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From the Alphabet to AI-Algorithms: Co-Learning and Co-Construction of Knowledge with AI

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Abstract

From the Alphabet to AI-Algorithms: Co-Learning and the Co-Construction of Knowledge with Artificial Intelligence examines the emergence of Artificial Intelligence (AI) in engineering education as an epistemic transformation comparable to the historical transition from orality to literacy enabled by the technology of writing. Drawing upon media ecology, ecological psychology, and hermeneutic inquiry, the paper situates contemporary AI phenomena within a longer intellectual epistemic arc -- from Plato's critique of writing, through Walter Ong's account of literacy's restructuring of consciousness, to Catherine Z. Elgin's framing of epistemic ecology.

This conceptual paper integrates interdisciplinary theory-building with illustrative use cases in engineering education to articulate an epistemic continuum that bridges theory and practice. Within this framework, epistemic achievements are understood not as fixed or final, but as provisional and generative foundations for further knowledge and understanding. The analysis argues that AI functions not merely as an instructional tool but increasingly as an epistemic agent -- an autonomous co-learning partner engaged in interpretation, modeling, and the co-construction of knowledge.

Insights derived from applications involving MATLAB Copilot and Simulink Copilot inform a framework for AI-mediated engineering education that connects conceptual theory with practice. These affordance-rich computational environments challenge fixed, linear, and hierarchical models of learning, including Bloom's taxonomy, and support more relational, recursive, and ecological approaches to understanding.

The paper concludes by outlining implications for curriculum design, assessment, and governance aimed at fostering adaptive epistemic environments capable of supporting sustainable and socially responsible engineering education.

Keywords: recursive knowledge, distributed cognition, co-learning, epistemic ecology, knowledge artifacts.

I. Introduction

The technology of writing fundamentally transformed human cognition by externalizing memory, reshaping patterns of reasoning, and enabling sustained abstraction beyond the constraints of purely oral cultures [1]. Plato's ambivalence toward writing reflected an early awareness that technologies of inscription alter epistemic structures [1, p. 24]. As Walter J. Ong and subsequent scholars have demonstrated, literacy reconfigured not merely communication but consciousness itself, restructuring how knowledge is organized and transmitted.

In a comparable manner, this conceptual paper argues that the contemporary rise of Artificial Intelligence (AI) externalizes elements of interpretation, modeling, and problem-solving, thereby reshaping the epistemic ecology within which engineering education unfolds [2] - [3]. As AI systems evolve from passive computational tools to active participants in cognitive workflows, learning increasingly emerges as a co-constructive process among what Catherine Elgin calls autonomous epistemic agents [4, p. 3].

Elgin's concept of epistemic ecology provides a framework for understanding this transformation as part of a broader intellectual trajectory. She defines it as "the process of inquiry into ways finite and fallible people individually and collectively develop increasingly viable understandings of themselves and their environment" [4, p. 3]. Within this ecology, epistemic agents continuously adapt to social and technological contexts in pursuit of evolving epistemic goals.

Epistemic achievements -- such as knowledge, understanding, and wisdom -- are not fixed endpoints, but provisional and generative platforms for further inquiry, enabling the development of instruments and techniques that extend perception. As Elgin observes, epistemic ecology "is a story of mutual adjustments between organisms and environments" [4, p. 5], where such achievements function as "springboards for further epistemic gains" [4, p. 12].

Drawing on its literature review, this paper advances a conceptual framework supported by illustrative analyses from engineering education contexts to enhance clarity, demonstrate feasibility, and bridge theory with practice [5], [6]. It situates AI-enabled pedagogy within a broader epistemic trajectory extending from classical critiques of writing to contemporary theories of distributed cognition, reframing AI not as a tool for automation, but as a transformation in the ecology of knowledge and understanding in which autonomous epistemic agents participate in co-learning and knowledge co-construction.

This framework is informed by interdisciplinary observations from classroom and laboratory implementations involving MATLAB and Simulink Copilot systems [7], [8], demonstrating how AI-enabled environments operate within complex socio-technical systems to support conceptual development and applied reasoning.

The implications of this framework suggest that AI represents not merely an extension of external memory [1, p. 78], but a substantive externalization of analytical and interpretive cognition across interacting epistemic agents. AI-assisted modeling and simulation environments extend human reasoning into hybrid cognitive systems that integrate human and machine intelligence within distributed cognitive networks [9], [10]. This transformation raises fundamental philosophical and pedagogical questions: (1) What forms of agency are strengthened, relinquished, or outsourced when AI participates in reasoning processes? (2) How does interpretive authority shift when explanation, modeling, and problem-solving become shared tasks between human learners and autonomous technological agents? (3) How must qualitative, design-based, and engineering inquiry evolve to account for distributed, recursive, and dialogical cognition?

In response, this paper advances an initial step toward a relational reinterpretation of Bloom's taxonomy, in which learning is understood as recursive, dialogical, and ecological rather than strictly linear and cumulative.

II. Literature Review

Understanding the pedagogical impact of Artificial Intelligence (AI) requires situating it within the broader historical trajectory of cognitive and communicative technologies. The concept of epistemic ecology [4] provides a productive analytical framework through which overlapping clusters of interdisciplinary scholarship can be synthesized to examine transformation. These clusters include (1) Media Ecology and Epistemic Change, (2) Hermeneutics and Dialogical Understanding, (3) Distributed Cognition and Engineering Learning, (4) AI Offloading Cognitive Functions in Education, and (5) Emerging reinterpretations of Bloom's Taxonomy under conditions of AI-Mediated Cognition.

