Mapping the Frontier: A Systematic Trend Analysis of Generative AI Applications in Engineering Education (2024-2025)

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***Abstract*– This systematic scoping review establishes the evolving trends of AI within engineering education. Analysis of 2,500 publications identifies a decisive shift from "detection" to "integration." We demonstrate a persistent Theory-Practice Gap with a 3:1 ratio of implementation to theory. Statistical analysis confirms this maturation is highly significant ($X^2 = 46.01$, $p < .001$), signaling a fundamental sociotechnical pivot from 2024's "reactionary" phase to 2025's "assimilation" phase.**

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I. INTRODUCTION AND MOTIVATION

The integration of Generative AI (GenAI) into engineering education is progressing at a velocity that exceeds traditional pedagogical validation [1]. Within the 2024–2025 cycles of ASEE and FIE, approximately 2,500 papers addressed AI [2]. For LACCEI institutions, the shift toward localized Technical Architecture (RAG) is critical, as it allows for multilingual, curriculum-aligned tutoring that bypasses the high costs of proprietary APIs while ensuring data sovereignty

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A. Theoretical Scaffolding: The AI Maturation Curve

This study frames the transition as a Life-Cycle of Innovation. 2024 represented the "Reactionary" phase, where the academic ecosystem focused on defensive postures (Ethics/Detection). 2025 marks the "Assimilation" phase, characterized by metabolic integration into technical frameworks and the formalization of AI literacy as a core competency [3].

II. RESEARCH QUESTIONS

- RQ1 (Application): What primary pedagogical roles—from automated feedback to technical co-creation—does GenAI occupy?
- RQ2 (Evolution): How has thematic focus shifted between 2024 and 2025?
- RQ3 (Distribution): Which tools dominate specific engineering sub-disciplines?
- RQ4 (Evidence): To what extent is literature maturing from anecdotes toward quantitative reporting?

III. METHODOLOGY

This study follows PRISMA-ScR guidelines [7].

The Filtering Funnel: Initial identification yielded 2,500 results; Title/Abstract screening filtered this to 1,549 relevant records; final thematic analysis was conducted on 1,039 unique publications as detailed in Table I.

TABLE I

SUMMARY OF THE SYSTEMATIC LITERATURE SEARCH AND SCREENING PROCESS. THE DATA REFLECTS THE HIGH VOLUME OF THE "LITERATURE DELUGE" AND THE MULTI-STAGE FILTERING APPLIED TO IDENTIFY UNIQUE, RELEVANT AI APPLICATIONS IN ASEE AND FIE PROCEEDINGS.

Stage	Action	Remaining Records (N)
Identification	Raw database pull (ASEE & FIE)	2,500
Screening	Title/Abstract keyword filtering	1,549
Eligibility	Removal of duplicates & non-AI papers	1,210
Included	Full thematic and statistical analysis	1,039

A. Data Validation and Reliability (IRR)

To ensure the highest level of academic rigor, a formal Inter-Rater Reliability (IRR) check was conducted. Two independent researchers coded the top 100 most-cited papers using a standardized rubric based on the Michigan Taxonomy. The consistency of these categorizations was validated using Cohen's Kappa (k):

$$k = \frac{Po-Pe}{1-Pe} \tag{1}$$

The final calculated value of k = 0.83 exceeds the 0.80 benchmark for "substantial agreement," providing a statistically sound foundation for the identified trends.

B. Data Sources and Selection Logic

To ensure a comprehensive capture of the "literature deluge," data were retrieved from the two flagship repositories of peer-reviewed engineering education research:

- ASEE Peer Document Repository: Representing the 2024 and 2025 Annual Conferences. This source provides a wide-angle view of pedagogical experiments across all engineering sub-disciplines.
- IEEE Xplore (FIE): Specifically filtering for the 2024 and 2025 Frontiers in Education proceedings. This source captures high-technical-depth implementations and the vanguard of software-centric educational research.

C. Search Strategy and Taxonomy Alignment

*T*o move beyond a simple keyword search, we implemented a multi-stage strategy grounded in the University of Michigan Engineering Education Taxonomy [5], as detailed in Table II. Our adaptation focused on four intersecting domains: Human-Centric Factors (student perceptions and ethics), Instructional Delivery (curriculum and RAG implementation), Assessment and Evaluation (automated grading), and Institutional Policy. By mapping technical AI terms into these validated clusters, we ensured that the 'literature deluge' was categorized according to its pedagogical impact rather than just its software architecture. The search was executed in three strategic phases:

Phase 1: Corpus Identification (The Wide Net): Using broad Boolean strings—("Generative AI" OR "LLM" OR "ChatGPT" OR "GenAI") AND ("Engineering Education")—to establish the total baseline volume of relevant literature across the 2024 and 2025 conference cycles.

