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Evolving Perceptions and Practices: A Comparative Study of Freshman Students' Engagement with Artificial Intelligence Tools

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Abstract
This is a Complete Research paper. The rapid normalization of generative artificial intelligence (AI) tools has significantly altered the context in which students enter engineering programs. While prior research has documented early student perceptions of AI during its initial emergence in educational settings, less is known about how those perceptions evolve as AI use becomes commonplace prior to formal instruction. This study extends our earlier work by providing a longitudinal, cohort-based comparison of first-year engineering students' engagement with generative AI tools across consecutive academic years. Using pre- and post-survey data collected from two cohorts enrolled in an *Introduction to Engineering and Computing* course, the study examines changes in perceived familiarity, experiential familiarity (measured through frequency of use), perceived usefulness, trust, and reliability. A conceptual framework integrating the Technology Acceptance Model (TAM) with AI literacy theory guides analysis and interpretation. Quantitative analyses include pre–post comparisons, correlation analyses, and between-cohort tests, complemented by qualitative analysis of open-ended student reflections.

Results indicate that incoming students report higher baseline familiarity with AI over time; however, perceived familiarity consistently recalibrates through experience, as reflected in lower post-survey frequency measures. Trust and perceived reliability—rather than exposure or frequency alone—emerge as the strongest predictors of meaningful engagement. Structured first-year instruction produces significant gains in perceived reliability and supports the development of evaluative judgment and strategic AI interaction, even among students with substantial prior exposure. These findings demonstrate that increased pre-college exposure does not lead to uncritical reliance on AI. Instead, first-year engineering courses play a critical role in shaping responsible, selective, and trust-informed AI use. The study provides timely empirical guidance for First-Year Programs seeking to integrate AI into early curricula in ways that align with professional engineering practice and ethical responsibility.

1. Introduction
Advances in computational power, the availability of large-scale datasets, and the maturation of machine learning—particularly deep neural networks—have accelerated the deployment of artificial intelligence (AI) systems across natural language processing, computer vision, robotics, and decision-support applications [5]-[11]. These developments have not only transformed industry but have also reshaped expectations for how engineers are educated and prepared for professional practice. Within higher education, AI-enabled systems increasingly support instructional, administrative, and research workflows, offering opportunities for personalized learning, automated feedback, intelligent tutoring, and large-scale data analysis [12]-[20]. At the same time, the rapid emergence of generative AI tools—most notably large language models capable of producing fluent, context-aware text—has introduced new challenges for academic integrity, assessment design, and the cultivation of critical thinking skills [21]-[23]. As these tools become more accessible and increasingly indistinguishable from human-generated content, educators are compelled to reconsider how learning objectives, assignments, and ethical expectations are framed.

These challenges are particularly salient in first-year engineering education. The freshman year represents a critical developmental period during which students form foundational study habits, professional norms, and early engineering identity. Decisions made during this stage influence not only academic performance but also long-term persistence in engineering programs. Consequently, understanding how incoming students perceive, adopt, and critically evaluate AI tools is essential for designing curricula that promote responsible and effective use rather than passive dependence or outright prohibition.

In prior work published in 2025 [24], the authors examined freshmen students' perceptions of AI through pre- and post-surveys administered around an AI-focused lecture and reflective assignment in an *Introduction to Engineering and Computing* course. That study demonstrated that structured exposure increased students' confidence and awareness of AI while also revealing persistent concerns regarding accuracy, reliability, and ethical boundaries. Students viewed AI as a helpful academic aid, yet expressed uncertainties about when AI use might undermine authentic learning or violate academic integrity expectations.

Since the completion of that study, however, the educational context surrounding AI has changed rapidly. Incoming freshmen now arrive with substantially more informal exposure to generative AI tools, acquired through secondary education, social media, and personal experimentation. This shift raises a critical question for engineering education research: *how do student perceptions and practices evolve as AI tools move from novelty to expectation prior to formal instruction?*

This paper addresses that question by extending our prior study through a longitudinal, cohort-based comparison of first-year engineering students surveyed in consecutive academic years. By examining two cohorts within a stable instructional environment, the study distinguishes cohort effects from instructional effects and moves beyond documenting AI adoption to examining the calibration of student perceptions through experience. In doing so, the paper provides empirical evidence that early engineering instruction continues to play a critical role in shaping trust, evaluative judgment, and responsible AI use, even as incoming students arrive with substantial prior exposure.

