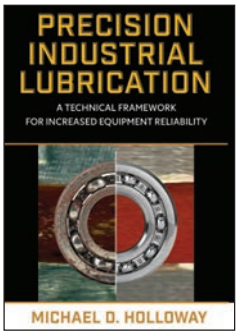
Featuring NEW, UPDATED, and EXPANDED Information on...

- Additive Manufacturing
- Dimensioning and Measuring
- Fasteners, Threads, and Threading
- Machine Elements
- Metalworking and Manufacturing
- Part Design and Production
- Properties and Selection of Materials
- Plus thousands of revisions throughout, updated standards, and expanded metric content

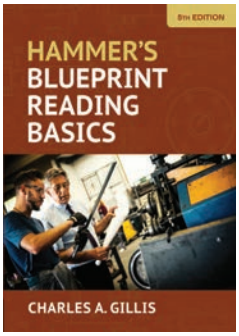


Toolbox: 3,008 pages, ISBN 9780831137328, $169.95
Large Print: 23,008 pages, ISBN 97808311338325, $199.95
Digital Edition: 4,178 pages, ISBN 9780831139322 $174.95
Digital Upgrade: 4,178 pages, ISBN 9780831140328, $89.95
Toolbox/Digital Edition: ISBN 9780831141325, $249.95
Large Print/Digital Edition: ISBN 9780831142322 $274.95
Toolbox and Magnifier: ISBN 9780831143329, $189.95
Guide: 312 pages, illustrated, ISBN 9780831150327, $54.95

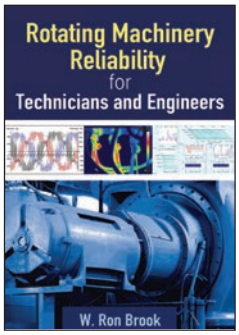
Toolbox/Guide Combo: 3,320 pages, ISBN 9780831148324 $194.95
Large Print/Guide Combo: 3,320 pages, ISBN 9780831149321 $224.95
Pocket Companion: 424 pages, ISBN 9780831151324 $59.95
Toolbox/4090 Sheet Metal HVAC Calc Pro Set: ISBN 9780831146320 $199.95
Large Print/4090 Sheet Metal Calc Pro Set: ISBN 9780831147327 $224.95
Toolbox/Calc Pro 2 Combo: ISBN 9780831144326 $224.95
Large Print/Calc Pro 2 Combo: ISBN 9780831145323 $249.95



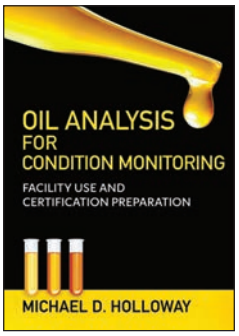
528 pages
9780831137014, $109.95



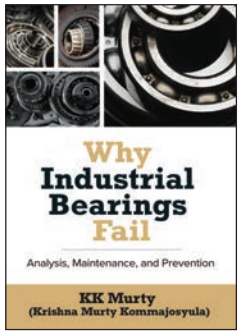
640 pages
9780831136925, $69.95



400 pages
9780831136857, $99.95



304 pages
9780831137021, $10.95



256 pages
9780831136802, $99.95

For more information, Go to books.industrialpress.com. To Request a Review Copy, Go to https://books.industrialpress.com/ebook-review-copy-request-form/.

Industrial Press, Inc.

Excellence by the Book

Mailing Address: P.O. Box 320, Norwalk, CT 06856 • Phone 888.528.7852
Email: info@industrialpress.com • Website: books.industrialpress.com • Digital Store: ebooks.industrialpress.com

Omni-Directional Wall-Climbing Robot: A Novel Mechatronic System with Propulsion-Based Adhesion

Mahdi Yazdanpour and Boshra Karimi

DOI: 10.18260/jet.43.2.4

Abstract

This paper presents the design, implementation, prototype development, and qualitative evaluation of an omni-directional wall-climbing robot using a propulsion-based adhesion mechanism. The proposed system integrates a three-wheel omni-directional drive with thrust generated by brushless propeller units to maintain stable contact with vertical and inclined surfaces. Unlike conventional wall-climbing robots that rely on magnetic or suction-based adhesion, the proposed approach provides broader surface adaptability, including operation on non-ferrous and rough surfaces, without requiring surface-specific adhesion mechanisms. The robot is controlled by an Arduino Mega-based embedded architecture incorporating real-time inertial measurement unit feedback and PID-based control for locomotion and adhesion stabilization. A simplified dynamic model is developed to estimate the thrust required for reliable adhesion, while inverse-kinematic coordination of the omni-wheels enables holonomic motion and precise maneuverability. Qualitative prototype evaluation on multiple surface types indicates stable climbing performance, maintained adhesion, and smooth directional transitions under representative operating conditions. The results support the feasibility of combining propulsion-assisted adhesion with omni-directional mobility in a compact robotic platform for applications such as infrastructure inspection, high-rise maintenance, and industrial surveillance in complex environments.

1. Introduction

The advancement of robots capable of navigating diverse terrains and surfaces is increasingly vital in modern society. Wall-climbing robots have received significant attention in robotics research due to their potential for automation in hazardous and hard-to-reach environments, including infrastructure inspection, industrial maintenance, security surveillance, and rescue operations (Lou et al. 2025; Nguyen et al. 2020; Yang et al. 2024; Yu et al. 2024). The ability to traverse vertical and inclined surfaces offers substantial advantages in situations where human access is difficult, dangerous, or costly. Recent studies have also explored wall-climbing robots with omni-directional motion to improve maneuverability on complex surfaces (Jia et al. 2025).

Wall-climbing robots are commonly classified based on three core design strategies: adhesion, locomotion, and control. Adhesion methods include magnetic (Eto and Asada 2020; Wang et al. 2025), negative pressure (suction) (Hernando et al. 2021), electrostatic (Chen 2015; Yamamoto et al. 2007), and bio-inspired techniques (Wang et al. 2014), each presenting trade-offs related to surface compatibility, energy consumption, and payload capacity. Locomotion strategies include tracked (Kermorgant 2018), wheeled (Eto and Asada 2020), legged (Hong et al. 2022), and hybrid configurations (Tovarnov and Bykov 2024), which balance maneuverability and adaptability. Control strategies range from predefined motion planning to dynamic approaches that incorporate real-time sensory feedback for environmental adaptation (Zhu et al. 2024).

Despite extensive research, traditional wall-climbing robots often remain limited by surface dependency and energy inefficiency. Suction-based systems perform well on smooth surfaces but require substantial power and airtight contact, while magnetic adhesion is restricted to ferromagnetic materials. Electrostatic adhesion offers broader surface compatibility but is sensitive to environmental conditions such as humidity. Bio-inspired adhesion methods, while energy efficient, are often constrained by limited payload capacity (Zhu et al. 2024). To address these challenges, recent studies have explored hybrid adhesion strategies, including the integration of thrust-based mechanisms with conventional adhesion methods, demonstrating improved versatility and stability across diverse surface conditions (Liang et al. 2021; Tovarnov and Bykov 2024).

Building upon recent advances in propulsion-assisted climbing robots, this work presents an omni-directional wall-climbing robot that employs a

drone-propulsion-based adhesion mechanism integrated with omni-wheel kinematics to achieve holonomic motion. Unlike conventional systems that rely solely on passive adhesion, the proposed approach generates a controllable and adjustable normal force, allowing the robot to reliably adhere to vertical and inclined surfaces, including rough and non-ferrous materials. Omni-directional wheels were selected over Mecanum wheels because they provide a mechanically simpler holonomic drive configuration and can offer smoother motion with reduced vibration on flat operating surfaces, making them well suited for this application (Akkad and Almusawi 2023; Hijikata et al. 2023; Taheri and Zhao 2020).

The control architecture is implemented using an Arduino Mega microcontroller and incorporates a PID-based feedback loop to ensure precise motor control and real-time stability adjustment. By integrating thrust-based adhesion with omni-directional locomotion, the proposed system expands the operational capabilities of wall-climbing robots while maintaining manageable system complexity. Furthermore, the use of a three-wheel omni-directional configuration reduces mechanical complexity while preserving full planar mobility, making the system well suited for compact robotic platforms. Related work on ground-based omni-directional robotic platforms has also demonstrated the value of holonomic mobility for maneuvering in constrained environments and for integrating sensing, perception, and embedded control within a unified mechatronic system (Yazdanpour et al. 2026).

In addition to its technical contribution, the project was developed within a senior capstone experience in Mechatronics Engineering Technology, providing a practical setting for system-level integration of mechanical design, embedded control, mechatronics, and prototype testing. As such, the work also reflects the role of applied, project-based learning in engineering technology education through hands-on system development and iterative refinement.

The primary contribution of this work is the integration of propulsion-based adhesion with a compact three-wheel omni-directional locomotion platform for wall-climbing operation on diverse surface types. In addition to the mechanical and embedded-system design, the study presents a simplified dynamic model for thrust estimation and a closed-loop control architecture based on IMU feedback and PID regulation. The remainder of the paper describes the system methodology, qualitative prototype evaluation, and key challenges identified during testing.

Although propulsion-assisted wall-climbing has been explored in prior studies, the novelty of the present work lies in the integration of propulsion-based adhesion with a compact three-wheel omni-directional holonomic drive and embedded IMU-based PID stabilization in a single wall-climbing platform. In contrast to prior systems that primarily emphasize adhesion feasibility or conventional locomotion architectures, the proposed design focuses on combining thrust-assisted multi-surface adhesion with compact holonomic maneuverability and simplified mechatronic integration. This combination enables directional flexibility, reduced mechanical complexity, and practical proof-of-concept implementation within an engineering technology capstone framework.

2. Capstone and Educational Context

This project was completed within a senior-level capstone course in the Mechatronics Engineering Technology program. The capstone required student teams to conceive, design, prototype, and validate a functional system addressing an open-ended engineering problem. The instructional structure included concept proposal, mechanical and electrical design review, prototype fabrication, iterative testing and refinement, and final demonstration, with faculty serving in an advisory role while students maintained primary responsibility for design and implementation decisions. This structure was intended to support system-level engineering competencies and reinforce disciplined engineering practice rather than ad hoc prototyping.

Educational outcomes were assessed qualitatively through milestone-based faculty review of concept selection, subsystem integration, prototype fabrication, troubleshooting, and final demonstration. Particular emphasis was placed on system integration, embedded control implementation, iterative refinement, and validation under prototype testing constraints. The project therefore served not only as a technical prototype effort, but also as an applied assessment of student competency in mechatronic system development. These milestone reviews provided the qualitative assessment basis for the educational findings discussed in Section 6.

3. Methodology

The proposed framework for the omni-directional wall-climbing robotic system integrates five primary subsystems: Mechanical Design, Propulsion System, Embedded System and Control, Software and Control Algorithms, and Dynamic Modeling. All subsystems were designed, developed, and integrated through an iterative engineering process including concept selection, prototyping, testing, and refinement.

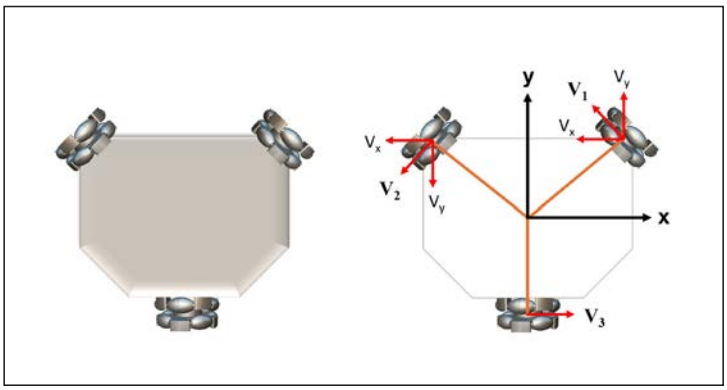


Figure 1. Robot chassis and the omni-directional wheel configuration.

3.1 Mechanical Design

The robot chassis was fabricated using 3D-printed Polyethylene Terephthalate Glycol (PETG) material, selected to provide a practical balance of structural strength, durability, and low mass. The frame accommodates the locomotion, propulsion, sensing, and control components while maintaining a compact configuration suitable for vertical operation. Three omni-directional wheels are arranged at 120° intervals, as shown in Figure 1, to provide holonomic planar motion.

The symmetric wheel arrangement allows the individual wheel-velocity vectors to be combined for translational and rotational motion. Integrated mounting features accommodate the drive motors, propulsion units, and sensors while minimizing the overall system footprint. The corresponding wheel kinematics and motion modes are described in Section 3.4.

3.2 Propulsion System

A thrust-based adhesion mechanism was implemented using Readytosky 2212 920KV brushless motors, each driving a propeller to generate a controlled normal force toward the climbing surface. The motor–propeller assemblies were mounted at an inverted angle to direct the generated thrust toward the surface while limiting undesirable torque disturbances on the chassis. To improve aerodynamic performance, a custom propeller shroud was designed and fabricated to enhance airflow directionality and reduce thrust losses due to turbulence. The propulsion units were selected to provide sufficient thrust margin for vertical and inclined operation while maintaining a compact system configuration. Propulsion output can be adjusted using orientation feedback from the onboard inertial measurement unit (IMU), allowing the adhesion force to respond to changes in robot orientation. The force-balance basis for propulsion-system sizing is presented in Section 3.5.

3.3 Embedded System and Control

The Arduino Mega microcontroller serves as the central processing unit, managing real-time sensor feedback and executing control commands. The drive system is powered by Greartisan 12 V DC motors controlled through a BTS7960 motor driver, which supports high-current operation and bidirectional motor control. Wireless user control is implemented using an FS-i6 transmitter and an FS-IA6B receiver. An onboard IMU continuously provides orientation and motion data for PID-based feedback control. The principal hardware components and key design specifications of the prototype are summarized in Table 1.

