2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC
Host Sponsor UNC Charlotte
Paper ID #53833

Perceptions of AI Readiness in Engineering: A Mixed-Methods Analysis of Alignment Between Academia, Students, and Industry

Paul Kremer
Salihcan Paul Kremer, Purdue University – West Lafayette (College of Engineering)
Dr. Gül E. Kremer, University of Dayton

Gül E. Kremer received her PhD from the Department of Engineering Management and Systems Engineering of Missouri University of Science & Technology. Her research interests include multi-criteria decision analysis methods applied to improvement of products and systems. She is a senior member of IIE, a fellow of ASME, a former Fulbright scholar and NRC Faculty Fellow. Her recent research focus includes sustainable product design and enhancing creativity in engineering design settings.

Perceptions of AI Readiness in Engineering: A Mixed-Methods Analysis of Alignment Between Academia, Students, and Industry

This paper presents a pilot study examining how engineering faculty, students, and industry practitioners perceive AI utility and readiness. Engineering programs grapple with these questions and need this integrated understanding. Curricula must keep pace with workforce tools that integrate AI without sacrificing the disciplinary rigor that defines the profession. The workplace is signaling that demonstrated AI proficiency functions as a hiring criterion [1]. Yet insufficient research examines whether faculty, students, and employers agree on what AI readiness means. We address this research gap by building and pilot testing a parallel survey suite, deploying one version each for engineering faculty, undergraduate students, and industry practitioners across engineering disciplines, institutions, and workplace settings.

Our survey suite draws on the Technology Acceptance Model, an AI taxonomy aligned with U.S. federal standards based on capabilities, and the UNESCO AI competency framework for teachers. By integrating these established foundations, we create a diverse framework to measure perceptions of technical skill, applied competence, and ethical judgment. The survey instruments are structured for analysis of variance (ANOVA) to detect significant perceptual gaps across survey stakeholder groups along with other analyses made possible by the survey constructs. Semi-structured interviews with a subset of participants probe the reasons behind any divergence.

Preliminary analysis of our pilot data shows that all three stakeholder groups are close in their rating of perceived value of AI and their intent to use it, but their ratings diverge on proper usage and readiness assessments. Practitioners rate graduate's AI readiness significantly below students' self-assessments. One qualitative finding from interviews came forward. The perceived "readiness gap" between academic preparation and industry expectation may be less a skills deficit than a "translation gap" rooted in differing terminologies and contextual priorities. Industry participants consistently value deep understanding of engineering fundamentals over proficiency with specific AI software, which they view as transient. We define translational skills herein as the competencies required to bridge theoretical AI knowledge and its practical, responsible application within engineering workflows. These include selecting appropriate tools, verifying outputs against required standards, and communicating AI-assisted decisions to stakeholders.

These preliminary findings suggest that engineering programs should develop shared AI-Engineering Technology lexicons with industry partners and treat ethical reasoning as a core competency that spans disciplines. The consistent priority placed on fundamentals indicates that curricula should teach durable AI principles instead of training students on specific tools. This study's sample is concentrated in the U.S. Midwest, yet it provides a foundation for wider dialogue on aligning engineering education with the AI readiness demands of the engineering profession.

Introduction

Artificial intelligence (AI) is now embedded in engineering practice, influencing and reshaping how engineers design systems, analyze data, manage risk, and make decisions across domains such as manufacturing, aerospace, energy, and infrastructure. Recent advances in machine learning, generative AI and agentic workflows have expanded the range of cognitive tasks that can be automated or augmented. Gains in productivity are being demonstrated. So are the new technical, ethical, and organizational risks. The rapid adoption of generative AI across professions that demand specialized knowledge has created an urgency for engineering education to define its posture toward these tools [1]. Industry leaders now treat AI literacy as foundational to engineering practice, with 66% of executives surveyed stating they would decline applicants who lack AI competencies [1]. A recent consensus study by the National Academies of Sciences, Engineering, and Medicine characterizes AI as a general-purpose technology with broad applicability, noting that its impacts on productivity, expertise, and labor demand are expected to unfold unevenly and remain highly uncertain in both magnitude and timing [2].

National policy and workforce analyses reinforce the urgency of these developments for engineering education. For example, reporting by Congressional Research Service documents the rapid spread of AI technologies across sectors and emphasizes growing federal attention to issues of workforce preparedness and responsible AI deployment in technical domains [3]. Industry-facing workforce studies indicate that AI-enabled work is becoming routine for a large share of knowledge workers, with employers now expecting graduates to engage effectively with AI-assisted tools instead of treating them as peripheral technologies [4]. Future engineers will therefore need to understand AI-enabled systems and exercise professional judgment regarding verification, limitations, ethical use, and accountability in AI-augmented engineering work.

Engineering education faces a distinctive challenge in responding to this transformation. Unlike general business or information technology contexts, engineering programs must prepare graduates to apply AI tools within disciplinary frameworks governed by physical laws, safety constraints, professional ethics, and regulatory requirements [5]. A generative AI tool can produce plausible-looking results that violate core engineering principles and introduce errors with safety implications. UNESCO's framework argues that educators must therefore cultivate both AI tool proficiency and the evaluative judgment to assess AI outputs against engineering standards [6]. The National Academies caution that while AI has the potential to augment expert work, achieving its benefits will require complementary investments in skills, organizational processes, and education, not narrow training on specific tools [2].

Accreditation requirements add complexity to curriculum decisions. Three of the seven ABET student outcomes most relevant to this study involve the ability to identify, formulate, and solve complex engineering problems; to apply engineering design compliant to specified needs; and to recognize ethical and professional responsibilities [5]. Although these outcomes provide enduring guidance, they do not indicate which AI competencies should be integrated or at what depth. Programs face difficult trade-offs between adding AI content and maintaining coverage of core engineering topics within tight credit hour limits. Evidence from higher education commentary further suggests that misalignment may already be emerging between institutional strategies, faculty practices, and workforce expectations. Analyses of AI adoption in universities argue that institutions face growing pressure to demonstrate AI integration for reasons ranging from enrollment competitiveness to operational efficiency, often without clear agreement on pedagogical purpose or professional outcomes [7].