2. Motivation and Background

Early research on AI adoption in education emphasizes that initial exposure to new technologies is often accompanied by optimism tempered by uncertainty regarding trust, accuracy, and appropriate use [21]-[23]. In the authors' previously published study, first-year engineering students encountered generative AI tools at a relatively early stage of their diffusion into academic environments. Students recognized AI's potential to support learning and productivity, yet expressed skepticism about reliability and ethical boundaries—findings consistent with broader educational literature on early-stage technology adoption [12]-[20].

By contrast, the fall 2025 cohort entered the same introductory engineering course under markedly different conditions. Within a single year, generative AI tools became widely accessible and increasingly normalized through media coverage, institutional policy discussions, and informal peer use. Prior research on technology adoption suggests that perceived usefulness and ease of use strongly influence acceptance, particularly as technologies become embedded in everyday workflows [3]. As a result, incoming students are now more likely to arrive with direct experience using AI systems for writing, problem-solving, and creative tasks prior to receiving formal instruction.

However, prior literature cautions that familiarity alone does not equate to literacy. Studies of generative AI in education highlight that fluent outputs can obscure underlying limitations, biases, or inaccuracies, potentially encouraging over-reliance or uncritical acceptance [21][22]. In engineering contexts, where correctness and verification are essential, such risks are particularly pronounced. Technology acceptance models further emphasize trust as a key determinant of sustained and appropriate use, especially when system outputs are probabilistic or opaque [3][11].

These developments motivate the need to move beyond cross-sectional snapshots toward a longitudinal, cohort-based perspective. By administering parallel pre- and post-surveys to successive freshman cohorts and comparing results within a consistent institutional and curricular context, this study examines how baseline familiarity, experiential engagement, trust, and evaluative judgment evolve over time. Longitudinal comparison strengthens the ability to distinguish cohort effects from instructional influences, an approach recommended in studies of educational technology adoption [3][12].

Finally, this study responds to calls within engineering education research to treat AI as a socio-technical system rather than a purely technical tool. Ethical reasoning, trust calibration, and human–AI interaction are increasingly recognized as core competencies for future engineers [11][23]. By explicitly contrasting the 2024 and 2025 cohorts, this study provides empirical evidence on how rapidly student perceptions evolve and where persistent concerns remain, informing curriculum design in an era of accelerating AI integration.

3. Conceptual Framework

This study adopts an integrated conceptual framework that combines the Technology Acceptance Model (TAM) with emerging conceptions of AI literacy to examine first-year engineering students' engagement with generative artificial intelligence tools. The framework explicitly distinguishes between perceived familiarity, behavioral engagement, and evaluative judgment, enabling longitudinal interpretation of how student perceptions evolve as AI use becomes normalized.

3.1 Technology Acceptance Model and AI Engagement

The Technology Acceptance Model posits that user adoption of technology is primarily driven by perceived usefulness and perceived ease of use, which in turn influence behavioral intention and actual usage [3]. TAM has been widely applied in educational contexts to explain student adoption of learning technologies and intelligent systems [12]-[20]. However, generative AI systems introduce additional complexity due to their probabilistic outputs, opaque reasoning processes, and capacity to generate fluent but potentially inaccurate responses. To address this complexity, this study extends TAM by explicitly incorporating trust-related constructs, including perceived accuracy and reliability. Prior research emphasizes that trust becomes a critical mediator of adoption when users cannot easily verify system outputs or internal decision processes [11]. In such contexts, adoption is not simply a function of exposure or convenience, but of users' evolving judgments about when and how system outputs are appropriate. Within this framework, 1) perceived usefulness captures students' beliefs about the academic value of AI tools; 2) behavioral engagement is reflected in frequency of use, representing actual interaction rather than intention alone; and 3) trust and reliability capture evaluative judgments that shape selective and appropriate use.

3.2 AI Literacy as a Developmental Construct

While TAM explains why students adopt AI tools, it does not fully account for how students engage with them in learning contexts. To address this limitation, the present framework incorporates AI literacy as a complementary construct. AI literacy is increasingly defined as a multidimensional capability encompassing understanding of AI systems, effective interaction, critical evaluation of outputs, and ethical reasoning [23]. In this study, AI literacy is conceptualized as a developmental process, rather than a static skill set. Three dimensions are particularly salient for first-year engineering students:

1. Perceived Familiarity (Cognitive Awareness): Pre-survey familiarity reflects students' self-assessed awareness and prior exposure to AI tools. This measure captures perceived knowledge rather than demonstrated competence and is susceptible to overestimation, particularly in early stages of adoption.

2. Experiential Familiarity via Frequency of Use (Behavioral Engagement): Post-survey frequency of AI use is treated as a behavioral indicator of experiential familiarity developed through repeated interaction. Unlike self-reported familiarity, frequency reflects actual engagement and provides a more grounded measure of how AI is incorporated into students' workflows.