User commands from the RC transmitter define the desired platform motion and are processed by the Arduino Mega to generate wheel-drive and propul-

Table 1. Main hardware components and design specifications.

Component/Parameter	Specification / Model	Function
Chassis Material	Polyethylene Terephthalate Glycol (PETG)	Structural frame
Wheel Configuration	3 Omni-wheels at 120°	Holonomic locomotion
Microcontroller	Arduino Mega	Central control
Drive Motors	Greartisan 12 V DC motors	Wheel actuation
Propulsion Motors	Readytosky 2212 920KV brushless motors	Adhesion thrust
Motor Driver	BTS7960	Drive motor control
IMU	Onboard inertial measurement unit	Orientation feedback
RC Transmitter	FS-I6	User control input
RC Receiver	FS-IA6B	Wireless signal reception
Propeller Shroud	Custom fabricated	Airflow guidance/thrust efficiency

Table 2. The different motions of the omni-wheels.

Movement	Omni-Wheel Motion Principle
Forward	Wheel velocities are coordinated according to Equation (1) to generate forward translation
Backward	Wheel velocities are coordinated to generate backward translation
Rightward	Wheel velocities are coordinated to generate rightward translation
Leftward	Wheel velocities are coordinated to generate leftward translation
Diagonal Motion	Translational components are combined to generate the desired diagonal motion
Clockwise Rotation	Wheel velocities are coordinated to generate clockwise rotation about the robot center
Counter-Clockwise Rotation	Wheel velocities are coordinated to generate counterclockwise rotation about the robot center

sion commands. Real-time IMU feedback is used within the PID loop to correct orientation deviations by adjusting wheel velocities and propulsion thrust, thereby supporting stable wall contact and controlled motion. This embedded architecture coordinates sensing, actuation, and feedback regulation within a compact robotic platform.

3.4 Software and Control Algorithms

The omni-directional wheel configuration enables holonomic motion, allowing the robot to move in any planar direction without requiring reorientation. The principal motion modes associated with this configuration are summarized in Table 2. As illustrated in Figure 1 and Figure 2, the robot's movement is determined by an inverse kinematics algorithm that computes individual wheel velocities to achieve the desired translational and rotational motion.

The control system dynamically adjusts propulsion thrust based on real-time IMU feedback. To support accurate locomotion, the kinematic model for the omni-directional wheels accounts for wheel-placement geometry and the translational and rotational components of platform motion. Each wheel's angular velocity is computed as a function of the desired translational velocities and rotational rate, enabling coordinated omni-directional motion. The resulting kinematic relationship is expressed as:

$$\begin{bmatrix}\omega_1\\ \omega_2\\ \omega_3\end{bmatrix} = \frac{1}{R}\begin{bmatrix}-\sin\theta_1 & \cos\theta_1 & L\\ -\sin\theta_2 & \cos\theta_2 & L\\ -\sin\theta_3 & \cos\theta_3 & L\end{bmatrix}\begin{bmatrix}V_x\\ V_y\\ \omega\end{bmatrix} \quad (1)$$

where V_x and V_y represent the translational velocities in the planar directions, ω denotes the rotational velocity, ω_1, ω_2, and ω_3 are the corresponding angular velocities, R is the omni-wheel radius, and L is the wheel-placement radius. The angles θ_1, θ_2, and θ_3 define the orientation of each wheel relative to the robot center, according to the coordinate convention shown in Figure 1, and are spaced at 120° intervals for the three-wheel configuration. Figure 2 illustrates the principal translational and rotational motion modes associated with this arrangement.

Equation (1) describes the inverse kinematic relationship between the desired platform motion and the corresponding wheel angular velocities. It allows translational motion in the x- and y-directions to be combined with rotation about the robot center, enabling holonomic maneuvering without prior re-

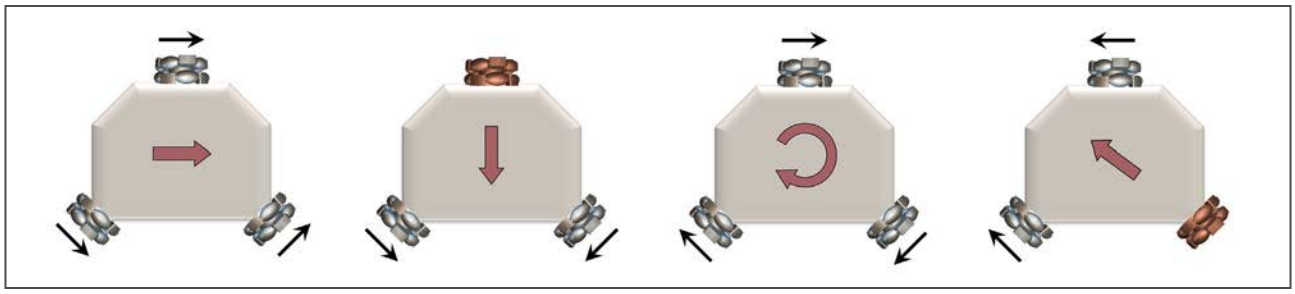


Figure 2. Moving vectors and rotation mechanisms of the omni-wheels.

orientation. The symmetric 120° wheel arrangement supports coordinated wheel-speed distribution while maintaining a compact mechanical configuration.

3.5 Dynamic Modeling

To ensure reliable adhesion during wall-climbing operation, a simplified dynamic model was developed to analyze the balance of forces acting on the robot. The primary objective of this model is to determine the thrust force required to maintain stable contact with the climbing surface while providing sufficient frictional support for locomotion.

For a robot operating on a surface inclined at an angle α measured from the horizontal, the gravitational load can be resolved into components normal and tangential to the surface. The propulsion system generates an effective normal thrust component F_t directed toward the climbing surface, increasing the normal contact force and thereby increasing the friction force available to resist slip. Under quasi-static operating conditions, the normal force can be approximated as

$$N = F_t + mg\cos(\alpha) \qquad (2)$$

where N is the surface normal reaction force, m is the robot mass, and g is gravitational acceleration. To prevent sliding, the available friction force must be greater than or equal to the tangential component of gravity. Thus, the no-slip condition may be written as

$$\mu N \geq mgsin(\alpha) \qquad (3)$$

where μ is the effective coefficient of friction between the robot and the climbing surface. Substituting the expression for normal force gives

$$\mu(F_t+mgcos(\alpha)) \geq mgsin(\alpha) \qquad (4)$$

which shows that stable wall-climbing depends on the interaction among propulsion thrust, robot weight, surface inclination, and available friction. For vertical climbing, sufficient propulsion-induced normal force is required to provide the frictional support needed to resist downward sliding.

In addition to the no-slip condition, a safety margin F_s was included in the design-stage thrust requirement to account for surface irregularities, airflow losses, local vibration, and transient disturbances. Based on Equation (4), the required propulsion thrust can therefore be expressed as

$$F_t \geq mg\left(\frac{sin(\alpha)}{\mu} - cos(\alpha)\right) + F_s \qquad (5)$$

where F_s represents the additional safety margin used during preliminary system sizing. This relation provides a simplified design-stage estimate rather than a complete dynamic representation of the robot.

Assuming quasi-static operating conditions, the proposed force-balance model provides a first-order representation of the conditions required to maintain contact with inclined and vertical surfaces. The model relates propulsion thrust to the normal contact force and the friction available to resist sliding, while the safety-margin term accounts approximately for disturbances that are not explicitly represented. Although simplified, the model provided a practical basis for propulsion-system selection and preliminary performance assessment.

Figure 3 illustrates the principal forces acting on the wall-climbing robot. The gravitational force mg acts downward, while the propulsion thrust F_t acts toward the climbing surface and increases the normal contact force. The surface reaction force N and friction force F_f contribute to maintaining contact and resisting tangential slippage. The safety margin F_s is incorporated in the preliminary thrust estimate to account for surface irregularities, airflow losses, vibration, and other transient effects not explicitly represented in the simplified model.

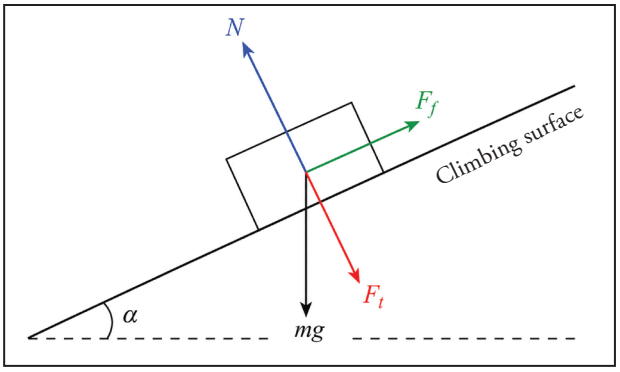


Figure 3. Force diagram for wall-climbing robot.

3.6 Closed-Loop Control System

A closed-loop control system was implemented to regulate both the robot's locomotion and propulsion-assisted adhesion. Figure 4 illustrates the interaction among user command input, IMU-based feedback, PID regulation, and actuation of the locomotion and propulsion subsystems. User inputs from the RC transmitter are processed by the Arduino Mega to generate wheel-motion and propulsion-thrust commands.

The control strategy uses orientation feedback from the onboard inertial measurement unit (IMU), which provides real-time attitude information during

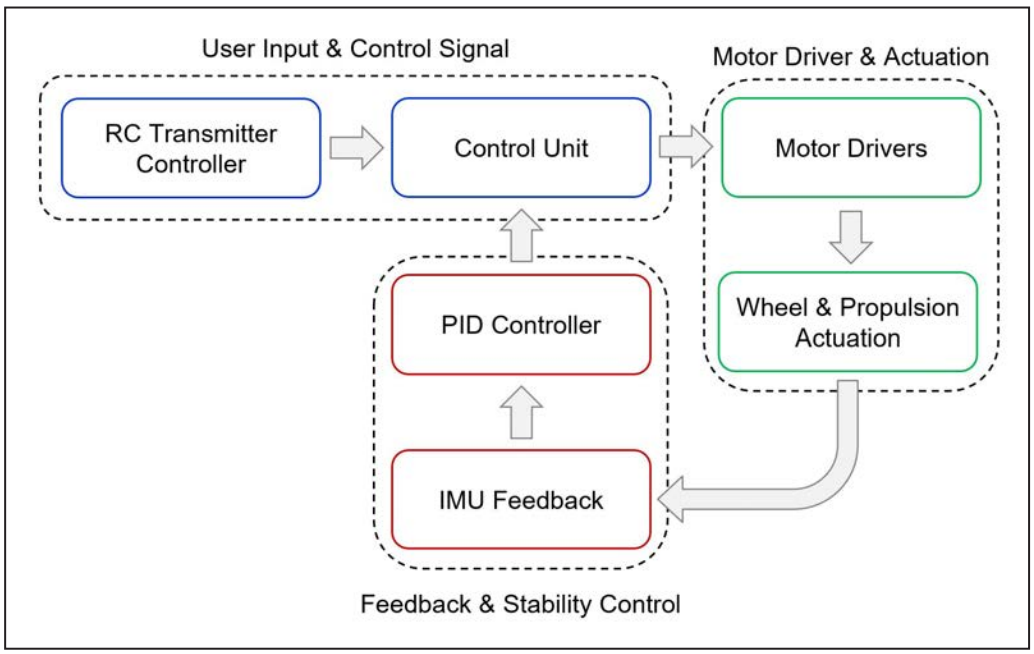


Figure 4. Closed-loop control system architecture.

wall-climbing operation. The measured orientation is compared with the desired climbing orientation to generate an orientation error, $e(t)$. The PID controller processes this error to produce a corrective control output, $u(t)$, which is applied through wheel-velocity commands and propulsion-thrust adjustments to improve stability and reduce drift.

In this control structure, the proportional term K_p provides the primary corrective response to orientation error, the integral term K_i reduces steady-state drift, and the derivative term K_d suppresses oscillatory behavior and improves transient stability. Controller gains were tuned empirically during prototype testing through iterative adjustment while observing robot behavior on vertical surfaces. The tuning process began with proportional control to establish basic corrective action, followed by derivative adjustment to improve damping and reduce oscillation. Integral action was then introduced conservatively to reduce residual drift during steady climbing operation.

Because the system was developed as a senior capstone prototype, the exact archived gain values were not preserved; however, the controller structure and tuning procedure are documented here to provide technical transparency regarding the implemented control approach. Overall, the closed-loop feedback was observed to improve balance, surface adherence, and motion stability during wall-climbing operation.

4. Results and Discussion

4.1 Qualitative Prototype Evaluation

Figure 5 shows the fabricated prototype used for experimental evaluation. Experimental trials were conducted on multiple vertical surfaces, including smooth walls, rough concrete, and metallic surfaces. Across all test environments, the robot successfully

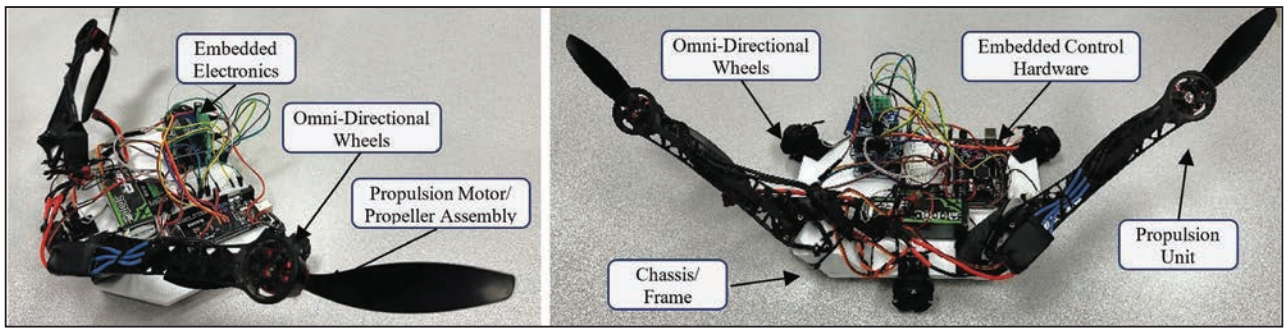


Figure 5. Fabricated omni-directional wall-climbing robot prototype: (a) Angled view showing the omni-wheel locomotion system, propulsion motor/propeller assembly, chassis, and embedded electronics; and (b) Top view showing the three-wheel arrangement, propulsion units, and integrated control hardware.