Systematic research examining how key stakeholders (engineering faculty, students, and industry professionals) perceive AI readiness requirements remains limited. Prior work on AI in engineering education has largely focused on classroom applications, instructional tools, or single-stakeholder perspectives (most commonly faculty or students). Far fewer studies examine simultaneously and comparatively how faculty, students, and engineering practitioners conceptualize AI competencies, readiness, and professional expectations. Decisions about curriculum design, faculty development, assessment, and partnerships with industry function as managerial decisions that depend on shared understanding across the education-to-workforce pipeline. Misalignment among stakeholder expectations risks inefficient investment, curricular drift, and graduates who are perceived as either underprepared or misprepared for AI-enabled engineering roles.

We address this gap by presenting the formative design and initial piloting of a mixed-methods measurement framework intended to assess perceived AI readiness among three stakeholder groups (engineering faculty, engineering students, and engineering practitioners). The study was initiated within an engineering management program but deliberately extends across multiple engineering disciplines to capture the breadth of AI integration challenges across the profession. Drawing on established models of technology acceptance [8], AI classifications organized by capability and aligned with U.S. policy [9], and internationally recognized AI competency frameworks [6], the study aims to identify areas of convergence and divergence in how AI-related skills, ethical reasoning, and preparedness are understood. Because we focus on perception alignment over proficiency with specific tools, this work informs decisions about how AI should be integrated into engineering education in ways that persist despite rapid changes in technology and preserve disciplinary rigor, professional responsibility, and long-term workforce relevance.

Literature Review

AI Integration in Engineering Practice

AI adoption in engineering practice has accelerated dramatically since the widespread release of generative AI tools in late 2022. By mid-2024, 75% of global knowledge workers reported using generative AI at work, with 78% bringing their own AI tools to work without waiting for organizational guidance [1]. In engineering specifically, AI applications span from traditional machine learning for predictive maintenance and process optimization to generative tools that assist with code development, technical documentation, and design iteration [10]. Industry leaders treat AI literacy as a baseline expectation, not a specialized skill. In fact, 71% of leaders indicate they would hire a less experienced candidate with AI skills over a more experienced one without those skills [1].

These shifts shape how engineering work is structured and evaluated. The World Economic Forum identifies AI and big data skills as the fastest-rising competencies for the 2025-2030 period, followed by networks and cybersecurity, and technological literacy [4]. However, the report also emphasizes that human skills such as analytical thinking, creative thinking, and resilience remain essential complements to technical capabilities. Engineering practitioners must therefore manage to develop sufficient AI fluency for emerging tools while maintaining the domain expertise and professional judgment that define engineering practice [11].

Challenges for Engineering Education

Research on AI integration in engineering curricula reveals substantial variation in approaches across institutions and disciplines. A systematic review of Industry 4.0 in engineering education identified implementation patterns across 178 studies spanning the period of 2015-2024 [12]. The review found disparities in adoption rates across engineering fields but also surfaced successful interdisciplinary approaches. Because Industry 4.0 already treats AI and machine learning as core enabling technologies [11], faculty preparation gaps and uneven cross-disciplinary uptake recur as institutions integrate contemporary AI tools. Studies of generative AI adoption using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework [13] found high student uptake when AI tools were designed to support authentic engineering tasks [14]. However, faculty adoption of AI tools has been slow, with research indicating that only 22% of faculty members incorporate AI tools into their instructional practices, while inadequate training remains a major barrier [15].

The Technology Acceptance Model (TAM), introduced by Davis [8], provides a foundational framework for understanding technology adoption in educational contexts. TAM posits two core constructs, perceived usefulness and perceived ease of use. Both have been validated across numerous educational technology implementations [16], and in other settings (e.g., [17]). A systematic literature review of TAM in educational settings identified 71 relevant studies between 2003 and 2018, confirming that perceived usefulness and perceived ease of use are consistent antecedent factors affecting acceptance of learning technologies [16].

Student Engagement with AI Tools

Student use of generative AI tools has been researched extensively in engineering education. Studies from ASEE indicate a statistically significant rise in use from 2023 to 2024, as students cite greater efficiency and understanding alongside concerns about reliability as factors relating to their use [18]. As AI tools are integrated further into engineering schoolwork, ethics and academic integrity have become pressing issues [19]. Research on engineering students' perceptions and use of generative AI argues for clear policies and pedagogical approaches that balance AI's potential benefits with maintaining academic integrity and developing core engineering competencies [19]. A recent first-person account of GenAI adoption in an undergraduate engineering computations course at George Washington University documents how students defaulted to copying assignment prompts into an AI chatbot, with attendance falling to roughly 30% and assessment validity undermined by unrestricted AI access [20].

Ethical and Human-Centered Dimensions

Ethical dimensions of AI use in engineering contexts now shape curriculum design directly. UNESCO's AI Competency Framework for Teachers (2024) identifies 15 competencies across five dimensions, including human-centered mindset, ethics of AI, AI foundations and applications, AI pedagogy, and AI for professional learning [6]. Although developed for teachers broadly, the framework's emphasis on human agency, bias awareness, privacy considerations, and evaluative judgment maps well onto professional engineering responsibilities. In engineering management contexts, these competencies shift from primarily instructional guidance toward organizational governance concerns, including risk oversight, accountability, policy enforcement, and decision-making under uncertainty. The framework provides a structured approach to ensuring that AI use supports rather than supplants professional judgment.

