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Reimagining Engineering Competencies in the Generative AI Era: A Socio-Technical Analysis of Student Perceptions

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Abstract

This empirical research full paper study investigates how senior mechanical engineering students perceive Generative AI (GenAI) and which professional competencies they view as most critical for success in an AI-augmented engineering landscape. Using a cross-sectional survey of 80 senior mechanical engineering students at a large R1 university, we examine: (1) students' perceptions, usage patterns, and concerns regarding GenAI; (2) the perceived importance hierarchy among 36 engineering Knowledge, Skills, and Abilities (KSAs); and (3) whether internship experience is associated with differences in KSA valuation. Grounded in the JO-HAI (Joint Optimization of Human-skill and Artificial Intelligence) Framework, a tripartite synthesis integrating Socio-Technical Systems (STS) theory, the hidden curriculum concept, and a proposed Dynamic Competency Interaction Model (DCIM), results show that students prioritize human-centric competencies (communication, $M = 4.79$; critical thinking, $M = 4.77$; teamwork, $M = 4.70$; adaptability, $M = 4.56$) over specialized technical knowledge. A pronounced awareness–adoption gap characterizes GenAI engagement (89.5% familiar; 4.7% daily use), with accuracy (66.3%), job displacement (65.1%), and ethics (60.5%) as leading concerns. Exploratory analyses at the uncorrected $p < 0.05$ level suggest internship experience may modestly shift competency valuations (interns rating flexibility higher, $p = 0.036$; non-interns rating applied technical knowledge higher, $p = 0.027$); however, these effects do not survive Bonferroni correction and should be interpreted as hypothesis-generating. The JO-HAI Framework offers an integrative lens for understanding competency development in AI-augmented professions, with implications for curriculum design, AI literacy, responsible AI use, and experiential learning.

Keywords: engineering education, generative AI, knowledge skills and abilities (KSAs), socio-technical systems, JO-HAI framework, experiential learning, professional competencies

1. Introduction: The New Socio-Technical Reality of Engineering

The rapid mainstream adoption of Generative AI (GenAI) tools, such as ChatGPT, Gemini, and Claude, marks a watershed moment for the engineering profession and signals a paradigm shift that is reshaping engineering practice [1]. From generative design systems that can autonomously explore thousands of potential solutions to advanced simulations that predict system behavior with unprecedented accuracy, AI is increasingly integrated into core engineering workflows, including supply chain optimization, smart manufacturing, and predictive maintenance [2]-[4]. The consensus among industry leaders and academics is clear: AI is no longer a peripheral competency but an essential and transformative force redefining the nature of engineering work [5]. This technological transformation demands a corresponding evolution in engineering education. Pedagogical models that primarily emphasize transmitting established technical knowledge and analytical procedures are increasingly insufficient in a world where AI can execute many of these tasks with greater speed and efficiency [6]. Accordingly, the central question for educators is no longer whether AI will change the profession, but how to prepare students to "command AI wisely, rather than being commanded by it" [7]. This shift creates an urgent need to move beyond teaching tool proficiency and to critically re-examine the fundamental competencies that will define the value and effectiveness of the human engineer in the twenty-first century [8]. As AI automates calculations, drafting, and routine coding, competencies that require creativity, ethical judgment, interdisciplinary reasoning, and decision-making under uncertainty become increasingly central [9]. While the literature contains extensive theoretical discussions of AI's risks and opportunities in education, a significant empirical gap remains: limited research directly captures the perceptions of those most immediately affected, engineering students themselves [10]. Because students are entering a profession in transition, their GenAI usage patterns, concerns, and evolving valuations of professional competencies provide essential evidence for guiding curriculum reform. Understanding how students perceive the relative importance of competencies is critical for aligning educational outcomes with the real-world demands of an AI-augmented industry [11]. To address this gap, this study offers an empirical snapshot of this transitional moment through the lens of senior engineering students by examining their perceptions of GenAI and the hierarchy of competencies they believe are most crucial for success. It also investigates the formative role of experiential learning, positing that internships provide a distinctive window into the practical demands of contemporary engineering practice. The study is guided by three research questions:

- ***RQ1:*** *How do senior engineering students perceive, use, and express concerns about Generative AI in the context of their future careers?*
- ***RQ2:*** *Based on student perceptions, what is the hierarchy of importance among a comprehensive set of 36 engineering Knowledge, Skills, and Abilities (KSAs)?*
- ***RQ3:*** *How does practical, in-workplace experience (i.e., internships) influence students' valuation of these KSAs, and what does this reveal about the alignment between formal engineering curricula and the demands of the contemporary, AI-augmented workplace?*

By answering these questions, this paper makes a dual contribution. Theoretically, it introduces the **JO-HAI (Joint Optimization of Human-skill and Artificial Intelligence) Framework**, an innovative synthesis coupling Socio-Technical Systems (STS) theory, hidden curriculum dynamics, and the proposed Dynamic Competency Interaction Model (DCIM), as an integrative lens for understanding competency development in AI-augmented professions. Empirically, it provides initial data-driven insights for educators, curriculum designers, and policymakers, supporting the development of engineering education that is responsive to technological change while centered on cultivating enduring human capabilities that will define the next generation of engineering leaders.