Across these domains, scholars converge on the proposition that evolving technological tools do not merely support learning but actively restructure the conditions under which knowledge is produced, interpreted, and applied. These propositions align with and extend the six central themes identified in the Inclusive Engineering Mindset Report [11], which emphasize adaptability, systems thinking, collaboration, and the integration of human and technological capabilities in engineering practice.

Collectively, this body of literature suggests that AI should not be understood solely as an instructional aid, but as a transformative participant in epistemic processes—reshaping how learners engage with abstraction, modeling, and problem-solving in engineering contexts. The following subsections synthesize these thematic clusters to establish the theoretical foundation for the proposed conceptual theoretical framework.

1. Media Ecology and Epistemic Change

Media ecology scholars argue that major cognitive technologies -- speech, writing, print, and digital media -- reshape the organization of thought, social institutions, systems of knowledge production, while altering the "ratios of the senses" [12], [13]. Ong and others observe that writing externalized thought, stabilized language, and enabled sustained abstraction and analytical reasoning beyond what oral cultures could not maintain [1, p. Ch. 4]. McLuhan similarly characterizes media as extensions of human faculties that reorganize perception and cognition [2]. Postman extends this argument by demonstrating how transitions between dominant media forms -- oral, typographic, televisual, and digital -- transform epistemological norms and the social authority of knowledge [14]. More recently, Hayles frames digital systems as part of an ongoing process of "techno-genesis", in which human cognition and technological systems co-evolve [3], while Elgin suggest that evolving technologies reflect "humanity's relentless attempt to improve our epistemic lot" [4, p. 2].

Within this historical arc, Artificial Intelligence (AI) represents a further epistemic shift. Writing reorganized memory and abstraction; AI reorganizes analytical and interpretive reasoning. In engineering contexts, AI-mediated computational environments mark a transition from the externalization of memory storage to the externalization of interpretive and modeling processes. Algorithms now simulate systems, analyze data, generate explanations, and assist in designs -- functions traditionally associated with human reasoning.

From a media-ecological perspective, AI should therefore be understood not merely as a productivity tool but as a cognitive technology that reshapes how engineering knowledge is constructed, validated, and transmitted. Examining AI's pedagogical impact requires attention not only to instructional efficiency but also to its broader sociocultural and epistemic implications.

2. Hermeneutics and Dialogical Understanding

Hermeneutic traditions articulated by Hans-Georg Gadamer, Paul Ricoeur, and others emphasize that understanding is recursive and dialogical rather than linear and passive [15], [16].

Interpretation emerges through iterative questioning and response, shaped by prior knowledge, context, and evolving interpretive horizons. Knowledge, therefore, is not passively received but actively negotiated.

In engineering contexts, understanding develops through what Gadamer describes as a "fusion of horizons" -- an ongoing negotiation between the learner and the subject matter mediated by tools, texts, and collaborators. AI-enabled systems increasingly participate in this interpretive cycle [17]. This dynamic aligns with Donald A. Schön's concept of reflection-in-action, in which professional competence emerges through iterative reframing, experimentation, and responsive adjustment during problem-solving processes [18]. Within this framework, AI becomes embedded in the interpretive loops central to engineering reasoning, raising important questions about authorship, authority, and agency.

Digital technologies introduce new forms of interpretive participation within this hermeneutic process. Scholars in digital hermeneutics argue that algorithmic systems participate in meaning-making by structuring what information is presented, how it is visualized, and which pathways of inquiry are foregrounded [19], [20]. As a result, epistemic authority becomes partially distributed, with human learners and machine systems jointly shaping interpretation.

From a philosophical hermeneutic perspective, AI pedagogical agents are not neutral tools, but mediators that influence how engineering concepts are framed and understood [21, p. 39]. In modeling and simulation environments, such as those involving MATLAB and Simulink, AI systems function as co-interpreters, shaping learners' conceptualizations of system behavior, physical constraints, and design trade-offs. This distributed interpretive structure challenges traditional assumptions of individual cognition, raising foundational questions regarding authorship, agency, and responsibility in AI-mediated engineering education.

3. Distributed Cognition and Dynamic Complexity

Distributed cognition theory posits that cognitive processes extend beyond the individual to include interactions among people, tools, and artifacts within a broader sociotechnical system [22]. In engineering education, classrooms increasingly function as such systems, where reasoning is mediated through computational platforms, collaborative workflows, and AI-enabled tools.

Within this context, MATLAB Copilot supports the translation of mathematical formulations into executable code, assists with debugging, and facilitates iterative refinement of computational models. Similarly, Simulink Copilot enables learners to construct, modify, and analyze block-diagram representations of dynamic systems [7] - [8]. These tools actively participate in the problem-solving process by structuring workflows, suggesting representations, and accelerating computational execution.

Rather than replacing human cognition, these systems redistribute cognitive effort across human and machine agents. This redistribution allows learners to engage more readily with complex, dynamic systems, but it also introduces new dependencies on tool-mediated reasoning. As a result, effective pedagogy must balance the affordances of computational assistance with the preservation of deep conceptual understanding.

In domains such as differential equations and control systems, where students often struggle to translate mathematical models into executable simulations, AI-assisted environments can reduce procedural barriers while maintaining engagement with underlying concepts [23]. From a distributed cognition perspective, learning emerges not solely within the individual, but through interactions across a network of human and computational agents operating within dynamically evolving problem spaces [24], [25].