Responsible use of AI, centered on human judgment, in education must also be considered. UNESCO guidance flags persistent gaps. Safeguards can be unclear, and data privacy and validation capacity remain inconsistent [21]. The longstanding commitment of engineering education to verification, ethics, and accountability speaks to these concerns. Engineering education has also long treated ethical reasoning and professional responsibility as core competencies [5]. Adding AI tools to the curriculum creates new dimensions of ethical consideration, including questions of attribution when AI assists with design or analysis, accountability when AI-assisted systems fail, and appropriate disclosure of AI use in professional contexts [6].

Stakeholder Alignment in Engineering Education

Researchers have examined the relationship between engineering education and industry through several theoretical lenses. The Triple Helix model conceptualizes university-industry-government interactions as overlapping spheres that co-evolve to drive innovation and economic development [22]. Applied to engineering education, the Triple Helix view suggests that curriculum decisions should emerge from ongoing dialogue among academic, industry, and policy stakeholders instead of through unilateral academic determinations.

Empirical studies of academia-industry alignment in engineering have yielded mixed findings. Research on stakeholder perceptions of engineering employability skills found general agreement on the value of technical competencies but notable variation in assessments of graduate preparedness [23]. A systematic analysis of 95 papers across engineering disciplines found considerable disagreement among educators on how to prepare students for an AI-augmented profession [24]. Industry expectations may shift faster than academic programs adapt. Alignment gaps persist even when curricula undergo regular revision.

Prior work shows that AI tool use is common among students [25], growing in engineering education [18], and shaped by perceived usefulness alongside ethical considerations [19], [21]. These trends support an assessment of engineering students' perceptions and readiness to adopt AI tools in different contexts. Most studies examine single stakeholder groups in isolation instead of comparing perspectives along the education-to-practice pipeline. Published work has also centered on applications of specific tools rather than on broader questions of readiness and competency development. Ethical and evaluative dimensions of AI use, while acknowledged as important, remain underrepresented in empirical studies relative to technical skill acquisition.

Research Questions

Four research questions guide our work to address the needs and gaps identified in our literature review.

RQ1: How do engineering students, faculty, and industry practitioners perceive the usefulness, ease of use, and trustworthiness of AI tools for engineering work?

RQ2: To what extent do stakeholder groups align or diverge in their perceptions of ethical and evaluative AI competencies for engineering graduates?

RQ3: How do stakeholders perceive the current state of AI readiness, their own or that of engineering graduates, for AI-integrated professional practice?

RQ4: What themes emerge from stakeholder discussions that explain perceived alignment gaps or inform instrument refinement?

By examining these questions, we aim to provide engineering managers, program leaders, and curriculum designers with data-grounded insights for aligning educational practices with evolving workforce expectations around AI.

Methods

We report herein on the initial design and piloting of a practical measurement suite intended to inform engineering management decisions around Artificial Intelligence (AI) integration in engineering education and practice. The work spans three stakeholder perspectives, engineering students, engineering faculty, and engineering practitioners/hiring professionals, and captures their perceptions using parallel instruments grounded in validated frameworks. Engineering management decisions about AI readiness and capability development run the full pipeline from education to workforce deployment. The goal of this initial phase is not hypothesis testing or broad generalization but developing survey instruments that can credibly support programmatic and organizational decision-making about AI-enabled engineering work [26].

Instrument development draws on three complementary frameworks selected for their relevance to engineering management and workforce readiness: (1) the Technology Acceptance Model (TAM), which provides a validated foundation for assessing perceived usefulness, ease of use, trust/responsible use, and behavioral intention regarding AI tool adoption [8]; (2) an AI taxonomy organized by capability [9] aligned with U.S. policy and technical classifications, used to characterize AI tool exposure in a way that remains stable across rapidly changing platforms; and (3) the UNESCO AI Competency Framework, which informs ethical, evaluative, and human-centered dimensions of AI use that bear on managerial oversight, risk management, governance, and professional accountability [6]. A short AI Readiness subscale was additionally incorporated to capture preparedness at a given point in time for AI-integrated engineering work, which may over time point to ways that curriculum leaders and engineering organizations can act [27].

The overall study follows a two-stage design consisting of a formative piloting and qualitative validation stage 1 and a planned broader deployment stage 2. This paper covers Stage 1 only. We report limited formative data with emphasis on instrument clarity and usability rather than population-level inference [26]. Stage 2 (to be reported in a subsequent paper) will involve full-scale administration of the refined surveys and interviews to support larger-scale analysis and reporting.

We piloted across faculty, students, and industry practitioners across multiple engineering disciplines. The sample size is too small for confirmatory factor analysis or generalizable inferential claims, which we reserve for Stage 2. It does, however, exceed recommended thresholds for formative instrument evaluation. The pilot has three formative purposes. We assess item clarity, completion time, and respondent burden. We compute preliminary internal consistency estimates (e.g., Cronbach's alpha) to flag constructs needing refinement. And we identify floor/ceiling effects or low-variance items. Hertzog [28] recommends pilot samples of 10 to 40 per group for these purposes, and Johanson and Brooks [29] suggest that 30 participants are adequate for preliminary survey development. Our student subsample meets these thresholds, as do the faculty and practitioner subsamples. The semi-structured interviews complement the quantitative pilot. They expose interpretive difficulties and construct gaps that statistical methods cannot detect at small sample sizes.

During Stage 1, we pilot both components of the measurement suite, the parallel surveys and a set of semi-structured interviews designed to complement survey findings [30]. Piloting tests how respondents interpret AI categories, example tools, and item wording. It also tests whether items reflect authentic learning, teaching, and professional expectations, and whether the overall length and structure work in educational and workplace contexts [31]. We pay particular attention to respondent burden and survey fatigue, given practical constraints in academic and workplace settings [32].

