AI-First Critique Learning (AFCL): A Framework for Restoring Assessment Integrity in the Age of Generative AI

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Abstract

The pervasive adoption of generative artificial intelligence by students has precipitated a widespread challenge to traditional assessment validity in higher education. This article introduces the AI-First Critique Learning (AFCL) framework as a conceptual framework with practical implementation guidance and a proposed research agenda. AFCL is a pedagogical innovation that transforms AI from an assessment threat into a catalyst for developing critical thinking, metacognition, and ethical judgment. Grounded in distributed cognition and supported by meta-analytic evidence showing AI's positive impact on higher-order thinking, AFCL operates through three interconnected elements: Classroom-Locked Prompts that ensure contextual specificity, Thinking Lenses that scaffold analytical rigor, and Standardized AI Interaction Environments that generate verifiable reasoning traces. By shifting assessment from products to documented critique processes, AFCL aims to restore evaluative validity while cultivating "critique literacy" as an essential digital-age competency. The framework includes a rapid four-month implementation pathway, enabling institutions to respond effectively to contemporary assessment challenges while preparing learners for AI-augmented professional futures. This work contributes a theoretically grounded framework and actionable guidance to the domains of AI pedagogy and assessment innovation, concluding with a defined agenda for necessary empirical research.

Keywords: AI-integrated assessment, critical thinking, metacognition, authentic assessment, distributed cognition, higher education

Introduction: The AI Assessment Challenge and Pedagogical Imperative

The diffusion of generative AI tools into student academic practice represents one of the fastest technological adoptions in educational history, creating both profound pedagogical opportunities and significant assessment challenges. Recent studies indicate that a significant and growing number of university students use AI tools for academic tasks (Al Mashagbeh et al., 2025; Pearson, 2025)—some productively, some problematically, and most without clear institutional guidance. This widespread integration has prompted a serious re-evaluation of assessment validity, particularly for traditional product-focused evaluations that now face disruption across numerous disciplinary contexts. This widespread integration fundamentally alters traditional knowledge production, making essays, problem sets, and analyses increasingly problematic as sole indicators of authentic learning. The resulting "trust deficit" threatens not only individual course grades but institutional credibility and the value of academic credentials.

Initial institutional reactions—prohibition, detection, surveillance—have proven pedagogically and technically inadequate. AI detection tools demonstrate unacceptable false-positive rates, exceeding 60% for non-native English writers, and disproportionately impact multilingual students (Liang et al., 2023). More fundamentally, the prohibition-surveillance paradigm fosters adversarial classroom dynamics, misallocates faculty effort from teaching to policing, and ignores the normative reality of AI as a component of contemporary academic practice—a reality that demands pedagogical innovation rather than technological restriction (Zhao et al., 2025; Selwyn, 2024).

Emerging research demonstrates that strategically integrated AI can enhance rather than undermine higher-order thinking. A recent meta-analysis of 29 experimental studies found a moderate positive effect (Hedges' $g \approx 0.61$) of generative AI on students' critical thinking and problem-solving abilities, particularly when interactions are scaffolded (Zhao et al., 2025). Research has shown that AI tools employing Socratic questioning improved quiz scores and metacognitive reflection, especially for lower-performing students (Lee et al., 2025). These findings align with established educational theories: distributed cognition frames AI as a cognitive partner in learning systems; authentic assessment prioritizes tasks requiring judgment and context—capabilities that resist automation; and metacognition becomes essential for regulating learning in technology-rich environments.

This article presents AI-First Critique Learning (AFCL), a conceptual framework with implementation guidance that addresses the assessment challenge through pedagogical innovation rather than restriction. AFCL's core premise is that in an era where polished academic products can be generated on demand, the most valid evidence of learning becomes the quality of intellectual work students perform upon those products. The framework transparently integrates AI by making documented critique—not product generation—the primary assessable activity. This manuscript serves to articulate the AFCL framework, provide actionable guidance for its implementation, and propose a subsequent research agenda for empirical validation. By shifting evaluation from outputs to reasoning processes, AFCL seeks to restore assessment validity while developing the critical judgment, contextual reasoning, and metacognitive agility essential for human-AI collaborative futures. This work contributes to three interconnected domains: AI pedagogy, assessment innovation, and institutional transformation in response to technological disruption. This manuscript advances a theoretically grounded conceptual and design-oriented contribution rather than reporting empirical findings, with the aim of guiding implementation and informing future research.