Table 3. Qualitative observations from prototype testing across surface types.

Surface Type	Orientation Tested	Adhesion Maintained	Locomotion Observed	Qualitative Observation
Smooth Wall	Vertical	Yes	Yes	Stable directional motion observed
Rough Concrete	Vertical/Inclined	Yes	Limited	Increased vibration and reduced smoothness of motion
Metallic Surface	Vertical	Yes	Yes	Stable adhesion observed during manual control

maintained surface adhesion, demonstrating the reliability and adaptability of the propulsion-based adhesion mechanism. The omni-directional wheel configuration enabled smooth directional transitions and controlled directional motion, highlighting the advantages of holonomic mobility during wall-climbing operations. Because quantitative logs were not recorded during prototype testing, the observed performance across tested surfaces is summarized qualitatively in Table 3. The table is intended to document proof-of-concept behavior under representative operating conditions rather than provide a statistical performance benchmark.

As shown in Table 3, the prototype maintained adhesion on all tested surfaces, while locomotion quality varied with surface condition. Smooth wall and metallic surface trials showed more stable directional movement, whereas rough concrete introduced increased vibration and reduced motion smoothness, likely due to increased rolling disturbance and local surface irregularities. These observations indicate that the propulsion-based adhesion mechanism was effective in maintaining surface contact across all tested materials, including non-ferrous and rough surfaces. Overall, the findings support the feasibility of combining omni-directional locomotion with thrust-assisted adhesion, while also identifying surface-induced vibration and control refinement as key areas for future improvement.

4.2 Reconstructed Quantitative Indicators

Because the original prototype testing did not include fully instrumented performance logging, limited quantitative indicators were reconstructed from archived video footage and prototype records. Based on the observed travel distance and elapsed time, the robot exhibited an approximate climbing speed of about 5 cm/s on a smooth vertical surface under proof-of-concept operating conditions. In addition, the prototype successfully completed 3 of 4 observed climbing trials under the smooth vertical surface condition, indicating partial repeatability of the prototype behavior. These reconstructed values are intended only as supplementary performance indicators and not as definitive benchmark measurements.

4.3 Experimental Limitations

Although the present evaluation is limited to qualitative prototype observations and a small amount of reconstructed quantitative evidence, the results indicate that the integrated mechatronic architecture can achieve controlled wall-climbing under multiple conditions. Future work should include quantitative measurements of thrust margin, climbing speed, power consumption, payload capacity, repeatability, and controller response to provide a more complete performance characterization.

5. Challenges, Optimizations, and Experimental Observations

Several challenges were identified during initial testing. Early prototypes exhibited instability due to uneven thrust distribution, which affected the robot's ability to maintain consistent adhesion on vertical surfaces. This issue was addressed through iterative refinement of propeller placement, resulting in more uniform force distribution and improved stability. Control precision also posed a challenge, as initial PID tuning led to oscillatory behavior and positional drift. Through systematic adjustment of PID parameters, the system achieved smoother motion transitions, reduced oscillations, and enhanced maneuverability. Repeated testing on multiple surface types also supported the refinement of experimental procedures and helped improve the repeatability of adhesion and locomotion trials.

Energy consumption also emerged as an important design consideration because propulsion-based adhesion requires continuous thrust generation. Because power consumption and operating duration were not instrumented during prototype testing, energy efficiency was not quantified in the present study. Future work should include measurements of power consumption, battery duration, and propulsion efficiency together with improvements in motor selection and control strategies.

Future iterations of the system could benefit from the integration of advanced control interfaces, such as semi-autonomous operation and brain–computer interfaces (Yazdanpour et al. 2024a), to improve operational flexibility and user adaptability. Prior research on autonomous omni-directional mobile robots has demonstrated the effectiveness of sensor-based stability mechanisms, including infrared sensing and AI-driven visual perception (Yazdanpour et al. 2024b). Incorporating similar sensor fusion techniques could further enhance dynamic adhesion control, enabling real-time adaptation to varying surface conditions.

6. Experiential Learning and Educational Impact

Capstone design experiences provide an important setting for integrating prior learning, addressing open-ended engineering problems, and developing competencies associated with professional engineering practice (Webster and Turner 2024). The wall-climbing robot project provided a hands-on experiential learning environment in which students integrated mechanical design, additive manufacturing, embedded systems, sensing, control, and prototype testing within a single multidisciplinary system. Rather than addressing these topics as isolated course activities, the capstone required students to make design decisions, integrate multiple subsystems, identify system-level failures, and iteratively refine the prototype based on observed performance. This process connected theoretical concepts in mechatronics and control with the practical constraints encountered during fabrication, integration, and testing, consistent with prior engineering technology work emphasizing hands-on system development as a means of connecting theoretical knowledge with practical problem solving (Ma and Pecen 2024).

Educational outcomes were evaluated qualitatively through faculty review of project milestones and observation of the students' progression from concept development to a functional integrated prototype. Evidence of learning was reflected in the students' ability to integrate mechanical, electrical, and control subsystems, identify and correct uneven thrust distribution, iteratively tune the PID controller to reduce oscillation and drift, and refine the design based on prototype testing. These activities provided evidence of developing competency in system integration, troubleshooting, iterative engineering design, and prototype validation. Because formal pre/post surveys, standardized assessment instruments, or quantitative educational measures were not administered, these findings are interpreted as qualitative evidence of student learning rather than quantitative measures of educational effectiveness.

7. Conclusion

This paper presented the design, implementation, and qualitative prototype evaluation of an omni-directional wall-climbing robot using a propulsion-based adhesion mechanism. The proposed system combines a three-wheel omni-directional locomotion platform with thrust-assisted adhesion to address limitations commonly associated with conventional suction- and magnetic-based wall-climbing robots. By integrating holonomic mobility, PID-based closed-loop control, and IMU feedback, the robot achieved stable motion, reliable surface adhesion, and smooth maneuverability on vertical and inclined surfaces. Dynamic modeling supported the estimation of thrust requirements for surface adherence, while prototype testing supported the feasibility of the overall system on multiple surface types. The results demonstrate that propulsion-assisted adhesion combined with omni-directional mobility provides a practical approach for wall-climbing robotic platforms intended for applications such as infrastructure inspection, maintenance, and industrial monitoring. Future work will focus on improving energy efficiency, extending operational duration, and incorporating more advanced sensing and autonomous control capabilities. In addition to its technical contribution, the project illustrates how capstone-based implementation can support applied engineering technology education through hands-on system integration, control, and prototype validation.

Acknowledgment

The authors acknowledge the contributions of the senior capstone student team who assisted with prototype design, fabrication, assembly, and testing during the development of the wall-climbing robot.

References

Akkad, Hussam, and Almusawi, Husam. 2023. "A comparative review of omnidirectional wheel types for mobile robotics.", *Social Science Research Network (SSRN)*. https://doi.org/10.2139/ssrn.4488112.

Chen, Rui. 2015. "A gecko-inspired electroadhesive wall-climbing robot.", *IEEE Potentials*, 34(2), 15–19. https://doi.org/10.1109/MPOT.2014.2360020.

Eto, Haruhiko, and Asada, H. Harry. 2020. "Development of a wheeled wall-climbing robot with a shape-adaptive magnetic adhesion mechanism.", *IEEE International Conference on Robotics and Automation (ICRA)*, 9329-9335. https://doi.org/10.1109/ICRA40945.2020.9196919.

Hernando, Miguel, Gómez, Virgilio, Brunete, Alberto, and Gambao, Ernesto. 2021. "CFD modelling and optimization procedure of an adhesive system for a modular climbing robot.", *Sensors*, 21(4), 1117. https://doi.org/10.3390/s21041117.

Hijikata, Masaaki, Miyagusuku, Renato, and Ozaki, Koichi. 2023. "Omni Wheel Arrangement Evaluation Method Using Velocity Moments.", *Applied Sciences*, 13(3), 1584. https://doi.org/10.3390/app13031584.

Hong, Seungwoo, Um, Yong, Park, Jaejun, and Park, Hae-Won. 2022. "Agile and versatile climbing on ferromagnetic surfaces with a quadrupedal robot.", *Science Robotics*, 7(73), https://doi.org/10.1126/scirobotics.add1017.

Jia, Pei, Tianyu Zheng, Manhong Li, Minglu Zhang, and Zhexuan Huang. 2025. "Design and Analysis of Wall-Climbing Robot with Passive Adaptive Parallel Mechanism." *Applied Ocean Research*, 161: 104690. https://doi.org/10.1016/j.apor.2025.104690.

Kermorgant, Olivier. 2018. "A magnetic climbing robot to perform autonomous welding in the shipbuilding industry.", *Robotics and Computer-Integrated Manufacturing*, 53, 178-186. https://doi.org/10.1016/j.rcim.2018.04.008.

Liang, Peng, Gao, Xueshan, Zhang, Qingfang, Gao, Rui, Li, Mingkang, Xu, Yuxin, and Zhu, Wei. 2021. "Design and stability analysis of a wall-climbing robot using propulsive force of propeller.", *Symmetry*, 13(1), 37. https://doi.org/10.3390/sym13010037.

Lou, Shengjie, Wei, Zhong, Guo, Jinlin, Ding, Yu, Liu, Jia, and Song, Aiguo. 2025. "Current status and trends of wall-climbing robots research.", *Machines*, 13(6), 521. https://doi.org/10.3390/machines13060521.

Ma, Junkun, and Reg Recayi Pecen. 2024. "Incorporating the Design and Development of an Educational Automated Manufacturing System Utilizing Desktop Equipment into Instruction of Various Courses." *Journal of Engineering Technology*, 41(2), 6–14.

Nguyen, Son T., Pham, Anh Q., Motley, Cadence, and La, Hung M. 2020. "A Practical Climbing Robot for Steel Bridge Inspection.", *IEEE International Conference on Robotics and Automation (ICRA)*, 9322-9328. https://doi.org/10.1109/ICRA40945.2020.9196892.

Taheri, Hamid, and Zhao, Chun Xia. 2020. "Omnidirectional mobile robots, mechanisms and navigation approaches.", *Mechanism and Machine Theory,* 153, 103958. https://doi.org/10.1016/j.mechmachtheory.2020.103958.

Tovarnov, Mikhail S., and Bykov, Nikita V. 2024. "A novel hybrid adhesion method and autonomous locomotion mechanism for wall-climbing robots.", *Robotics and Autonomous Systems*, 181, 104779. https://doi.org/10.1016/j.robot.2024.104779.

Wang, Zhongyuan, Dai, Z., Yu, Zhiwei, and Shen, Danni. 2014. "Optimal attaching and detaching trajectory for bio-inspired climbing robot using dry adhesive." *IEEE/ASME International Conference on Advanced Intelligent Mechatronics,* 990-993. https://doi.org/10.1109/AIM.2014.6878209.

Wang, Baoyu, Li, Peixing, Li, Peibo, Zhang, Lin, Guan, Enguang, Liu, Xun, Hu, Xudong, and Zhao, Yanzheng. 2025. "Development of a wheeled wall-climbing robot with an internal corner wall adaptive magnetic adhesion mechanism.", *Journal of Field Robotics*, 42(1), 97-114. https://doi.org/10.1002/rob.22402.

Webster, Rustin, and Matthew Turner. 2024. "Engineering Technology Capstone: Exploring the Current State." *Journal of Engineering Technology,* 41(2), 34-39.

Yamamoto, Akio, Nakashima, Takumi, and Higuchi, Toshiro. 2007. "Wall climbing mechanisms using electrostatic attraction generated by flexible electrodes.", *International Symposium on Micro-NanoMechatronics and Human Science,* IEEE, 389–394. https://doi.org/10.1109/MHS.2007.4420886.

Yang, Pei, Sun, Lingyu, and Zhang, Minglu. 2024. "Design and analysis of a passive adaptive wall-climbing robot on variable curvature ship facades.", *Applied Ocean Research*, 143, 103879. https://doi.org/10.1016/j.apor.2024.103879.

Yazdanpour, Mahdi, Ferrao, Leslie, and Ale, Biplov. 2024a. "Development of an EEG-based brain-controlled mini-industrial robotic arm.", *ASEE Conference for Industry and Education Collaboration (CIEC).* https://doi.org/10.18260/1-2-1139-49066.

Yazdanpour, Mahdi, Nick Delaet, Seth Burghard, and Mason Powers. 2026. "A ROS2-Based Omni-Directional AGV for Indoor Industrial

Mobility with LiDAR-Guided Obstacle Response and Vision-Based Command Recognition." *IEEE Annual Conference of the IEEE Industrial Electronics Society (IECON)*.

