2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC
Host Sponsor UNC Charlotte
Paper ID #52201

Teaching with (and About) AI: A Convergence–Divergence Framework for Engineering Education

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Abstract. The use of generative artificial intelligence (AI) has outpaced pedagogical guidance in engineering education. This paper reports on the work of a Faculty Learning Community (FLC) at Worcester Polytechnic Institute (WPI), composed of faculty from systems engineering, data science, business, economics, political science, geography and global studies, who are experimenting with teaching AI through a humanistic lens. WPI is a technological university in Worcester, Massachusetts. We propose a convergence–divergence framework for integrating AI into STEM education. The convergence (core) defines common outcomes across disciplines: developing AI literacy (effective prompting, critique, and awareness of limits), raising ethical and risk awareness, and situating projects within governance and standards frameworks. The divergence (petals) reflects discipline-specific applications and challenges.

Vignettes illustrate this framework in practice: systems engineering capstone teams are required to embed AI in design revealed unexamined ethical risks in concept-of-operations work; business/data science students used AI to support blockchain-based data tokenization while checking compliance against ISO/NIST/IEEE standards; social science students explored the societal benefits and risks of AI through in-class writing and design-for-change exercises; economics students tested AI on graph interpretation and simulated AI's impact on labor markets; and global project-based learning leveraged an AI-driven avatar chatbot to surface multi-stakeholder perspectives.

Our contribution is threefold: (1) a portable framework for designing AI-infused project-based courses; (2) pedagogical strategies and rubrics linking classroom activities to governance/standards; and (3) lessons learned from multidisciplinary teaching contexts navigating uneven institutional AI policy. We conclude with implications for project advising, industry readiness, and fostering ethically resilient design practices.

1. Introduction

We are living in the age of artificial intelligence (AI), and teaching and learning are profoundly impacted by this transformation. Faculty and students across academia are experiencing these changes from multiple directions and with a spectrum of responses ranging from enthusiastic adoption to cautious skepticism. This paper addresses this diversity of experiences by examining how academia can respond using its traditional strengths, shared inquiry and collaborative learning, while adapting to new realities. In the tradition of experience-based scholarship in engineering education, this paper offers a structured, reflective account of adaptation process. Drawing on collaborative autoethnography [60] within a Faculty Learning Community [58], we use a shared reflective protocol to surface patterns of convergence and divergence across seven disciplines—an approach grounded in the Scholarship of Teaching and Learning (SoTL) and consistent with qualitative inquiry into emerging pedagogical practice [59].

Our central question is: *What are the common aspects of AI integration across disciplines, and where do the differences lie?* Unlike prescriptive approaches that attempt to provide definitive answers, we take an exploratory stance, drawing on our experiences as a multidisciplinary Faculty Learning Community to identify points of convergence and divergence. To conceptualize this, we employ the metaphor of a daisy: the center represents core ideas common to all disciplines, while the petals represent discipline-specific perspectives. We hypothesize that the center includes shared pedagogical principles for teaching with AI—AI literacy, ethical awareness, and governance frameworks—while each petal reflects unique disciplinary applications and challenges.

Our goal is to use the convergence-divergence framework to probe commonalities and unique approaches that are emerging across diverse fields that faculty are making as they navigate AI integration within the pedagogical norms, expectations and requirements. Henry Kissinger and his co-authors in the book "The Age of AI: And Our Human Future" observed that "AI is going to transform human history, but we approach it without a guiding philosophy" [1]. This observation captures the pedagogical imperative facing STEM education. We have moved past asking whether AI will transform how we teach and learn—it already has. What remains unsettled is whether we approach this transformation with intentionality, grounding AI integration in disciplinary expertise and ethical frameworks, or allow ourselves to be swept along by technological momentum without critical reflection.

The convergence–divergence framework proposed in this paper offers a response to Kissinger's challenge: common foundations (AI literacy, ethical awareness, standards frameworks) provide the structure for intentional integration, while discipline-specific applications (the petals) allow each field to determine how AI best serves its pedagogical goals. Through vignettes drawn from computer science, management information systems, economics, development studies, political science, and geography, we illustrate how this framework operates in practice and discuss implications for project-based learning, industry readiness, and ethically resilient design.

1.1 Theoretical Gaps in Existing AI-Education Frameworks

Existing AI-in-education models suffer from two interrelated limitations. First, many frameworks adopt a predominantly tool-centric perspective that positions AI as an instructional delivery mechanism or efficiency enhancer, neglecting the deeper pedagogical transformations required for meaningful integration. Frameworks like SAMR (Substitution, Augmentation, Modification, Redefinition) and TPACK (Technological Pedagogical Content Knowledge), while valuable for technology adoption broadly, were not designed to address AI's unique characteristics—its generativity, unpredictability, and capacity for co-creation [62], [63]. Second, most models treat AI integration as a linear implementation process rather than an iterative design challenge, failing to account for the need to oscillate between exploring possibilities and converging pedagogically sound applications. As Luckin et al. [64] argue, effective AI integration requires educators to simultaneously understand AI capabilities and reimagine learning design—a dual cognitive demand that linear models inadequately support.

The Double Diamond model addresses these gaps by structuring innovation through four phases—Discover, Define, Develop, and Deliver—alternating between divergent exploration and convergent synthesis. This convergence-divergence rhythm is critical for AI pedagogy because teaching *with* AI (as a tool) and teaching *about* AI (as a subject) require fundamentally different but interconnected design moves. During divergent phases, educators explore AI's affordances and critically examine its societal implications; during convergent phases, they define specific learning objectives and develop assessable implementations. This iterative structure aligns with recent calls for AI literacy frameworks that integrate critical, ethical, and practical dimensions simultaneously [65], [66].

2. Methodology

This paper is situated within the tradition of experience-based scholarship in engineering education, a genre that ASEE has long recognized as a legitimate vehicle for sharing pedagogical innovation and practitioner insight [58]. Rather than testing hypotheses or reporting experimental outcomes, experience papers contribute to the scholarly community by offering structured, reflective accounts of teaching practice that others can learn from, adapt, and build upon. Our work follows this tradition: we report on the process and insights of a multidisciplinary Faculty Learning Community engaged in a shared pedagogical challenge.

2.1 Faculty Learning Communities as Scholarly Practice

Faculty Learning Communities (FLCs) are cross-disciplinary groups of faculty who engage in sustained collaborative inquiry around a shared teaching and learning question over an extended period, typically an academic year or longer [58]. Research on FLCs has demonstrated their effectiveness in promoting pedagogical innovation, fostering interdisciplinary dialogue, and supporting the Scholarship of Teaching and Learning (SoTL) [59]. Our FLC at Worcester Polytechnic Institute comprised seven faculty members from systems engineering, computer science, management information systems, economics, development studies, political science, and geography. The group met regularly during the 2024–2025 academic year to examine how each member was integrating AI into their teaching, with the shared aim of identifying common ground and discipline-specific variation.

The FLC model is well suited to the inquiry reported here because it provides the sustained, structured interaction necessary for collaborative knowledge construction. Unlike one-time surveys or interviews, the FLC format allowed our reflections to develop iteratively—each member's perspective was shaped not only by their own classroom experience but by ongoing dialogue with colleagues whose disciplinary assumptions and pedagogical contexts differed substantially from their own.

2.2 Research Questions

Our inquiry was guided by two research questions:

RQ1: What shared pedagogical principles and challenges emerge when faculty from diverse disciplines integrate AI into their teaching?

RQ2: How do disciplinary epistemologies and professional contexts shape the specific ways AI is conceptualized, taught, and critically engaged with across fields?

These questions reflect the convergence–divergence structure of the paper itself: RQ1 addresses the shared core (convergence), while RQ2 addresses the discipline-specific petals (divergence).

2.3 Approach: Collaborative Reflective Inquiry

Our methodological approach draws on collaborative autoethnography, a qualitative research method in which multiple practitioner-researchers use a shared protocol to systematically examine their own professional practice [60], [61]. In collaborative autoethnography, the unit of

analysis is the practitioners' own experience, and the scholarly contribution emerges from the structured comparison of those experiences across participants. This approach is particularly appropriate for emerging pedagogical phenomena like AI integration, where the field lacks established best practices and practitioner knowledge constitutes a primary source of insight.
Our process unfolded in four phases:

Phase 1 — Protocol Development. Mapping to Double Diamond's *Discover*, the FLC collectively developed a shared reflective protocol organized around two foundational questions: (1) *What is AI in your discipline?* and (2) *What do you teach when you teach AI in your discipline?* The first question invited each contributor to articulate the ontological and epistemological assumptions shaping their discipline's engagement with AI. The second encompassed both content and pedagogy: the concepts, tools, ethical frameworks, and classroom practices through which AI education is delivered. These questions were designed to create structured points of comparison across disciplines while allowing sufficient latitude for each contributor's distinctive voice and concerns.