The extension of cognitive processes beyond the individual introduces dynamic complexity, wherein well-intentioned distributed affordances within a system may be counteracted by the system's own responses [26]. Such complexity is characteristic of sociotechnical environments in which interactions among human and computational agents produce nonlinear and often unintended outcomes. This process reflects Schön's concept of reflection-in-action, as learners iteratively refine models in response to feedback within AI-mediated environments [18].

4. AI Offloading Cognitive Functions in Education

The integration of Artificial Intelligence (AI) in education has introduced significant debate regarding its impact on cognitive development. On one hand, AI systems can enhance learning by reducing procedural burdens and enabling students to focus on higher-order thinking. On the other hand, concerns persist that excessive reliance on AI may hinder skill development and reduce analytical capacity.

AI-assisted tools can reduce cognitive load by automating routine tasks such as syntax generation, computation, and debugging. This allows learners to allocate cognitive resources toward conceptual understanding, problem framing, and system-level reasoning. According to J. Sweller's Cognitive Load Theory, reducing extraneous load can improve learning efficiency [27]. Similarly, AI-enabled environments support distributed cognition, where thinking is shared across human and technological agents, enhancing problem-solving capacity [28]. Studies in engineering education further show that simulation and AI tools improve conceptual understanding and iterative design thinking [29].

Critics argue that excessive reliance on AI may lead to skill atrophy, particularly in foundational areas such as mathematical reasoning, coding fluency, and analytical problem-solving. Carr suggests that digital technologies may weaken deep thinking and sustained attention [30]. In educational contexts, over-automation can reduce opportunities for productive struggle, which is essential for developing expertise [31]. Additionally, concerns have been raised that reliance on AI-generated outputs may diminish critical evaluation skills, as students may accept results without fully understanding underlying processes [32].

The literature suggests that AI-mediated cognitive offloading is neither inherently beneficial nor detrimental; its impact depends on pedagogical design. When appropriately structured, AI can augment higher-order cognition by supporting deeper engagement with conceptual reasoning, synthesis, and evaluation. However, uncritical reliance on AI risks undermining the development of foundational analytical skills. Effective integration therefore requires a deliberate balance between automation and sustained engagement in reasoning processes, grounded in the recognition that epistemic achievements are dynamic, provisional, and continuously refined within evolving learning environments [4, p. 132].

5. Reinterpretations of Bloom's Taxonomy

Bloom's taxonomy traditionally organizes cognitive processes hierarchically, progressing from lower-order skills such as remembering and understanding to higher-order processes such as analysis, evaluation, and creation [20]. AI-mediated environments complicate this linear progression. When lower-level tasks -- such as syntax generation and procedural implementation -- are partially automated, learners may engage more directly with higher-order processes, including synthesis, evaluation, and design.

Rather than rendering Bloom's framework obsolete, this shift suggests the need for a reinterpretation grounded in an epistemic ecology perspective. In this view, cognition is not strictly hierarchical but recursive, relational, and distributed across interactions among human and technological agents. Learning emerges through iterative cycles of interpretation, evaluation, and adaptation, in which "autonomous epistemic agents extend, modify, and adapt to their environments, both social and natural, in order to frame and promote their epistemic ends" [4, p. 3].

Accordingly, with AI affordances, Bloom's taxonomy may be more appropriately understood not as a fixed sequence, but as a dynamic structure in which cognitive processes are revisited, reorganized, and co-constructed within AI-mediated learning environments.

III. Conceptual Framework

The following adopted instruments and techniques, including MATLAB and Simulink Copilots, are examined as epistemic agents that inform the development of the conceptual framework presented in this paper. Following a brief review of their capabilities, mappings of computational translation using MATLAB Copilot and model-based simulation using Simulink Copilot are introduced, together with the associated analysis methodology.

Engineering education use-cases analysis are then presented as "desirable stable platforms" [4, p. 3] for demonstrating the proposed pedagogical framework, grounded in insights derived from MATLAB and Simulink Copilot applications.

A Brief Review of MATLAB and Simulink Copilots

Recent developments within the MathWorks ecosystem include AI-enabled assistants designed to support engineering workflows. Specifically, MATLAB Copilot is optimized for code-based computational environments, whereas Simulink Copilot is optimized for graphical modeling, simulation, and system-level design workflows [7], [33].

MATLAB Copilot operates within the MATLAB programming environment, assisting users with script generation, function development, debugging, code explanation, and performance optimization. It supports computational workflows common in signal processing, control systems, numerical methods, and data analysis. By reducing syntactic barriers and accelerating the translation of mathematical expressions into executable code, MATLAB Copilot enables learners to focus more directly on conceptual reasoning, model validation, and interpretation.

Simulink Copilot operates within the Simulink graphical modeling environment, assisting users with block-diagram construction, subsystem configuration, parameter tuning, and the interpretation of simulation results. Because Simulink underpins many Model-Based Design workflows, Simulink Copilot supports dynamic system modeling, controller design, and simulation-based verification [8]. Its orientation is structural and system-level, rather than text-based [34], [35].

Together, these tools exemplify the redistribution of cognitive processes described in distributed cognition theory, as they actively participate in model construction, execution, and interpretation.

Computational Translation with MATLAB Copilot:

Students frequently struggle with translating differential equations and control laws into executable code [31]. MATLAB Copilot assists in this process by supporting script generation, debugging, and code explanation [33], thereby mediating the transition from mathematical abstraction to computational implementation.

Observed outcomes include: (1) reduced syntactic friction, (2) increased focus on conceptual validation, and (3) improved alignment between mathematical formulation and simulation. When appropriately structured, AI assistance accelerates iterative development while preserving engagement with underlying analytical reasoning, reflecting a redistribution of cognitive effort within AI-mediated learning environments.