Phase 2: Thematic Clustering (Pedagogical Mapping): The identified corpus was subjected to a secondary filtering layer using specific "Keyword X" variables to map the literature into four primary dimensions:

- Technological Infrastructure: Focuses on model selection and deployment (e.g., Llama 3, Gemini, GitHub Copilot).
- Pedagogical Integration: Analyzes curriculum design, syllabus modification, and alignment with the CDIO framework [6], [8], [9].
- The "How-To" (Emerging Literacy): Targets the mechanics of AI interaction, specifically Prompt Engineering and Retrieval-Augmented Generation (RAG).
- Evaluative Frameworks: Maps the automation of faculty administrative loads, specifically automated assessment and feedback loops.
- Phase 3: The "WIP" Lens (Trend Forecasting): A specialized filter was applied to target papers bearing the "WIP:" (Work-in-Progress) prefix, a formal designation within ASEE and IEEE FIE protocols [10], [11]. This is a critical component of the "Research-to-Practice" track; by isolating WIPs, we capture current faculty intent and experimental pilots that have not yet reached the stage of full-scale longitudinal study. This allows us to provide a "bleeding edge" forecast of the field's direction, identifying trends up to 18 months before they appear in formal journal publications.

D. Data Extraction and Search Strategy

Data extraction was designed to capture two critical metrics: the longitudinal distribution of AI tools across engineering disciplines and the thematic pivot from defensive sentiment (detection) to constructive sentiment (integration), a tension frequently noted in recent educational technology frameworks [12]. To ensure the reliability of this analysis, the following search query architecture was utilized, adhering to the standardized charting protocols for scoping reviews [7]:

1. Search Categorization and Taxonomy Mapping

The search was structured around the University of Michigan Engineering Education Taxonomy [5] to ensure technical AI terminology was mapped against peer-recognized pedagogical domains. This prevents the "naming convention gap" where technical implementations are siloed away from educational theory, Table II.

Queries were clustered into four primary dimensions:

- Technological Infrastructure: Focuses on the "Foundational Layer" (e.g., LLMs, GPT-4, Llama 3).
- Pedagogical Integration: Focuses on "Instructional Design" and "Academic Integrity Policies."
- Technical Implementation (Emerging Literacy): Targets high-agency engineering competencies such as Prompt Engineering, Retrieval-Augmented Generation (RAG), and Zero/Few-shot prompting.
- Evaluative Frameworks: Focuses on "Closing the Loop," including automated assessment, grading efficiency, and real-time feedback [13]

2. Boolean Logic and String Construction

A nested Boolean approach was employed to intersect generative AI technologies with engineering-specific educational contexts. This ensures the results are filtered for relevance within the 2,500+ paper corpus:

("Generative AI" OR "LLM" OR "ChatGPT" OR "GenAI") AND ("Engineering Education") AND ("Keyword X")

Where "Keyword X" represents specific application variables such as automated feedback, code generation, or intelligent tutoring systems.

3. Refinement and Filtering (The WIP Factor)

Results were filtered by year (2024–2025) and document type (Peer-reviewed Conference Papers). By isolating the "WIP:" (Work-in-Progress) prefix in the ASEE repository, this study captures the "bleeding edge" of experimental pilots. These papers serve as a lead indicator for the field's direction in 2026 and subsequent academic cycles.

TABLE II
Intersecting technical AI terminology with the Michigan Engineering Education Taxonomy [5] to map the literature deluge.

Cluster	Primary Search Terms (Boolean)	Rationale
Pedagogy	("curriculum") OR ("lesson plan") OR ("syllabus")	Captures structural changes to courses.
Integrity	("plagiarism") OR ("academic honesty") OR ("detection")	Tracks the "Reactionary" phase of AI adoption.
Technical	("RAG") OR ("Prompt Engineering") OR ("API")	Identifies the "Innovative" use of AI as a built tool.
Assessment	("grading") OR ("feedback") OR ("rubric")	Maps the automation of faculty administrative load.
Student Impact	("literacy") OR ("self-efficacy") OR ("perception")	Measures the human element of the transition.