To complement the surveys, we conducted semi-structured interviews with a subset of pilot participants from each stakeholder group. All faculty members and hiring representatives had engineering backgrounds with substantive knowledge of AI tools and practical experience. Interview participants spanned multiple engineering disciplines. Interview protocols are aligned with the survey sections and are designed to elicit deeper interpretive and managerial insights that fixed-response items may not capture, including how respondents define "appropriate" AI use, what verification and accountability practices are expected in engineering work, and where they perceive gaps between current practice and desired readiness [30]. The interviews also probe the organizational and educational conditions that enable responsible AI integration, such as governance expectations, policy clarity, and perceived risks related to bias and privacy [6]. The semi-structured format provides consistency across interviews yet still lets participants raise context-specific concerns salient to engineering management [30].

We also piloted and refined the interview protocols themselves. We used initial interviews to evaluate question clarity, sequencing, sensitivity (e.g., organizational policy and risk discussions), and whether prompts elicit concrete information for engineering education and workforce decisions [33]. Feedback from early interviewees and review by the research team informed revisions to interview wording, follow-up prompts, and ordering to improve interpretability and reduce respondent burden, analogous to the iterative refinement process used for the surveys.

Insights from the pilot surveys and interviews allowed us to refine the instruments iteratively. Our revisions focused on clarifying AI category definitions, updating example tool lists to better reflect academic and professional practice, and refining item wording to ensure framing appropriate to each role while preserving construct meaning across populations [26]. Section ordering and construct grouping are confirmed to support interpretability, reduce ambiguity, and minimize fatigue [32]. After these revisions, we produced final versions of the surveys and interview protocols suitable for broader administration. Cross-group alignment analysis proceeds through (1) comparison of construct-level means using one-way ANOVA, (2) examination of item-level response distributions to identify specific points of convergence and divergence, (3) analysis of AI tool category adoption patterns across groups, and (4) qualitative thematic analysis of interview data to contextualize quantitative divergences.

Results: Stage 1

Our pilot administration of the survey instruments confirmed the feasibility and internal coherence of the parallel design across students, faculty, and practitioners. All three instruments shared a common four-section structure and response scale. The shared structure supports future cross-group comparison, with role-specific wording for each stakeholder group. Section A captured Perceived Value and Usability of AI across five constructs (15 to 16 Likert items); Section B addressed AI Use Practices, Guardrails, and Ownership across six constructs (21 to 24 Likert items); Section C measured AI Readiness and Career/Workforce Preparedness across two constructs (9 to 13 Likert items); and Section D documented AI Tool Usage by nine capability-based categories using curated tool lists and open-ended responses to accommodate emerging tools. Item wording was systematically adapted by role referent, with students responding based on their learning behaviors, faculty on instructional and academic integration practices, and practitioners on expectations for graduate preparedness. Appendix A provides access to all three instruments.

Pilot participants and cognitive interviews surfaced several insights about the instruments relevant to engineering management and curriculum decision-making. Respondents generally found the survey length and structure feasible, with completion times averaging approximately 10 to 12 minutes depending on applicable tool categories. Interview protocols were similarly judged to be practical for faculty and industry participants. Pilot results indicate the measurement suite is ready for broader use in academic and professional settings.

A more substantive concern emerged about sensitivity. Pilot feedback indicated that while Sections A and B effectively captured attitudes and ethical orientation toward AI, they may overstate meaningful AI readiness if interpreted without additional contextualization. Participants noted that TAM-based items in Section B do not differentiate between AI use that primarily improves efficiency and AI use that substantively supports learning, reasoning, or professional judgment. Practices varied sharply across respondents. Those who used AI in controlled, verification-first ways could report perceived usefulness, ease of use, and behavioral intention scores similar to those who used it with little structure. Trust-oriented items tended to capture confidence in one's ability to judge AI outputs and not whether verification, justification, or testing is structurally required in instructional or learning activities.

Feedback on Section C suggested that while the human-centered and ethical constructs aligned well with responsible-AI principles, several items were framed at an aspirational level. Value statements outpaced practice. Agreement with value-oriented statements (e.g., designing learning activities to promote responsible AI use) did not necessarily correspond to explicit instructional guardrails, disclosure requirements, or mechanisms that preserve student cognitive ownership. Evaluation-focused items emphasized verification and correctness but did not fully capture other educationally relevant uses of AI, such as design exploration, critique, iteration, or metacognitive reflection. Consequently, the instrument appears to insufficiently distinguish surface adoption from instructionally mature integration.

Cross-section feedback also indicated that the survey did not explicitly capture when AI is used in the learning process (e.g., before, during, or after independent reasoning), nor did it consistently differentiate between faculty AI use and student AI use within courses. For students in particular, pilot responses suggested that Sections A and B emphasize confidence and efficiency without directly assessing practices associated with professional readiness, such as articulating one's own contribution relative to AI assistance, defending AI-supported decisions, or understanding how to present AI use appropriately in workforce contexts.

Respondents also noted that Section D, which catalogs AI tools by capability category, may prime perceptions of competence and should be positioned after ethical and readiness sections to reduce potential anchoring effects. Pilot feedback also suggested that additional stakeholder perspectives such as academic administrators responsible for setting expectations and guidance around AI use, may warrant inclusion in future stages of the study.

These Stage-1 findings informed targeted instrument refinements, including reordering sections to reduce priming and clarifying item wording to better distinguish efficiency from learning and readiness. We also strengthened how guardrails, verification practices, and student ownership are operationalized. Consistent with the formative scope of this phase, these results do not constitute claims about AI readiness at the population level, but rather establish the validity and usability of the measurement framework prior to broader deployment.

Figure 1 summarizes AI tool adoption rates across the three stakeholder groups. As expected, Generative AI dominates across all groups. Faculty show the broadest tool adoption across categories, while practitioners report higher adoption of domain-specific tools but lower adoption of general-purpose Natural Language Processing (NLP) tools.