Theoretical Underpinnings: Distributed Cognition, Metacognition, and Critique Literacy

Distributed Cognition with AI Systems

The AFCL framework is fundamentally grounded in distributed cognition theory, which conceptualizes intelligence as distributed across people, tools, and environments rather than contained within individual minds (Pea, 1993). This perspective provides a powerful lens for understanding human-AI learning systems: when students interact with AI tools, cognition is distributed across the human learner and the artificial system, with each contributing distinct capabilities. In this framework, AI functions as a cognitive artifact—a tool that extends, scaffolds, and transforms cognitive processes rather than replacing human thinking. The educational challenge becomes designing interactions that leverage the respective strengths of both: AI's capacity for pattern recognition, information synthesis, and rapid generation; and human capacities for contextual judgment, ethical reasoning, metacognitive regulation, and creative insight. AFCL positions assessment precisely at this human-AI interface, evaluating how students coordinate with, regulate, and direct AI's cognitive contributions toward meaningful learning goals.

Metacognition and Self-Regulated Learning in AI-Mediated Environments

Metacognition—"thinking about one's thinking" (Flavell, 1979)—encompasses the planning, monitoring, and evaluation of cognitive processes. In AI-mediated environments, metacognitive competencies become particularly crucial as students must regulate not only their own thinking but also their interaction with AI systems. Research confirms that metacognition plays a key moderating role in developing problem-solving skills through AI-enhanced learning, suggesting that metacognitive development should be an explicit instructional goal rather than a hoped-for byproduct (Zhang et al., 2025). AFCL deliberately cultivates metacognition through its structured critique process. Students must plan their critique strategy, monitor their understanding relative to AI outputs, and evaluate their analytical corrections. The reflective synthesis component specifically targets metacognitive articulation, requiring students to articulate their thinking processes, strategy choices, and insights gained—facilitating what Flavell (1979) identifies as cognitive monitoring through metacognitive experiences.

Complementary Pedagogical Traditions and the Limits of AI Mediation

AFCL operates at the intersection of technological innovation and longstanding educational values. Scholarship on contemplative pedagogy (Palmer et al., 2010) and deep reading (Wolf, 2018) emphasizes cognitive processes that resist automation: sustained attention, embodied observation, and the slow cultivation of personal voice. These traditions remind us that certain forms of knowing emerge through deep, sustained engagement (Csikszentmihalyi, 2014), which can occur in both technologically mediated and unmediated activities but is nonetheless vulnerable to shallow, rapid-output workflows that bypass productive struggle.

The framework intentionally does not propose that all learning should be AI-mediated. Rather, AFCL responds to an increasingly common reality in many higher-education contexts: students report using generative AI tools for academic tasks, though patterns of use vary substantially by discipline, institution, and region (Al Mashagbeh et al., 2025; Pearson, 2025). The pedagogical challenge becomes: How can we preserve space for unmediated human experience while acknowledging that students will use AI outside structured activities? AFCL addresses this not by requiring AI use in every assignment, but by providing a structured approach for those assignments where AI engagement is appropriate or inevitable. This aligns with what Veletsianos (2020) describes as a negotiated relationship with technology—a stance of human-centered pragmatism that acknowledges digital realities while prioritizing the empathy, care, and pedagogical values essential to student experience.

Critique Literacy as a Fundamental Digital-Age Competency

AFCL introduces and develops critique literacy as a core educational outcome: the disciplined capacity to analyze, evaluate, deconstruct, and constructively improve ideas, arguments, and artifacts—with particular emphasis on AI-generated content. Critique literacy is related to (but not synonymous with) critical thinking, AI literacy, or disciplinary judgment. Critical thinking names the broader family of reasoning skills (e.g., analyzing claims, evaluating evidence, drawing warranted conclusions); AI literacy emphasizes understanding AI systems, their affordances, and their limitations; and disciplinary judgment reflects field-specific standards for what counts as credible methods, evidence, and argument. Critique literacy integrates these constructs at the point of practice: it is the situated skill of interrogating an AI output against disciplinary criteria and course context, diagnosing failure modes (e.g., generic formulations, contextual blindness, hallucinated evidence, embedded biases), and then producing reasoned corrections and improvements that are transparently grounded in human expertise and values. In professional contexts, critique literacy enables productive human–AI collaboration, where professionals direct, evaluate, and refine AI outputs rather than passively accepting them (Long & Magerko, 2020; Stewart & Rodgers, 2025).

Taken together, distributed cognition, metacognition, and critique literacy form the theoretical foundation of AFCL. The framework builds upon broader assessment reform movements advocating for authentic, process-oriented evaluation (Wiggins, 1990) and assessment security through circumstance-based design (Dawson, 2020). These established principles provide crucial foundations for adapting assessment to AI-mediated learning environments.

The AFCL Framework: Conceptual Model and Operational Components

Conceptual Overview

The AFCL framework operationalizes its theoretical foundations through three interlocking elements deployed in deliberate pedagogical sequence. These elements work in pedagogical sequence to transform AI from assessment threat to learning catalyst, developing critique literacy as an essential digital-age competency.

Importantly, the operationalization of these elements must be guided by clear institutional policies regarding data privacy, accessibility, and student consent, which are addressed in subsequent sections.