3. Evaluative Judgment (Trust Calibration and Effectiveness): Perceived accuracy, reliability, and effectiveness represent students' ability to judge AI outputs critically. This dimension reflects maturation of AI literacy, as students learn to distinguish between fluent responses and trustworthy information.

This distinction allows for the possibility that perceived familiarity may decrease even as experiential familiarity increases, a pattern consistent with calibration effects observed in learning research when students move from abstract confidence to experience-based judgment.

3.3 Mapping Survey Constructs to the Framework

The survey instruments used in this study were designed to operationalize these constructs across pre- and post-surveys such that:

- pre-survey familiarity measures perceived awareness and self-assessed knowledge of AI tools;
- post-survey frequency of use measures behavioral engagement and serves as a proxy for experiential familiarity;
- perceived usefulness aligns with TAM and reflects academic value judgments;
- accuracy and reliability capture trust calibration, extending TAM for AI systems;
- confidence/effectiveness reflects perceived competence in using AI productively; and
- ethical awareness captures normative judgments related to responsible use.

By design, the pre- and post-survey familiarity-related items are not identical. Rather than treating this as a limitation, the framework interprets this shift as analytically meaningful: it enables examination of how self-perceived familiarity compares with experience-grounded engagement, a distinction that becomes critical as AI use becomes normalized.

3.4 Longitudinal Interpretation and Calibration Effects

The integration of TAM and AI literacy supports longitudinal interpretation of changes across cohorts and instructional interventions. Increased baseline familiarity in later cohorts reflects broader societal exposure, while changes in frequency, trust, and effectiveness reflect instructional and experiential influences. Within this framework, a decrease from pre-survey familiarity to post-survey frequency does not indicate disengagement. Instead, it is interpreted as calibration—a transition from optimistic self-assessment to realistic appraisal informed by actual use. This interpretation is further supported by correlational patterns in which frequency decouples from confidence, while trust and effectiveness become more strongly associated with perceived usefulness.

3.5 Implications for Results Interpretation

By explicitly distinguishing perceived familiarity from experiential familiarity, the framework provides a coherent basis for interpreting the results presented in Section 5. It anticipates:

- higher baseline familiarity in later cohorts,
- post-instruction calibration of familiarity judgments,
- strong instructional effects on trust and reliability, and
- the central role of evaluative judgment in meaningful AI engagement.

This conceptual grounding ensures that the observed results are interpreted not as contradictions, but as indicators of maturing AI literacy among first-year engineering students.

4. Methods

This study employs a mixed-methods research design to examine first-year engineering students' engagement with generative AI tools across two academic cohorts. The methodology was explicitly designed to support longitudinal comparison while operationalizing the conceptual distinctions introduced in Section 3 between perceived familiarity, experiential familiarity (frequency of use), and evaluative judgment. The design draws on prior work applying technology adoption theory and AI literacy frameworks in educational contexts [3][12]-[20][23].

4.1 Study Context and Participants

Participants were enrolled in a multi-section "Introduction to Engineering and Computing" course at a private comprehensive university. The course serves as a common first-year experience for students pursuing majors in engineering and computing disciplines, including Mechanical Engineering, Electrical Engineering, Computer Science, Cybersecurity, Software Engineering, and Environmental Engineering. To support valid year-over-year comparison, the instructional structure, learning objectives, and major assignments were held constant across cohorts. Data were collected from two cohorts: 1) 2024 cohort: students enrolled during the 2024 academic year; and 2) 2025 cohort: students enrolled during the 2025 academic year. Response counts for each cohort are reported in the corresponding tables in Section 5. Participation was voluntary, and all responses were anonymized prior to analysis in accordance with institutional guidelines for educational research.

4.2 Instructional Intervention

The instructional intervention replicated the design used in the authors' prior study [24] to ensure methodological consistency. Students received a guest lecture introducing foundational AI concepts, with emphasis on generative AI systems and their application in academic and engineering contexts. Lecture content addressed AI capabilities and limitations, probabilistic output generation, accuracy versus fluency, academic integrity, and responsible use, reflecting recommendations in the AI-in-education literature [12]-[20][21]-[23]. Following the lecture, students completed a reflective Spirit of Engineering assignment in two stages:

1. Human-only response: Students completed the reflection independently, without AI assistance.
2. AI-assisted response: Students revisited the same prompt using a generative AI tool of their choice.

This paired-task design aligns with prior studies that use comparative reflection to examine perceived usefulness, trust calibration, and learning impact of AI-supported tools [13][14].

4.3 Survey Design and Constructs

Two survey instruments—a pre-survey and a post-survey—were administered. While the instruments were not identical, they were intentionally designed to capture different stages of AI literacy development, consistent with the developmental framing outlined in Section 3.