2. Theoretical Framework: JO-HAI (Joint Optimization of Human-skill and Artificial Intelligence)

To interpret how students' GenAI perceptions relate to professional competency priorities, this study employs the JO-HAI Framework where, STS theory frames engineering as a hybrid system in which performance depends on the joint optimization of technical and social subsystems; DCIM specifies how competency domains interact recursively within this AI-augmented system; and the hidden curriculum explains how experiential learning, particularly internships, recalibrates students' values and professional identity through workplace immersion. The JO-HAI Framework is summarized in Figure 1.

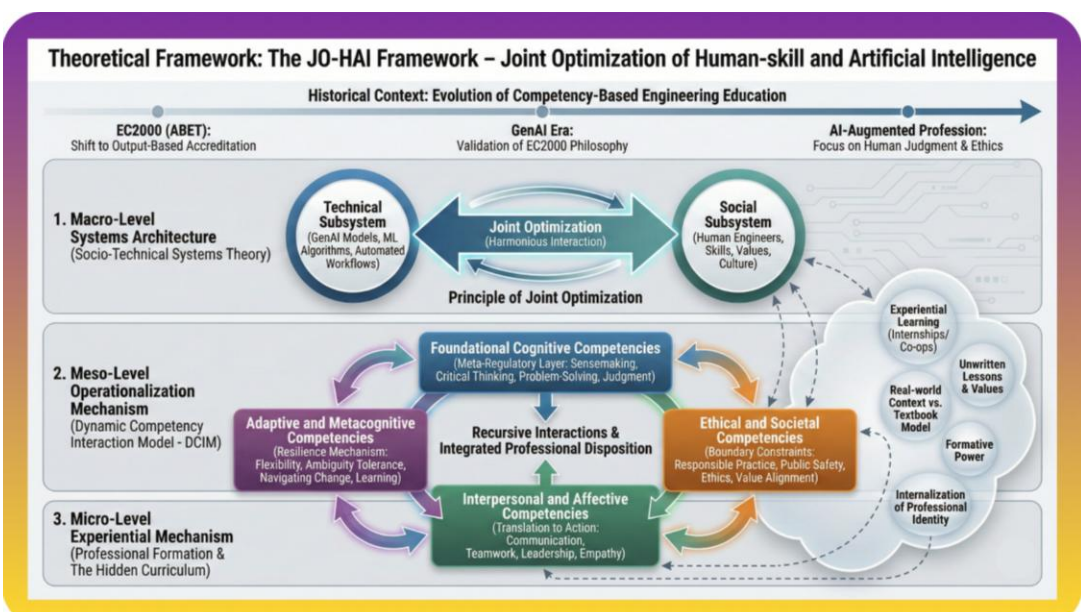

Figure 1. Joint Optimization of Human-skill and Artificial Intelligence Framework

2.1 The Evolution of Competency-Based Engineering Education

The renewed emphasis on professional competencies in engineering represents an acceleration of a decades-long shift toward outcomes-based education. A key inflection point was ABET's Engineering Criteria 2000 (EC2000), which moved accreditation from inputs (e.g., prescribed credit hours) to outcomes, what graduates can demonstrably do upon graduation [12]. EC2000 elevated outcomes beyond technical proficiency, including teamwork, communication, ethical responsibility, and lifelong learning [13], [14]. The rise of GenAI intensifies the relevance of this shift: as AI systems increasingly automate routine technical tasks, human-centered capacities such as judgment, ethical reasoning, creative problem framing, and empathetic communication become more central to professional engineering practice [5], [15].

2.2 A Socio-Technical Systems Lens for an AI-Augmented Profession

STS theory conceptualizes organizational systems as comprising interdependent technical and social subsystems [16], and argues that robust performance emerges through their joint optimization [17]. In contemporary engineering, the technical subsystem now includes GenAI models, machine-learning workflows, and automation pipelines, while the social subsystem includes engineers' domain knowledge, cognitive and interpersonal skills, ethical commitments, and collaborative structures. From this perspective, engineering education must prepare students not only to use AI tools, but to strategically guide, validate, and ethically deploy them in ways that optimize the broader socio-technical system [18].