Phase 2 — Individual Vignette Composition. Mapping to Double Diamond's *Define*, each FLC member independently authored a disciplinary vignette responding to the shared protocol. Contributors were encouraged to ground their reflections in concrete pedagogical practices—specific assignments, classroom activities, and student interactions—rather than offering purely abstract commentary. The vignettes varied in form, reflecting the diversity of the disciplines represented: some centered on detailed teaching cases (e.g., the blockchain compliance exercise in management information systems), while others foregrounded broader disciplinary tensions (e.g., economics' analysis of AI as a general-purpose technology disrupting labor markets).

Phase 3 — Collective Analysis. Mapping to Double Diamond's *Develop*, the FLC engaged in several rounds of reading and discussions using the convergence–divergence framework as an analytic lens. Through this process, we identified recurring themes that constituted the shared core—AI literacy, ethical and risk awareness, governance frameworks, and the tension between teaching *about* AI and teaching *with* AI—as well as the discipline-specific adaptations that formed the divergence petals. The deliberate ordering of contributions in the paper, from technology-centered disciplines (builders) through economics (bridging) to the social sciences (critics), emerged from this collective analysis as a way of making the convergence–divergence pattern visible to readers.

Phase 4 — Iterative Revision. Mapping to Double Diamond's *Deliver,* contributors revised their vignettes considering the collective discussion to strengthen connections to the shared framework and sharpen the points of convergence and divergence that the group had identified. The paper thus reflects not only individual reflection but a layered process of collaborative meaning-making.

2.4 Scope and Limitations of the Approach

As a collaborative study, this work prioritizes depth of practitioner insight and the surfacing of cross-disciplinary patterns over statistical generalizability. The seven vignettes represent a purposive sample of disciplines within a single technological university; they are not intended to be exhaustive or representative of all possible disciplinary engagements with AI. We do not report student outcome data, assessment results, or formal course evaluations, as our focus is on the faculty experience of designing and navigating AI-integrated pedagogy rather than on measuring its effects. Future research should extend this work by examining how the convergence–divergence framework performs across institutional contexts and student populations, and by incorporating systematic collection of student learning outcomes.

3. Framework for Contributions

To ensure coherence across our diverse disciplinary perspectives while preserving the distinctive voice of each contributor, our Faculty Learning Community developed a shared framework to guide individual contributions. This framework asked each member to address two foundational questions. First, *what is AI in your discipline?*—that is, how do you understand or conceptualize AI within the context of your field? This question invites contributors to articulate the ontological and epistemological assumptions that shape how their discipline engages with artificial intelligence, whether as a technical system to be designed, an economic force to be analyzed, or a social phenomenon to be critiqued.

Second, *what do you teach when you teach AI in your discipline?* This question encompasses both content and pedagogy: the concepts, tools, ethical considerations, and policy frameworks that constitute the substance of AI education in each field, as well as the assignments, activities, and classroom practices through which that content is delivered. By grounding each contribution in these shared questions, we aimed to create points of comparison that would reveal both convergence and divergence across disciplines. Another distinction emerged as central to our discussions was the difference between teaching *about* AI and teaching *with* AI. Teaching about AI involves making artificial intelligence itself the object of study examining how it works, what it can and cannot do, and what risks and opportunities it presents. Teaching with AI, by contrast, involves integrating AI tools into the teaching of traditional disciplinary content, whether by permitting students to use generative AI for assignments, designing AI-mediated learning activities, or experimenting with AI as a pedagogical partner. Many contributors address both dimensions, reflecting the reality that AI has become simultaneously a subject of inquiry and an instrument of instruction across the academy.

Organizing the Perspectives. The ordering of disciplinary contributions in this paper reflects a deliberate progression that mirrors our perspective of how AI impacts society. We begin with perspectives from technology-centered disciplines—computer science, management information systems, and systems engineering—where AI is primarily understood as something to be *designed, built, and implemented*. These fields carry a distinct obligation: they produce the systems that other disciplines will analyze, regulate, critique, and apply. Faculty in these areas teach students not only how AI works technically, but also how design choices create downstream consequences for reliability, fairness, and accountability. The convergence here lies in shared concerns about responsible development; the divergence emerges from the technical depth required to understand system behavior and failure modes.

From this technical foundation, we move to economics, which occupies a bridging position between the technical and social sciences. Economics examines AI through the lens of technological innovation and its effects on production, labor markets, and inequality, providing analytical frameworks for understanding how AI reshapes economic structures in ways that parallel earlier general-purpose technologies. This perspective connects the *creation* of AI systems to their *market and workforce impacts*, setting the stage for broader societal analysis.

We then turn to the social sciences such as development studies, political science, and geography where AI is examined primarily as a *social and political phenomenon* rather than a technical artifact. These disciplines interrogate how AI systems interact with power, governance, inequality, and place. Faculty here teach students to evaluate AI critically: to identify bias, question knowledge production, and understand how algorithmic systems can reproduce or amplify existing asymmetries. The convergence lies in shared commitments to AI literacy and ethical awareness; the divergence emerges from the distinct analytical lenses each discipline brings whether examining AI through the frameworks of risk and modernity, democratic accountability and state power, or place-based socio-ecological systems.

This progression—from builders to analyzers to critics—reflects the multidirectional flow of AI's impact across academia. It also embodies the daisy metaphor central to this paper: while each petal represents a distinct disciplinary perspective with its own questions and methods, all remain connected to the shared core of developing AI literacy, ethical awareness, and an understanding of governance frameworks. By presenting these perspectives in sequence, we invite readers to trace how a single technological development is understood, taught, and contested across the diverse landscape of STEM and social science education.

3.1 Computer Science

In my courses, artificial intelligence is understood as the study and construction of computational systems that can learn from data, make predictions, and support decision-making under uncertainty. Rather than treating AI as a single technology or application, I present it as a collection of methods and systems that operate within broader technical and social contexts. This framing emphasizes that AI systems do not exist in isolation; they are shaped by data, design choices, institutional constraints, and the environments in which they are deployed. Within this disciplinary perspective, AI is both a technical and a sociotechnical endeavor. While algorithms and models are central, equal attention is given to how these systems interact with people, organizations, and society. As a result, performance alone is not sufficient for evaluating success. Reliability, transparency, robustness, and accountability are treated as core system properties rather than optional considerations.

This understanding aligns with the broader goal of preparing students not only to build AI systems, but to do so responsibly and with an awareness of their broader impact. This perspective reflects both convergence and divergence within the interdisciplinary landscape of AI education. The convergence lies in shared concerns across disciplines, such as trust in AI systems, ethical use, and the challenges posed by rapid technological change. The divergence emerges from the responsibility placed on technology-centered disciplines to design and implement the systems that others will later analyze, regulate, or apply. Teaching AI in this context therefore carries a distinct obligation to foreground system behavior, failure modes, and downstream consequences.

What I Teach and When I Teach AI. My courses cover the foundational concepts of artificial intelligence and machine learning, with an emphasis on building systems that are reliable, transparent, and socially responsible. Core topics include data representation, feature engineering, model selection, training procedures, and evaluation techniques. Students learn how models are constructed, how learning algorithms operate, and how design decisions affect system behavior in practice. These technical foundations are consistently grounded in questions of trustworthiness, fairness, robustness, and accountability. Responsible AI is not treated as a separate unit or add-on, but is integrated throughout the curriculum. For example, discussions of model evaluation extend beyond accuracy or efficiency to include questions about bias, uncertainty, and performance across different populations. Similarly, conversations about data address not only statistical properties, but also issues of data quality, representativeness, and provenance. Real-world case studies play an important role in connecting theory to practice. Students examine examples of successful AI deployments as well as cases where systems failed or caused harm. These cases are used to explore ethical trade-offs, governance challenges, and the limits of purely technical solutions. By engaging with concrete examples, students develop a more nuanced understanding of how AI systems behave outside controlled settings and why responsible design requires ongoing reflection.