4.3.1 Pre-Survey: Perceived Familiarity and Baseline Perceptions

The pre-survey was administered prior to the AI-focused lecture and assessed baseline perceptions and prior exposure. Key constructs included:

- Perceived Familiarity: Students rated their familiarity with AI tools using Likert-scale items. This construct captures self-assessed awareness and perceived exposure rather than demonstrated competence, consistent with early-stage adoption measures used in technology acceptance research [3].
- Perceived Usefulness: Items assessed the extent to which students believed AI tools could be helpful for academic tasks, aligning directly with the Technology Acceptance Model [3].
- Trust/Accuracy and Reliability: Students rated baseline perceptions of AI accuracy and reliability, reflecting trust judgments that are particularly salient for probabilistic AI systems [11].
- Ethical Awareness: Items probed concerns related to plagiarism, misuse, and appropriate academic boundaries, reflecting calls for early integration of AI ethics in education [21]-[23].

4.3.2 Post-Survey: Experiential Familiarity and Evaluative Judgment

The post-survey was administered after completion of the AI-assisted assignment and focused on experience-grounded engagement. Importantly, the post-survey operationalized familiarity differently to reflect behavioral rather than perceptual measures:

- Frequency of AI Use (Experiential Familiarity): Students reported how often they used AI tools during the assignment and related academic tasks. In this study, frequency of use is treated as a behavioral indicator of experiential familiarity developed through repeated interaction. Prior adoption research supports frequency as a valid proxy for experience-based familiarity and engagement [3][12].

- Perceived Usefulness: Parallel items assessed whether AI tools were helpful in completing the task, enabling pre/post comparison consistent with TAM-based studies [3].
- Perceived Reliability: Students reassessed AI reliability after direct experience, capturing trust calibration following authentic use [11].
- Confidence/Effectiveness: Items measured students' perceived effectiveness and confidence when using AI tools productively, reflecting self-efficacy and evaluative judgment components of AI literacy [23].
- AI Communication Strategies: Open-ended questions asked students to describe how they refined prompts or interacted with AI to improve output quality. Prompt refinement and iterative interaction are increasingly recognized as core AI literacy skills in educational settings [13][14].

The intentional shift from perceived familiarity (pre-survey) to frequency-based engagement (post-survey) supports analysis of calibration effects as students transition from abstract self-assessment to experience-informed judgment.

4.4 Data Collection Procedures

The pre-survey was administered approximately four weeks into the semester, prior to the AI-lecture, to capture students' baseline perceptions. The post-survey was administered after students completed both stages of the reflective assignment. Surveys were delivered electronically and required approximately 5–10 minutes to complete. Participation was voluntary, and responses were anonymized prior to analysis.

4.5 Quantitative Analysis

Quantitative analyses were conducted both within and across cohorts:

- Pre–post comparisons of perceived familiarity (pre) and frequency of use (post) were analyzed using two-sample t-tests assuming unequal variances. While the measures differ, this comparison was theoretically motivated to examine calibration between perceived and experiential familiarity, as supported by the conceptual framework in Section 3.
- Perceived usefulness and perceived reliability were analyzed using pre/post t-tests within each cohort to assess instructional effects.
- Correlational analyses using Pearson's r examined relationships among familiarity/frequency, usefulness, reliability, confidence, and trust-related constructs, consistent with TAM-based analytic approaches [3][11].
- Between-cohort comparisons of pre-survey measures were conducted using Mann–Whitney U tests with Cliff's delta to account for non-normality and unequal sample sizes, a recommended approach for ordinal survey data in educational research.

Statistical significance was evaluated using $\alpha = 0.05$.

4.6 Qualitative Analysis

Open-ended responses from both surveys were analyzed using an inductive thematic coding approach. Responses were coded for evidence of:

- Prompt refinement strategies,
- Recognition of AI limitations,
- Verification and cross-checking behavior, and
- Reflections on human–AI differences.

These qualitative findings were used to contextualize quantitative results related to AI communication competence and trust calibration, consistent with mixed-methods approaches in AI education research [13][14][23].

4.7 Validity and Limitations

Content validity was supported through alignment with established theoretical frameworks, including TAM and AI literacy literature [3][23]. The use of frequency as a proxy for experiential familiarity is theoretically justified but represents a limitation, as the pre- and post-survey items are not identical. However, this design choice enables meaningful examination of calibration effects as students transition from perceived awareness to experience-based judgment. As with many educational studies, results are limited to a single institutional context and rely on self-reported data. Nonetheless, the consistent instructional design across cohorts strengthens internal validity for longitudinal comparison.