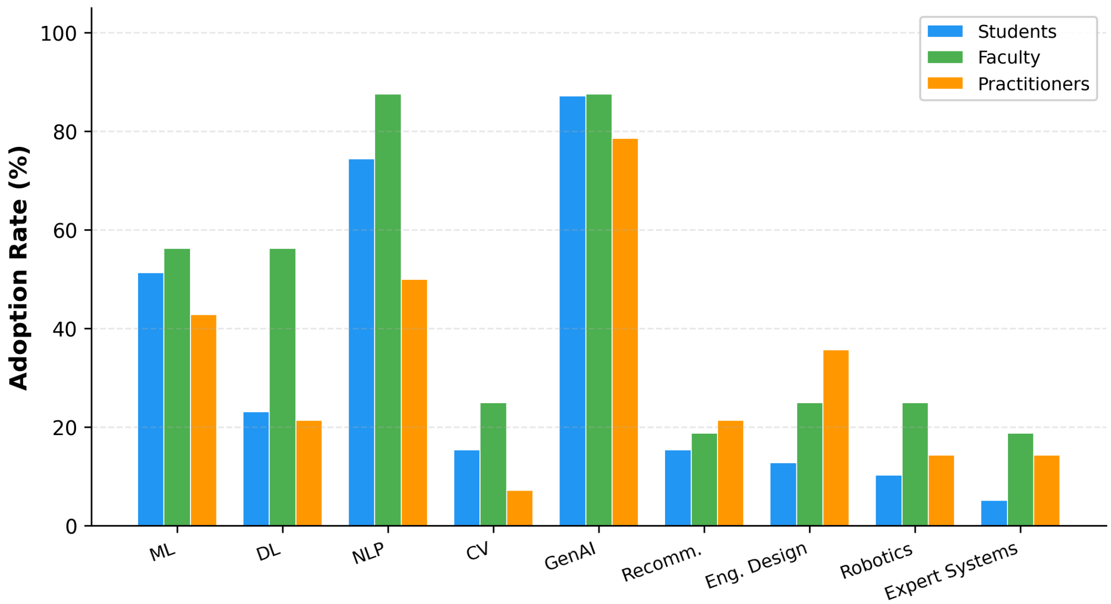

Figure 1. AI tool category adoption rates by stakeholder group.

Discussion

We contribute a formative measurement approach for understanding AI integration and readiness within the engineering education and practice continuum. Instead of focusing narrowly on technology adoption, the study integrates acceptance, ethical and evaluative competence, and readiness constructs in a way that reflects how AI is now managed as an organizational and technical system within engineering organizations [34]. By explicitly capturing perspectives from students, faculty, and practitioners, the instruments support a system-level view of AI readiness that aligns with engineering management concerns about workforce preparation and accountability.

Figure 2 reports internal consistency for each TAM construct. Reliability varies by group in ways that reflect sample characteristics and authentic response patterns. Practitioners achieve $\alpha \geq 0.70$ on all 13 constructs, faculty on 9 of 13, and students on 6 of 13. Student constructs falling below threshold (e.g., LP, PEU, EV) likely reflect genuine variation in a classroom sample where some students have minimal AI exposure. These constructs are flagged for possible item revisions or scale augmentation in Stage 2.

A central pilot-stage finding is the value of distinguishing AI use from AI readiness. Pilot feedback suggests that respondents can meaningfully differentiate between being willing to use AI tools, trusting them in limited contexts, and feeling prepared to use them responsibly in engineering work. Barba's experience integrating GenAI in an engineering computations course provides a cautionary example. Students reported finding AI useful, but their actual practices bypassed independent reasoning and compromised learning outcomes [20]. For engineering managers and academic leaders, the distinction has direct curriculum implications. High adoption or enthusiasm does not guarantee readiness. The AI Readiness subscale provides a practical mechanism for identifying these gaps before they manifest as performance, quality, or governance issues [27].

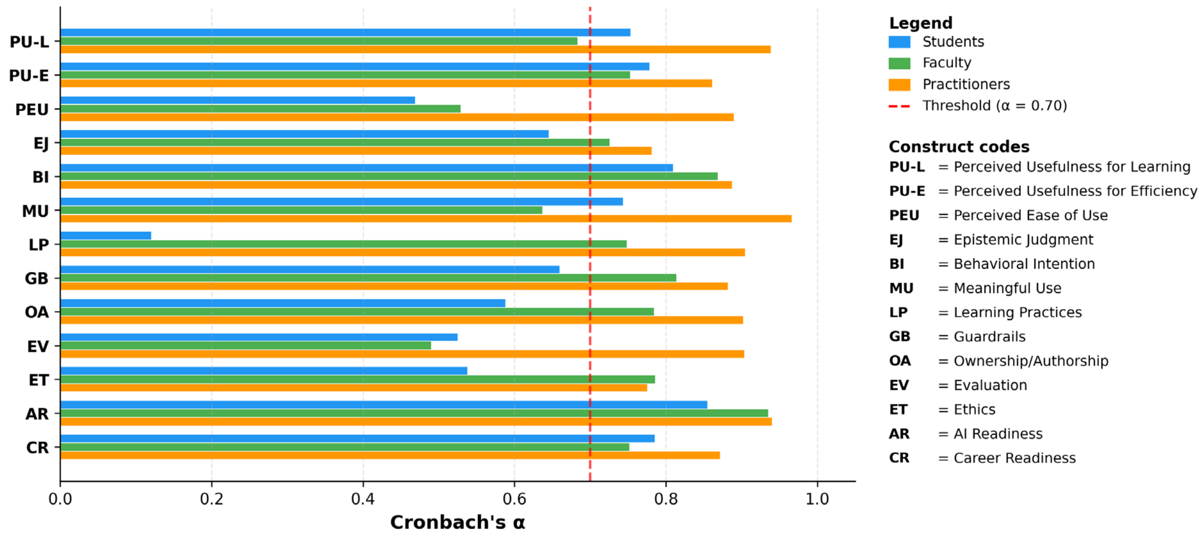

Figure 2. Internal consistency for each TAM construct (Cronbach's α). Constructs are listed in survey-tool order.