Yazdanpour, Mahdi, Tran, Vu, and Tayabee, Shariqa. 2024b. "Autonomous omnidirectional mobile robot for indoor navigation.", *IEEE International Conference on Electro Information Technology (eIT)*, 53–57. https://doi.org/10.1109/eIT60633.2024.10609938.

Yu, Zhenwei, Shen, Yonggang, Zhang, Yiping, and Xiang, Yiqiang. 2024. "Automatic crack detection and 3D reconstruction of structural appearance using underwater wall-climbing robot.", *Automation in Construction*, 160, 105322. https://doi.org/10.1016/j.autcon.2024.105322.

Zhu, Junru, Zhu, Yongqiang, and Zhang, Pingxia. 2024. "Review of advancements in wall climbing robot techniques.", *Franklin Open*, 8, 100148. https://doi.org/10.1016/j.fraope.2024.100148.

Mahdi Yazdanpour

Mahdi Yazdanpour, Ph.D., is an Associate Professor and the Dr. James Russell Myers Endowed Engineering Technology Professor at Miami University. He earned his Ph.D. in Electrical Engineering from Oklahoma State University. His research focuses on intelligent mechatronic systems, human-robot interaction, brain-computer interfaces, brain-controlled systems, autonomous systems, and industrial automation. He is a Senior Member of IEEE and serves as an ABET Program Evaluator.

Boshra Karimi

Boshra Karimi, Ph.D., is an Associate Professor of Construction Management at Northern Kentucky University. She earned her Ph.D. in Civil and Environmental Engineering with a focus on Construction Management from Oklahoma State University. Her research interests include sustainable technologies, sustainability assessment, smart buildings, supply chain management, decision-making modeling, and big data applications in construction. She is also a LEED Green Associate.

National Honors

National Honors for Engineering Technology Students

Tau Alpha Pi National Honor Society provides recognition for high standards of scholarship among students in technical colleges and universities, and fosters desirable qualities of personality, intellect, and character among engineering technology programs. Both associate and baccalaureate degree students are eligible. Membership in Tau Alpha Pi does not conflict with membership in any local honor society.

Realizing student achievement is an important aspect of every educational institution. If you are interested in establishing a chapter at your institution, or in obtaining additional information, please contact **Tom Walker**, ASEE Headquarters.

TEL: (202) 331-3531 **WEB**: http://TauAlphaPi.org **E-MAIL:** TAP@asee.org

A Hierarchical Framework of the Impact of End-User Machine Learning Tools on Applied Machine Learning Education

Jonathan Niemirowski, David Hall, Krystal Cruse and Mary Fendley

DOI: 10.18260/jet.43.2.5

Abstract

Development of end-user tools for machine learning (ML) has increased accessibility to ML projects, but current literature lacks pedagogical guidance on using these tools to assess or develop course content in higher education. This exploratory study presents an abstraction hierarchy model as a preliminary course design framework for assessing the information and functions associated with applied ML classroom projects from engineering and technology courses. These projects were designed for students without a robust computer science or software development background. To investigate how end-user ML tools impact the required knowledge and skills to complete an applied ML project, and how these observations might inform future course design, three applied ML projects were qualitatively evaluated and organized into the abstraction hierarchy model based on instructor observation. Each component was assessed for whether it required less instructional time due to the inclusion of end-user ML tools. Results indicated that contemporary tools streamlined the teaching of the creating, training, testing, and deploying ML models, allowing for increased focus on the initial design of an ML project, the creation and processing of data, and the evaluation of the final design in a real-world context, as opposed to typical training and testing metrics. These preliminary observations suggest that a barrier of entry allows non-experts to more readily approach and utilize ML technologies, though further validation across additional courses and instructors is needed to assess how broadly this framework applies.

1. Introduction

Artificial intelligence (AI) and machine learning (ML) are fast-growing technologies in STEM industries. The past decade has seen the introduction of the fourth industrial revolution, characterized by an explosive connection of devices, information, and automated processes (Pedota & Piscitello, 2022). Machine learning stands at the forefront of this advance, thanks in part to advances in processing and data transfer/storage speeds (Jordan & Mitchell, 2015). The rapid adoption of AI has led many to consider this decade to be the start of the fifth industrial revolution, characterized by more mindful human-machine interaction and concerns of ethical AI usage (Ali et al., 2022).

At Louisiana Tech University, one of many initiatives to keep pace with this rapidly changing landscape has been to incorporate machine learning content within the Instrumentation and Control Systems Engineering Technology (ICET) Program. This four-year bachelor's program employs project-based learning to develop students' practical skillsets in electrical and mechanical systems. Previously, machine learning education was dependent on a strong background in computer science (CS) and mathematics. During the development of course content for this program, a need emerged for ML tinkerers with the skills to effectively apply machine learning concepts to industrial problems; students should have experience in preparing and managing data for training as well as implementation of solutions within real-world contexts. With recent advances in machine learning tools, engineering students can utilize the technology without rigorous mathematics and computer science backgrounds (Sundberg & Holmström, 2024). While these new tools allow for increased complexity and depth in course content, they also allow for significant knowledge gaps to form within students' understanding of the material. These gaps in content knowledge show a clear need for better guidance on maximizing student learning and confidence in applied ML courses (Niemirowski, 2023; Sundberg & Holmström, 2024).

This article reflects on selected applied ML projects from engineering courses, exploring how end-user tools impacted the project's scope and difficulty for the instructor and the students. The background literature will outline the increasing need for ML education in non-computer science programs; the current challenges in teaching ML to non-CS students; the development of current end-user ML tools

that enable a new population of ML tinkerers; and abstraction hierarchy models. Several sample classroom ML projects will be described, modeled using abstraction hierarchies, and commented on for the implications, limitations, contributions, and recommendations for future studies.

2. Materials and Methods

2.1 End-User Tools for Machine Learning Applications

The advance of machine learning has expanded hardware and software tools that support practical ML applications (Huyen, 2020; Giraldo & Laso, 2025). Of note are end-user tools designed to lower the technical barrier to developing ML projects. Low-code and no-code AI now enable users to build ML systems with limited programming experience (Sundberg & Holmström, 2024). For example, Edge Impulse provides simplified visual interfaces and an MLOps wizard for data processing, model creation, and training, with minimal computer science knowledge required for model creation (Hymel et al., 2022).

These innovations have broadened access to ML in numerous fields (Aggarwal et al., 2022; Jordan & Mitchell, 2015; Khalajzadeh et al., 2018; Tai, 2020). Domain experts can now develop ML projects without the extensive technical expertise once required, further accelerating the adoption of MLOps in diverse disciplines (Sundberg & Holmström, 2023). Engineering is one such field, applying ML in areas such as computer vision, predictive maintenance, and control systems. This rapid development of ML necessitates equally rapid developments in ML education.

2.2. The State of Machine Learning Education

Current ML courses can generally fall into two categories: ML fluency courses aim to educate students on the theory and mechanisms of ML technologies for the purpose of application, research, and development, while ML literacy focuses on providing context and fundamental knowledge so that students can participate in conversations surrounding the technology (Long & Magerko, 2020). ML literacy courses also equip students for the application of developed AI platforms, such as generative AI (Neumann et al., 2024; Shailendra et al., 2024). While ML literacy courses are common across K-12 and higher education, ML fluency courses tend to be restricted to computer science education.

It has been observed that the teaching experience for a computer science machine learning course is distinctive from teaching non-CS students. Machine learning content will often focus on theory, demonstrating the technology on benchmark datasets to demonstrate how machine learning functions. These courses can be offered as advanced courses and electives, with a foundation of mathematics and programming pre-requisites completed before accessing them. As such, pedagogical content knowledge in these traditional machine learning courses can assume a familiarity with programming and statistics before exploring machine learning content.

In contrast, non-CS students approach machine learning with a far less robust background. To be approachable, many non-CS courses must either cover the requisite math and programming or deliver content on machine learning that does not require these skills. Significant pre-requisite content will create a steep learning curve for students to climb before they can engage in machine learning content, which also limits the scope of the ML content that the course may cover. A common method of translating CS content to non-CS students is to produce a lightweight version of the same content (Chilana et al., 2015). However, this may result in learning outcomes where students are only familiar with the content and are unable to develop or apply it. This is counterintuitive, as non-CS students are not expecting to develop deep theoretical knowledge of ML, but hands-on skills and experience that can be applied to their respective fields (Wilson & DeJong, 2024).

Lao (2020) explored methods to provide ML education to "tinkerers", recognizing that ML tools are increasing accessibility to the technology. Lao (2020) noted three audiences of ML education: high-end technical users, general adults seeking to implement ML in their work, and K-12 students. Technical ML courses assume an existing background in computer science with a high barrier of entry, requiring CS competence, statistics, calculus, and linear algebra. General adult courses are far more accessible but do not provide sufficient depth for implementation. Instead, many of these courses focus on providing a context for conversations with others who will implement ML. Finally, K-12 courses provide smaller activities and projects that develop skills related to model implementation but are simple and abstract enough to bypass math and programming requirements.

Though resources exist for introducing non-CS majors to ML, these workshops and programs are often fleeting glimpses into the field and technology. These benchmark applications offer students opportunities to implement ML models in curated sandboxes and prepared datasets, such as MNIST (Deng, 2012; Wagstaff, 2012). Students are often not required to perform data analysis or processing to implement their models, and evaluation may involve a cursory analysis of training and testing metrics. This

focused approach is excellent for teaching theoretical frameworks for ML and model design. While CS students will often continue in courses that provide data science methods and more in-depth projects, non-CS students may only receive one course and thus require more cohesive coverage. Course content needs to include the context and challenges of ML implementation in industrial settings where small, noisy, and incomplete data sets must be processed to identify underlying patterns and determine whether ML methods are applicable.

A review of papers covering machine learning courses for engineers were evaluated (Dixit et al., 2018; Kim, 2022; Muqri et al., 2022; Zhang, 2020). These courses demonstrate a preference toward teaching ML methods with benchmark applications. Datasets are preprocessed, and model development is simplified to a unique ML sandbox that is not representative of commercial tools or real-world applications. Dixit et al. (2018) showed a step away from this approach, incorporating pre-processing and feature generation in their learning modules.

Focusing on theory and benchmark applications is not a problem unique to engineering students. Academic research sees a similar gap in ML knowledge for computer science; Cadavid et al. (2020) found that half of their investigated papers reached implementation of a model. Likewise, Wagstaff (2012) found that only 1 of 148 ML algorithm papers presented at ICML 2011 interpreted their results in the context of the problem's domain.

Additional concerns were discovered within the literature. One concern of machine learning education is the development of responsible knowledge and skillsets (Weerts & Pechenizkiy, 2022). Ethical concerns include overcoming the common perception that ML is a one-size-fits-all solution to any problem, given sufficient model complexity (Narayanan, 2019). Students should develop an awareness for the scope and limitations of ML, not simply the tools required to apply them (Smith et al., 2022).

Sulmont et al. (2019) explored the methods and content knowledge required to teach ML to non-CS majors classifying learning outcomes from surveyed instructors into the Structure of Observed Learning Outcome (SOLO) taxonomy (Biggs & Collis, 2014), where learning outcomes are categorized by the student's expected stage of learning. Sulmont et al. (2019) also noted three preconceptions that non-CS students had for machine learning. First, that ML is important and that students are motivated to develop their understanding. Second, students have mostly heard of ML technology through popular media sources, which can risk warped perspectives of the technology and require that instructors debunk myths perpetuated by sensational sources. Third, that ML implementation is inaccessible to them, and that the lack of a solid math and programming background prevents them from utilizing ML technology.

2.3. Abstraction Hierarchy Model

Abstraction hierarchy models are used in human factors to describe complex tasks or processes, particularly when they involve human-machine interaction (Rasmussen, 1985). In an abstraction hierarchy, the purpose and functions of a process are classified into five layers of decreasing abstraction. This begins with the general purpose – the primary objective(s) of the system. Abstract functions are the constituent tasks that accomplish the general purpose(s), and general functions are the further abstracted tasks that are connected to each abstract function. This continues downward into physical functions and physical forms, the tangible steps and components of the system. Each element is connected through means-ends links to other elements. The "why" of an element is answered by the elements above it, while the "how" of an element is answered by the elements below it. These elements can be further decomposed on a secondary axis. Part-whole relations are a common example, decomposing from the total system to individual components.

While initially developed for supervisory control applications, abstraction hierarchy models have also been extensively applied in other domains to outline and assess complex systems. It has been used to structure library resources (Jacob et al., 2006), to examine road transport systems (Salmon et al., 2019), and to organize classroom content (Vongalis-Macrow, 2010). Abstraction hierarchy modeling was selected for this study due to its versatility and ability to categorize functions, tasks, and resources in a form that identifies why and how a function is achieved.