5. Results

Results are summarized in Tables 1~6 below and organized to mirror the conceptual framework, with subsections aligned to TAM constructs and AI literacy dimensions. Quantitative findings from pre- and post-surveys are complemented by correlational and between-year analyses. Comparisons between the 2024 and 2025 cohorts emphasize changes in baseline perceptions while holding instructional context constant.

5.1 Familiarity and Frequency of AI Use (AI Literacy: Foundational Awareness)

Table 1 shows the results of two-sample *t*-tests assuming unequal variances comparing pre-survey familiarity with post-survey frequency of AI use, where frequency is interpreted as an operational indicator of familiarity gained through repeated interaction. Although the pre- and post-survey items are phrased differently, prior educational research supports frequency of use as a valid behavioral proxy for experiential familiarity, particularly in technology adoption contexts. For the 2024 cohort, mean familiarity decreased from 3.4286 (pre) to 2.9615 (post

Table 1. Familiarity: Two-Sample t-Test Assuming Unequal Variances: (a) 2024 (b) 2025.

(a) 2024	(Pre) Familiarity	(Post) Frequency (Familiarity)
Mean	3.4286	2.9615
Variance	0.8985	0.6608
Observations	84.0000	78.0000
Hypothesized Mean Difference	0.0000	
df	159.0000	
t Stat	3.3733	
P(T<=t) one-tail	0.0005	
t Critical one-tail	1.6545	
P(T<=t) two-tail	0.0009	
t Critical two-tail	1.9750	

(b) 2025	(Pre) Familiarity	(Post) Frequency (Familiarity)
Mean	3.7447	3.1304
Variance	1.1073	0.6048
Observations	47.0000	46.0000
Hypothesized Mean Difference	0.0000	
df	85.0000	
t Stat	3.2060	
P(T<=t) one-tail	0.0009	
t Critical one-tail	1.6630	
P(T<=t) two-tail	0.0019	
t Critical two-tail	1.9883	

Table 2. Helpfulness: Two-Sample t-Test Assuming Unequal Variances: (a) 2024 (b) 2025.

(a) 2024	(Pre) Helpfulness	(Post) Helpfulness
Mean	4.0145	4.1538
Variance	0.8086	0.4695
Observations	69.0000	78.0000
Hypothesized Mean Difference	0.0000	
df	126.0000	
t Stat	-1.0463	
P(T<=t) one-tail	0.1487	
t Critical one-tail	1.6570	
P(T<=t) two-tail	0.2974	
t Critical two-tail	1.9790	

(b) 2025	(Pre) Helpfulness	(Post) Helpfulness
Mean	4.0455	4.2826
Variance	0.4630	0.5628
Observations	44.0000	46.0000
Hypothesized Mean Difference	0.0000	
df	88.0000	
t Stat	-1.5721	
P(T<=t) one-tail	0.0598	
t Critical one-tail	1.6624	
P(T<=t) two-tail	0.1195	
t Critical two-tail	1.9873	

frequency) (t = 3.3733, df = 159.0, p = 0.0009, two-tailed). Similarly, the 2025 cohort showed a decrease from 3.7447 (pre) to 3.1304 (post frequency) (t = 3.2060, df = 85.0, p = 0.0019, two-tailed). While the numerical decrease may appear counterintuitive, this pattern is best interpreted as familiarity calibration rather than loss. As students engage more frequently with AI tools and encounter their limitations, their self-assessments shift from abstract perceptions of familiarity to experience-grounded judgments reflected in actual usage patterns. The higher pre-survey familiarity mean in 2025 confirms greater incoming exposure relative to the 2024 cohort.

5.2 Perceived Helpfulness (TAM: Perceived Usefulness)

Table 2 summarizes perceived helpfulness results. For the 2024 cohort, helpfulness increased from 4.0145 (pre) to 4.1538 (post), though the change was not statistically significant (t = −1.0463, df = 126.0, p = 0.2974). The 2025 cohort exhibited a similar increase from 4.0455 (pre) to 4.2826 (post) (t = −1.5721, df = 88.0, p = 0.1195). Despite the lack of statistical significance, both cohorts demonstrate consistently high post-survey means. This ceiling effect suggests that perceived usefulness is already well established prior to instruction and remains stable as AI tools become normalized, consistent with Technology Acceptance Model predictions.

Table 3. Reliability: Two-Sample t-Test Assuming Unequal Variances: (a) 2024 (b) 2025.