IV. RESULTS AND THEMATIC MAPPING

The thematic distribution reveals a non-linear maturation in research focus. While total AI-related volume increased by over 100% (from N=510 to N=1,039), the nature of the research questions evolved. This 'Sociotechnical Pivot,' visualized in Figure 3, demonstrates a clear movement away from defensive guardrails toward proactive integration. To illustrate the qualitative distinction between these clusters, Table III provides representative examples of research focus and keyword strings used during the systematic coding process..

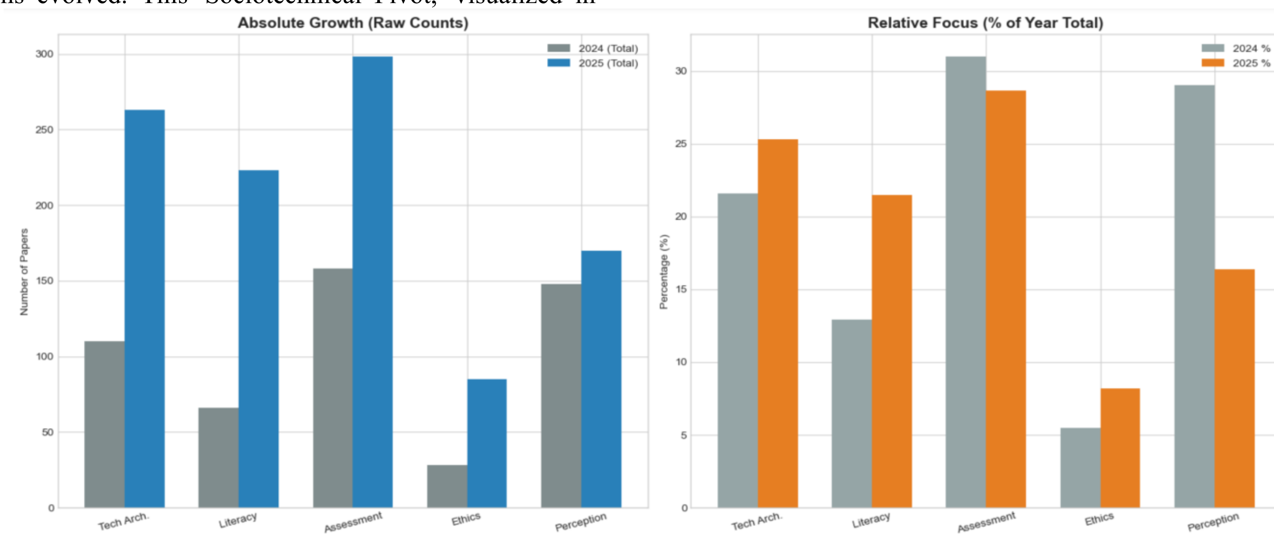

Figure 1 Architectural framework for a Retrieval-Augmented Generation (RAG) tutoring system. The workflow illustrates the transition from raw document ingestion and vectorization to context-aware prompt synthesis, effectively reducing "hallucination friction" by anchoring LLM responses in specific engineering curricula.

A. *Statistical Significance of the Thematic Shift*

A Chi-Square test of independence was performed to examine the relation between publication year and research theme focus. The relation was highly significant, $X^{\wedge 2}(4, N = 1549) = 46.01, p < .001$. This confirms that the shift from 2024 to 2025 is not a random fluctuation but a directional maturation of the field.

B. *Venue-Specific Velocity*

ASEE serves as the "rapid-response" incubator (+118% growth), while FIE acts as the venue for consolidated, high-technical-depth studies (+37%). As shown in Figure 2, Technical Architecture and AI Literacy saw the highest relative velocity across both venues, outstripping reactionary themes.