2.4. Model Development

To visualize how end-user ML tools assist ML education in non-CS courses, course content from two engineering courses was reviewed by the authors. Abstraction hierarchy models were developed by the course instructor through direct observation of instructional time allocated to each physical function across the quarter, informed by comparison against the instructor's experience teaching equivalent content without the selected end-user tools. A generalized form of the abstraction hierarchy model is presented in Figure 1. This general design encompasses every step from initial data collection to model deployment and monitoring. The primary objectives of the project are defined in the general purpose. The objective is decomposed into three broad categories

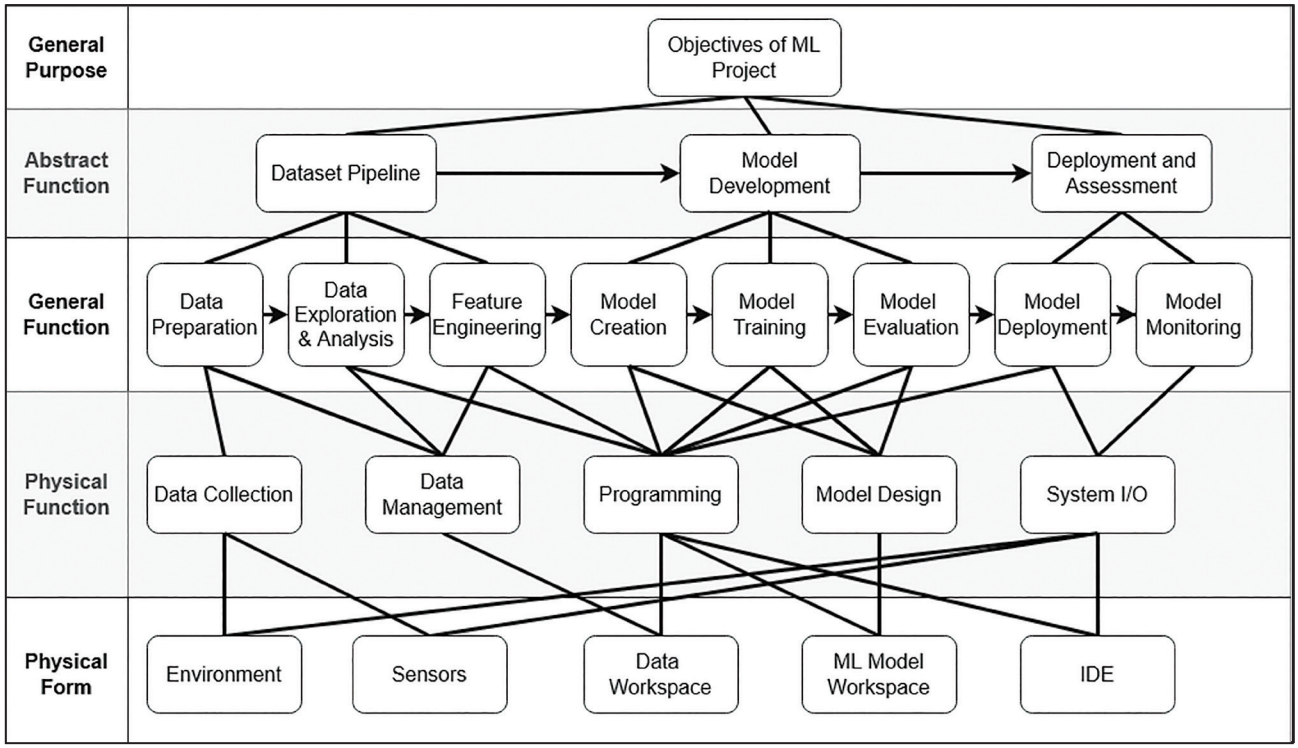


Figure 1. Abstraction hierarchy of a generic ML project.

and nine general functions that are linked to MLOps terms provided by the literature (John et al., 2021; Kreuzberger et al., 2023; Wazir et al., 2023). Physical functions are identified as skillsets that users are expected to develop and perform to accomplish the respective functions. Each of these skillsets is supported and/or enabled by selected tools and resources, identified under physical forms.

A component was marked as streamlined when the instructor observed a reduction in instructional time devoted to that function. For example, an ML model software reduces the time spent learning how to create, train, and test models, and allows for additional time to be spent on best practices in model creation and development.

2.5. Handwriting Classification Project: Our Baseline ML Project

MNIST is a dataset that comprises 70,000 images of handwritten digits from 0 to 9 (Deng, 2012). Each sample is a black and white image normalized into a 28x28 pixel space. The dataset is frequently used for an ML tinkerer's first computer vision project by classifying each digit. A similar dataset is Fashion MNIST, containing images of various clothing articles (Xiao et al., 2017). This dataset is well-explored, relatively small, and requires little to no processing. These factors allow a tinkerer to focus on understanding the fundamentals and mechanics of the ML implementation, and as such demonstrates the quintessential ML project.

A traditional introductory ML course may instruct students to create a neural network model in a selected programming language. Such a project may take a day to develop with ML-focused libraries such as TensorFlow, or weeks if students are expected to develop their model "from scratch." Conversely, MNIST-based projects are commonly used in introductory workshops as an initial demonstration of an ML tool's functionality and are often brief enough to perform multiple times within a single workshop. This dataset also serves as a platform from which to evaluate more advanced topics. Student projects can apply and compare various ML algorithms to assess their performance. Noise can also be added to the data when teaching data processing techniques (Snehith et al., 2023).

2.6. Predictive Maintenance Project

One of the engineering technology courses explored machine learning applications in predictive maintenance. Most of the course was spent on a dataset of simulated turbofan operation and failure (Saxena et al., 2008). This dataset was selected due to the need to filter, normalize, and process the data before use. Students were tasked with applying various data processing methods and ML algorithms to the dataset. Google Colaboratory was used as a Python

environment. The platform includes numerous modules, like Pandas, TensorFlow, scikit-learn, for processing the data and managing ML artifacts (Abadi et al., 2016; McKinney, 2010; Pedregosa et al., 2011).

The predictive maintenance course was selected for this study due to the emphasis on dataset generation and feature extraction over ML model development. Students were expected to perform multiple rounds of ML training and testing to compare data processing methods. The data processing initially only required a conversion of data to arrays that could be utilized by the regression models, but would culminate in creating time-dependent samples for use with recurrent neural network models.

2.7. Image Classification Project

Another course introduced engineering technology students to various machine learning applications, with a focus on computer vision. Students were supplied with OpenMV camera microcontrollers and access to Edge Impulse, a cloud-based ML development platform (Abdelkader et al., 2017; Hymel et al., 2022). A common project was to develop an image classification program that could distinguish an individual's face from others. To complete this project, students collected sample images, which were compiled into a single dataset that was distributed and uploaded to Edge Impulse. There, students explored different designs of convolutional neural networks and transfer learning models to implement and evaluate through training, testing, and implementation on the OpenMV platform.

This project was selected for evaluation as the instructor observed that the chosen end-user tools enabled a course project that spanned the full pipeline from data collection to deployment. OpenMV and Edge Impulse enabled the creation and management of a dataset, model, and initial deployment on the OpenMV platform, all of which required little to no programming to complete the tasks. This allowed students to focus on the quality of the dataset they were creating as well as testing and evaluating their project with a real-world implementation, providing an opportunity to understand various challenges within the scope of the project. Students engaged in various challenges in dataset creation: defining the scope of the project and data to collect; identifying valuable features within their data; as well as reducing various types of bias in their data collection.

3. Results

The following abstraction hierarchy models are produced from observations of the three ML projects described above. The following examples will provide specific combinations of project tasks and tools. Elements that were positively affected by the incorporation of selected ML tools are highlighted in green within each model.

Figure 2 outlines the abstraction hierarchy model for a simple ML project to classify handwritten digits. There is no initial data collection or real-world implementation observed with most example projects; the objective of such a project is to create and observe the function of ML models against a well-known and refined dataset. As such, the general purpose and abstract function are reduced to model development and a limited pipeline for preparing the dataset.

First, features must be identified and extracted from the dataset; in this example the features are simply the normalized pixel values of each image sample, often stored as a single array. These features are then passed to an ML model for training and testing. Introductory MNIST projects often do not include any significant modification of the data before use in the selected ML model, which further reduces the scope of the project. Such data augmentation could be included as a third general function, as will be shown in later examples of ML projects. Finally, these physical functions are supported by three physical forms: a workspace for data management; a similar workspace for ML model development; and an IDE to write code within. Because Google Colaboratory provided a workspace for the dataset, model design, and programming, it is treated as a single object within the hierarchy.

Note that this model does not highlight any elements in green to indicate positive effects from the selected tools. It is observed that many MNIST projects use one single workspace for all three components. This is also true of the predictive maintenance and computer vision projects discussed later in this section. The choice of workspace(s) is based on the objectives and expected skill level of the learner. An MNIST project may use a fundamental programming language without any additional tools and expect students to write the code for their model and training algorithms independently. Alternatively, a no-code ML tool may function as the entire physical form and even automatically complete the physical functions for the user.

As outlined in the methodology, this project is intended to demonstrate a typical baseline ML project. It will be demonstrated in later examples that the inclusion of select ML tools can streamline this core development process and provide room to focus on the initial design and final deployment of the model.

Figure 3 displays the abstraction hierarchy for the Predictive Maintenance projects. The abstract function now includes additional dataset exploration, analysis, and feature engineering. This is due to the

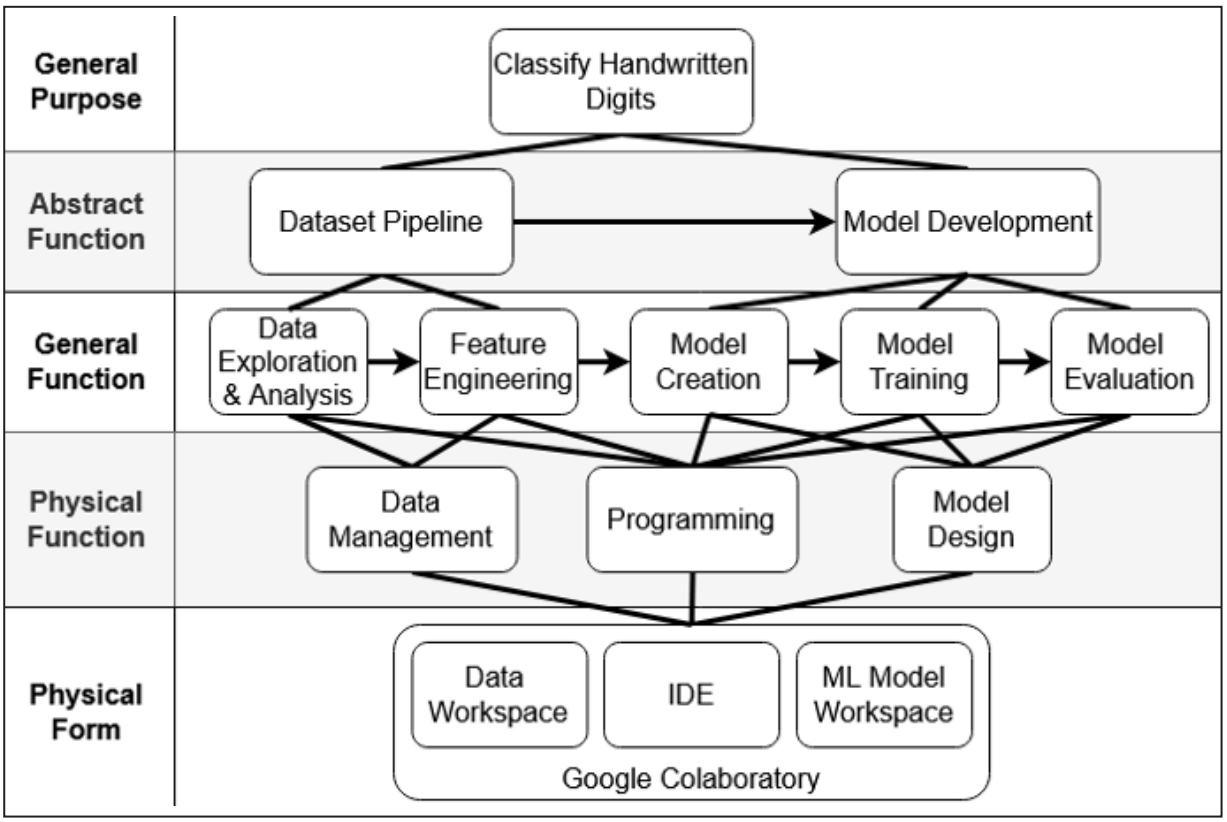


Figure 2. Abstraction hierarchy of a handwriting classification project.

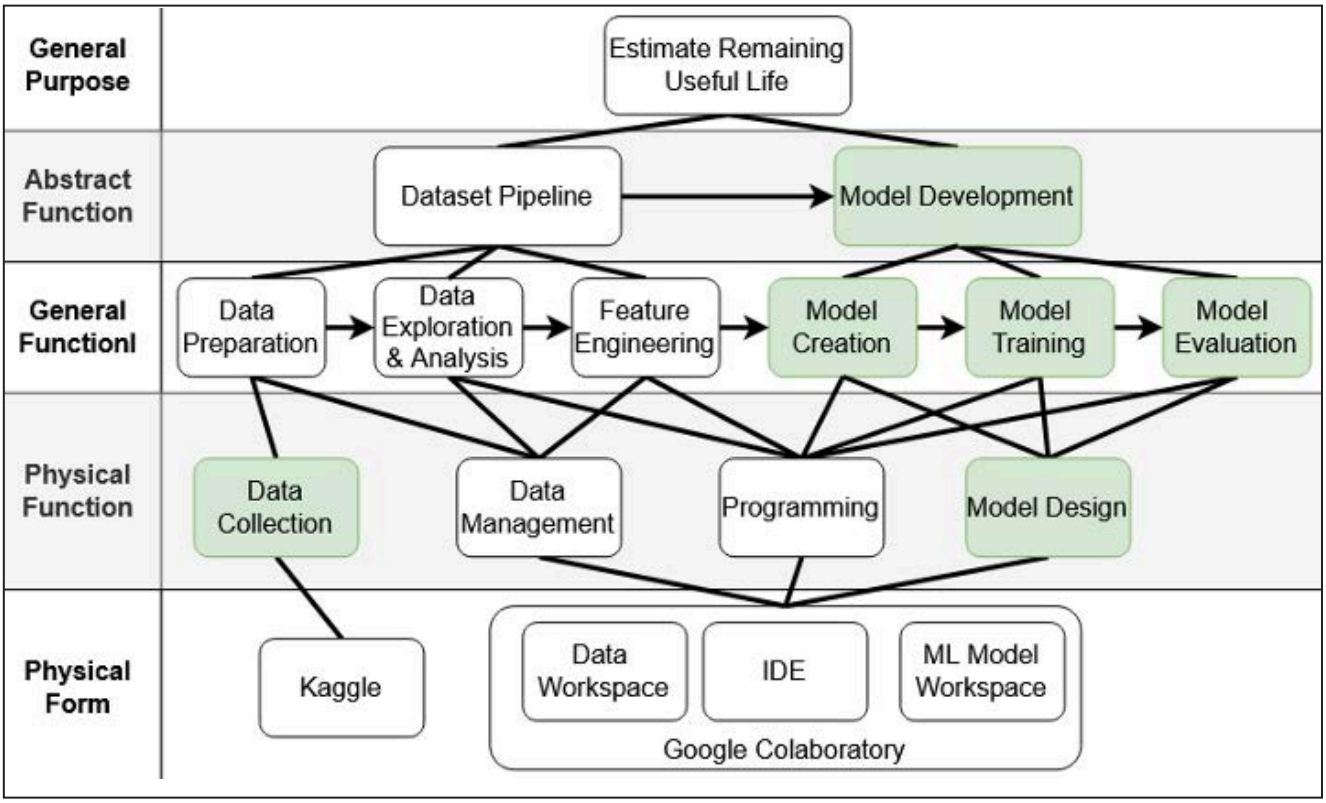


Figure 3. Abstraction hierarchy of a predictive maintenance project.

need for initial data processing and filtering before the data can be effectively used by a ML model; such data processing has been added as a general function to the project. The increased dataset pipeline was a primary focus of the course project. The NASA CMAPPS dataset was acquired through Kaggle, which satisfied the requirement for data collection within the project.