Consistent with this framing, the 36 KSAs examined in this study are organized into four domains: (1) Foundational Cognitive Competencies for oversight and sensemaking (e.g., critical thinking, problem-solving); (2) Interpersonal and Affective Competencies for collaboration and leadership (e.g., communication, teamwork); (3) Adaptive and Metacognitive Competencies for navigating change (e.g., flexibility, ambiguity tolerance); and (4) Ethical and Societal Competencies for responsible practice (e.g., ethical standards, public safety awareness) [19]. DCIM specifies how these domains function together under AI-augmented conditions: cognitive competencies regulate evaluation and validation of AI outputs; interpersonal competencies translate validated outputs into stakeholder-aligned action; adaptive competencies enable recalibration as technologies and contexts evolve; and ethical competencies operate as boundary conditions for responsible deployment. These relations are recursive, ethical reasoning shapes evaluation practices, which influence communication and teamwork, which in turn informs adaptive capacity, positioning competence as an integrated disposition required for joint optimization.

2.3 Professional Formation and the Hidden Curriculum

To explain why competency valuations may differ by work experience, the JO-HAI Framework also draws on professional identity formation and the hidden curriculum. Engineering education aims not only to develop technical capability, but also to support the formation of a professional identity, an internalized sense of self, values, and purpose as an engineer [20]. The hidden curriculum refers to the informal, often unspoken lessons and norms absorbed through immersion in particular cultural settings [21]. Internships and co-op experiences are primary pathways through which students encounter this hidden curriculum [22], observing which competencies are rewarded in practice, how teams navigate conflict, and how business pressures shape technical decisions [23]. Accordingly, differences in KSA ratings between students with and without internship experience can be interpreted as empirical traces of workplace-based recalibration and potential misalignment between formal curricular emphases and the lived realities of professional engineering practice [24].

Grounded in this framework, the following section describes the study design, survey instrumentation, and analytic procedures used to examine students' GenAI perceptions, competency hierarchies, and the role of internship experience.

3. Methodology

3.1 Research Design and Participants

This study employed a cross-sectional survey design to capture senior engineering students' perceptions of Generative AI (GenAI) and workforce-relevant competencies during Fall 2024. Participants were senior-level undergraduates enrolled in two mechanical engineering courses, MCHE 4000 (Mechanical Engineering Professional Practice) and MCHE 4190 (Capstone Design I), at a large public R1 university in the Southeastern United States. Seniors were targeted because they had completed most of the formal curriculum, were approaching entry into the labor market, and were engaged in professional practice and capstone design experiences that closely resemble authentic engineering work. A total of 80 unique students completed the survey in MCHE 4000; 24 of these respondents were concurrently enrolled in MCHE 4190. All participants were mechanical engineering majors, which limits disciplinary generalizability (see Section 7).

At the time of data collection, the university had not established a centralized policy governing GenAI use in coursework and did not provide institutional licenses for commercial GenAI platforms (e.g., ChatGPT Plus, Claude Pro). Consequently, GenAI policies varied by instructor (from prohibition to encouraged use with disclosure), and the department had not issued unit-level guidance. This institutional context is important for interpretation because students' reported adoption patterns likely reflect self-directed exploration rather than institutionally scaffolded engagement.

3.2 Survey Instrument

The electronic survey consisted of two sections. The first collected demographic/background variables and GenAI-related perceptions, including internship/co-op experience (terms), undergraduate research experience (terms), self-rated GenAI familiarity (scale reported consistently throughout the manuscript), GenAI usage frequency (*Never* to *Daily*), usage purposes (multi-select), agreement that GenAI will significantly change engineering job markets (5-point Likert scale), and concerns (multi-select; e.g., accuracy/reliability, job displacement, ethical implications, data privacy). The second section asked respondents to rate the importance of 36 Knowledge, Skills, and Abilities (KSAs) for success in engineering careers on a 5-point scale (1 = *Not Important* at All; 5 = *Very Important*). The KSA list was adapted from established engineering competency literature, including Transforming Undergraduate Education in Engineering (TUEE) Phase 1 and ABET criteria, spanning technical, professional, and affective domains [25], [26]. To support consistent interpretation, the instrument included brief examples distinguishing Knowledge (e.g., applied engineering knowledge), Skills (e.g., communication across audiences), and Abilities (e.g., flexibility/adaptability under changing constraints).

3.3 Data Analysis

Data were analyzed in three stages. First, descriptive statistics (frequencies and percentages) were computed for demographic variables and GenAI perceptions to characterize the cohort. Second, KSAs were rank-ordered using mean importance ratings and the proportion of respondents selecting *"Very Important"* to establish the perceived competency hierarchy. Third, comparative analyses examined whether internship exposure was associated with differences in KSA valuation by dividing respondents into those with no internship experience ($n = 32$) and those with one or more internship terms ($n = 54$). Given non-normal distributions, Mann-Whitney U tests were conducted for each KSA, and Cohen's d effect sizes were reported. To address multiple comparisons, Bonferroni correction was applied ($\alpha = 0.05/36 = 0.0014$). Results are presented using a two-tier reporting approach: uncorrected $p < 0.05$ findings are reported as exploratory and hypothesis-generating, while emphasizing which results remain significant after correction and therefore warrant greater inferential confidence.

The following section reports descriptive patterns of GenAI perceptions and usage, the KSA importance hierarchy, and internship-related differences in competency valuation.