Model-Based Simulation with Simulink Copilot:

Simulink Copilot supports block-diagram construction and parameter tuning within graphical modeling environments. In control systems and renewable energy modules, students iteratively modify system parameters and visualize dynamic responses, strengthening the feedback loop between theoretical formulation and simulation-based validation.

Across these contexts, four patterns emerged: (1) increased modeling iteration, (2) enhanced systems-level reasoning, (3) accelerated debugging cycles, and (4) cross-domain transfer of modeling principles.

Analysis of MATLAB and Simulink Copilot use demonstrates that AI functions not merely as a neutral instructional aid, but as a cognitive partner and interpretive agent within ecological co-learning environments [36]. This partnership reflects a mode of "thinking together," in which human learners and AI systems operate as collaborative epistemic agents rather than as users and passive tools.

Within distributed learning systems, these AI tools function as cognitive scaffolds that support model construction, simulation, and interpretation. Collectively, they instantiate hermeneutic cycles of interpretation and re-interpretation that underpin co-learning processes through which knowledge is dynamically co-constructed in AI-mediated engineering learning environments [37], [38].

Analysis Methodology:

This study adopts a qualitative philosophical inquiry grounded in hermeneutics, media ecology, and interpretive phenomenology. Its purpose is twofold: (1) to analyze the parallel cognitive and sociocultural impacts of Artificial Intelligence (AI) and the historical development of alphabetic writing, and (2) to examine how contemporary AI-enabled tools -- specifically MATLAB and Simulink Copilots -- function as pedagogical agents that shape co-learning and knowledge construction in engineering education.

The methodology is structured through three interrelated components -- conceptual analysis, hermeneutic case study, and interpretive evaluation of digital artifacts -- enabling a multi-layered examination, synthesis, and theoretical integration of AI-mediated learning environments.

1. Conceptual and Historical Analysis

The first component consists of an interpretive analysis that draws on media ecology and the history of knowledge technologies to establish a conceptual framework for comparison. Following the interpretive traditions of Ong [1], McLuhan [39], and Postman [40], this framework examines how writing externalized thought, restructured cognition, and transformed educational institutions. This analysis serves as a historical analogue for evaluating AI as an emergent epistemological technology that externalizes reasoning, modeling, and explanation. It further illustrates how "we relentlessly seek to expand our "epistemic range" [4, p. 2]

This phase involves: (1) A systematic review of foundational texts in media ecology and digital hermeneutics; (2) Mapping conceptual parallels between writing-as-technology and AI-as-technology; and (3) Identifying cognitive, epistemological, and pedagogical shifts associated with both transitions.

This conceptual grounding establishes the theoretical foundation for the subsequent empirical–interpretive inquiry into AI-mediated engineering learning environments.

2. Hermeneutic Case Study of Engineering Learning Environments

The second methodological component employs a hermeneutic case study approach to examine how AI-enabled tools operate as pedagogical agents within engineering learning environments. Drawing on Gadamer's concept of the "fusion of horizons" [15] and Ricoeur's notion of recursive interpretive structures [17], this phase frames meaning-making as a dialogical process among learners, instructors, and autonomous digital systems.

Data sources for the case study include the following: (1) Classroom observations from undergraduate engineering courses utilizing MATLAB Copilot; (2) Instructor reflections and interviews regarding pedagogical shifts enabled by AI features; (3) Student work samples illustrating AI-supported modeling, problem-solving, and debugging; (4) Informal learning artifacts, including MATLAB Copilot chat transcripts, modeling iterations, and code generation histories.

These qualitative data are analyzed to identify recurring interpretive patterns and interaction dynamics that characterize how learners construct understanding in AI-mediated environments.

3. Interpretive Evaluation of AI-Artifacts

The third methodological component focuses on the interpretive analysis of epistemic digital artifacts produced through student and instructor interactions with MATLAB Copilot. Following the hermeneutic principles articulated by Capurro and Kimmerle [41], these artifacts -- such as code suggestions, model simulations, AI-generated explanations, and error diagnostics -- are treated as manifestations of distributed cognition [42], [43].

Artifact analysis examines the following: (1) The extent to which AI-generated guidance influences conceptual understanding; (2) Evidence of recursive interpretation, wherein learners refine meaning through iterative cycles of human–machine dialogue; (3) Shifts in students' perceptions of engineering systems as mediated by autonomous simulations; (4) Patterns of co-construction, in which human reasoning and AI-supported modeling jointly produce new knowledge structures.

This analysis demonstrates that AI functions not merely as a computational tool, but as an active epistemic participant in the co-construction of engineering understanding.

Methodology Synthesis and Theoretical Integration

Finally, insights derived from the three methodological components are integrated to produce a synthesized interpretation of AI's pedagogical role. This interpretive synthesis articulates: (1) Parallels between the historical cognitive transformations associated with writing and the contemporary pedagogical impacts of AI; (2) The role of hermeneutic cycles in structuring AI-mediated learning processes; (3) The conditions under which AI fosters epistemic agency, conceptual stability, and deeper understanding.

Rather than pursuing statistical generalization, this analysis advances a conceptual framework that illuminates emerging pedagogical possibilities and informs future research on autonomous digital agents in engineering education.

Use-Case Analysis: MathWorks Copilots as Pedagogical Agents

AI-enhanced engineering tools -- particularly MATLAB and Simulink Copilots -- provide a compelling context for examining how autonomous digital systems function as pedagogical participants within AI-mediated learning environments. This section analyzes use cases drawn from undergraduate engineering courses and informal learning contexts in which students and instructors engage with these tools to model systems, troubleshoot designs, and construct domain knowledge.