It was observed throughout the course that the development of the ML models was somewhat streamlined by the selection of Python libraries. The creation, training, and testing of ML algorithms was enabled using the scikit-learn and TensorFlow modules. Pandas enabled students to perform their data processing techniques but did not significantly reduce the technical skills required to do so. As such, the data processing and management were not identified as streamlined components. After three weeks of introductory topics on Python programming and ML, students were able to employ new data processing techniques and ML algorithms within a single class and were able to run multiple iterations to assess different combinations for each assignment. This was particularly useful within the final project, where students were instructed to create three unique models and compare their performance.

Figure 4 shows the computer vision project, which expands the project scope to include model deployment and review. Dataset generation is now produced through both data collection and data management, both of which were streamlined by the selected tools. OpenMV enabled students to capture images that were stored in a format ready to upload to Edge Impulse, which then provided a workspace to evaluate the dataset at large and prune their data with various tools and visualization features.

Edge Impulse's ML workspace also allowed for the rapid creation, training, and testing of ML models. These models were also ready to deploy with sample implementation code back into the OpenMV platform, which provided students with a springboard to integrate their trained ML model into their system response. Combined, these streamlined components allowed for the creation of image datasets containing thousands of pictures in a single week (crowdsourced by students), and for the creation and implementation of their ML model in as much time. The only component of this project not streamlined by the ML tools was the system response.

4. Discussion

The utilization of end-user and no-code ML tools in curricula may reduce the need for pre-requisite knowledge and skills before students can engage ML content, potentially allowing non-CS majors to more readily approach ML technologies within a single course (Sulmont et al., 2019; Sundberg & Holmström, 2023). The importance of technical skills in programming also shifts under this framework. Courses may be able to cover the creation and train-

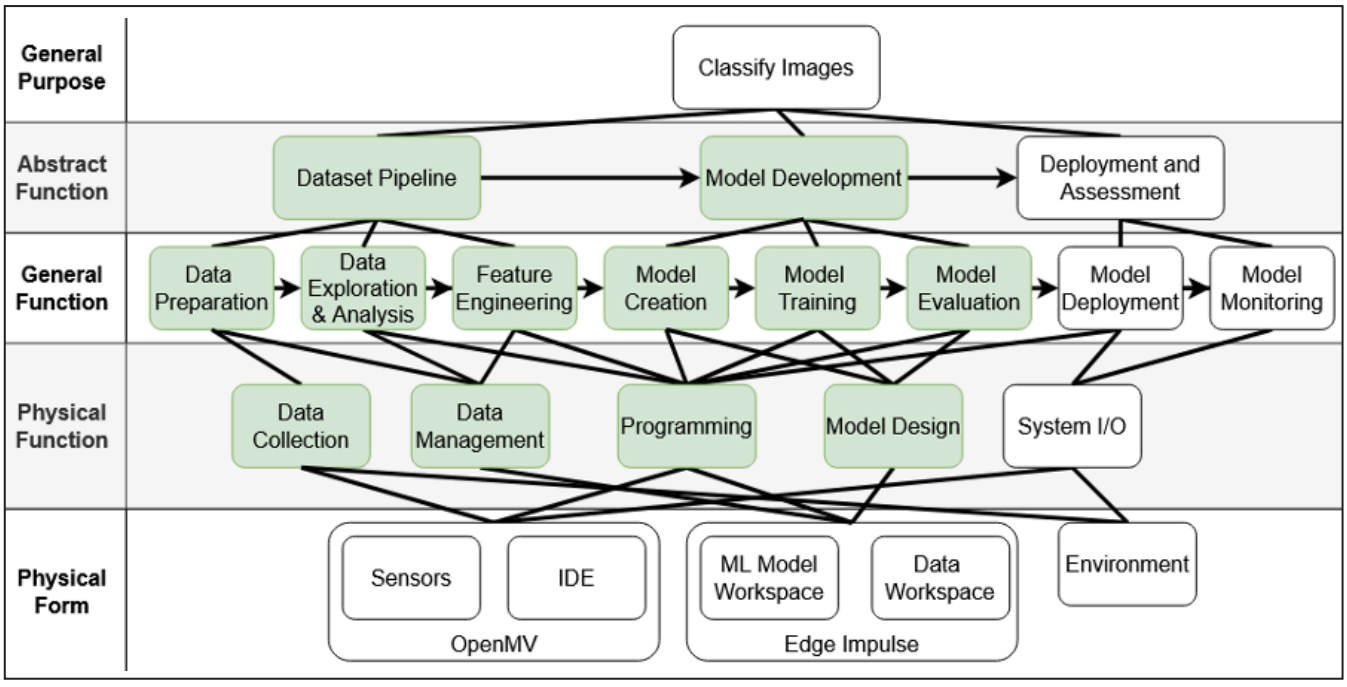


Figure 4. Abstraction hierarchy of a computer vision project.

ing of ML models more quickly, focusing instead on data science, model deployment, and high-level design considerations. As an exploratory study based on qualitative observation of three courses, these findings should be read as preliminary indications rather than established outcomes. It should be mentioned that the intent is not to bypass or skip fundamental course content. Without a solid foundation of math and computer science, students' abilities to explore and utilize machine learning will be limited. However, the depth of the required math and computer science content can be variable from course to course. A careful selection of ML tools can provide an accessible ML project that can be tailored to the time, effort, and resources available to the course.

4.1. Applications of Model

The purpose of this framework is to serve as an illustrative tool for instructors preparing ML projects within their course. They can identify which elements of MLOps should be included in the scope of the project. From here, they can identify the skillsets required of students to complete those tasks. These skillsets can be identified as pre-requisites for the project; topics to include in the course design; or elements to streamline through the selection of end-user tools. Student capabilities can then be assessed to determine where they would benefit from support, and tools selected and assessed for their degree of support. The framework can also provide reflections on the performance of a project and the tools selected.

4.2. Limitations and Future Studies

While this paper serves to highlight the need for new educational material, more insight is required to effectively assess and design courses with end-user ML tools in mind. Each abstraction hierarchy is a qualitative assessment of a limited selection of applied ML courses, developed as an illustrative rather than empirically validated tool. It is expected that this framework may be transferable to ML curricula in other contexts, but further validation is necessary. Future studies would expand this work to assess additional courses across K-12 and higher education. Furthermore, insight would be sought from ML instructors in various backgrounds to validate the performance and flexibility of the model.

The three classroom projects examined in this study varied considerably in tools and scope, from an introductory benchmark to a multi-week predictive maintenance analysis and full-pipeline image classification. The variety limits the extent to which any single hierarchy can be assumed to generalize to any specific ML project. However, a common structural pattern was observed within each project. End-user tools reduced instructional time devoted to core model creation, training, and testing; that freed time was redirected toward the broader functions of data management and real-world deployment and evaluation. Instructors adapting the framework to a new project should expect similar categories of end-user tools to affect similar general functions, while validating that expectation against their own course context.

In addition, the model would benefit from a quantitative element to measure the amount of time and effort that is originally required in each component, or how much is saved by the inclusion of a tool. Future studies would identify measurable educational outcomes and assessment tools to better quantify the impact of ML tools on ML projects, the requisite course material, and instructor/student time and effort within the classroom.

Generative AI tools are a separate and deliberate consideration in project or course design. Its integration into applied ML coursework is a new and rapidly evolving matter, substantial enough to warrant dedicated study beyond the scope of this paper (Yelamarthi et al., 2024). Future work could directly examine how generative AI tools affect the instructional time and skillsets required across the hierarchy.

4.3. Contributions

The primary contribution of this study is to provide a pilot study on the impact of end-user ML tools on applied ML project design. By outlining course projects with the abstraction hierarchy model, an instructor may identify elements that can be pared down or require additional scaffolding, as well as achieve a larger scope that can provide much needed real-world context to their course projects (Webster & Turner, 2024).

The need for ML literacy continues to grow as industries adopt new ML technologies into their operations. The abstraction hierarchy models presented here emphasize how end-user tools can broaden the scope of ML instruction, enabling educators to expand classroom content beyond core concepts in ML and engage learners at higher levels of understanding. This also provides time to address important issues such as the ethical and responsible application of ML. Such skills are currently lacking within ML education content and will prove crucial as ML adoption continues to rapidly expand.

Declaration of Interest

The authors declare that they have no competing interests.

References

Abadi, Martín, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, et al. 2016. "TensorFlow: A System for Large-Scale Machine Learning." In *Proceedings of the 12th USENIX Conference on Operating Systems Design and Implementation*, 265–83. Berkeley, CA: USENIX Association.

Abdelkader, Ibrahim, Youssef El-Sonbaty, and Mohamed El-Habrouk. 2017. "OpenMV: A Python Powered, Extensible Machine Vision Camera." arXiv. https://doi.org/10.48550/ARXIV.1711.10464.

Aggarwal, K., Mamoun M. Mijwil, Aws-Hasan Al-Mistarehi, Sinan Alomari, Müjde Gök, Anas M. Z. Alaabdin, Souzan Haydar Abdulrhman, et al. 2022. "Has the Future Started? The Current Growth of Artificial Intelligence, Machine Learning, and Deep Learning." *Iraqi Journal for Computer Science and Mathematics* 3, no. 1: 115–23.

Ali, Syed Hammad, Hussam A. Al-Sultan, and Mahmood T. Al Rubaie. 2022. "Fifth Industrial Revolution: New Perspectives." *International Journal of Business, Management and Economics* 3, no. 3: 196–212.

Biggs, John B., and Kevin F. Collis. 2014. *Evaluating the Quality of Learning: The SOLO Taxonomy (Structure of the Observed Learning Outcome)*. New York: Academic Press.

Cadavid, Juan Pablo Usuga, Samir Lamouri, Bernard Grabot, Robert Pellerin, and André Fortin. 2020. "Machine Learning Applied in Production Planning and Control: A State-of-the-Art in the Era of Industry 4.0." *Journal of Intelligent Manufacturing* 31, no. 6: 1531–58. https://doi.org/10.1007/s10845-019-01531-7.

Chilana, Parmit K., Caroline Alcock, Shruti Dembla, Anne Ho, Amy Hurst, Brice Armstrong, and Philip J. Guo. 2015. "Perceptions of Non-CS Majors in Intro Programming: The Rise of the Conversational Programmer." In *2015 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC)*, 251–59. Washington, DC: IEEE.

Deng, Li. 2012. "The MNIST Database of Handwritten Digit Images for Machine Learning Research [Best of the Web]." *IEEE Signal Processing Magazine* 29, no. 6: 141–42. https://doi.org/10.1109/MSP.2012.2211477.

Dixit, Ayan, Uday Shankar Shanthamallu, Andreas Spanias, Sathwik Rao, Sandeep Katoch, Mahesh K. Banavar, Gautam Muniraju, et al. 2018. "Multidisciplinary Modules on Sensors and Machine Learning." In *Proceedings of the 125th ASEE Annual Conference and Exposition*. Washington, DC: American Society for Engineering Education.

Giraldo, Luis, & Sergio Laso. 2025. "Democratizing Machine Learning: A Practical Comparison of Low-Code and No-Code Platforms." *Machine Learning and Knowledge Extraction*, 7(4), 141. https://doi.org/10.3390/make7040141

Huyen, Chip. 2020. "Machine Learning Tools Landscape v2 (+84 New Tools)." December 30, 2020. https://huyenchip.com/2020/12/30/mlops-v2.html.

Hymel, Shawn, Colby Banbury, Daniel Situnayake, Alex Elium, Cart Ward, Matthew Kelcey, Mathijs Baaijens, et al. 2022. "Edge Impulse: An MLOps Platform for Tiny Machine Learning." arXiv. https://doi.org/10.48550/ARXIV.2212.03332.