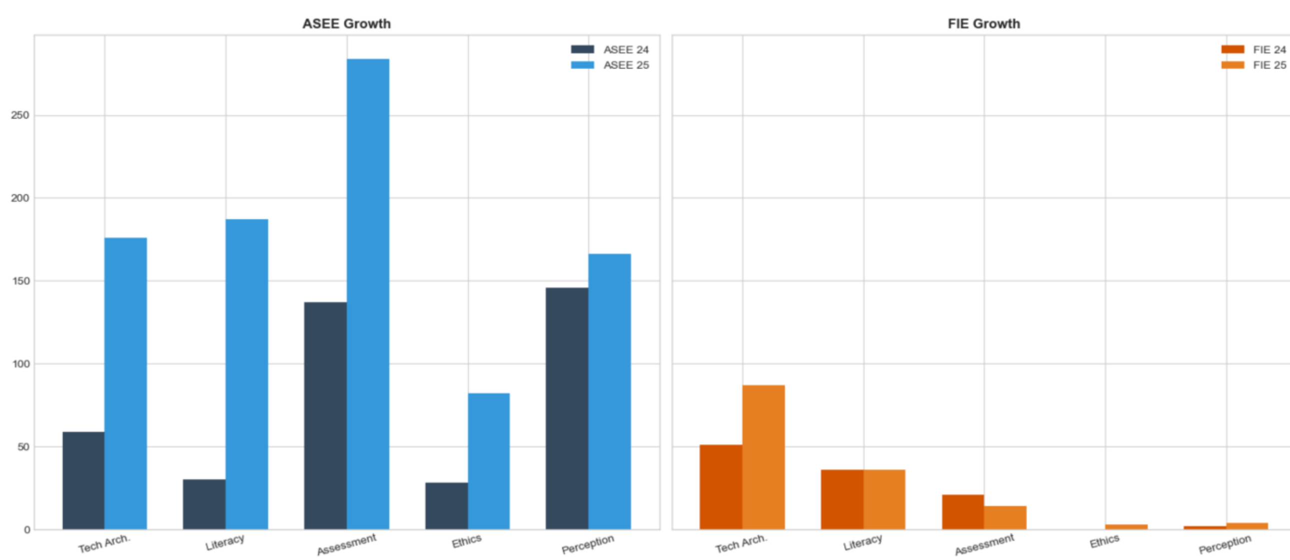

Figure 1 Comparative growth velocity of AI research clusters in ASEE and FIE. The disparity in growth rates between "Integrity" and "Technical/Literacy" clusters across both venues visually confirms the field-wide pivot from defensive guardrails toward proactive technical integration.

TABLE III
Thematic classification schema based on the adapted Michigan Taxonomy. Examples demonstrate the mapping of technical AI implementation keywords to specific pedagogical domains.

Cluster	Keyword Examples	Sample Research Focus
Reactionary	Detection, Integrity, Cheating	Tools to mitigate LLM use in take-home exams.
Assimilation	RAG, Prompting, Literacy	Training students to use AI for code refactoring.
Evaluative	Rubric, Feedback, Autograder	Automated generation of personalized lab feedback.
Human-Centric	Perception, Efficacy, Anxiety	Measuring student trust in AI-generated hints.

V. DISCUSSION: THE MATURATION OF AI

The transition from 2024 to 2025 indicates a move from establishing defensive guardrails to building sophisticated, AI-augmented environments.

A. *Technical Architecture and Co-Creation (RQ1)*

The pivot toward AI Literacy is driven by the recognized fallibility of "detection" tools. Institutions are increasingly prioritizing proactive, socio-technical curricula that treat prompt design as an essential human-computer interaction skill [4]. This is evidenced by the relative decrease in "Ethics & Policy" share, despite its raw volume growth.

B. *The 3:1 Theory-Practice Gap and Cognitive Load*

We identify a persistent gap: for every 1 paper discussing pedagogical theory, there are 3 papers discussing raw technical implementation. As illustrated in the technical framework in Figure 1, the surge in RAG-driven tutoring offers a potential bridge for this gap. Applying Cognitive Load Theory [14], we argue that RAG-driven tutoring reduces extraneous cognitive load. By providing curriculum-aligned hints, these systems prevent the "hallucination friction" found in generalist LLMs, allowing students to focus on germane engineering problem-solving.