The analysis is organized around three interrelated dimensions of co-learning that characterize AI-mediated engineering practice: (1) Interpretive guidance; (2) Recursive knowledge construction; (3) Situated application within engineering problem-solving contexts.

1. Interpretive Guidance and Conceptual Scaffolding

Use-Case 1: AI-Supported Understanding of Differential Equations

In introductory systems courses, students often struggle to conceptualize the relationship between differential equations, system dynamics, and underlying physical phenomena [44]. Simulink provides a visual modeling environment in which AI-assisted block recommendations support the mapping of conceptual relationships into executable representations.

For example, a student modeling a first-order RC circuit may begin by assembling integrator and gain blocks within the simulation canvas. Simulink's AI-driven block recommendation features suggest appropriate components based on context -- for instance, recommending a "Transfer Fcn" block when the system is expressed in standard linear form. Students frequently interpret these suggestions not merely as procedural hints, but as conceptual cues that guide their understanding of system behavior.

This process mirrors the "externalization of thinking" described in media ecology: just as writing rendered cognitive processes visible and stable, AI-enhanced modeling environments make dynamic system relationships observable, manipulable, and open to interpretation.

The pedagogical effect is notable: (1) Students identify relationships between mathematical expressions and physical behaviors earlier [45]; (2) AI-mediated guidance reduces cognitive load by foregrounding conceptual structure rather than syntactic detail [46]; and (3) Instructors report more efficient classroom discussions that emphasize interpretation over mechanical translation [44].

In this context, Simulink functions as a conceptual and hermeneutic partner, actively shaping how learners interpret and construct engineering meaning.

2. Recursive Knowledge Construction Through MATLAB and Simulink Copilots

Use-Case 2: Dialogical Modeling and Explanation-Seeking

MATLAB and Simulink Copilots introduce interactive conversational agents capable of generating MATLAB scripts, explaining Simulink models, suggesting debugging strategies, and providing conceptual clarification. Students frequently engage with these tools through recursive interpretive loops—iterative cycles of questioning, testing, revising, and reflecting [34].

A representative example involves a student troubleshooting a nonlinear pendulum model. The student queries MATLAB Copilot: “Why is my simulation diverging when I increase the angle?” The AI identifies likely causes -- such as insufficient solver accuracy or missing damping terms -- proposes modifications to the model and explains the associated physical implications. The student then tests these changes in Simulink, observes the resulting system behavior, and returns to MATLAB Copilot for further refinement [17].

This recursive dialogue produces several pedagogical outcomes: (1) Progressive refinement of conceptual understanding; (2) Integration of mathematical, physical, and computational knowledge; and (3) Co-construction of meaning between the learner and AI agents.

Through these iterative cycles, MATLAB and Simulink Copilots enable learners to observe their reasoning reflected back with variation, a defining characteristic of hermeneutic interpretation. Rather than simply providing answers, these AI systems facilitate an interpretive process in which students refine understanding across multiple horizons, including the mathematical, physical, and computational domains.

This process exemplifies distributed and dialogical cognition, in which understanding emerges through sustained interaction between human learners and AI-mediated systems.

3. Situated Application in Engineering Problem-Solving

Use-Case 3: Multibody Dynamics and Real-World Engineering Scenarios

In upper-level mechanical engineering courses, students frequently use Simscape Multibody to simulate complex mechanical systems, including robotic manipulators and vehicle suspensions. With MATLAB Copilot functioning as an autonomous assistant, students develop highly iterative models that progressively converge toward viable engineering designs [33].

A typical workflow proceeds as follows: (1) Students describe a real-world system (e.g., a robotic arm with two degrees of freedom); (2) MATLAB Copilot proposes a block-level architecture, including joints, links, sensors, and actuation components; (3) The student instantiates the model in Simscape Multibody and evaluates system performance; (4) The AI interprets simulation results (e.g., overshoot, energy inefficiency) and suggests design modifications; and (5) The student applies these changes and reflects on their engineering significance within the given context.

This iterative cycle reveals several pedagogical insights: (1) AI enables rapid exploration of multiple design alternatives, supporting the development of engineering intuition through accelerated iteration; and (2) Students interpret AI-generated feedback as part of a shared decision-making process, mirroring collaborative design practices in professional engineering contexts.

By enabling rapid, hermeneutically informed iteration, AI functions as a co-designer, actively participating in the co-construction of engineering knowledge and design reasoning.

Emergent Themes Across Use-Cases

The analysis of use cases reveals several recurring themes that characterize AI-mediated engineering learning environments: (1) AI agents as interpretive partners: AI systems guide learners toward meaning-making by revealing underlying structures, offering explanations, and prompting conceptual inquiry; (2) Distributed knowledge construction: Understanding emerges not solely from individual cognition, but through recursive interactions among students, AI systems, and simulation environments; (3) Dialogical and non-linear learning processes: Learning becomes increasingly dialogical, as students engage with engineering content through iterative cycles of conversational exploration, experimentation, and reflection; and (4) Acceleration of engineering intuition: Through rapid modeling and simulation cycles, students develop a qualitative understanding of system behavior, often earlier than through equation-based analysis alone.

IV. Theoretical Development

The conceptual ecological framework presented above, incorporating Artificial Intelligence (AI), establishes a theoretical foundation for understanding emerging clusters of epistemic and pedagogical affordances. These include: (1) simulation, visualization, co-learning, and the co-construction of knowledge in engineering education, and (2) the emergence of AI as an autonomous epistemic and pedagogical agent.