Jacob, Elin K., Hanne Albrechtsen, and Nayana George. 2006. "Empirical Analysis and Evaluation of a Metadata Scheme for Representing Pedagogical Resources in a Digital Library for Educators." *Knowledge Organization for a Global Learning Society*. 205 – 212.

John, Mercy Malu, Helena Holmström Olsson, and Jan Bosch. 2021. "Towards MLOps: A Framework and Maturity Model." In 2021 *47th Euromicro Conference on Software Engineering and Advanced Applications (SEAA)*, 1–8. Washington, DC: IEEE.

Jordan, Michael I., and Tom M. Mitchell. 2015. "Machine Learning: Trends, Perspectives, and Prospects." Science 349, no. 6245: 255–60. https://doi.org/10.1126/science.aaa8415.

Khalajzadeh, Hourieh, Mohamed Abdelrazek, John Grundy, John Hosking, and Qiang He. 2018. "A Survey of Current End-User Data Analytics Tool Support." In *Proceedings - 2018 IEEE International Congress on Big Data, BigData Congress 2018*, 41–48. Washington, DC: IEEE. https://doi.org/10.1109/BigDataCongress.2018.00013.

Kim, Hyunju. 2022. "Lessons Learned from Collaborative Initialization of Machine Learning Class and STEM Contest with University and

Industry Partnership." Paper presented at the 2022 ASEE Annual Conference & Exposition, Minneapolis, MN, June 2022.

Kreuzberger, Dominik, Niklas Kühl, and Sebastian Hirschl. 2023. "Machine Learning Operations (MLOps): Overview, Definition, and Architecture." *IEEE Access* 11: 31866–79.

Lao, Natalie. 2020. "Reorienting Machine Learning Education Towards Tinkerers and ML-Engaged Citizens." PhD diss., Massachusetts Institute of Technology. http://appinventor.mit.edu/assets/files/NatalieLao_PhD_Dissertation.pdf.

Long, Duri, and Brian Magerko. 2020. "What Is AI Literacy? Competencies and Design Considerations." In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16. New York: Association for Computing Machinery.

McKinney, Wes. 2010. "Data Structures for Statistical Computing in Python." In *Proceedings of the 9th Python in Science Conference*, edited by Stéfan van der Walt and Jarrod Millman, 51–56. Austin, TX: SciPy.

Muqri, Mustafa, Sheila Boghikian-Whitby, Mushtaq Muqri, Zaid Muqri, and Saba Muqri. 2022. "Leveraging the Power of Python, Octave and Matlab for Machine Learning." Paper presented at the 2022 ASEE Annual Conference & Exposition, Minneapolis, MN, June 2022.

Narayanan, Arvind. 2019. "How to Recognize AI Snake Oil." Arthur Miller Lecture on Science and Ethics, Massachusetts Institute of Technology, Cambridge, MA, November 21, 2019.

Neumann, Alexander T., Yu Yin, Suleman Sowe, Stefan Decker, and Matthias Jarke. 2024. "An LLM-Driven Chatbot in Higher Education for Databases and Information Systems." *IEEE Transactions on Education*.

Niemirowski, Jonathan. 2023. "Threads, Buckets, and Impact: A Framework for Tool Accelerated Machine Learning Courses." PhD diss., Louisiana Tech University.

Pedota, Michele, and Lucia Piscitello. 2022. "A New Perspective on Technology-Driven Creativity Enhancement in the Fourth Industrial Revolution." *Creativity and Innovation Management* 31, no. 1: 109–22. https://doi.org/10.1111/caim.12468.

Pedregosa, Fabian, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, et al. 2011. "Scikit-Learn: Machine Learning in Python." *Journal of Machine Learning Research* 12: 2825–30.

Rasmussen, Jens. 1985. "The Role of Hierarchical Knowledge Representation in Decision Making and System Management." *IEEE Transactions on Systems, Man and Cybernetics* SMC-15, no. 2: 234–43. https://doi.org/10.1109/TSMC.1985.6313353.

Salmon, Paul M., Gemma J. M. Read, Nicholas Stevens, Guy H. Walker, Vanessa Beanland, Roderick McClure, Bryan Hughes, Ian R. Johnston, and Neville A. Stanton. 2019. "Using the Abstraction Hierarchy to Identify How the Purpose and Structure of Road Transport Systems Contributes to Road Trauma." *Transportation Research Interdisciplinary Perspectives* 3: 100067.

Saxena, Abhinav, Kai Goebel, Don Simon, and Neil Eklund. 2008. "Damage Propagation Modeling for Aircraft Engine Run-to-Failure Simulation." In *2008 International Conference on Prognostics and Health Management, PHM 2008.* Washington, DC: IEEE. https://doi.org/10.1109/PHM.2008.4711414.

Shailendra, Shalini, Ramhari Kadel, and Akhilesh Sharma. 2024. "Framework for Adoption of Generative Artificial Intelligence (GenAI) in Education." *IEEE Transactions on Education* 67, no. 5: 777–85.

Smith, J. J., Saleema Amershi, Solon Barocas, Hanna Wallach, and Jennifer Wortman Vaughan. 2022. "REAL ML: Recognizing, Exploring, and Articulating Limitations of Machine Learning Research." In *2022 ACM Conference on Fairness, Accountability, and Transparency*, 587–97. New York: Association for Computing Machinery. https://doi.org/10.1145/3531146.3533122.

Snehith, N., M. T. N. D. S. Harsha, Srilatha Bodempudi, L. R. L. Bailundo, S. Shameem, and J. V. Namgiri. 2023. "Reconstructing Noised Images of Fashion-MNIST Dataset Using Autoencoders." In *2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE)*, 1–6. Washington, DC: IEEE. https://doi.org/10.1109/AIKIIE60097.2023.10390180.

Sulmont, Elisa, Elizabeth Patitsas, and Jeremy R. Cooperstock. 2019. "What Is Hard about Teaching Machine Learning to Non-

Majors? Insights from Classifying Instructors' Learning Goals." *ACM Transactions on Computing Education* 19, no. 4. https://doi.org/10.1145/3336124.

Sundberg, Linus, and Jonny Holmström. 2023. "Democratizing Artificial Intelligence: How No-Code AI Can Leverage Machine Learning Operations." *Business Horizons 66*, no. 6: 777–88. https://doi.org/10.1016/j.bushor.2023.04.003.

Sundberg, Linus, & Jonny Holmström. 2024. "Teaching Tip: Using No-Code AI to Teach Machine Learning in Higher Education." *Journal of Information Systems Education* 35(1), 56-66. https://doi.org/10.62273/CYPL2902

Tai, Ming-Tsan. 2020. "The Impact of Artificial Intelligence on Human Society and Bioethics." *Tzu Chi Medical Journal* 32, no. 4: 339–43. https://doi.org/10.4103/tcmj.tcmj_71_20.

Vongalis-Macrow, Athena. 2010. "Reconceptualising Access in Education Policy: Method and Mindset." *Policy Futures in Education* 8, no. 5: 513–27.

Wagstaff, Kiri L. 2012. "Machine Learning That Matters." In *Proceedings of the 29th International Conference on Machine Learning*, 1851–56. Madison, WI: Omnipress. https://doi.org/10.48550/arXiv.1206.4656.

Wazir, Saddam, Gaurav Saxena Kashyap, and Pushpanjali Saxena. 2023. "MLOps: A Review." arXiv preprint arXiv:2308.10908.

Webster, Rustin, and Matthew Turner. 2024. "Engineering Technology Capstone: Exploring the Current State." *Journal of Engineering Technology* 41(2), 34–39.

Weerts, Hilde J. P., and Mykola Pechenizkiy. 2022. "Teaching Responsible Machine Learning to Engineers." In *Proceedings of the Second Teaching Machine Learning and Artificial Intelligence Workshop*. https://github.com/hildeweerts/.

Wilson, D.M. and DeJong, B.P., 2024. "Why Students Select Engineering Technology Majors." *Journal of Engineering Technology,* 41(2), 42-53.

Xiao, Han, Kashif Rasul, and Roland Vollgraf. 2017. "Fashion-MNIST: A Novel Image Dataset for Benchmarking Machine Learning Algorithms." arXiv preprint arXiv:1708.07747.

Yelamarthi, Kumar, Raju Dandu, Mohan Rao, Venkata Prasanth Yanambaka, and Satish Mahajan. 2024. "Exploring the Potential of Generative AI in Shaping Engineering Education: Opportunities and Challenges." *Journal of Engineering Education Transformations* 37, no. 2: 439–45. https://doi.org/10.16920/jeet/2024/v37is2/24072

Zhang, Yajun. 2020. "Teach Machine Learning with Excel." Paper presented at the 2020 ASEE Virtual Annual Conference, Virtual Online, June 2020. https://doi.org/10.18260/1-2--35268.

Jonathan Niemirowski

Jonathan Niemirowski received his degrees from Louisiana Tech University. He holds a PhD in Engineering with the Engineering Education track and received an MS in Molecular Sciences and Nanotechnology and a BS in Nanosystems Engineering in 2018 and 2015, respectively. His research interests are course design frameworks for machine learning education within engineering and engineering technology. Dr. Niemirowski is a member of the International Society of Automation and the American Society for Engineering Education.

David Hall

David Hall earned his Ph.D. in mechanical engineering from Georgia Institute of Technology and his B.S. degree in mechanical engineering from Louisiana Tech University. His research has focused on engineering education, trenchless technology, fracture mechanics, and computer graphics. He is currently an Associate Professor of Mechanical Engineering at Louisiana Tech University. Dr. Hall is a member of the American Society for Engineering Education.

Krystal Cruse

Krystal Cruse received her PhD in Engineering within the track of Engineering Education at Louisiana Tech University in 2012. She received an MS in Mathematics, an MS in Mechanical Engineering, and a BS in Mechanical Engineering from Louisiana Tech University in 2012, 2010, and 2008, respectively. She works as an Assistant Professor in Mechanical Engineering at Louisiana Tech University in Ruston, Louisiana. Her research interests are student engagement and retention. Dr. Cruse is a member of the American Society for Engineering Education.

Mary Fendley

Mary Fendley holds degrees from Indiana University and Wright State University. She is currently an Associate Professor in Industrial Engineering at Louisiana Tech University, and has been teaching both in-class and virtually for the past 12 years. Her research interests are in the areas of cognitive engineering, modeling, decision analysis, training, and human factors.

Index of Advertisers

ABET 75

CADCIM Technologies 19

Indiana State University. 19

Industrial Press 47

Miami University 2

Purdue University Polytechnic 3

Texas A&M University Galveston 73

TAMU Job Posting 46

Texas A&M University 76

Weber State University. 74

Call for Short Papers

ASEE *Journal of Engineering Technology*® Call for Short Papers

ASEE Journal of Engineering Technology® (JET) Editorial Team invites the engineering technology community to submit short papers reporting on the latest developments in innovative pedagogy and/or educational materials that contribute to advancing the teaching and learning of engineering technology topics.

The papers should demonstrate unique contributions to the engineering technology field and they should include some preliminary assessment and evaluation findings. Papers presenting pure and/or fundamental research studies without any educational component will not be accepted. The JET will not publish articles that appeared in previous conference proceedings. The recommended length of a short paper is about 2500 words.

All papers will be subject to double blind peer review, with decisions made on the basis of accept, minor revision, or rejection. Each submitted paper should follow the author guidelines detailed at https://engtech.org/jet/authors-guide/

Manuscripts should be submitted using the "Submit via Scholastica" at https://jet.scholasticahq.com/for-authors

Each submitted paper has a $10 submission fee, which is charged by Scholastica. Authors of accepted manuscripts are responsible for page charges of $75 per journal page.

Advertising & Subscriptions

The *Journal of Engineering Technology* ® is dedicated to the professional interests of the faculties of departments or schools offering associate, bachelor, or postgraduate degrees in the engineering technologies. Editorial interest includes papers that address the following topics: the improvement of engineering technology educational techniques; the cost-effective use of educational equipment and resources; new educational products and services; new technologies; and events affecting engineering technology educators in general.

The circulation base is the membership of the Engineering Technology Division of ASEE. Nonmembers of ASEE are solicited for subscriptions. External subscriptions are $25.00 per year ($35.00 outside the US). The Journal is published in the spring and fall of each year.

For an advertising rate card and mechanical specifications, contact:

John L Irwin
Michigan Technological University
1400 Townsend Drive
Houghton, Michigan 49931
Tel: (906) 487-2525
E-Mail: jlirwin@mtu.edu

To subscribe, complete the form below and send the form and payment by check or bank money order (no drafts) to:

Ankit Gupta
California State University, LA
5151 State University Dr.
Los Angeles, CA 90032
Tel: (931) 284-3029
E-Mail: agupta26@calstatela.edu

Enclosed is my payment in US funds for _____ $25.00 _____ $35.00 (outside US) for a one-year subscription (2 issues) of the Journal of Engineering Technology®.

Name _____

Street _____

City _____ State_____ Zip _____

Back Issues

The Subscription Editor maintains a back issue service of the *JOURNAL OF ENGINEERING TECHNOLOGY* ®. The price is $15.00 per issue, pending availability. The back issue service is available to any individual or institution.

To order back issues contact:

Ankit Gupta
California State University, LA
5151 State University Dr.
Los Angeles, CA 90032

Tel: (931) 284-3029

E-Mail: agupta26@calstatela.edu



Consider Submitting Your Paper to the *Journal of Engineering Technology®*

Papers submitted to the *Journal of Engineering Technology®* are reviewed for their contribution to the advancement of the field of engineering technology.