(a) 2024	(Pre) Reliability	(Post) Reliability
Mean	3.1310	4.3974
Variance	1.0790	0.2686
Observations	84.0000	78.0000
Hypothesized Mean Difference	0.0000	
df	124.0000	
t Stat	-9.9233	
P(T<=t) one-tail	0.0000	
t Critical one-tail	1.6572	
P(T<=t) two-tail	0.0000	
t Critical two-tail	1.9793	

(b) 2025	(Pre) Reliability	(Post) Reliability
Mean	3.4894	4.3696
Variance	0.6901	0.2826
Observations	47.0000	46.0000
Hypothesized Mean Difference	0.0000	
df	78.0000	
t Stat	-6.0992	
P(T<=t) one-tail	0.0000	
t Critical one-tail	1.6646	
P(T<=t) two-tail	0.0000	
t Critical two-tail	1.9908	

5.3 Perceived Reliability (Extended TAM: Trust and Reliability)
Table 3 shows the strongest instructional effects across all constructs. For the 2024 cohort, perceived reliability increased from 3.1310 (pre) to 4.3974 (post) ($t = -9.9233$, $df = 124.0$, $p < 0.0001$). Similarly, the 2025 cohort exhibited a significant increase from 3.4894 (pre) to 4.3696 (post) ($t = -6.0992$, $df = 78.0$, $p < 0.0001$). Notably, post-survey reliability means converge across cohorts despite differing baselines. This convergence indicates that structured instructional exposure—rather than prior experience—plays a dominant role in shaping students' trust calibration.

5.4 Correlational Relationships Among Constructs
Table 4 presents Pearson correlation matrices for pre- and post-surveys for both cohorts. In the 2024 pre-survey, familiarity was moderately correlated with helpfulness ($r = 0.462$), while helpfulness showed a strong association with reliability ($r = 0.604$). The 2025 pre-survey exhibited a similar structure, with reliability strongly correlated with trust/accuracy ($r = 0.636$) and moderately with helpfulness ($r = 0.496$). Post-survey correlations reveal a notable structural shift. In both cohorts, frequency (familiarity) exhibits weak or negligible correlations with other constructs, while confidence/effectiveness becomes more strongly associated with helpfulness (2024: $r = 0.652$; 2025: $r = 0.459$). This shift reinforces the interpretation that experiential familiarity alone does not drive effective AI engagement; rather, perceived effectiveness and trust play a more central role.

Table 4. Correlations: (a) 2024 (b) 2025.

(a) 2024

2024 Pre

	Familiarity	*Helpfulness*	*Trust/ Accurate*	*Reliability*
Familiarity	1.000			
Helpfulness	0.462	1.000		
Trust/ Accurate	0.316	0.512	1.000	
Reliability	0.359	0.604	0.585	1.000

2024 Post

	Frequency (Familiarity)	*Helpfulness*	*Confidence/ Effective*	*Reliability*
Frequency (Familiarity)	1.000			
Helpfulness	0.197	1.000		
Confidence/ Effective	-0.022	0.652	1.000	
Reliability	0.006	0.155	0.203	1.000

(b) 2025

2025 Pre

	Familiarity	*Helpfulness*	*Trust/ Accurate*	*Reliability*
Familiarity	1.000			
Helpfulness	0.343	1.000		
Trust/ Accurate	0.353	0.487	1.000	
Reliability	0.345	0.496	0.636	1.000

2025 Post

	Frequency (Familiarity)	*Helpfulness*	*Confidence / Effective*	*Reliability*
Frequency (Familiarity)	1.000			
Helpfulness	0.088	1.000		
Confidence/ Effective	-0.093	0.459	1.000	
Reliability	-0.119	0.178	-0.011	1.000

5.5 Between-Year Comparisons of Baseline Perceptions
Table 5 reports Mann–Whitney U tests comparing pre-survey responses between cohorts. Differences in familiarity ($U = 1608.0$, $p = 0.065$, Cliff's $\delta = -0.185$), trust/accuracy ($U = 1702.0$, $p = 0.158$, $\delta = -0.138$), and reliability ($U = 1605.0$, $p = 0.063$, $\delta = -0.187$) did not reach conventional significance thresholds. However, the composite score differed significantly ($U = 1557.0$, $p = 0.045$, $\delta = -0.211$), indicating a modest but systematic shift in overall AI-related perceptions from 2024 to 2025.

Table 5. Between-Year Tests on Pre survey results.

Scale	Mann-Whitney U	p-value	Cliffs-delta
Familiarity	1608.0	0.065	-0.185
Helpfulness	1537.5	0.905	0.013
Trust/Accuracy	1702.0	0.158	-0.138
Reliability	1605.0	0.063	-0.187
Composite	1557.0	0.045	-0.211

5.6 Reliability of Survey Instruments
Table 6 reports internal consistency metrics for the pre-survey instruments. Cronbach's alpha values of 0.78 (2024) and 0.70 (2025) exceed accepted thresholds for exploratory educational research, supporting the reliability of the survey constructs and the validity of both within-cohort and longitudinal comparisons.