This model challenges traditional views of learning as strictly linear, fixed, and hierarchical. Instead, engineering education is reconceptualized as a recursive, interpretive ecology of distributed cognition, characterized by a relational model of co-learning and knowledge co-construction in which: (1) human learners frame problems; (2) AI systems provide computational and interpretive support; (3) simulation environments generate dynamic feedback; and (4) reflective processes iteratively reshape understanding.

Within this framework, cognition is distributed and co-constructed across networks of human and non-human epistemic agents. Rather than diminishing human reasoning, AI redistributes cognitive processes across these networks. Accordingly, the central pedagogical objective shifts toward the intentional orchestration of distributed cognition and autonomous epistemic agency within AI-mediated learning environments. This framework repositions AI not as a supplementary instructional tool, but as an integral participant in the evolving epistemic ecology of engineering education.

1. Simulation, Visualization, and Engineering Pedagogy

Research in engineering education demonstrates that simulation-based learning improves conceptual understanding, supports experimentation, and reduces cognitive load for novice learners. Roselli and Brophy show that Simulink-based instruction enhances students' ability to connect mathematical representations with dynamic system behavior [17]. Simulation environments provide scaffolds that enable students to visualize relationships among variables, debug models, and explore "what-if" scenarios without the constraints of physical laboratories.

Similarly, studies by Aljarrah, Saleh, and colleagues indicate that simulation tools support iterative design thinking by enabling rapid prototyping and immediate feedback [47], [41]. These affordances align with constructivist and experiential learning theories, in which deep understanding emerges through cycles of model construction, testing, and refinement.

AI-enhanced tools further extend these capabilities. MATLAB Copilot assists students in generating code, explaining errors, clarifying mathematical relationships, and proposing alternative modeling strategies. These features support adaptive and personalized learning pathways while reinforcing conceptual engagement, thereby positioning AI-enhanced simulation environments as active epistemic contributors to conceptual development in engineering education.

2. AI as an Epistemic and Pedagogical Agent

The literature on Artificial Intelligence (AI) in education increasingly conceptualizes AI systems as pedagogical actors rather than merely instructional tools. AI tutors, code assistants, and simulation platforms provide formative feedback, support metacognitive processes, and facilitate distributed problem-solving. Dede and Richards argue that emerging AI systems reshape not only educational content but also the processes through which understanding is constructed [48]. Similarly, Luckin and Holmes describe the emergence of "intelligence infrastructures," in which learning results from orchestrated interactions among human and non-human agents [49].

In engineering contexts, AI-enabled simulation and modeling platforms constitute a form of cognitive apprenticeship in which machine intelligence supplements and extends human reasoning. These systems enable students to navigate complex problem spaces, test hypotheses, and visualize system behavior that would otherwise remain abstract, thereby enhancing conceptual understanding and design-oriented thinking. Accordingly, they operate as epistemic partners, actively participating in the co-construction of engineering knowledge within AI-mediated learning environments.

V. Implications for Engineering Education

The implications of this conceptual analysis for engineering education are organized into five primary domains. The first three -- curriculum design, assessment, and governance -- address the sociocultural dimensions of engineering education as an evolving epistemic ecology. The remaining two -- reimagining engineering education through AI affordances and the reconfiguration of Bloom's taxonomy -- foreground shifts in epistemic relationships and emerging opportunities for action within AI-mediated learning environments.

1. Curriculum Design

Implications for curriculum design suggest that pedagogical engagements should systematically incorporate assignments requiring: (a) explicit conceptual explanation; (b) validation of AI-generated outputs; (c) comparative analysis between manual and AI-assisted approaches; and (d) integration of knowledge artifacts within the curriculum [42], [43], [50].

2. Assessment

Implications for assessment indicate that evaluation frameworks should prioritize: (a) model interpretation; (b) ethical reasoning; and (c) system-level integration, rather than syntactic correctness alone.

3. Governance

Implications for governance suggest that institutions must address: (a) academic integrity in AI-assisted work; (b) transparency in AI usage; and (c) equity in access to AI-enabled tools.

4. Epistemic Ecology: Reimagining Engineering Education with AI Affordances

This paper advances the concept of epistemic ecology as a productive framework for reimagining engineering education in the presence of AI-enabled affordances. Epistemic ecology examines how knowledge emerges, circulates, and evolves within dynamic systems, conceptualizing knowing not as the accumulation of static facts, but as an interactive and adaptive process shaped by relationships among agents, tools, institutions, and environments. From this perspective, knowledge production occurs within interconnected systems -- including scientific disciplines, local experience, and technological infrastructures -- that continuously interact, adapt, and self-correct, particularly in addressing complex challenges such as sustainability [51], [52].

The rise of AI introduces new epistemological affordances that enable past and present pedagogical paradigms to inform one another. As Ong observes, the study of media transformations -- from orality to digital systems -- provides a framework in which historical and contemporary forms of knowing mutually illuminate one another [1, p. 2]. Within this trajectory, AI can be understood not as a rupture, but as a continuation of cognitive and pedagogical evolution.

Concepts such as affordance and ecological niche further enrich this perspective. Following Gibson’s formulation, affordances represent opportunities for action that emerge relationally between organisms and their environments [53]. Subsequent developments emphasize that these affordances are perceived and enacted within dynamic, often digitally mediated contexts [54]. In this sense, learners and their environments are not independent entities, but reciprocal and interdependent components of a shared ecological system [55], [56].