Pedagogy and Learning Activities. I use a hands-on, student-centered teaching approach that combines coding, system design, and critical engagement with research. Interactive coding workshops are a core component of the courses. In these sessions, students implement algorithms, experiment with models, and explore how changes in data or parameters affect outcomes. Guided practice helps students build intuition and confidence while reinforcing foundational concepts. Students also complete projects that emphasize end-to-end AI system development. These projects require students to engage in problem formulation, data analysis, model development, and evaluation. Importantly, projects include explicit reflection on potential impact and risk. Students are asked to consider who might be affected by their systems, what assumptions are embedded in their design choices, and how failures or misuse could occur. This structure reinforces the idea that technical competence and responsible practice are inseparable. In addition to practical work, students read and discuss research papers to engage with current developments in the field. These discussions focus on understanding new methods, evaluating empirical claims, and connecting theoretical advances to practical applications. By learning how to read and critique research, students develop skills that allow them to adapt to a rapidly evolving field and to assess new tools and techniques beyond the classroom.

Teaching With Generative AI. I include a clear and intentional generative AI policy in my courses that frames AI tools as learning aids rather than substitutes for student effort. Students are taught when and how generative AI can be used responsibly, such as for brainstorming ideas, debugging code, or exploring alternative approaches. At the same time, they are required to demonstrate their own understanding, reasoning, and original contributions. We explicitly discuss how generative AI is changing the way artificial intelligence itself is taught and practiced. These discussions address issues such as overreliance on automated tools, the need for verification and validation of AI-generated outputs, and the shifting boundaries between human expertise and machine assistance. By making these dynamics visible, students are better equipped to use generative tools thoughtfully rather than uncritically. This approach also prepares students to use AI tools across other courses and disciplines. By emphasizing foundational knowledge, clear reasoning, and critical evaluation, students gain skills that transfer beyond any specific tool or platform. The goal is not mastery of current systems alone, but the ability to adapt, assess limitations, and use AI responsibly in diverse academic and professional contexts.

Contribution to the Convergence–Divergence Framework. This perspective illustrates how AI functions as both a unifying and differentiating force within academia. Shared challenges, such as maintaining academic integrity, supporting learning, and governing AI use, create points of convergence across disciplines. At the same time, differences in how AI is developed, taught, and applied generate meaningful divergence. By foregrounding system design, hands-on learning, and responsible practice, this contribution highlights the specific role of technology-centered disciplines within the broader conversation. It demonstrates how shared inquiry and collaborative learning can coexist with discipline-specific responsibilities, reinforcing the value of multiple perspectives in understanding and teaching artificial intelligence.

3.2 Management Information Systems

Consider a farmer with decades of experience cultivating and harvesting quality produce. When introduced to new farming tools and technologies—satellite imaging, precision irrigation, soil sensors—with appropriate training, they markedly increase their yield while maintaining quality. The technology amplifies existing expertise; it does not replace it. AI functions similarly in education: without the foundational knowledge and practical experience of the discipline—the "soil quality" of the learner's understanding—the tool produces less desirable outcomes.

As Kissinger et al. [1] observe, new technology has been developed, but remains in need of a guiding philosophy. The farmer without understanding of seasons and soil cannot simply operate machinery to success; the student without disciplinary foundations cannot simply query an AI to mastery. Lee [7] reinforces this point in *AI Superpowers*, arguing that the future belongs not to those who can merely use AI but to those who can determine when and how AI should be used—and when human judgment must remain paramount.

This analogy illuminates two critical pedagogical challenges in STEM education: the imposition challenge and the scaffolding challenge. The imposition challenge involves force-feeding AI knowledge without the practical experience of its implications creates shallow competency. Students learn to prompt but not to critique; to generate but not to evaluate. When AI produces plausible-sounding technical documentation, students without foundational understanding cannot distinguish accurate analysis from sophisticated hallucination. The tool becomes a crutch rather than an amplifier. The scaffolding challenge begs the question of how we sequence learning so that AI augments rather than replaces the development of fundamental understanding? The answer lies in establishing what constructivist learning theory calls "prior knowledge structures"—the cognitive frameworks that allow new information to be meaningfully integrated [8]. Without these structures, AI-generated content has nothing to attach to; it remains surface-level information rather than integrated knowledge.

I address these challenges in the context of teaching blockchain technology to STEM students, predominantly information systems and fintech students. Here, history offers a powerful pedagogical scaffold. The evolution of money—from barter to commodity currency to coinage to paper money to digital transactions to blockchain—provides more than a historical narrative; it offers a model for understanding technological transformation itself [9]. The barter system was constrained by the "double coincidence of wants"—two parties each needing what the other possessed [10]. This inefficiency drove innovation toward standardized value exchange. Currency solved this problem by creating a shared medium that held value independently of the specific goods being traded. But currency required trust in intermediaries (banks, governments, mints) who guaranteed that value.

Similarly, traditional database systems faced their own "double coincidence"—the need for mutual trust between transacting parties and centralized authorities. When two parties wish to exchange value digitally, they typically rely on a trusted third party (a bank, a payment processor, a central database administrator) to verify the transaction. Blockchain technology, like the invention of currency, solves this "double coincidence of trust" through a new paradigm: decentralized consensus that establishes trust without requiring parties to know or trust each other directly; giving rise to use cases in cryptocurrencies, tokenization and new forms of ownership.Students are introduced to my blockchain class through cryptographic hashing, Merkle trees and consensus mechanisms which are at the heart of a new architecture of trust – algorithmic trust. Traditional trust mechanisms underlie historical barter trade systems, the Buttonwood Tree Agreement – the 18th-century foundations of the New York Stock Exchange – to the current financial systems. Questions such as: *What problem did currency solve? What new problems did it create? What intermediaries emerged, and why?* are posed to students. This historical scaffolding—what Kolb [8] calls "experience as the source of learning"—prepares students to understand blockchain not as novel technology but as the latest iteration in humanity's ongoing negotiation between trust, value, and verification. This scaffolding proves essential when AI enters the learning environment. Students who understand the historical evolution of trust mechanisms can critically evaluate AI-generated analyses of blockchain systems. They recognize when AI oversimplifies the relationship between decentralization and trust; they identify when AI-generated compliance analyses miss the nuance of regulatory frameworks designed for centralized systems. The "soil knowledge" of historical context enables them to use AI as the farmer uses new equipment—skillfully, critically, and in service of outcomes that the tool alone cannot achieve.

Vignette: The HealthData Token Project. The following vignette illustrates an internalized convergence-divergence framework in practice, demonstrating how AI-augmented learning can surface compliance gaps that students—working without foundational preparation—would likely miss. The HealthData Token Project is one of three module projects undertaken by the students. The others are a cross-border payment system project (GlobalRemit Project) and a real estate tokenization project (FractionalEstate Project). The compliance analysis constitutes one aspect of deliberate AI use in my class.

The Scenario. A student team in *my* business applications of blockchain technology course was tasked with designing a data tokenization platform for a hypothetical healthcare startup. The concept: patients would own tokens representing their health data and could selectively share (or sell) access to researchers, pharmaceutical companies, and healthcare providers. The team's initial design was technically sophisticated—they proposed a permissioned Ethereum-based blockchain with smart contracts governing data access, off-chain storage for actual health records, and a token economy that would compensate patients for data sharing.

Phase 1: Pre-AI Foundation (Divergence). Before engaging any AI tools, students completed a regulatory mapping exercise using course materials and independent research. They identified HIPAA as the primary framework for U.S. health data, noted ISO 27001 requirements for the information security management and acknowledged GDPR implications for any European data subjects [11] , [12]. Their initial architecture addressed several compliance considerations: encryption at rest and in transit, role-based access controls, and audit logging for all data access. The team felt confident they had designed a compliant system.

Phase 2: AI-Augmented Analysis (Convergence). Following the scaffolding principle, students then used AI tools to conduct structured compliance analysis. The prompt framework I provide for the team required them to describe their architecture in detail and request specific analysis against HIPAA, GDPR, ISO 27001, and- the NIST AI Risk Management Framework [13]. The AI analysis surfaced three critical gaps the team had not considered:

Gap 1: The “Right to Be Forgotten” Paradox The AI identified a fundamental tension: blockchain's immutability conflicts directly with GDPR Article 17 (the "right to erasure"). If a patient's data access history is recorded on an immutable ledger, how can it be "forgotten"? The team had not considered this because their mental model—shaped by the benefits of immutability for data integrity—had not encompassed regulatory frameworks designed for systems where deletion is possible.

Gap 2: The Secondary Use Problem The team had designed their consent mechanism as a binary switch: patients could grant or deny access. The AI analysis surfaced the HIPAA "minimum necessary" standard and GDPR's purpose limitation principle, revealing that their design failed to distinguish between initial consent and secondary uses. A patient who tokenizes their diabetes data for a clinical trial might not have consented to that same data being used to train an AI model for drug pricing optimization.