Table 6. Reliability Analysis on Pre survey results.

Year	Cronbach's alpha	Item	Corrected item-total correlations, r
2024	0.8		
2024		Familiarity	0.447
2024		Helpfulness	0.673
2024		TrustAccuracy	0.596
2024		Reliability	0.664
2025	0.7		
2025		Familiarity	0.311
2025		Helpfulness	0.584
2025		TrustAccuracy	0.547
2025		Reliability	0.563

5.7 Clarification on Familiarity vs. Frequency
Although the post-survey item measures frequency of AI use, it is interpreted here as an experiential indicator of familiarity developed through repeated interaction. This interpretation is supported by the observed calibration effects and by the post-survey correlation structure, where frequency decouples from confidence and effectiveness—indicating maturation rather than disengagement.

6. Discussion
This study extends prior work by providing a near-term longitudinal comparison of first-year engineering students' engagement with generative AI tools across two cohorts, interpreted through a unified Technology Acceptance Model and AI literacy framework. By distinguishing perceived familiarity from experiential familiarity and evaluative judgment, the results offer insight into how student engagement with AI matures as these tools become normalized.

6.1 Cohort-Level Shifts in Baseline Engagement
Results from the pre-survey analyses indicate that students in the 2025 cohort entered the course with higher baseline familiarity and more widespread prior academic AI use than the 2024 cohort. Although between-year differences for individual constructs were modest, the significant difference in the composite score suggests a meaningful shift in the overall AI perception profile

within a single year. This finding reflects the rapid diffusion of generative AI tools into pre-college learning environments and supports the need for longitudinal approaches when studying AI adoption in education. Importantly, higher baseline familiarity did not eliminate the instructional impact observed within cohorts, indicating that increased exposure alone does not obviate the need for structured educational intervention.

6.2 Calibration of Familiarity Through Experience

A key finding across both cohorts is the systematic decrease from pre-survey perceived familiarity to post-survey frequency of use. When interpreted through the conceptual framework, this pattern reflects calibration rather than disengagement. Students' initial self-assessments appear to give way to experience-grounded judgments as they interact with AI tools in an academic context. This calibration effect is consistent across cohorts and reinforces the value of distinguishing perceptual familiarity from behavioral engagement. The decoupling of frequency from confidence and effectiveness in post-survey correlations further supports the interpretation that repeated use leads to more selective and intentional engagement rather than indiscriminate adoption.

6.3 Trust and Reliability as Central Drivers of Effective Use

Across cohorts and survey phases, trust-related constructs—accuracy and reliability—emerged as the strongest correlates of perceived usefulness. Correlational analyses indicate that students' judgments about AI effectiveness are shaped more by evaluative criteria than by exposure or frequency alone. This finding aligns with extensions of TAM for AI-mediated systems, where trust plays a central role in determining appropriate use. The large and consistent post-survey gains in perceived reliability underscore the instructional impact of guided exposure and reflection. The convergence of post-survey reliability scores across cohorts suggests that structured learning experiences, rather than prior familiarity, are the dominant influence on trust calibration.

6.4 Stability of Perceived Usefulness Amid Normalization

Perceived usefulness remained high across both cohorts, with only modest pre–post changes. This stability likely reflects a ceiling effect as AI tools become normalized and their academic value is broadly recognized by students prior to formal instruction. While usefulness alone does not differentiate levels of engagement, its strong associations with trust and effectiveness indicate that it remains a necessary—but not sufficient—condition for meaningful AI adoption.

6.5 Emergence of Strategic AI Interaction

Qualitative results demonstrate that students increasingly engage with AI tools strategically, employing prompt refinement, contextualization, and specificity to improve output quality. These behaviors indicate the development of AI communication competence and align with the observed shift from exposure-driven use toward evaluative and intentional interaction. The prevalence of such strategies across cohorts suggests that communication competence develops through authentic use rather than prior familiarity alone.

6.6 Longitudinal Implications

Taken together, the findings depict AI literacy development as a multidimensional and non-linear process. Increased exposure leads to higher baseline familiarity, but effective engagement is shaped by calibration, trust development, and strategic interaction. The persistence of these patterns across cohorts suggests that first-year engineering courses play a critical role in shaping how students integrate AI into their academic practices, even as pre-college exposure increases. From a longitudinal perspective, this study demonstrates that year-over-year comparisons can reveal subtle but meaningful shifts in student engagement that are not captured by cross-sectional analyses alone. These insights provide an empirical foundation for curriculum design decisions aimed at fostering responsible, effective, and professionally aligned AI use in engineering education.