Categorizing AI by capability also proved especially useful in the pilot phase. Participants across roles reported that categorizing AI by functional capability instead of by brand helped clarify discussions of expectations and preparedness. For engineering management, the capability framing supports more durable planning and assessment. It avoids dependence on rapidly changing platforms and still captures meaningful differences in AI use across domains such as design, analysis, decision support, and autonomy [9]. This capability-level framing aligns with how organizations often think about skills and roles, not specific tools.

Our finding that industry practitioners value engineering fundamentals over specific AI tool proficiency carries a direct implication for the type of AI exposure curricula should prioritize. Our data support a layered interpretation. Practitioners value (a) strong engineering fundamentals as the non-negotiable foundation, (b) conceptual AI literacy, meaning understanding how AI systems function, where they fail, and when their outputs require verification, as essential, and (c) proficiency with specific AI tools as useful but explicitly subordinate to the first two layers. This priority structure suggests that engineering programs should invest in durable conceptual frameworks for AI (e.g., understanding training data, model limitations, verification strategies) instead of tutorials on specific tools that risk rapid obsolescence. The capability-based AI taxonomy used in Section D of our instrument (drawn from NIST categories) offers one such framework, organizing AI understanding by what systems can do, not which products to use.

The pilot data, while not generalizable, illustrate the instrument's sensitivity to cross-group variation. Mean construct scores ranged from 4.26 (practitioner average) to 5.68 (student average), with the three groups converging most closely on Behavioral Intention and the two

Perceived Usefulness constructs (spreads of 0.61 or smaller). The largest spreads appeared on Learning Practices, AI Readiness, Epistemic Judgment, and Guardrails (each ≥ 2.07 Likert points), with practitioners scoring lowest on the readiness, accountability, and judgment constructs. These descriptive patterns are not tested for statistical significance given the formative-stage sample size; they demonstrate that the instrument distinguishes meaningfully across stakeholder groups, supporting its design for Stage 2 confirmatory analysis.

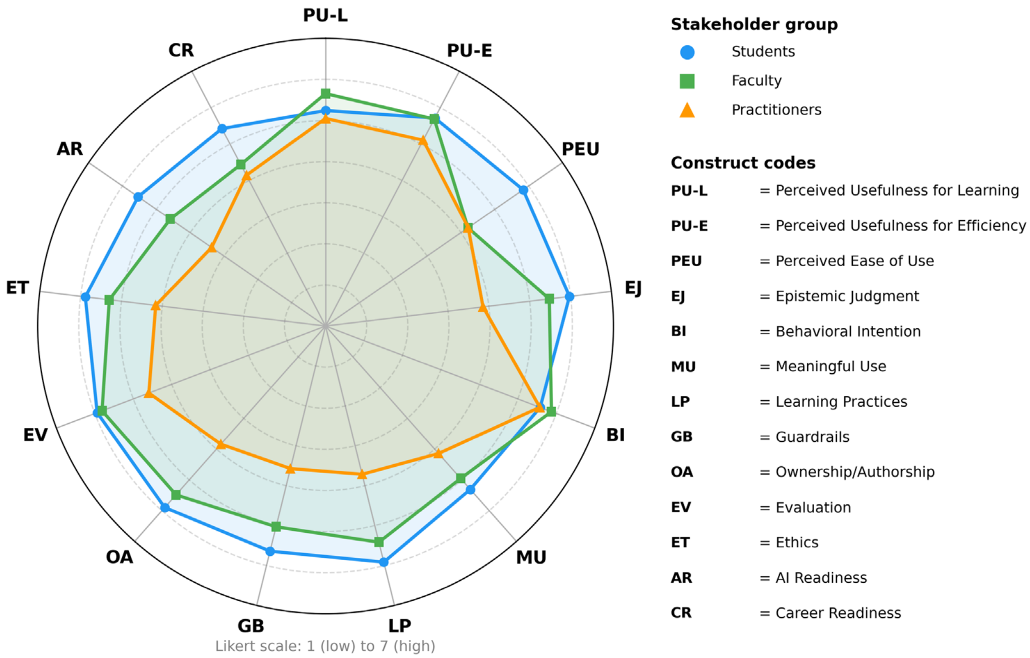

Figure 3. Construct mean profiles by stakeholder group across all 13 TAM constructs.

The UNESCO-aligned items and semi-structured interviews together emphasize human-centered and evaluative dimensions of AI use that are often underrepresented in technology-focused assessments [6]. Pilot participants frequently emphasized verification, boundary-setting, and accountability as core to responsible AI use in engineering contexts. These observations reinforce the case for embedding ethical awareness and evaluative judgment within AI readiness discussions, particularly from an engineering management perspective where liability and professional responsibility are paramount [5]. Barba's redesign of course assessments after an initial GenAI integration attempt failed further illustrates the same dynamic. When students had unrestricted AI access without structural guardrails, the instructor replaced take-home assignments with in-class exercises where AI use could be observed, restoring assessment validity [20].

Developing shared lexicons between academia and industry may seem like a perennial challenge in engineering curriculum design. Yet the AI context intensifies this challenge in ways that demand specific attention. AI-related terminology is marked by instability and interdisciplinary boundary-crossing, and AI introduces normative concepts with no historical engineering analog, such as "responsible AI" and "algorithmic accountability." Our pilot data illustrate this well. When practitioners report valuing "AI fundamentals" over specific tool proficiency, the meaning of "fundamentals" itself varies. Establishing shared definitions is therefore a prerequisite for coherent curriculum design and productive industry partnerships around AI readiness.

Surveys and interviews proved complementary during the pilot. The surveys provide a scalable mechanism for capturing perceptions across populations, while the interviews surfaced organizational nuances that matter for managerial interpretation [35]. Practitioners frequently framed readiness in relation to organizational policy clarity and communication expectations, not just technical competence.