Gap 3: AI in the Loop Most striking: the team's design included a smart matching algorithm to connect patients with researchers using smart contracts in blockchain. The AI they used for compliance analysis identified that this matching algorithm was itself an AI system requiring NIST AI Risk Management Framework (RMF) compliance—a recursive oversight they had completely missed [13]. Their use of AI to analyze compliance had revealed that their system would itself require AI governance that they had not planned for.

Phase 3: Critical Evaluation and Revision. The pedagogical value emerged not from the AI's analysis alone but from the students' subsequent critical evaluation. They verified the GDPR immutability concern against primary sources and discovered the AI had accurately represented the tension. However, they also found that the AI had overstated the HIPAA implications for certain token structures—the AI's analysis assumed the tokens would contain Protected Health Information (PHI) when the team's design had tokens contain only access pointers, not the data itself. This critical evaluation demonstrated the convergence outcomes in action: AI literacy (recognizing both the value and limitations of AI analysis), ethical awareness (understanding the societal implications of their design choices), and standards framework application (using NIST AI RMF as an evaluation lens) [13].

Outcomes. Two categories of outcomes were observed. (1) The team revised their architecture to include: crypto-shredding capability (destroying encryption keys to effectively "delete" data even if the encrypted data remains on-chain), granular consent management with purpose limitation built into smart contracts, and a NIST AI RMF-compliant governance framework for their matching algorithm. Their final presentation explicitly credited the AI-augmented analysis while also documenting where human judgment had corrected or refined the AI's output. (2) The recursive paradox—students using AI to find compliance gaps while remaining blind to the compliance gaps AI creates. Three specific, concrete AI failures that students encountered included: The Phantom Standard (IEEE 2418.2 mischaracterization), The Jurisdictional Collapse (Travel Rule thresholds flattened for data tokens that could be security-classified and transacted across jurisdictions), and The Temporal Confusion (conflating two regulations). Students who skipped scaffolding produced work that looked better but demonstrated worse judgment. This is counterintuitive and important—it challenges assessment practices, not just pedagogy.

Connecting to the Converge-Divergence Framework. The paper's convergence-divergence framework provides a useful lens for blockchain pedagogy with AI integration.

Convergence (Core). Across my fintech and information systems courses, certain AI-related outcomes apply universally: (1) AI literacy **-** students must develop effective prompting skills, ability to critique AI outputs, and awareness of AI limitations—particularly hallucinations in technical contexts where precision matters. (2) Ethical and risk awareness - Blockchain's promise of decentralization raises questions about regulatory compliance, environmental impact, and financial inclusion that AI can help explore but not resolve and (3) Standards alignment - the NIST AI Risk Management Framework, among others, provides a structure for evaluating AI use in professional contexts, teaching students to "govern, map, measure, and manage" AI-related risks.

Divergence (Petals). Discipline-specific applications emerge; in the Blockchain course, designed for Business majors, especially Information Systems and Fintech students, AI assists with regulatory compliance analysis and risk modeling for blockchain-based financial products. AI also supports requirements documentation and stakeholder communication for enterprise blockchain implementations. In data tokenization projects, students use AI to evaluate compliance against ISO 27001 (information security), IEEE blockchain standards, and emerging data governance frameworks.

Lessons Learned. Three insights have emerged from integrating AI into blockchain education: (1) Sequence matters - introducing AI before foundational concepts produces students who can generate plausible-sounding technical documentation but cannot evaluate its accuracy. The farmer must understand soil before operating the tractor. (2) Trust requires understanding - just as blockchain enables trustless transactions through transparent consensus mechanisms, effective AI use in education requires students to understand *how* AI generates outputs—not to trust blindly but to verify critically. (3) Standards provide scaffolding - frameworks like NIST AI RMF give students concrete criteria for evaluating AI use, moving discussions from abstract concerns ("Is AI good or bad?") to practical assessment ("Does this use case satisfy governance requirements?").

Concluding Remarks on Constructive Engagement. The barter-to-blockchain parallel that structures my blockchain education approach exemplifies our convergence-divergence framework in action. Historical scaffolding establishes the foundational understanding that enables critical AI use; AI augmentation surfaces considerations that human analysis alone might miss; critical evaluation distinguishes valid insights from plausible errors. The farmer's knowledge of soil enables effective use of new equipment; the student's knowledge of trust mechanisms enables effective use of AI analysis tools.

The contribution of this section— a portable framework in a technical class, pedagogical strategies, and lessons learned—emerges from the recognition that we cannot avoid AI's transformation of education. We can only choose whether to engage that transformation intentionally, grounded in disciplinary expertise and ethical reflection, or allow ourselves to be shaped by technological forces we do not understand and cannot evaluate. The choice, as Kissinger suggests, is ours. The framework we propose aims to ensure that choice is informed.

3.3. Systems Engineering

When I teach systems engineering, I frame AI through the two domains widely recognized in the field: AI4SE and SE4AI. AI4SE focuses on using AI—especially machine learning and language model-based tools—to enhance systems engineering practice. These tools help automate routine engineering tasks, scale model construction, and support design exploration, improving both efficiency and accessibility in engineering workflows. SE4AI, on the other hand, applies systems engineering principles to AI-native and learning based systems, where challenges like safety, robustness, explainability, and lifecycle evolution demand rigorous engineering approaches beyond traditional software verification [14].

In my courses, I emphasize AI literacy, so students understand how AI behaves and how it fits within larger systems. This includes the basics of machine learning, typical AI failure modes, and the implications of nondeterministic system behavior, which aligns with foundational descriptions of AI systems and their engineering challenges. I also use AI tools directly in the classroom—not as shortcuts, but as learning partners. Language model tools help students draft and refine system requirements, interpret documentation, and critique engineering artifacts. These uses reflect current AI4SE applications such as requirements of synthesis, architecture generation, and model interpretation that are already influencing SE practice [13], [14].

A major part of my teaching focuses on critical evaluation of AI systems, which is central to SE4AI. I teach students how to approach verification and validation for systems whose behavior emerges from data rather than explicit programming. We discuss explainability, safety analysis, and the need for system level thinking when dealing with autonomous or AI enabled components, reflecting documented SE4AI challenges in verifying AI intensive systems across diverse operational scenarios.

Risk analysis is another essential theme. I rely on the NIST AI Risk Management Framework to help students structure their thinking about trustworthy AI [13]. The framework's functions—Govern, Map, Measure, and Manage—provide a practical way for them to identify risks, assess impacts, and propose mitigation strategies for AI enabled systems. This aligns with NIST's goal of helping organizations address safety, transparency, fairness, and other dimensions of AI risk throughout the lifecycle of a system [13]. By integrating the NIST AI RMF into coursework, students gain hands-on experience applying an industry adopted approach to the uncertainties inherent in nondeterministic AI models. Overall, my goal is to help students understand both how AI can improve systems engineering practice and how systems engineering must evolve to responsibly design and evaluate AI native systems.

3.4 Economics

AI as a Technological Innovation in an Economic FrameworkIn my economics courses, I frame artificial intelligence (AI) as part of the long historic trend of technological innovations that transformed production. Just as past technological breakthroughs such as agriculture, the steam engine, electrification, computing, and the Internet changed production and organizational structures, AI represents the next major shift in how economies produce goods and services. This perspective allows students to apply established economic frameworks to understand AI rather than treating it as an unprecedented technological anomaly. This approach is consistent with recent research emphasizing AI as a general-purpose technology with broad, economy-wide implications [15].

As with many earlier technologies, AI's economic effects are felt across industries and occupations. Research shows that AI exposure varies widely based on the cognitive, physical, and social skills required by jobs. For instance, while high-wage occupations are often more exposed to AI, they are typically complemented rather than replaced, because AI supports peripheral "side skills," increasing worker productivity [16]. Low-wage occupations, in contrast, may face substitution risks if their core tasks fall within AI's capabilities, especially in structured cognitive or routine administrative work.

Business Model Transformation and Hard-to-Predict Innovation I emphasize to students that any attempts at predicting AIs future business impact mirrors the uncertainty seen in past technological epochs. The early Internet era, for example, gave little indication of what would later become e-commerce, ridesharing, or global gig work. AI is likely to follow this pattern of radical but unpredictable business model innovation. Research on generative AI suggests that productivity enhancements and task redistribution inside firms vary significantly depending on the concentration of tasks exposed to AI [17]. These dynamics imply that entirely new complementarities and industries may emerge as AI becomes integrated across sectors. Labor Market Impacts: Augmentation vs. Substitution. Economics offers a useful framework for understanding how technological change shapes labor outcomes.