Applied to engineering education, this ecological framing has significant implications for the organization and practice of learning. AI-enabled tools allow educators to design environments in which students actively engage with systems through simulation, modeling, and iterative experimentation. For example, MATLAB and Simulink translate complex engineering equations into interactive, real-time visual systems, enabling learners to manipulate and test concepts such as feedback control and signal processing. Copilot systems further scaffold these processes by functioning as distributed cognitive agents that support problem framing, conceptual synthesis, and adaptive learning strategies.

These developments suggest a shift away from viewing learners as isolated individuals progressing through fixed instructional sequences, toward understanding them as participants within dynamic epistemic ecosystems. While the long-term implications of AI in engineering education remain emergent [11], [57], it is increasingly evident that learning is best understood as situated within relational, adaptive, and co-constructed environments shaped by human and artificial agents.

This reconceptualization positions engineering education as an adaptive epistemic ecology in which learning emerges through continuous interaction among human and artificial agents.

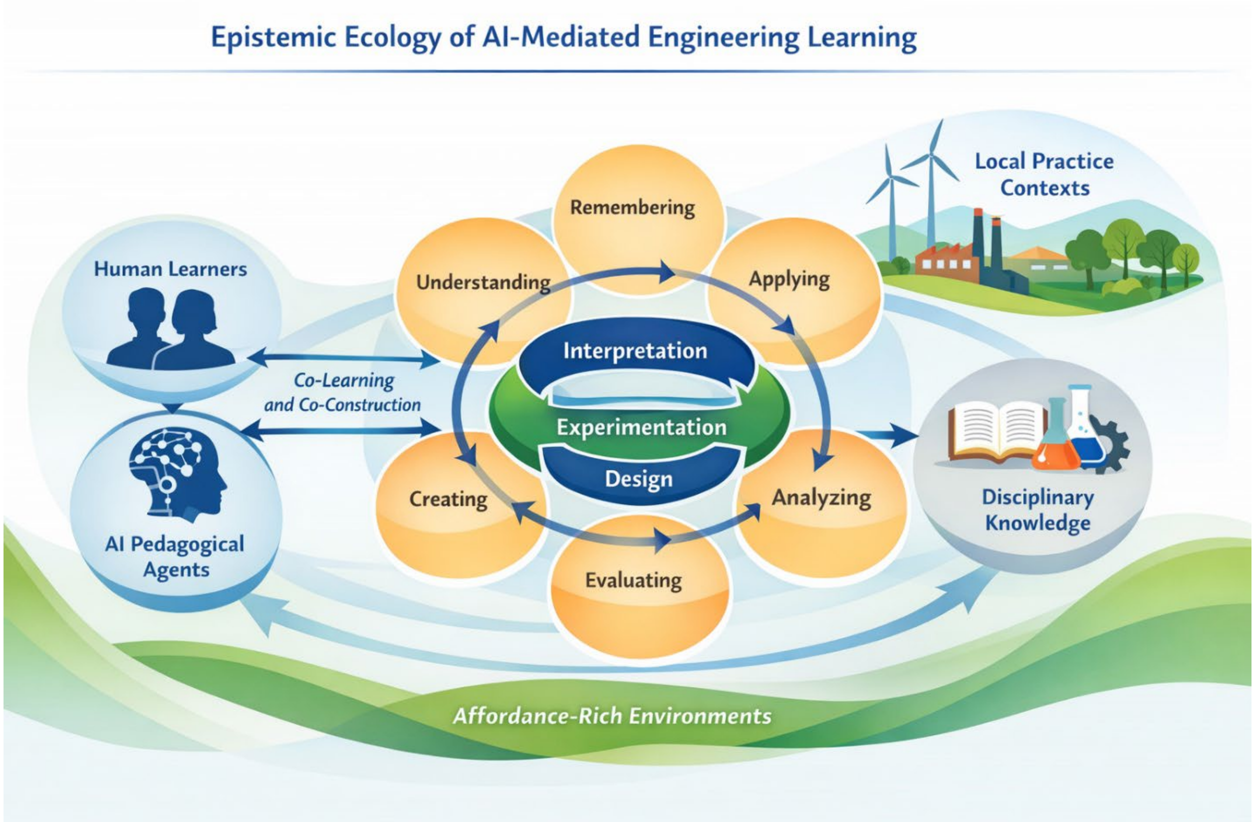

Figure 1: A ChatGPT 5.2 (2026) Visual rendition of Epistemic Ecology as use case example in an Ai-Mediated ecological co-learning environments. Sections of this paper were presented to ChatGPT for its graphical interpretation. All aspects of this image (design, labeling, organization, colors etc.) were autonomously created by ChatGPT.

5. Epistemic Ecology: Reconfiguration of Bloom's Taxonomy

When viewed through the lens of epistemic ecology, several limitations of traditional formulations of Bloom's taxonomy become apparent. Bloom's hierarchical model -- progressing from remembering and understanding toward analysis, evaluation, and creation -- reflects assumptions rooted in print-era epistemologies, where knowledge is treated as stable, decontextualized, and sequentially acquired by individual learners [58], [59].

In contrast, epistemic ecology conceptualizes knowing and doing as situated, relational, and recursive processes. Within AI-mediated engineering education, learners frequently engage simultaneously in analysis, application, evaluation, and creation through interaction with intelligent simulations, modeling environments, and AI-supported feedback systems. These environments effectively collapse Bloom's staged progression by enabling learners to explore, test, revise, and reinterpret ideas in real time, often prior to formal articulation of understanding.