4. Results

4.1 RQ1: Cohort Profile and Engagement with Generative AI

Table 1 (Appendix A) summarizes participant characteristics for the 80 senior mechanical engineering students surveyed in Fall 2024. The cohort reported substantial professional exposure through internships/co-ops but limited undergraduate research experience. Specifically, 62.5% (n=50) reported at least one internship/co-op term (28.7% one term; 20.0% two terms; 13.8% three or more), while 37.5% (n=30) reported none. Undergraduate research experience was uncommon, with 91.2% (n=73) reporting no participation. Students reported high GenAI familiarity but low routine use. Overall, 90.0% indicated being at least somewhat familiar with GenAI (73.8% somewhat; 16.2% very), yet only 3.8% reported daily use; 26.2% reported weekly use, 26.2% monthly use, 32.5% rare use, and 11.2% never. Students' most frequently selected concerns were accuracy/reliability (66.2%, n=53), job displacement (63.7%, n=51), ethical implications (58.8%, n=47), and data privacy (50.0%, n=40). Figure 2 visualizes cohort distributions for demographics, internship exposure, and GenAI familiarity.

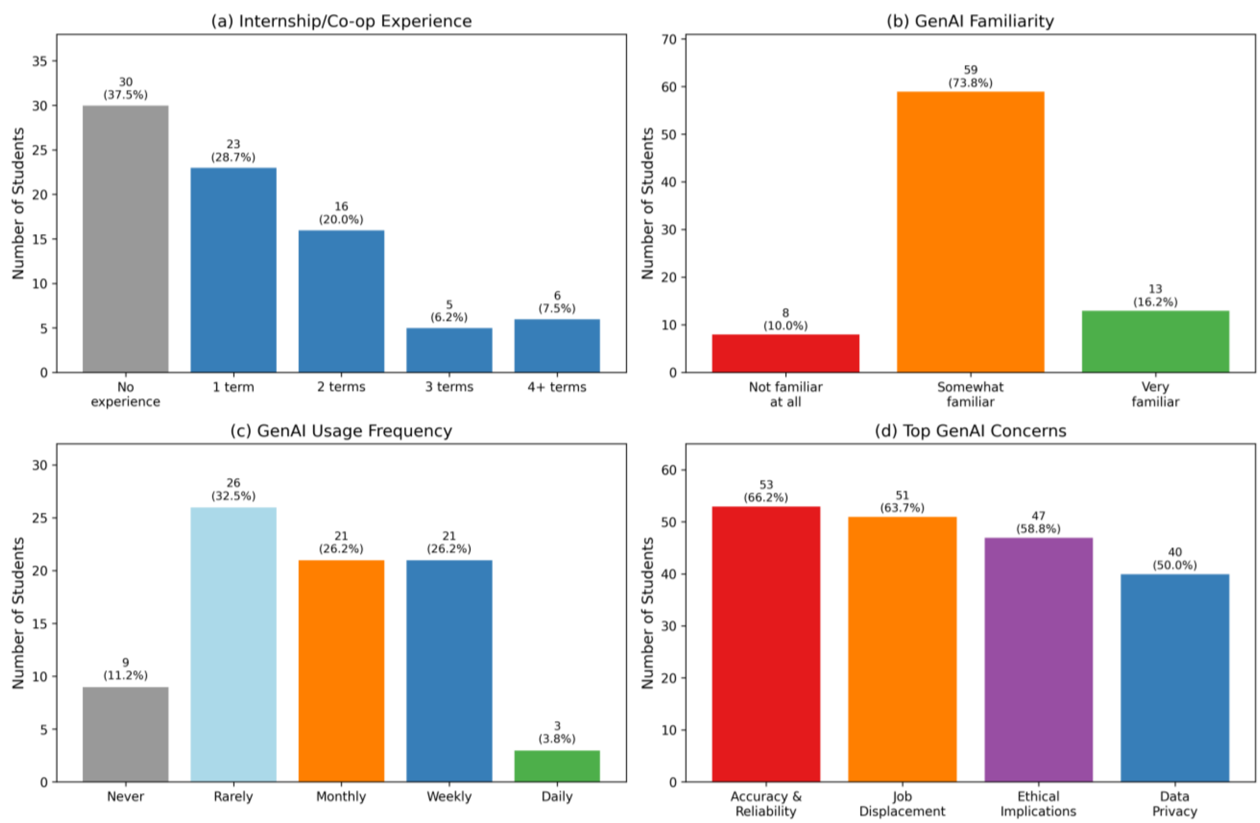

Figure 2. Student Demographics, Internship Experience, and GenAI Familiarity Distribution (N=80)