Manuscript Submission Requirements

Manuscripts should be typed, double-spaced, prepared using Microsoft Word, and submitted through *jet.scholasticahq.com.* The manuscript should include the following:

- title page
- brief abstract
- appropriate headings and subheadings
- consecutively numbered pages
- titled and numbered figures and tables
- complete references
- proper metric (SI) or English (FPS) units
- use of the Chicago Manual style

To facilitate blind peer reviews:

- the title page, abstract, and manuscript text should not include names of authors
- the organizational affiliations of authors should be removed from the title page and should be eliminated from the abstract and text wherever practical

Manuscripts published in another journal or conference proceedings must be substantially different, at least 70%, to be published in the *Journal of Engineering Technology* .®

If the manuscript is accepted for publication, the lead author will receive further instructions for format, graphics, biographical sketches of authors, etc. to meet publication requirements. Authors of accepted manuscripts are asked to pay page charges of $75 per journal page. (A printed page of text contains approximately 750 words. The space required for tables and figures should be added to obtain a page estimate.) The page charge includes two complimentary copies of the issue in which the article is published.

Submit your manuscript at:
jet.scholasticahq.com

Send questions to **Farid El Breidi**

Purdue University

E-MAIL: breidi@purdue.edu

Style Guide for Authors

Review of Submitted Papers

Papers submitted to the *Journal of Engineering Technology*® are reviewed for their contribution to the advancement of the field of engineering technology. Membership status in the Engineering Technology Division of ASEE does not influence the review process. Material submitted should not be under consideration by another publication.

Unsolicited manuscripts should be sent to the manuscript editor, who will make an initial decision on the paper's suitability for review. Papers are then sent to two or more reviewers who represent a cross-section of the Engineering Technology Division membership interests. Both solicited and unsolicited papers are reviewed. At least two to three months must be allowed for reviewing. Articles are accepted with the understanding that they may be returned to the authors for revision on the reviewers' recommendation, and edited by the staff for the sake of clarity and conciseness. Alterations appear on galley proofs that authors receive before publication.

Writing an Article

Articles published in the *Journal of Engineering Technology*® are expected to be clear, informative, and accurate. Organize your material carefully, and make sure the significance of your work will be apparent to readers outside your own area of interest. Avoid specialized jargon and wordiness. Readers will skip a dull article or one they cannot understand. Standards of good usage can be found in The Chicago Manual of Style, and Skillin's Words into Type. See manuscript requirements printed elsewhere in this issue.

Appropriate Topics for Journal Articles

Some appropriate topics are:

- Applied Technology and High Technology
- Instructional Materials, Equipment, and Laboratories
- Applied Research: Case Situations, Methodology, and Results
- Specific Engineering Technology Disciplinary Interests
- Curricula and Teaching Methods
- Goals and Responsibilities of ET Education
- ABET/ETAC Accreditation
- Coordination of Institutional Aims and Programs
- Professional Ideals and Standards
- Cultivation of a Fraternal Spirit Among ET Professionals
- Place of ET in Spectrum of Science, Engineering, and Technology
- Relationships with Public and Professional Societies
- Interfacing/Articulation with other ET and Engineering Programs
- Measurement and Evaluation of ET Programs
- Women/Minorities in ET
- Personnel Practices and Administration

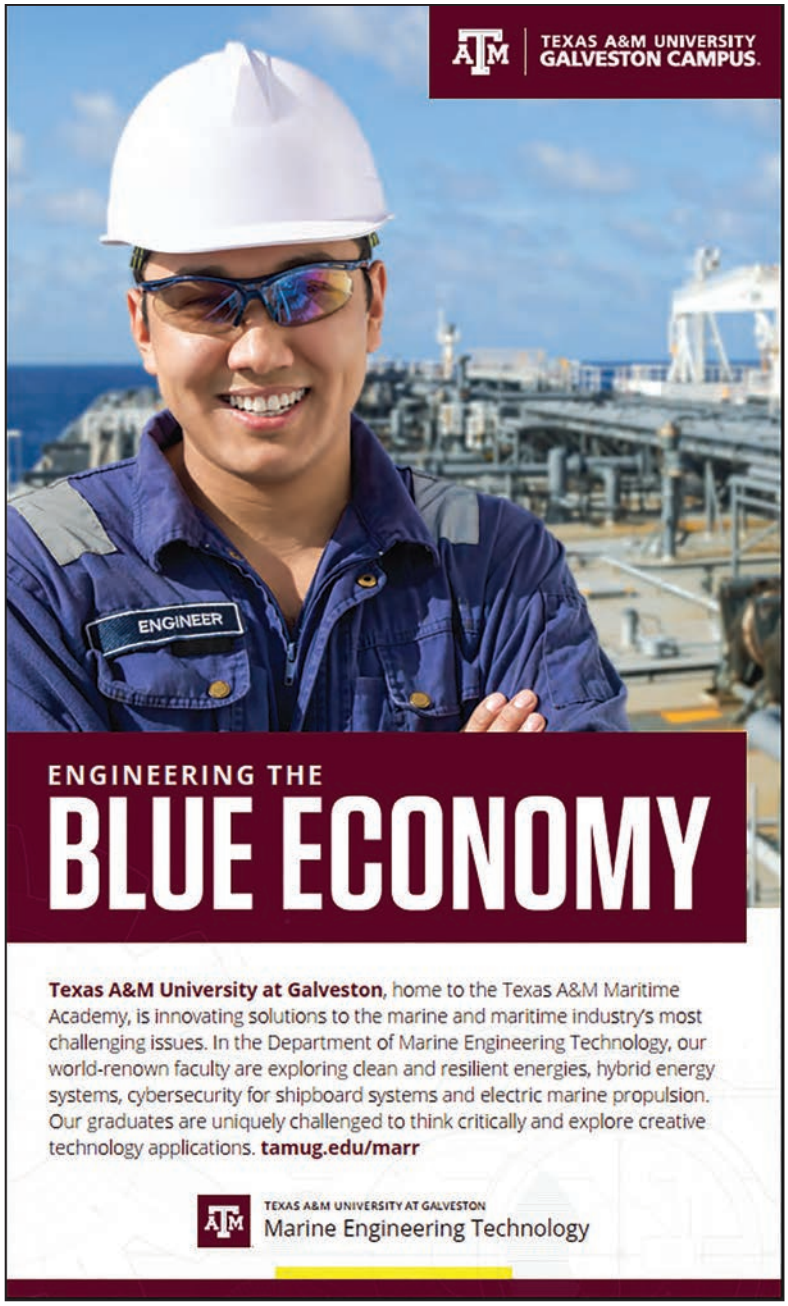
Papers are accepted for publication in one of three general interest areas. The interest areas mentioned here are examples, and are not meant to be all-inclusive:

Major Articles: Reviews of new developments or trends of broad significance to Journal readers; descriptions of a current problem or approach of interest to more than one engineering technology discipline; reviews and comparisons of programs and teaching methods, with supporting data; studies of an aspect of the practice, history, philosophy, or administration of engineering technology. (Average length: 8-11 pages*)

New Ideas: Succinct communications of ideas that have been applied to the practice or teaching of engineering technology with evaluation of their effectiveness. (Average length: 5-6 pages*)

New Findings: Brief reports of recent studies pertaining to engineering technology practice or education, emphasizing results and implications. (Average length: 4-6 pages*)

*Paper lengths stated here refer to standard (8-1/2" x 11") pages, typed with double spacing and 1-inch margins throughout, averaging one table or figure for every three pages of text.



Are You Moving?

Notify the *JET* subscription editor and ASEE. Please attach the form and address label and mail to:

Ankit Gupta
California State University, LA
5151 State University Dr.
Los Angeles, CA 90032
Tel: (931) 284-3029
E-Mail: agupta26@calstatela.edu

New Address Effective Date

_____

Name _____

Address _____

City _____

State _____ Zip _____

ATTACH LABEL HERE for address change or inquiry. The code line is the best way we have of identifying your records quickly. If you are receiving duplicate copies, please send both labels. List new address here, and include a current mailing label of your old address.



WEBER STATE UNIVERSITY

Engineering, Applied Science & Technology

Engineering Technology Degrees

- Manufacturing Engineering Technology
  - Plastics and Composites
  - Production Operations & Controls
  - Welding
- Mechanical Engineering Technology
- Product Design & Development

Explore More Engineering & Technology Degrees

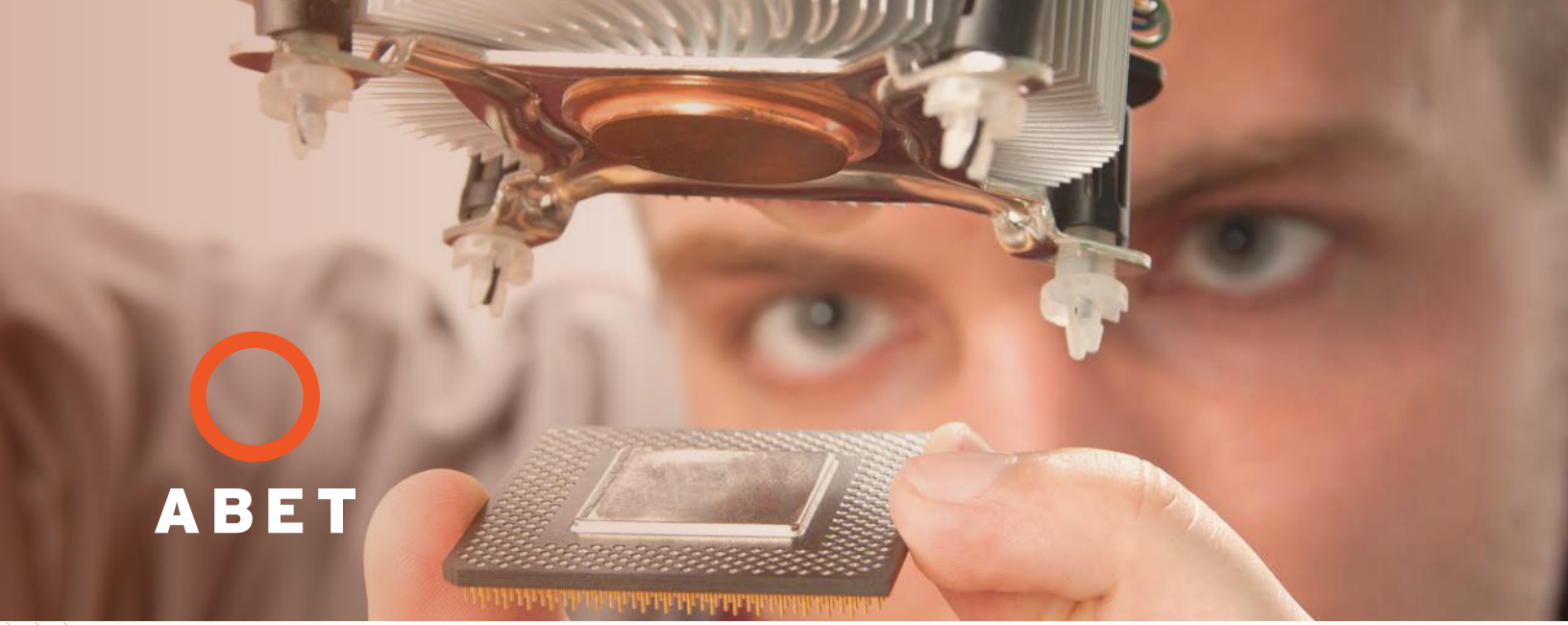
- Architectural Design
- Automotive Technology
- Automotive and Vehicle Engineering Technology
- Biomedical Engineering
- Computer Engineering
- Computer Science
- Construction Management
- Cybersecurity and Network Management
- Electrical Engineering
- Energy Engineering
- Interior Design
- Mechanical Engineering
- Professional Sales
- Web and User Experience



Master of Science

- Computer Science
- Computer Engineering
- Data Science
- Electrical Engineering
- Mechanical Engineering
- Systems Engineering - Online

weber.edu/east



QUALITY ASSURANCE ACROSS EVOLVING PATHWAYS

As science, technology, engineering and mathematics fields evolve, institutions are developing pathways to meet changing workforce and learner needs. ABET provides a flexible quality assurance framework that supports innovation for both programs and credentials.

ABET'S RECOGNITION OF CREDENTIALS

Quality Throughout A Learners Journey

Credential providers are shaping the future of learning through flexible, high-impact pathways that help learners build skills, advance careers and pursue higher education. ABET's fully virtual Recognition of Credentials service honors that leadership with a trusted mark of quality. Recognition demonstrates the value of your credentials, strengthening your reputation and inspiring confidence among learners, employers and regulators.

LEARN MORE AT
abet.org/recognition

ABET ACCREDITATION

Innovate with ABET

ABET accreditation empowers innovation without compromising quality. Our internationally recognized framework, meticulously crafted by experts, offers flexibility to foster innovation. It not only supports but actively encourages it. This framework promotes continuous improvement and industry alignment, instilling confidence in students, faculty, and employers that graduates are well-prepared to tackle contemporary challenges and drive meaningful change.

LEARN MORE AT
abet.org/accreditation

Explore your path to quality assurance with ABET



TEXAS A&M UNIVERSITY
Department of Engineering
Technology & Industrial Distribution

WHERE **HANDS-ON** LEARNING SOLVES **REAL-WORLD** PROBLEMS

Degree Programs:

- Electronic Systems Engineering Technology
- Industrial Distribution
- Manufacturing & Mechanical Engineering Technology
- Multidisciplinary Engineering Technology
- Master of Engineering Technical Management
- Master of Industrial Distribution
- Master of Science in Engineering Technology

In the Department of Engineering Technology and Industrial Distribution at Texas A&M University, innovation isn't just talked about- it's built, tested and applied.

Learn more at
tx.ag/TAMUETID

Follow on
LinkedIn