I teach students that new technologies can influence work in two ways: they may augment workers, boosting productivity and wages, or substitute for labor, reducing the demand for certain skills. Empirical studies on AI show that these two effects coexist, varying by occupations and skill levels. Research on AI-driven automation find strong substitution effects for structured cognitive tasks, whereas jobs involving human-machine collaboration tend to experience rising demand and skill complexity [18]. A related literature further distinguishes between automation-oriented AI and augmentation-oriented *AI.* Automation AI suppresses new job creation and depresses wages in low-skilled occupations, while augmentation AI increases the emergence of new work tasks and raises wages for high-skilled worker*s* [19]. Introducing this distinction helps students think more granularly about occupational exposure to AI *and* the implications for future workforce development.

Inequality and Potential Bubbles. AI also raises distributional questions: who benefits from productivity gains? Historical evidence suggests that technological change often increases inequality before any potential leveling effects. In class, I draw parallels to the Internet-driven inequality patterns of the 1990s and early 2000s, where high-skill workers experienced strong wage gains while routine work was automated. I also discuss the possibility of speculative bubbles analogous to the dot-com era. Given the rapid capital inflows into AI startups and infrastructure, there is a reasonable concern that investors may be overestimating future returns, a pattern that mirrors past technological cycles even though its magnitude and timing remain uncertain.

AI's Impact on Teaching Economic. AI also reshapes how we teach economics. Introductory economics courses rely heavily on conceptual explanations, graphical intuition, and basic algebra, all of which are tasks that generative AI models perform competently. Studies on AI in education show that generative tools already provide writing assistance, summarization, and real-time explanation [20]. Because AI can reliably generate coherent explanations and essays on standard economic concepts, traditional assignments that rely on students recalling material and writing essays no longer provide a meaningful measure of student understanding. At advanced levels, however, economics becomes mathematically intensive, requiring precision and conceptual accuracy. These instructional challenges point toward the need for redesigned assessments. In my own teaching, I integrate AI into coursework rather than restrict its use. For open-ended questions, students are free to consult AI tools, but they must then explain their answers during class discussion, ensuring that they understand any AI-supported reasoning. I also design comparative exercises in which some student teams complete tasks with AI assistance while others work without it, allowing them to directly observe the efficiency gains that AI will create in real workplace environments.

Implications for the Business Model of Universities. AI challenges traditional university business models by reshaping both what we teach and how we teach it. As AI changes labor-market skill requirements, universities must adapt curricula accordingly. At the same time, AI forces us to rethink the value of traditional instruction and assessments. Our systems-theoretic analysis [21] shows that higher education institutions face reinforcing pressures: technological adoption, competitive dynamics, and student expectations form interacting feedback loops that can either strengthen or destabilize institutional models. Ultimately, the evolution of universities under AI will mirror the evolution of firms: those that learn to leverage feedback loops, data capabilities, and new pedagogical models will adapt successfully, and those that do not risk obsolescence.

3.5 Development Studies

In the current phase of widespread adoption, generative artificial intelligence (AI) has become an unavoidable tool in higher education, comparable to earlier general-purpose technologies such as calculators or statistical software. However, unlike these predecessors, generative AI introduces novel epistemic, ethical, and cognitive risks that require deliberate pedagogical engagement rather than uncritical adoption. Emerging studies suggest that how AI, particularly large language models (LLMs), is used can influence patterns of cognitive engagement, including creative and critical thinking [22]. At the same time, generative AI systems are probabilistic rather than truth-seeking: they frequently produce plausible but incorrect, incomplete, or biased outputs, underscoring the need for structured critical oversight in classroom use [23].

To operationalize this pedagogical challenge, the Double Diamond design model, using its iterative cycles of divergence and convergence to structure how students explore, interrogate, and refine AI-generated knowledge. The first diamond emphasizes problem discovery and exploratory engagement with AI outputs, while the second diamond focuses on critical synthesis and application, enabling students to move from expansive inquiry to disciplined evaluation. Within the convergence–divergence framework proposed , social science pedagogy occupies a distinctive position. While I do not teach AI as a technical subject, my courses integrate AI in two broad ways: as an object of inquiry and as a practical tool for understanding how technology shapes society, governance, inequality, and development more generally. This approach aligns with the convergence core of AI literacy, developing students' ability to use AI effectively while critically evaluating its limitations, and ethical and risk awareness. Drawing on sociological theories of risk and modernity [24], [25] classroom discussions situate AI within broader debates about uncertainty, reflexivity, and technological governance in late modern societies.

A central pedagogical strategy involves making AI's limitations visible through structured classroom activities. For example, students are divided into two groups: one uses AI tools to answer a set of analytical questions, while the other works without AI support. The outputs are then compared and collectively evaluated. This exercise reveals that while AI often generates seemingly coherent, generalizable knowledge, its responses are frequently shallow, internally inconsistent, or factually incorrect, particularly when queries concern non-Western contexts. This exercise corresponds to the divergent phase of the first diamond, where multiple interpretations and outputs are surfaced, followed by a convergent phase in which students collectively critique and refine conclusions through evidence-based discussion.

In practice, AI-generated content tends to privilege Western-centric data sources and perspectives, often marginalizing or misrepresenting knowledge from the Global South. In this activity, we also observed that students without AI tools tend to remember what they wrote and respond more critically than students using AI tools. By engaging AI both as a tool and as a subject of critique, this pedagogical approach reinforces the divergence dimension of the framework, demonstrating how disciplinary contexts shape AI use and interpretation. For social science students, the emphasis is not on technical optimization but on epistemic vigilance: questioning sources, identifying bias, and understanding how algorithmic systems reproduce existing global power asymmetries. In this way, AI becomes a catalyst for deeper learning about knowledge production, inequality, and ethical responsibility rather than a substitute for critical thought.

3.6 Political Science

What is AI in Political Science? Generally, in political science, AI occupies a unique position because it is simultaneously a methodological tool, an object of governance, and a force reshaping geopolitical power. This framing reflects the discipline's core concern with how power is distributed, contested, and legitimized [26], [27]. In my courses, I conceptualize AI through these three lenses as well. In terms of this broader paper and contributions to the convergence–divergence framework, the convergence lies in shared concerns across disciplines—AI literacy to understand what AI can and cannot do, ethical awareness to recognize potential harms, and engagement with governance frameworks. The divergence emerges in political science's distinct focus on power: who controls AI systems, whose interests they serve, and how they reshape relationships between states, corporations, and citizens [28], [29]. Where computer science often asks, "How do we build trustworthy AI?", political science asks, "trustworthy for whom, and accountable to which democratic institutions?" [30].

AI as a Research Tool. AI as a research tool most often appears in political economy and electoral studies, where researchers use machine learning and data science methods to model voting behavior, forecast political outcomes, and analyze large-scale political and economic data [31], [32]. These tools allow scholars to identify patterns in voter turnout across thousands of precincts, detect shifts in public opinion using large survey datasets, and examine how economic shocks—such as inflation, unemployment, or housing instability—shape political preferences over time. AI is also increasingly used in text-as-data approaches to analyze political communication, including speeches, party platforms, legislative debates, news coverage, and social media content, enabling systematic study of framing, polarization, and misinformation at scale [33].

While these methods expand what political scientists can study empirically, they also demand methodological caution. Scholars must interrogate the assumptions embedded in models, the quality and representativeness of training data, and the distinction between prediction and explanation [34]. Datasets may underrepresent marginalized communities or reproduce institutional biases, and highly accurate predictions do not necessarily imply causal understanding [35]. For this reason, I emphasize that AI should strengthen rather than replace core political science skills such as theory building, careful measurement, transparency, and interpretive judgment [31].

AI as a Subject of Study. AI is also a central object of political study as societies grapple with how to govern emerging technologies. Political scientists examine how AI raises fundamental questions about rights, privacy, intellectual property, and the concentration of power in technology firms [29], [36]. Contemporary regulatory efforts—including the European Union's General Data Protection Regulation (GDPR), the California Consumer Privacy Act (CCPA), the EU AI Act, and proposed U.S. legislation—reflect ongoing attempts to balance innovation with democratic accountability and risk management [37], [38]. A key concern I emphasize in teaching is how AI, particularly generative AI, can homogenize thought by privileging algorithmically mediated knowledge over independent critical analysis, potentially narrowing the range of perspectives necessary for democratic deliberation [39], [40].