4.2 RQ2: The Perceived Hierarchy of Engineering Competencies

Table 2 (Appendix B) presents the rank-ordered importance ratings for the 36 KSAs. The hierarchy is led by broadly human-centric and foundational competencies, with specialized technical and business-oriented competencies ranking lower. The five highest-rated KSAs were critical thinking (*M=4.90*, SD=0.30; 90.0% *"Very Important"*), communication skills (*M=4.89*, SD=0.32; 88.8%), teamwork (*M=4.85*, SD=0.36; 85.0%), flexibility/adaptability (*M=4.78*, SD=0.42; 77.5%), and problem identification/formulation/solving *(M=4.76*, SD=0.43; 76.2%). Other highly rated competencies included motivation (*M=4.70*), ambiguity/complexity tolerance (*M=4.70*), accountability (*M=4.70*), prioritization (*M=4.69*), and design understanding (*M=4.69*). Lower-ranked KSAs included entrepreneurship (*M=3.75*), security knowledge (*M=3.88*), cultural awareness (*M=3.89*), mentoring skills (*M=3.96*), and information technology knowledge (*M=4.00*). Figure 3 visualizes the full hierarchy. By competency type, students rated Skills (*M=4.53*) and Abilities (*M=4.50*) higher than Knowledge domains (*M=4.27*), and a Kruskal-Wallis test indicated statistically significant differences across types (H=80.89, $p<0.001$).

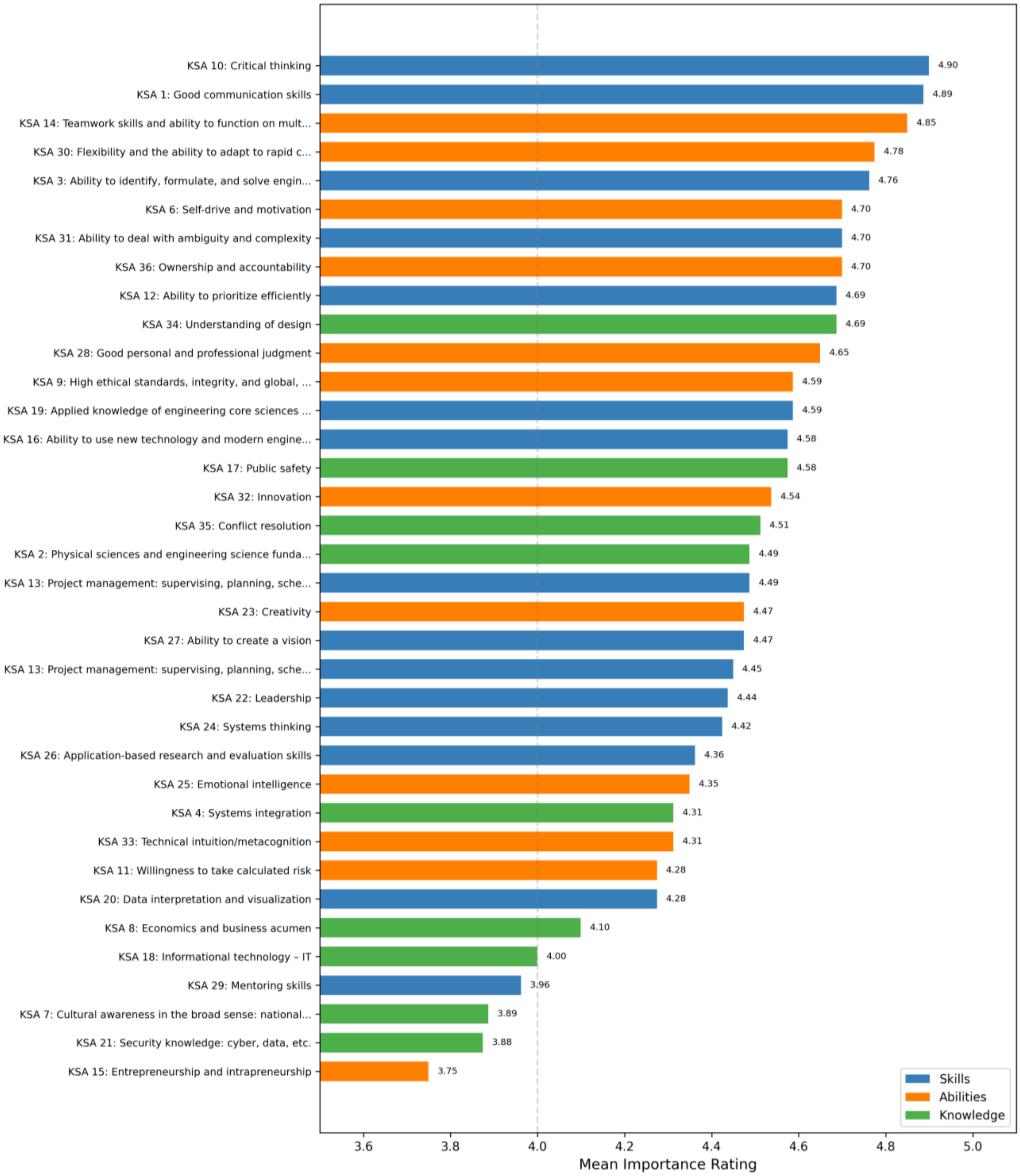

Figure 3. Complete KSA Importance Hierarchy Based on Mean Ratings (N=80)