Thus, the formative findings suggest that the proposed measurement suite can help engineering managers, program leaders, and curriculum designers identify where stakeholder expectations about AI use, verification, and accountability diverge [26]. The present paper reports only insights from the pilot stage, but the structure and early feedback indicate strong potential for the instruments to inform data-grounded decisions about curriculum design, professional development, and organizational readiness.

Limitations and Future Work

We acknowledge several limitations appropriate to the formative scope of this study. First, the data reported are intentionally limited in size and are drawn from purposive pilot samples not from representative populations [36]. Therefore, the findings should not be interpreted as generalizable claims about AI readiness across engineering programs or industries. Instead, they are intended to inform instrument refinement and demonstrate feasibility and relevance for broader deployment [31].

Sample size aside, full psychometric validation (confirmatory factor analysis, reliability assessment, and measurement invariance testing across populations) was beyond the scope of this formative stage [37]. These analyses are planned for subsequent work following large-scale administration of the refined instruments. The current paper intentionally avoids overclaiming validity and instead emphasizes transparency in the instrument development process.

The qualitative component carries its own constraints. The semi-structured interviews, though they offer detailed perspectives, reflect participants' self-reported perceptions and organizational contexts [30]. As with any qualitative method, interpretations may be influenced by local practices and norms. Piloting and refining the interview protocols mitigates this limitation by improving question clarity and ensuring that prompts elicit actionable information not anecdotal commentary [33].

Sector and organizational diversity also constrain the present findings. The pilot sample is adequate for pilot purposes. It does not, however, support disaggregation by industry sector, organization size, or AI implementation maturity. We may incorporate in Stage 2 North American Industry Classification System (NAICS) sector codes in practitioner demographics to enable formal cross-sector comparison. Our pilot practitioners span six industry sectors. Six sectors gives us early evidence of cross-sector relevance, but formal subgroup analysis has to wait for Stage 2.

Our future work will focus on the second stage of the study, wider deployment of the finalized surveys and interviews across multiple institutions and organizational contexts. This phase will enable formal validation of the measurement model, analysis of relationships among acceptance, ethical competence, and readiness, and comparison of perspectives across students, faculty, and practitioners [37]. Such analyses will support identification of alignment gaps between educational preparation and workforce expectations, a primary concern for engineering management [26].

Additional future directions include longitudinal deployment to examine changes in AI readiness over time, integration of the instruments into program-level assessment and continuous improvement processes, and exploration of how organizational policies and governance structures influence readiness outcomes [34]. We expect that these efforts will extend the present formative work into a credible evidence base for managing AI integration in engineering education and practice, though the pace of AI development may require ongoing instrument adaptation.

References

[1] Microsoft and LinkedIn, "2024 Work Trend Index Annual Report: AI at work is here. Now comes the hard part," 2024. [Online]. Available: https://www.microsoft.com/en-us/worklab/work-trend-index/ai-at-work-is-here-now-comes-the-hard-part

[2] National Academies of Sciences, Engineering, and Medicine, Artificial Intelligence and the Future of Work. Washington, DC, USA: National Academies Press, 2025. doi: 10.17226/27644

[3] Congressional Research Service, "Artificial intelligence: Overview, recent advances, and considerations for the 118th Congress," CRS Report R47644, 2023.

[4] World Economic Forum, "Future of Jobs Report 2025," Geneva, Switzerland, 2025. [Online]. Available: https://www.weforum.org/publications/the-future-of-jobs-report-2025/

[5] ABET, "Criteria for accrediting engineering programs, 2026-2027," Baltimore, MD, USA, 2025. [Online]. Available: https://www.abet.org/accreditation/accreditation-criteria/

[6] UNESCO, AI Competency Framework for Teachers. Paris, France: United Nations Educational, Scientific and Cultural Organization, 2024. [Online]. Available: https://unesdoc.unesco.org/ark:/48223/pf0000391104

[7] S. Latham, "Are you ready for the AI university?," Chronicle Higher Educ., vol. 71, no. 17, 2025.

[8] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Quarterly, vol. 13, no. 3, pp. 319-340, 1989. doi: 10.2307/249008

[9] National Institute of Standards and Technology, "U.S. leadership in AI: A plan for federal engagement in developing technical standards and related tools," Gaithersburg, MD, USA, 2019.

[10] J. Álvarez Ariza, M. Benitez Restrepo, and C. Hernández Hernández, "Generative AI in engineering and computing education: A scoping review," IEEE Access, vol. 13, pp. 30789-30810, 2025. doi: 10.1109/ACCESS.2025.3541424

[11] J. D. Azofeifa et al., "Future skills for Industry 4.0 integration and innovative learning for continuing engineering education," Frontiers Educ., vol. 9, 2024, Art. no. 1412018. doi: 10.3389/feduc.2024.1412018

[12] S. H. Khan and A. H. I. Mourad, "Integrating Industry 4.0 in engineering education: Implementation patterns, pedagogical strategies, and industry alignment," Cogent Educ., vol. 12, no. 1, 2025. doi: 10.1080/2331186X.2025.2588010

[13] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, “User acceptance of information technology: Toward a unified view,” MIS Quarterly, vol. 27, no. 3, pp. 425-478, 2003.