From an ecological psychology perspective, this collapse represents not a pedagogical limitation but a natural consequence of affordance-rich learning environments. As Gibson and subsequent ecological theorists argue, affordances are relational opportunities for action and meaning that emerge through interaction between learners and their environments [53], [55], [56]. AI-enabled tools amplify these affordances by externalizing interpretive, computational, and representational processes, allowing learners to operate within complex epistemic niches that support higher-order reasoning from the outset.

Within this framework, Bloom's taxonomy is not discarded but reconfigured. Rather than functioning as a fixed hierarchy, Bloom's cognitive categories are better understood as dynamically interacting dimensions within an epistemic ecology. Remembering and understanding are no longer prerequisites for creation; instead, they are continuously reshaped through iterative cycles of experimentation, simulation, feedback, and reflection. Knowledge construction thus becomes distributed across human and AI-based epistemic agents, consistent with theories of distributed cognition and co-learning [60], [22].

This ecological reinterpretation has significant implications for engineering education. It challenges assessment practices that privilege linear mastery and isolated performance, while supporting pedagogies that emphasize iterative design, system-level reasoning, and interpretive judgment. In such environments, students are better understood not as progressing along a cognitive hierarchy, but as navigating and shaping epistemic niches in which learning, doing, and meaning-making occur simultaneously [61].

Across these perspectives, a consistent theme emerges: AI is not merely a new instructional medium, but a transformative epistemological technology that participates in a "fusion of horizons" -- an ongoing, recursive negotiation between learners and subject matter mediated by tools, texts, and collaborators [62]. Like writing, AI reorganizes the cognitive and communicative environment of learning, enabling autonomous epistemic agents to extend, modify, and adapt their understanding in pursuit of evolving epistemic goals [4, p. 3]. In engineering education, tools such as MATLAB and Simulink Copilots exemplify this shift by reshaping how learners model systems, interpret feedback, and construct meaning within AI-mediated epistemic ecologies.

VI. Conclusion

From writing to Artificial Intelligence, major technological innovations reshape epistemic practice. AI-assisted computational environments extend cognition into hybrid learning ecologies where knowledge is co-constructed through recursive dialogue among learners, tools, and systems. When integrated intentionally, AI can bridge theory and practice, strengthen modeling fluency, and support iterative engineering reasoning.

This paper has argued that the contemporary rise of AI represents an epistemic transformation comparable in scale to the historical transition from orality to literacy. As with the alphabet, AI does not merely accelerate existing practices; it reorganizes the conditions under which thinking, learning, building, and meaning-making occur. Yet history suggests that the full implications of such transformations are rarely visible in their early stages. Although AI's development appears to be unfolding more rapidly than earlier media revolutions, we remain in the formative phase of understanding its long-term cognitive and institutional consequences.

Within engineering education, AI-mediated tools, particularly intelligent modeling and simulation environments, are already reshaping pedagogical relationships and processes of knowledge construction. These systems increasingly function not only as instructional aids but as co-learning partners participating in interpretation, experimentation, and design. In doing so, they challenge strictly hierarchical and linear models of learning and invite reconsideration of established frameworks, including Bloom's taxonomy, toward more relational and recursive forms of understanding consistent with hermeneutic traditions.

By situating AI within a broader epistemic arc, from classical critiques of writing through media ecology to contemporary digital cognition, this analysis underscores the need for reflective and historically informed engagement. The implications extend beyond efficiency and performance metrics; they concern epistemic agency, interpretive authority, responsibility, and accountable governance within human–AI learning systems.

Ultimately, the educational significance of AI will depend not on the technology itself, but on how institutions integrate it into curriculum design, assessment practices, professional formation, and ethical frameworks. Intentional, research-informed pedagogical experimentation is therefore essential, grounded in the recognition that epistemic achievements are dynamic, provisional, and continuously refined within evolving learning environments. Rather than being fixed or final, such achievements serve as generative foundations for further knowledge and understanding.

AI should be approached not as a replacement for human judgment, but as a configurable collaborator in the co-construction of engineering knowledge -- one that operates within clearly defined norms of ownership, accountability, and shared responsibility. In this sense, AI becomes not a substitute for human expertise, but a partner in shaping the future epistemic ecology of engineering education.

VII. Future Research Directions

Future research should extend beyond conceptual framing toward systematic empirical investigation. First, studies are needed to evaluate learning outcomes associated with AI-mediated instructional environments, including impacts on conceptual understanding, modeling fluency, and cross-domain transferability within engineering education. Particular attention should be given to how AI assistance influences the development of epistemic agency -- both individual and collective -- and how learners negotiate authorship, responsibility, and interpretive authority in co-learning contexts.

Second, longitudinal research is essential to examine how sustained engagement with intelligent modeling, simulation tools, and generative AI systems shapes professional identity formation and adaptive expertise. As AI increasingly participates in iterative design and analysis workflows, it is important to determine whether learners develop deeper systems-level reasoning or become overly dependent on automated scaffolds.

Third, assessment frameworks require reconsideration. Empirical studies should explore how ecological and recursive interpretations of Bloom's taxonomy can be operationalized to capture distributed cognition, iterative refinement, and the co-construction of knowledge. New assessment models may be required to evaluate interpretive reasoning, model validation practices, and ethical decision-making within AI-supported environments.

Finally, comparative and policy-oriented research should examine institutional governance, access, and ethical design decisions shaping AI integration. Such work must address issues of equity, transparency, and accountability to ensure that AI-mediated pedagogical ecologies promote inclusive, sustainable, and socially responsible outcomes across diverse engineering contexts.

Collectively, these research directions aim to ground the emerging theory of AI-enabled co-learning in robust empirical evidence, thereby guiding responsible innovation in engineering education.

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