4.3 RQ3: Internship Experience and Differences in KSA Valuation

To examine whether workplace exposure is associated with differences in competency valuation, KSA ratings were compared between students with internship experience (n=54) and those without (n=32). Two KSAs differed at the exploratory (uncorrected) threshold of $p<0.05$ (Table 3; Figure 4), but neither survived Bonferroni correction ($p<0.0014$). Non-interns rated public safety awareness higher

(M=4.77, SD=0.43) than interns (M=4.46, SD=0.71; p=0.038; d=-0.50), while interns rated flexibility/adaptability higher (M=4.86, SD=0.35) than non-interns (*M*=4.63, SD=0.49; *p=0.020*; *d=+0.56*). Although inferential confidence is limited in this sample, both effects were medium in magnitude, suggesting potentially meaningful differences that merit confirmation in larger, pre-registered studies. Across the remaining KSAs, group differences were generally small and non-significant, indicating broadly similar competency priorities with internship experience associated with modest shifts rather than wholesale reorientation.

Table 3. Internship Experience Comparison for Key KSAs ($p < 0.05$)*

KSA	With Internship *M (SD)*	No Internship *M (SD)*	Diff	p-value	Cohen's d
Applied engineering knowledge	4.52 (0.61)	4.70 (0.65)	-0.18	0.081	-0.29
Flexibility and adaptability	4.86 (0.35)	4.63 (0.49)	+0.23	0.020*	+0.56
Willingness to take risks	4.34 (0.77)	4.17 (0.65)	+0.17	0.122	+0.24
Deal with ambiguity	4.76 (0.43)	4.60 (0.50)	+0.16	0.135	+0.35
Public safety	4.46 (0.71)	4.77 (0.43)	-0.31	0.038*	-0.50

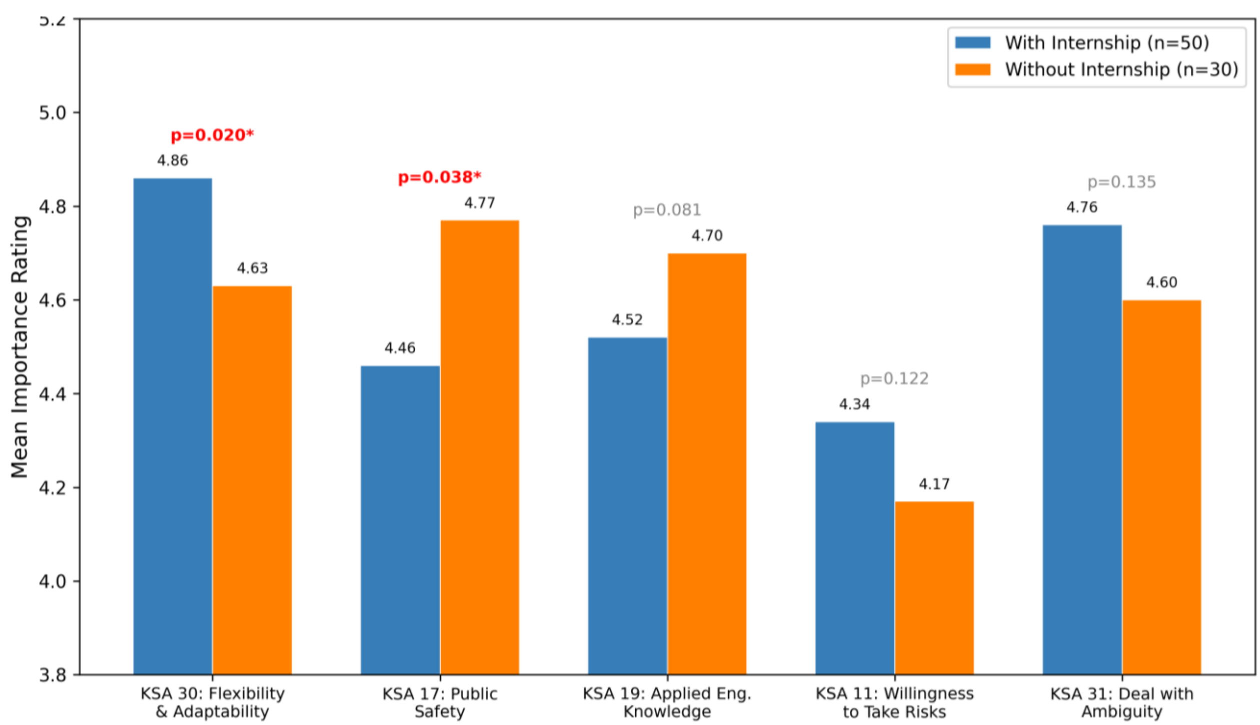

Figure 4. Comparison of KSA Valuations by Internship Experience (Significant Differences Highlighted).