[14] Y. Luo et al., “Generative AI in engineering education: A survey of student and instructor usage and attitudes,” Proc. Human Factors Ergonomics Soc., vol. 69, no. 1, pp. 272-277, 2025. doi: 10.1177/10711813251358792

[15] Y. Jiang, L. Xie, and X. Cao, “Exploring the effectiveness of institutional policies and regulations for generative AI usage in higher education,” Higher Educ. Quarterly, vol. 79, no. 4, 2025. doi: 10.1111/hequ.70054

[16] A. Granić and N. Marangunić, “Technology acceptance model in educational context: A systematic literature review,” Brit. J. Educ. Technol., vol. 50, no. 5, pp. 2572-2593, 2019. doi: 10.1111/bjet.12864

[17] D. Claudio, M. A. Velázquez, W. Bravo-Llerena, G. E. Okudan, and A. Freivalds, “Perceived usefulness and ease of use of wearable sensor-based systems in emergency departments,” IIE Trans. Occupational Ergonomics Human Factors, vol. 3, no. 3-4, pp. 177-187, 2015. doi: 10.1080/21577323.2015.1040559

[18] J. A. Ovi, G. T. Fierro, and E. C. Smith, “Assessing student adoption of generative artificial intelligence across engineering education from 2023 to 2024,” in Proc. ASEE Annu. Conf. Expo., 2025. doi: 10.18260/1-2--55471

[19] J. L. Jooste, K. E. Wolff, and J. G. Joubert, “Engineering students’ perceptions and use of generative artificial intelligence,” Comput. Appl. Eng. Educ., vol. 33, no. 4, 2025. doi: 10.1002/cae.70064

[20] L. A. Barba, “Embracing GenAI in an engineering computations course: What went wrong and what’s next,” IEEE Computer, vol. 58, no. 8, pp. 136-141, Aug. 2025. doi: 10.1109/MC.2025.3572654

[21] UNESCO, Guidance for Generative AI in Education and Research. Paris, France: United Nations Educational, Scientific and Cultural Organization, 2023. [Online]. Available: https://cdn.table.media/assets/wp-content/uploads/2023/09/386693eng.pdf

[22] H. Etzkowitz and L. Leydesdorff, Universities and the Global Knowledge Economy: A Triple Helix of University-Industry-Government Relations. London, UK: Pinter, 1997.

[23] J.-B. R. G. Souppez, “Engineering employability skills: Students, academics, and industry professionals perception,” Int. J. Mech. Eng. Educ., vol. 53, no. 1, 2025. doi: 10.1177/03064190231214178

[24] T. Mahalingam, “Bridging the gap between academia and industry: A case study of collaborative curriculum development,” Int. J. Bus. Perform. Manage., vol. 25, no. 4, pp. 589-603, 2024. doi: 10.1504/IJBPM.2024.139482

[25] J. Freeman, “Student generative AI survey 2025,” HEPI Policy Note 61, Higher Education Policy Institute, 2025. [Online]. Available: https://www.hepi.ac.uk/wp-content/uploads/2025/02/HEPI-Kortext-Student-Generative-AI-Survey-2025.pdf

[26] R. F. DeVellis and C. T. Thorpe, Scale Development: Theory and Applications, 5th ed. Thousand Oaks, CA, USA: SAGE Publications, 2022.

[27] A. Parasuraman and C. L. Colby, “An updated and streamlined technology readiness index: TRI 2.0,” J. Serv. Res., vol. 18, no. 1, pp. 59-74, 2015. doi: 10.1177/1094670514539730

[28] M. A. Hertzog, “Considerations in determining sample size for pilot studies,” Research in Nursing and Health, vol. 31, no. 2, pp. 180-191, 2008. doi: 10.1002/nur.20247

[29] G. A. Johanson and G. P. Brooks, “Initial scale development: Sample size for pilot studies,” Educational and Psychological Measurement, vol. 70, no. 3, pp. 394-400, 2010. doi: 10.1177/0013164409355692

[30] S. Brinkmann and S. Kvale, InterViews: Learning the Craft of Qualitative Research Interviewing, 3rd ed. Thousand Oaks, CA, USA: SAGE Publications, 2015.

[31] G. B. Willis, Cognitive Interviewing: A Tool for Improving Questionnaire Design. Thousand Oaks, CA, USA: SAGE Publications, 2005.

[32] N. M. Bradburn, “Respondent burden,” in Proc. Survey Research Methods Section Amer. Statistical Assoc., 1978, pp. 35-40.

[33] D. Collins, Cognitive Interviewing Practice. London, UK: SAGE Publications, 2015.

[34] E. L. Trist, “The evolution of socio-technical systems,” in Perspectives on Organization Design and Behavior, A. H. Van de Ven and W. F. Joyce, Eds. New York, NY, USA: Wiley, 1981, pp. 19-75.

[35] J. W. Creswell and V. L. Plano Clark, Designing and Conducting Mixed Methods Research, 3rd ed. Thousand Oaks, CA, USA: SAGE Publications, 2017.

[36] M. Q. Patton, Qualitative Research and Evaluation Methods, 4th ed. Thousand Oaks, CA, USA: SAGE Publications, 2015.

[37] J. F. Hair, B. J. Babin, R. E. Anderson, and W. C. Black, Multivariate Data Analysis, 8th ed. Cengage India, 2019.

Appendix A: Survey Instruments

The AI-Engineering Technology Acceptance Model (AI-Eng-TAM) measurement suite comprises three parallel survey instruments tailored to faculty, students, and industry practitioners/hiring managers. Each instrument contains four sections, namely (A) Perceived Value and Usability of AI for Teaching and Learning (Likert, 7-point scale, 15 to 16 items across five constructs); (B) Instructional Design, Guardrails, and Student Ownership in AI-Mediated Learning (Likert, 7-point scale, 21 to 24 items across six constructs); (C) AI Readiness for Educating AI-Ready Engineers (Likert, 7-point scale, 9 to 13 items across two constructs); and (D) AI Tool Usage by Category (nine capability-based AI categories with curated tool checklists). An optional demographics section concludes each instrument. Construct definitions and response scales remain constant across instruments, and item stems for constructs are systematically adapted by role referent. Read-only previews of the complete instruments are available for the Faculty Survey (https://ai-eng-tam-survey.vercel.app/preview/faculty), Student Survey (https://ai-eng-tam-survey.vercel.app/preview/student), and Practitioner Survey (https://ai-eng-tam-survey.vercel.app/preview/practitioner).