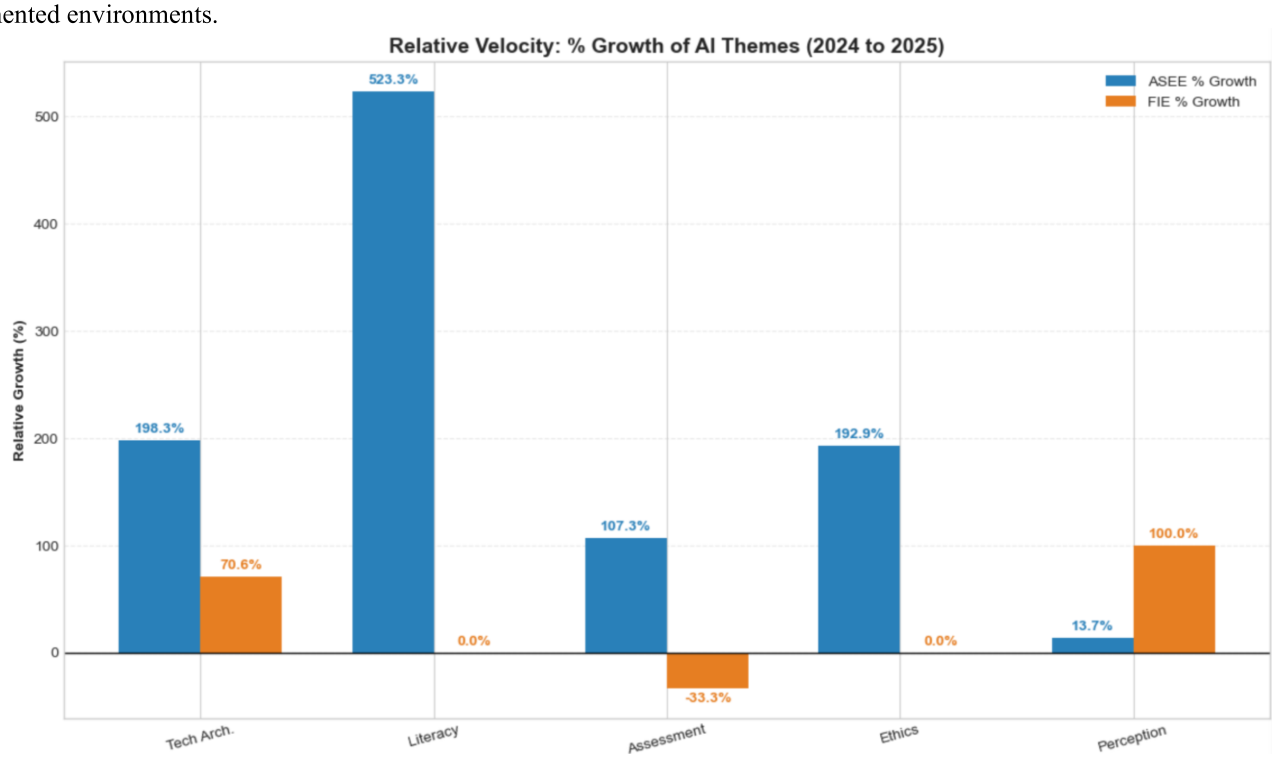

Figure 2 The "Sociotechnical Pivot" in Engineering Education. While publication volume increased across all categories, relative focus shifted from reactionary detection (Ethics) toward proactive implementation (Technical Architecture and RAG-driven systems).

VI. CONCLUSION AND FUTURE WORK

This systematic analysis demonstrates that the engineering education community has matured from a defensive, “reactionary” posture in early 2024 to a state of proactive, metabolic integration in 2025. By reframing Generative AI as an “innovative cognitive partner” rather than a disruptive threat, the discipline is successfully shifting its focus toward AI Literacy and RAG-driven tutoring architectures. This evolution follows a distinct AI Maturation Curve, transitioning from academic integrity concerns to the assimilation of AI as a core engineering competency.

Addressing the Theory-Practice Gap: To move beyond the current "literature deluge," future research must transcend tool-centric reporting. Our findings reveal a persistent 3:1 ratio of technical implementation to pedagogical theory, highlighting an urgent need to anchor AI applications in established frameworks such as Self-Regulated Learning (SRL) and Cognitive Load Theory [14]. Ensuring that technical implementations support deep conceptual mastery—rather than simple automated output—is essential to closing this gap.

Answering RQ3 and the AI-EngEd Dashboard: While our data identifies a clear trend toward specialized agents, the specific distribution of these tools across sub-disciplines (e.g., Mechanical vs. Civil engineering) remains granular. To solve this mapping challenge and democratize these insights for the global community, we are deploying the AI-EngEd Open-Access Dashboard. This multilingual platform (English, Spanish, and Portuguese) will allow LACCEI educators to benchmark regional implementation trends against the comprehensive 2,500-paper dataset.

Future Work: This study serves as a foundational step for a broader experimental agenda. The next phase of this WIP involves a longitudinal study within the University of Florida Department of Engineering Education. This research will utilize the RAG-driven tutoring framework (Fig. 1) to measure if scaffolded AI interactions significantly improve student SRL scores and conceptual retention across diverse engineering disciplines.

Limitations: This scoping review was limited to the ASEE and IEEE FIE conference repositories. Consequently, it may not capture longitudinal data found in journal-level publications or innovations documented in non-English academic repositories.

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