The following section interprets these patterns through the JO-HAI framework, situates the findings within prior literature on competency development and experiential learning, and outlines implications for engineering curricula and responsible GenAI integration.

5. Discussion

5.1 Interpreting the Findings Through the JO-HAI Framework

Viewed through the JO-HAI Framework, the results suggest that senior mechanical engineering students are already calibrating their professional value proposition for an AI-augmented engineering landscape. The observed competency hierarchy emphasizes human-centered capabilities, particularly problem-solving, critical thinking, and communication, which align with a socio-technical interpretation of engineering work in which optimal performance depends on joint optimization of technical systems (increasingly AI-enabled) and human judgment, coordination, and ethical oversight [16]. In this context, students' priorities appear oriented toward competencies that enable engineers to frame problems, validate AI-assisted outputs, and translate socio-technical results into stakeholder-relevant decisions [5], [15], [27]. These patterns are consistent with the DCIM proposition that Foundational Cognitive competencies support evaluation and oversight, while Interpersonal and Affective competencies enable translation and coordination within real organizational settings.

5.2 Internships, Professional Formation, and the Hidden Curriculum

Differences associated with internship experience, although exploratory and not robust to Bonferroni correction, offer theoretically meaningful signals consistent with the hidden curriculum mechanism [21]. Interns' higher valuation of flexibility/adaptability and non-interns' higher valuation of public safety awareness may reflect how workplace exposure recalibrates competency priorities by revealing organizational constraints, competing objectives, and the situated nature of safety, ethics, and decision-making in practice [23], [24]. Interpreted through professional formation, these trends suggest that internships can shape students' internal value structures and professional identity by moving them from idealized curricular framings toward practice-informed conceptions of competence [20]. Given the inferential limits of this sample, these results are best treated as hypothesis-generating and warrant replication in larger, multi-institutional and multi-disciplinary studies.

5.3 Student Concerns as Socio-Technical Friction Points

Students' dominant concerns about GenAI, accuracy/reliability, job displacement, and ethics, can be interpreted as socio-technical friction points that emerge when a new technical subsystem is integrated into established professional and educational systems [27]. Accuracy concerns reinforce the importance of engineers' validation and oversight roles, requiring domain knowledge and critical evaluation to detect error, bias, or implausible outputs [27]. Job displacement concerns reflect uncertainty about how engineering roles will evolve as AI automates tasks historically associated with competence and productivity [28]. Ethical concerns underscore student recognition that AI systems are not value-neutral and can introduce bias, privacy risks, and downstream societal consequences, supporting calls to embed ethics within core engineering practice rather than treating it as peripheral [29], [30]. Collectively, these concerns map onto JO-HAI's emphasis on recursive competency interactions: evaluation, adaptation, and ethical constraint-setting operate together in navigating AI-augmented practice.

6. Implications for Engineering Education

6.1 Pedagogy and Assessment in the GenAI Era

The findings suggest three instructional priorities. First, programs should develop critical AI literacy beyond tool proficiency, including effective prompting, systematic validation of AI outputs, bias awareness, and understanding model limitations [31]. Second, curricula should embed human-centered competencies, such as open-ended problem formulation, communication across technical and non-technical audiences, accountability, and ethical reasoning, throughout core technical coursework rather than isolating them in standalone seminars [32]. Third, assessment should shift from single-answer examinations, now increasingly vulnerable to GenAI automation, to formats that foreground judgment and process, such as portfolios, in-person demonstrations, and structured reflection evaluating how students frame problems, use AI strategically, critique outputs, and defend decisions [6].

One concrete example is an AI-integrated design critique exercise in capstone design: students generate an initial design, use GenAI to propose alternatives, then evaluate those outputs for plausibility, missing constraints (e.g., cost, manufacturability, safety), and stakeholder communication implications. Compared with instructor-only critique, this approach can scale exposure to alternative solution spaces while explicitly cultivating validation practices and socio-technical judgment.

Given students' ethics concerns and the awareness-adoption gap, programs should also implement Responsible AI Use frameworks that define productive use versus misconduct, require AI interaction logs when AI is used in assignments, incorporate reflective components that distinguish learning gains from AI assistance, and adopt AI-resilient assessments emphasizing contextual reasoning and decision justification.

6.2 Authentic Experiential Learning as a Core Educational Function

The internship-related patterns, combined with the broader literature on workplace learning, reinforce the role of experiential learning as a formative site of professional development rather than a peripheral add-on [22]. Universities can make workplace learning more equitable and instructionally visible by establishing structured post-internship debriefing seminars in which students analyze organizational dynamics, interpersonal challenges, and ethical dilemmas, thereby distributing key workplace-derived insights beyond the subset of students who secure internships [23]. In practical terms, students should pursue internships to calibrate expectations and build portfolios spanning technical and adaptive competencies, while employers can strengthen workforce readiness by offering meaningful projects, providing clearer feedback on technical expectations, and supporting responsible GenAI use while recognizing diversity in student competency profiles.