Political scientists also study AI as a geopolitical force that is reshaping how states project power, manage risk, and compete for influence [41]. In international relations, AI is embedded in military applications ranging from autonomous and semi-autonomous weapons systems to drone warfare, often compressing the time available for human judgment in crisis situations [42], [43]. AI has also become central to economic competition—particularly in U.S.–China–Russia technological rivalry—as states seek advantages through control over semiconductors, computing infrastructure, data access, and standard-setting institutions [44]. At the same time, AI is expanding state surveillance capacities through biometric identification, predictive analytics, and automated risk scoring systems that affect immigrants, travelers, and citizens [45]. These developments raise disputes over international norms, including what should be restricted or banned, how violations can be monitored, and who bears responsibility when AI systems cause harm—ultimately challenging traditional concepts of sovereignty, security, and international cooperation in international relations theory [47].

Teaching AI in Political Science. In my courses AI is not treated as a niche topic or technical aside. Instead, it is treated as both subject matter and analytical lens. In terms of comparative AI Governance, students examine how different political systems regulate and implement AI, comparing the EU's rights-based frameworks, the U.S.'s market-driven approach, and China's state-centric model [37]. Rather than memorizing policies, we explore how institutions and political values shape regulatory choices and what these choices reveal about broader theories of rights, risk, and responsibility. I also have students look at AI and Democracy to explore how algorithmic systems impact participation, representation, and deliberation in democratic contexts [46], [48]. Topics include AI-generated political content, microtargeted ads, algorithmic curation, and their implications for informed citizenship. The focus is on democratic accountability: how political information is mediated, manipulated, or distorted by AI systems.

Additionally, I focus on and teach about technology and international security. Students study the use of AI in autonomous weapons, surveillance, and cyber operations. Discussions focus on how AI changes timelines in crisis decision-making, expands surveillance capabilities, and blurs boundaries between military, intelligence, and commercial domains. The aim is to understand how technological competition affects global security, alliances, and state sovereignty. Another area of interest in my classroom is how AI impacts inequality and justice. From a political economy perspective, students analyze who benefits from AI and who bears the costs. They examine issues such as algorithmic bias, displacement, and surveillance, especially in marginalized communities [40], [49]. This section reinforces that bias is not just technical but political, rooted in decisions about data collection, institutional practices, and governance priorities. Overall, my core pedagogical principle is teaching students to interrogate AI systems as producers of knowledge. Students learn to ask: Whose data underpins these models? What assumptions guide their design? What incentives shape their outputs? This builds a critical orientation toward AI's role in shaping public knowledge and decision-making.

Teaching *With* AI: Experiential Learning. In terms of teaching with AI, my approach is to engage students in experiential learning through project-based activities. Particularly, in my research methods course, I have students use AI tools to find papers related to their research topic, create a literature review map using an AI tool to connect bodies of literature together, and edit their work using AI tools, etc. Students begin with traditional research, using policy documents and scholarly literature to build foundational knowledge [23]. Then they bring in generative AI to draft position papers, explore counterarguments, and simulate scenarios. I try to have students use AI to augment preparation for their literature review papers but not replace their own analysis of the literature.

Another assignment I have students do in my Science-Technology Policy course is select a generative AI system used in a political or governmental context. They begin with traditional research, documenting the system's purpose, data, and controversies. Then, they use AI tools to explore stakeholder perspectives, legal frameworks, and potential unintended consequences. The key task is to have students critically assess where AI-generated content aligns or diverges from established research [30]. They identify hallucinations, omissions, and political blind spots, especially around non-Western or marginalized contexts. The final deliverable is a policy brief recommending reforms, with clear attribution of what insights came from students versus AI tools. This process reinforces disciplined engagement and critical independence.

Implications for the Convergence–Divergence Framework. Political science contributes to convergence by promoting ethical and risk awareness around AI, connecting classroom learning to real-world governance frameworks, and prioritizing critical evaluation over tool proficiency. At the same time, it enriches divergence by centering power, accountability, and democratic legitimacy. Political science treats AI not just as a technical tool but as a geopolitical and institutional phenomenon. It helps students see that governance is a political process shaped by competing interests, ideologies, and institutional contexts. Ultimately, as mentioned previously, the discipline brings a necessary complement to technical and economic perspectives by foregrounding the question: Who governs AI, in whose interest, and with what mechanisms of accountability?

3.7 Geography

The discipline of geography embodies the tensions that accompany generative artificial intelligence. The discipline embraces innovative technologies, such as geographic information systems and remote sensing, that support advanced spatial analysis, enable real-time environmental monitoring and provide immersive and interactive learning experiences. The increasing availability of geographic big data, computer vision, machine learning and cloud computing expands the potential for geographic inquiry and situates geography at the center of the big data paradigm [50], [51]. On the other hand, the discipline's emphasis on place-based knowledge production, epistemic justice, social amplification of risk, the distal causes of economic and technical transformation, and the ways in which power operates through knowledge systems, positions geography to track the challenges and concerns that accompany ai as these emerging technologies transform communities, landscapes and climate. In this transformative moment, how can these multitudes within geography be accommodated through curriculum, pedagogy, assessment, and experiential learning? What are the opportunities of ai-integrated pedagogy in geography, and what objectives in geography education are not well served by ai integration? How is and should geography pedagogy be adapting in this disruptive moment in higher education?

My own teaching mobilizes geography in a particular way, and this shapes the implications around AI integration in my teaching. Working within a department of Integrative and Global Studies, which provides coursework and mentoring for a required project-based learning experience for engineering undergraduates, I draw on socio-technical systems, economic geography, development studies, applied geography, and community engaged and participatory research approaches to help students develop advanced framing of the social, technical and environmental context for the projects, which they students carry out as part of a team, working in partnership with community or civic organizations. The teams must situate their organization's research or design goals within this context, and engage with actors across the project ecosystem to understand particular elements of place, system and organization that are relevant to their project goals. I teach skills including research design and methods, qualitative and quantitative analysis, community engagement, project management, teamwork and leadership, and professional communication. Within the structure of these frameworks and skills, teams themselves pursue expertise in the areas germane to their projects – green infrastructure, water and sanitation planning, early childhood education, emergency management, exhibit design – integrating applied geography and design.

The use of technology is usually encouraged in project-based learning as the aim for students is to draw from available approaches, strategies and tools in an integrative manner to address an authentic project need [52]. Innovative, applied geographic tools for spatial analysis and visualization are powerful resources for teams, and are often requested by partner organizations. In Melbourne, Australia, a team partnered with a suburban municipality who sought to develop a drone-based invasive weed monitoring program using machine-based image interpretation [53], [54], while another team created AI-driven immersive photospheres to visualize heat risk in the central city. This action-learning approach allows students to develop AI skills by applying technologies in authentic project environments. The hands-on experience with technologies in authentic project environments demystifies AI, builds confidence in applying new technologies and allows students to gain a sense of agency, purpose and empowerment in the face of this transformative technological change [55].

Project based learning also provides ample opportunity for cultivating critical AI literacy. The application of emerging technologies highlights the risks, disruptions and concerns that attend to new technologies as they touch down in communities, landscapes and organizational realities. Impacts of data processing and data storage on water and energy resources. energy. transition in the energy-economy regime, and that the implications for landscapes, Earth systems and human geographies. Will the geographies of this emerging ai economy reflect the systems of extraction, pollution and centralized control, or can these technologies support democratic governance and the empowerment of people and communities. Thinking critically about the implications of AI is inescapable within the context of authentic project environments. Students learn to incorporate diverse cultural and place-based considerations and interdisciplinary perspectives, which is critical for building technological systems that avoid hidden bias and inadvertent harm.

Students are required to think critically about multiple aspects of a complex socio-technical-environmental context, to apply novel, creative approaches to understand the problem and design solutions. How do we treat these system level questions seriously in teaching while helping students mobilize new technologies to facilitate accomplishing project goals that will support the partner organization? If we take seriously these systemic critiques, we are able to develop interventions that are more-attuned to the geographic context and more supportive of community partner goals. The objective for students is that they emerge with critical ai literacy, a sense of agency and confidence in a rapidly changing world, and a well-informed, ethical perspective on that world, At a much finer scale, generative AI creates quandaries for the individual learner. Are their ways to participate in AI without compromising data security and privacy? Can we enlist machines to transcend limits on our cognitive capacities without compromising our ability to develop and communication concepts ourselves? This AI-integrated, project-based applied geography and design approach requires navigating ethical quandaries as they play out in real time across scales.