7. Implications for Curriculum Design of First-Year Programs

The findings of this study have direct implications for the design of first-year engineering curricula, particularly as generative AI tools become increasingly prevalent in students' pre-college experiences. For First-Year Programs (FYP), the key challenge is no longer whether students will encounter AI, but how early curricular experiences can shape productive, evaluative, and ethically grounded engagement.

7.1 Design for Calibration, Not Introduction

Results indicate that incoming students already report substantial familiarity with AI tools, yet this perceived familiarity is recalibrated through experience. First-year curricula should therefore be designed not to introduce AI as a novel technology, but to calibrate students' understanding of what AI can and cannot do in engineering contexts. Assignments that juxtapose human-only and AI-assisted work—such as the reflective comparison used in this study—encourage students to recognize limitations, ambiguities, and contextual dependencies in AI outputs. For FYP courses, this design principle aligns well with existing goals related to metacognition and professional formation.

7.2 Emphasize Trust Calibration and Verification Practices

Across cohorts, perceived reliability emerged as the construct most strongly influenced by instruction and most predictive of meaningful engagement. This suggests that first-year curricula should explicitly foreground trust calibration rather than assuming students will develop appropriate skepticism organically. Curriculum designs that require students to verify AI-generated information, justify acceptance or rejection of outputs, or compare AI suggestions with engineering principles reinforce core disciplinary norms. Such activities naturally integrate with first-year objectives related to problem-solving rigor and accountability without requiring extensive technical depth.

7.3 Treat AI Interaction as a Communication Skill

Qualitative results show that students increasingly recognize the importance of prompt refinement, contextualization, and specificity. For First-Year Programs, this finding supports treating human–AI interaction as a communication skill, analogous to technical writing or oral presentation. Structured reflection on how prompts are formulated—and how changes in wording affect outcomes—can be embedded into existing assignments with minimal curricular disruption. Framing prompt design as a communication exercise helps students see AI use as an active cognitive process rather than a shortcut.

7.4 Normalize Ethical Reasoning without Deterrence

Despite increased exposure and usage, students maintained strong ethical awareness regarding plagiarism and misuse. This suggests that early, explicit discussion of ethical expectations does not discourage engagement, but rather normalizes responsible use. For FYP courses, ethical reasoning around AI should be integrated into assignment framing and reflection prompts rather than treated as a separate policy discussion. This approach aligns with broader first-year goals of professional identity formation and helps students internalize norms before habits become entrenched.

7.5 Design for Selective, Intentional Use Rather Than Maximum Use

The observed decrease from perceived familiarity to frequency-based engagement underscores that effective AI literacy is not characterized by frequent use, but by selective and intentional use. First-year curricula should therefore avoid messaging that implicitly equates proficiency with usage volume. Instead, instructional designs should reward discernment—when students choose not to use AI, when they supplement AI outputs with human reasoning, and when they articulate limitations. This framing reinforces engineering judgment as a core competency.

7.6 Reinforce AI Literacy Longitudinally

Finally, the rapid shifts observed between adjacent cohorts highlight the importance of viewing AI literacy as a longitudinal developmental outcome, not a one-time first-year topic. While FYP courses play a critical role in setting norms, reinforcement across subsequent courses is essential. For First-Year Programs, this finding supports coordination with downstream courses to ensure consistent expectations regarding AI use, verification, and ethical reasoning. Establishing a shared language early helps students transfer these practices as AI tools continue to evolve.

8. Conclusions and Future Work

This study extends our prior work by providing a longitudinal comparison of first-year engineering students' engagement with generative AI tools across adjacent cohorts. By examining students entering under markedly different levels of prior AI exposure within a stable instructional context, the study isolates cohort effects from instructional influences and documents how student perceptions evolve as AI becomes normalized.

The results show that increased pre-college exposure does not lead to uncritical reliance. Instead, students demonstrate calibration of familiarity through experience, with trust and perceived reliability—rather than exposure or frequency of use—emerging as the strongest predictors of meaningful engagement. Structured first-year instruction continues to play a central role in shaping evaluative judgment and responsible use, even as incoming students arrive with substantial prior experience.

Together, these findings underscore the importance of treating AI literacy as a developmental competency grounded in judgment, verification, and communication rather than mere adoption. For First-Year Programs, the results provide empirical support for early curricular designs that emphasize trust calibration and intentional use over unrestricted access or avoidance. Future work will expand this longitudinal approach across institutions and track cohorts beyond the first year to examine how early AI literacy development influences later academic performance and professional formation.

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