7. Limitations and Future Research

This study is limited by its single-institution, single-discipline sample and cross-sectional design, and by the use of self-reported KSA importance ratings rather than direct performance measures. The small proportion of daily GenAI users (3.8%) further limits statistical power for adoption-related comparisons. Future research should prioritize longitudinal tracking into early careers, multi-institutional and cross-disciplinary replication, qualitative interviews to clarify mechanisms behind competency revaluation, and employer-perspective studies to examine alignment between student valuations and workforce expectations. Given the pace of AI evolution, repeated-measures designs (e.g., annual cohort resurveying) are especially important for distinguishing stable professional value orientations from perceptions shaped by the novelty and rapid change of GenAI.

8. Conclusion

This study provides empirical evidence that Generative AI is accelerating engineering's shift from a predominantly technical occupation toward a more holistic, human-centered socio-technical profession. Among 80 senior mechanical engineering students, the most highly valued competencies were enduring human capabilities: critical thinking, communication, teamwork, and adaptability, rather than specialized technical knowledge that GenAI can increasingly generate. At the same time, a pronounced awareness-adoption gap (90.0% familiar; 3.8% daily use) suggests that GenAI diffusion among students remains early and is moderated by concerns about accuracy, job displacement, and ethics.

The study contributes both empirically and theoretically. Empirically, it quantifies a competency hierarchy consistent with joint optimization demands and surfaces internship-associated, practice-informed shifts in valuation, most notably heightened emphasis on flexibility/adaptability and a more contextualized view of public safety, while recognizing these group differences as exploratory in the present sample. Theoretically, it advances the JO-HAI Framework, integrating Socio-Technical Systems (STS) theory, the hidden curriculum, and the Dynamic Competency Interaction Model (DCIM) to explain how competency revaluation emerges and how experiential learning calibrates professional identity formation in AI-augmented contexts. Overall, the findings underscore that engineering education should prioritize developing graduates who can critically evaluate and ethically govern AI-enabled work, equipping future engineers not only to use powerful tools, but to exercise judgment, responsibility, and adaptive leadership within the socio-technical systems they will design and steward.

Appendix A

Table 1. Sample Characteristics and Demographics (N=80)

Characteristic	**N**	**Percentage**
Total Sample Size	80	100.0%
Internship/Co-op Experience		
No experience	30	37.5%
1 term	23	28.7%
2 terms	16	20.0%
3 terms	5	6.2%
4+ terms	6	7.5%
Undergraduate Research Experience		
No experience	73	91.2%
1 term	3	3.8%
2 terms	2	2.5%
3+ terms	2	2.5%
GenAI Familiarity		
Not familiar at all	8	10.0%
Somewhat familiar	59	73.8%
Very familiar	13	16.2%
GenAI Usage Frequency		
Never	9	11.2%
Rarely	26	32.5%
Monthly	21	26.2%
Weekly	21	26.2%
Daily	3	3.8%
Top GenAI Concerns		
Accuracy and reliability	53	66.2%
Job displacement	51	63.7%
Ethical implications	47	58.8%
Data privacy	40	50.0%

Appendix B

Table 2. Top 15 and Bottom 4 Most Important KSAs by Mean Rating (N=86)

Rank	KSA Description	Mean (SD)	% Very Important
1	Critical thinking	4.90 (0.30)	90.0%
2	Good communication skills	4.89 (0.32)	88.8%
3	Teamwork and multidisciplinary collaboration	4.85 (0.36)	85.0%
4	Flexibility and ability to adapt to rapid change	4.78 (0.42)	77.5%
5	Ability to identify, formulate, and solve problems	4.76 (0.43)	76.2%
6	Self-drive and motivation	4.70 (0.46)	70.0%
7	Ability to deal with ambiguity and complexity	4.70 (0.46)	70.0%
8	Ownership and accountability	4.70 (0.56)	73.8%
9	Ability to prioritize efficiently	4.69 (0.47)	68.8%
10	Understanding of design	4.69 (0.47)	68.8%
11	Good personal and professional judgment	4.65 (0.51)	66.2%
12	High ethical standards and responsibility	4.59 (0.65)	65.0%
13	Applied knowledge of engineering core sciences	4.59 (0.63)	63.7%
14	Ability to use new technology and modern engineering tools	4.58 (0.50)	57.5%
15	Public safety awareness	4.58 (0.63)	62.5%
...	...	...	...
33	Mentoring skills	3.96 (1.02)	32.5%
34	Cultural awareness	3.89 (0.99)	26.2%
35	Security knowledge	3.88 (0.85)	17.5%
36	Entrepreneurship	3.75 (0.88)	12.5%

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