4. Discussion and Conclusion

This paper has presented a convergence-divergence framework for integrating artificial intelligence into STEM and social science education, drawing on the collaborative inquiry of a Faculty Learning Community at Worcester Polytechnic Institute. Through the metaphor of the daisy—a shared core surrounded by discipline-specific petals—we have illustrated how AI functions simultaneously as a unifying and differentiating force across the academy. The convergence core encompasses AI literacy, ethical and risk awareness, and familiarity with governance frameworks such as the NIST AI Risk Management Framework. The divergence petals reflect the distinct ways each discipline conceptualizes, teaches, and critically engages with AI, from the design imperatives of computer science and systems engineering to the critical interrogations of economics, development studies, political science, and geography. This framework offers practical guidance for faculty advising project-based learning, providing shared vocabulary and assessment strategies while honoring discipline-specific expectations for how AI competencies manifest in practice.

4.1 Theoretical Contribution: A Multi-Level Integration of Design Frameworks

Beyond the empirical findings from our Faculty Learning Community, this paper offers a theoretical contribution to the emerging field of AI pedagogy: a multi-level integration of the Double Diamond design model and the daisy convergence-divergence framework. Existing AI-in-education models suffer from two interrelated limitations. First, many frameworks adopt a predominantly tool-centric perspective that treats AI as an instructional delivery mechanism or an efficiency enhancer, neglecting the deeper pedagogical transformations required for meaningful integration. Frameworks such as SAMR (Substitution, Augmentation, Modification, Redefinition) and TPACK (Technological Pedagogical Content Knowledge), while valuable for technology adoption broadly, were not designed to address AI's unique characteristics—its generativity, unpredictability, and capacity for co-creation [62], [63]. Second, most models treat AI integration as a linear implementation process rather than an iterative design challenge, failing to account for the oscillation between exploring possibilities and converging on pedagogically sound applications that effective AI integration demands [64].Our contribution addresses these gaps by demonstrating that the Double Diamond and the daisy metaphor operate on complementary axes, and their integration reveals the multi-layered complexity inherent in AI pedagogy. We propose an integrative framework showing how these frameworks interact at three distinct levels:

At the macro level (institutional and faculty community design), the Double Diamond describes the process through which cross-disciplinary communities—such as our Faculty Learning Community—discover, define, develop, and deliver shared frameworks for AI education. The daisy is both the input to and the output of this process: we began with disciplinary perspectives (petals) and through iterative divergence and convergence, we articulated shared foundations (the core) while refining discipline-specific applications. Our FLC's collaborative inquiry enacted this structure: we diverged in exploring how AI functions in each field (Discover), converged on shared principles of AI literacy, ethical awareness, and governance frameworks (Define), diverged again as each member developed classroom applications suited to their disciplinary context (Develop), and converged through collective analysis and iterative revision that produced this paper (Deliver). The daisy framework is thus a methodological outcome of Double Diamond-structured collaborative inquiry. This macro-level integration aligns with educational design research emphasizing iterative, context-sensitive approaches to curriculum development [67].

At the meso level (course and pedagogical design), the Double Diamond structures the pedagogical experience within each disciplinary petal. When students engage with AI in a course—whether in systems engineering, economics, or political science—they move through iterative cycles of exploration and synthesis. In the first diamond, students discover AI's capabilities, limitations, and implications (divergent), then define specific problems, applications, or ethical tensions to address (convergent). In the second diamond, students develop AI-integrated solutions or critical analyses (divergent), then deliver refined, ethically-grounded outputs that have been tested against disciplinary standards and governance frameworks (convergent). The vignettes presented in this paper illustrate this pedagogical enactment: the MIS blockchain class compliance exercise (Section 3.2) guides students through the discovery of regulatory gaps, the definition of compliance requirements, the development of architectural revisions, and the delivery of governance-aligned designs. Similarly, the Development Studies classroom exercises (Section 3.5) structure divergent engagement with AI-generated outputs followed by convergent critical synthesis through evidence-based discussion.

At the meta level (epistemological complexity), the deliberate employment of two distinct metaphors reflects the irreducible complexity of AI education itself. The daisy captures a structural reality: AI means different things across disciplines while sharing common foundations, and effective AI pedagogy must honor both unity and diversity. The Double Diamond captures a process reality: integrating AI into teaching and learning is not a one-time implementation but an ongoing design challenge requiring iterative cycles of exploration and refinement. AI resists static frameworks precisely because it is simultaneously a technical artifact, a pedagogical tool, a subject of inquiry, and a force reshaping the disciplines that study it [68]. By holding these metaphors in productive tension, we acknowledge that AI education is both a structural challenge (what knowledge belongs where? how do convergent foundations relate to divergent applications?) and a process challenge (how do we design for uncertainty? how do we iterate toward responsible integration?). This dual framing equips faculty with complementary lenses: the daisy for curricular architecture, the Double Diamond for pedagogical design. Table 1 summarizes this three-level theoretical integration.

Table 1: Three-level integration of the Double Diamond and Daisy Frameworks in AI Pedagogy

Level	**Focus**	**Double Diamond Function**	**Daisy Function**	**Key Outcome**
Macro	Faculty/Institutional Design	Process for curriculum development	Structure that emerges from collaborative inquiry	Shared frameworks and disciplinary applications
Meso	Course/Student Pedagogy	Scaffolding for student learning within courses	Situating course content within broader AI landscape	Iterative skill development and critical evaluation
Meta	Epistemological Framing	Captures temporal/process complexity	Captures spatial/structural complexity	Productive tension enabling adaptive design

This multi-level theoretical contribution responds to calls for AI literacy frameworks that integrate critical, ethical, and practical dimensions simultaneously [65], [66], while providing actionable structure for faculty navigating the uncertainties of AI-integrated education.

4.2 Summary of Cross-Disciplinary Findings

Table 2 provides a concise summary of how the authors from different disciplines understand, teach, and work with artificial intelligence. It presents each field's perspective across four dimensions: how AI is conceptualized, the central themes emphasized when teaching about AI, the ways AI tools are incorporated into instruction, and the distinctive pedagogical concerns that shape each discipline's approach. Together, these entries illustrate the broader convergence–

divergence framework discussed in the paper. All authors share a commitment to AI literacy, ethical awareness, and critical evaluation, yet each discipline retains its own priorities that reflect its methods, epistemologies, and areas of practice. Table 1 therefore serves as a clear guide to both the shared foundations and the unique contributions that characterize AI integration across computer science, MIS, systems engineering, economics, development studies, political science, and geography.

Table 2: Cross-Disciplinary Perspectives on AI

Discipline	What AI Means in This Field	How the Field Teaches AI	How the Field Uses AI in Teaching	What Makes This Discipline Distinct
Computer Science	AI = systems that learn from data; must be reliable, transparent, accountable.	Teach ML foundations, model behavior, bias, failure modes.	GenAI allowed for coding ideas; students must verify correctness.	Discipline builds AI systems; prevents technical/ethical failures.
Management Information Systems	AI amplifies expertise but requires strong foundational knowledge.	Teach compliance (e.g. HIPAA/GDPR), blockchain–AI interactions, trust.	AI used for compliance analysis; students verify/correct AI.	Emphasizes scaffolding + human oversight in AI-supported decisions.
Systems Engineering	AI is a subsystem requiring safety, explainability, lifecycle risk management.	Teach V&V, risk analysis, NIST AI RMF.	AI assists requirement drafting; students evaluate risks.	Focus on system-level integration and managing nondeterminism.
Economics	AI as general-purpose tech transforming productivity and labor markets.	Teach augmentation vs substitution, task exposure, inequality.	AI vs non-AI comparisons; oral defenses ensure understanding by students.	Focus on market impacts and distributional changes.
Development Studies	AI as epistemic and ethical risk; often reproduces Western bias.	Teach bias/hallucination detection; global equity concerns.	AI vs no-AI assignments reveal bias + missing perspectives.	Focus on epistemic justice and Global South issues.
Political Science	AI as political tool, regulated object, and geopolitical force.	Teach governance (GDPR/AI Act), democracy, surveillance.	AI-assisted research mapping; policy briefs with bias checks.	Focus on power, accountability, and legitimacy.
Geography	AI as spatial tool + source of place-based environmental/social impacts.	Teach socio-technical systems and environmental impacts.	Applied community projects using drones/AI visualization.	Links AI to environmental footprint + community engagement.

The vignettes presented throughout this paper reveal a common pattern: AI tools surface possibilities and efficiencies, but they also obscure risks, embed assumptions, and reproduce biases that require human vigilance to detect. These findings underscore the necessity of designing curricula that develop students' capacity for epistemic vigilance alongside technical competence. This commitment to ethically grounded pedagogy must also attend to inclusion. Research demonstrates that students' sense of belonging and their experiences navigating institutional barriers shape their persistence and success in STEM [56]. Cultivating inclusive learning environments, through intentional syllabus design and attention to the diverse backgrounds students bring to the classroom, creates the conditions under which all students can develop the critical capacities that AI-integrated education demands [57]. As AI reshapes what and how we teach, we must remain attentive to *who* we are teaching and whether our pedagogical innovations serve all students equitably.

4.3 Limitations

This study has several limitations that warrant careful consideration and that circumscribe the generalizability of our findings. First, as a collaborative autoethnographic study grounded in a Faculty Learning Community, this work prioritizes depth of practitioner insight and cross-disciplinary pattern recognition over statistical generalizability. The seven vignettes constitute a purposive sample of disciplines at a single technological university; they indicate how faculty are navigating AI integration in real time but do not capture the full range of possible disciplinary or institutional responses. Institutions with different missions (e.g., community colleges, liberal arts colleges, research-intensive universities) may face distinct challenges and opportunities that our framework does not address.

Second, and most significantly, this paper does not report systematic student learning outcome data. While our vignettes describe pedagogical activities and faculty observations, we have not conducted controlled assessments comparing AI-integrated approaches with traditional instruction, measured changes in student AI literacy or ethical reasoning using validated instruments, or collected longitudinal data on how AI-integrated learning experiences shape students' subsequent academic or professional trajectories. The absence of rigorous student evaluation data represents a critical gap. Faculty perceptions of pedagogical effectiveness, while valuable for generating hypotheses and sharing practice, cannot substitute for empirical evidence of student learning. This limitation is particularly acute given AI's rapid evolution; pedagogical approaches that appear effective today may require substantial revision as AI capabilities and student familiarity with AI tools continue to change.

Third, our framework does not yet address the institutional and infrastructural conditions necessary for effective AI curriculum design. Questions of faculty development, institutional AI policy, resource allocation, technical infrastructure, and assessment policy remain outside the scope of this paper, though they significantly shape the feasibility of implementing the approaches we describe. The uneven institutional AI policies noted throughout our vignettes highlight this gap: faculty innovation often outpaces institutional guidance, creating uncertainty about academic integrity, data privacy, and pedagogical appropriateness.

Fourth, our FLC comprised faculty who had self-selected into exploring AI integration, potentially introducing selection bias. Faculty who are skeptical of AI, lack technical confidence, or face competing demands on their time may encounter different challenges than those represented here. The convergence-divergence framework's applicability to reluctant or resource-constrained adopters remains untested.

Fifth, our disciplinary coverage, while diverse, is not exhaustive. Notable absences include the humanities (literature, philosophy, history), the arts, health sciences, and laboratory-based natural sciences—fields where AI integration may raise distinct pedagogical and ethical considerations not captured by our framework.

4.4 Directions for Future Research

The limitations identified above suggest several productive directions for future scholarship, which we organize around four research priorities.

Priority 1: Systematic Student Learning Evaluation. The most pressing need is for rigorous empirical research on student outcomes in AI-integrated courses. Future studies should develop and validate assessment instruments for measuring AI literacy across its multiple dimensions, including technical understanding, critical evaluation, ethical reasoning, and practical application. Existing frameworks such as Long and Magerko's AI literacy competencies [65] and Ng et al.'s conceptualization [66] provide starting points, but discipline-specific adaptations and validated measurement tools remain underdeveloped. Comparative studies employing pre-post designs should examine learning outcomes in AI-integrated versus traditional approaches, while longitudinal research should track how sustained AI use affects students' independent reasoning and problem-solving capacities [22]. Critically, research should investigate equity implications—whether AI tools differentially benefit or disadvantage students based on prior technical experience, socioeconomic background, or other factors—to ensure that AI integration narrows rather than widens existing achievement gaps.

Priority 2: Curriculum Design and Implementation Research. Future research should move beyond individual course interventions to examine curriculum-level AI integration. This includes testing the convergence-divergence framework across institutional contexts: does the daisy structure—shared core with disciplinary petals—hold in institutions with different missions, student populations, and resource levels? Research should also develop and evaluate faculty development models for AI-integrated teaching, investigate how AI competencies should be sequenced across degree programs, and examine how effectively students transfer governance knowledge (e.g., NIST AI Risk Management Framework [13], HIPAA, GDPR) across contexts.

Priority 3: Longitudinal and Workforce Readiness Studies. The ultimate test of AI-integrated pedagogy is whether it prepares students for professional contexts where AI is increasingly prevalent. Longitudinal studies should track graduates' AI use in professional settings, examining whether students who experienced AI-integrated pedagogy demonstrate greater facility with AI tools, more sophisticated ethical reasoning, or better adaptation to AI-augmented workplaces. Collaborative research with industry partners could define employer-sought AI competencies and validate alignment between curricula and workforce expectations, while also investigating how learning with and about AI shapes students' emerging professional identities and conceptions of human-machine collaboration.

Priority 4: Theoretical Development. Our multi-level integration of the Double Diamond and daisy frameworks invites further theoretical elaboration. The macro-meso-meta framework proposed here emerged from a single FLC's experience; additional case studies from other institutions and disciplines would test and refine the model's explanatory power. Future work should integrate our framework with established theories of curriculum design, such as backward design [69], constructive alignment [70], and design-based research methodologies [67], while developing actionable design principles and heuristics for faculty implementation. Finally, research should examine framework applicability beyond higher education—to K-12 AI education, professional training, and public AI literacy initiatives—to test generalizability and reveal domain-specific adaptations.

4.5 Implications for Practice

Despite the limitations noted above, our experience suggests several practical implications for faculty and institutions navigating AI integration. For faculty, the convergence-divergence framework offers a conceptual tool for balancing shared foundations with disciplinary authenticity. Rather than adopting AI tools wholesale or avoiding them entirely, faculty can use the daisy structure to identify which AI competencies belong in the shared core (and thus warrant coordination across courses) and which represent discipline-specific applications (and thus warrant tailored approaches). The Double Diamond provides a complementary process lens, encouraging iterative design rather than one-time implementation. For project advisors and capstone supervisors, the framework provides shared vocabulary for discussing AI expectations with students across disciplines. The convergence core—AI literacy, ethical awareness, governance frameworks—can inform common rubric elements, while the divergence petals allow discipline-specific criteria for how AI competencies manifest in engineering design versus social science research versus business analysis.

For institutions, our experience highlights the need for proactive AI policy development that balances guidance with flexibility. Faculty innovation often outpaces institutional policy; institutions that develop clear but adaptable frameworks—addressing academic integrity, data privacy, accessibility, and pedagogical appropriateness—can support faculty experimentation while managing risk. For the field of engineering education, this paper models a collaborative, cross-disciplinary approach to pedagogical inquiry. The FLC structure enabled sustained dialogue across epistemological differences, generating insights that no single discipline could have produced alone. As AI continues to reshape engineering practice and education, such collaborative inquiry becomes increasingly essential.

4.6 Conclusion

We are living in the age of artificial intelligence, and teaching and learning are profoundly impacted by this transformation. This paper has offered both a practical framework—the convergence-divergence daisy with its shared core and disciplinary petals—and a theoretical contribution—the multi-level integration of structural and process metaphors that captures the complexity inherent in AI pedagogy. By grounding our approach in collaborative inquiry across seven disciplines, we have modeled the very process we advocate: using the academy's traditional strengths—shared inquiry, multiple perspectives, and critical reflection—to navigate the uncertainties of a transformative technological moment.

The path forward requires sustained empirical research on student learning outcomes, rigorous curriculum design studies, and continued theoretical development. Most urgently, it requires faculty communities willing to experiment, reflect, and share their experiences—recognizing that in a rapidly evolving landscape, our collective intelligence remains our most valuable resource. Kissinger's challenge—to use AI constructively or be engulfed by it—demands pedagogical responses that are both principled and practical. The convergence-divergence framework offers such a response: core competencies provide common ground, while discipline-specific applications allow each field to determine how AI best serves its educational mission.

The convergence-divergence framework is not a final answer but an invitation to continued inquiry: a structure for asking better questions about how we teach with and about AI, and a process for iteratively discovering better answers.

Acknowledgement

This project was supported by a Teaching Innovation Grant from the Morgan Teaching and Learning Center at Worcester Polytechnic Institute in Worcester, Massachusetts.

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