Element 1: Classroom-Locked Prompts (Designing for Contextual Specificity)
Classroom-Locked Prompts constitute the first and most critical design element in AFCL. These prompts are intentionally crafted to reference knowledge contexts, materials, or experiences that general-purpose AI systems typically cannot access directly, increasing the likelihood that AI responses will contain gaps, errors, or contextual misalignments that require substantive human correction. This "engineered imperfection" is intended to create a cognitive need for student intervention while shifting integrity protection toward contextual specificity rather than surveillance. Effective prompt design employs several locking strategies: Iterative-Process Locking references specific stages in ongoing student projects, personal research, or creative work; Local-Case Locking requires analysis of recent campus events, local community issues, or proprietary institutional datasets; Disciplinary-Debate Locking positions questions within nuanced scholarly conversations or requires application of specific theoretical frameworks; Recent-Input Locking incorporates content, discussions, or materials from immediate past class

sessions; Personal-Reflection Locking asks AI to analyze or respond to students' own previously written reflections, statements of values, or learning goals. These strategies do not guarantee authenticity in all contexts (e.g., where class recordings, transcripts, or shared notes become widely available), but they can raise the cost of outsourcing and make high-quality completion more dependent on situated course participation. This design approach is grounded in Dawson's (2020) principles of assessment security, which advocate for circumstance-based controls—securing a task by tying it to unique, localized contexts that are difficult for external agents (like AI or ghostwriters) to access, thereby strengthening the likelihood that authentic student engagement is the primary driver of success.

Element 2: Thinking Lenses (Structuring Analytical Rigor)
Thinking Lenses are structured analytical frameworks provided by instructors that translate the abstract directive to "critique" into disciplined, step-by-step intellectual procedures. These lenses scaffold rigorous interrogation aligned with disciplinary norms while making cognitive processes visible and teachable. Lenses typically fall into three interrelated categories, with individual assignments employing one or several as appropriate:

Analytical/Logical Lenses focus on the internal construction of AI-generated arguments or solutions: Assumptions & Gaps identifies unstated premises, missing information, or logical leaps; Evidence & Support evaluates the strength, relevance, and sourcing of provided evidence; Logical Structure maps argument flow, identifying non-sequiturs or weak causal links; Clarity & Precision flags ambiguous terminology, vague claims, or unnecessary jargon.

Contextual/Integrative Lenses focus on connecting AI outputs to specific course content and disciplinary knowledge: Theoretical Fidelity assesses alignment with key course theories, models, or frameworks; Conceptual Integration identifies where specific course concepts, terms, or case studies should have been incorporated; Stakeholder Consideration analyzes which relevant perspectives, stakeholders, or ethical considerations are present or absent; Disciplinary Convention evaluates adherence to field-specific norms regarding structure, methodology, or communication.

Ethical/Critical Lenses focus on values, biases, power dynamics, and broader implications: Bias & Representation identifies potential demographic, cultural, or ideological biases in language, examples, or recommendations; Power & Equity Analysis examines who benefits from proposed ideas and who might be marginalized or excluded; Ethical Implications unpacks potential consequences, risks, or moral dilemmas implied by AI suggestions; Sustainability & Systems Thinking considers long-term, environmental, or systemic impacts overlooked in the analysis.

These lenses operationalize the scaffolding shown to be effective in recent meta-analytic research (Zhao et al., 2025), providing structured pathways for developing the metacognitive regulation (Zhang et al., 2025) and critique literacy (Stewart & Rodgers, 2025) essential for engaging with AI systems (Sidra & Mason, 2025).

Element 3: Standardized AI Interaction Environment (Ensuring Consistency and Documentation)
The third AFCL element provides the technical and procedural container for generating consistent, complete, and verifiable records of reasoning processes. This "glass-box" environment ensures all students engage with AI under equivalent conditions while producing

the documentation needed for valid assessment. Implementation approaches include shared templates, dedicated learning management system modules configured for AFCL tasks, or institutionally provisioned AI instances with conversation logging enabled. To protect assessment validity, instructors should specify (and, when feasible, standardize) key tool parameters that materially affect outputs—such as the model/version, whether web browsing or retrieval is enabled, whether multimodal inputs are permitted, and whether students may iterate through multi-turn conversations versus a single-turn response. Where standardization is not possible (e.g., students use different models), the rubric should explicitly assess critique quality and course-based reasoning rather than model-dependent output quality, and students should be required to disclose tool/model settings within the trace.

The central assessable artifact is the AFCL Interaction Trace, typically implemented as a shared chat link or transcript containing four sequential components: the verbatim context-locked prompt submitted to the AI system, the complete unedited AI response, an annotated critique where students apply Thinking Lenses using clear formatting to link each critique point to specific text passages, and a reflective synthesis where students articulate major flaws identified, explain how course knowledge informed their critique, and provide corrected, improved versions of key output sections. This trace constitutes what has been termed 'process as product' (Wiggins, 1990)—the documented reasoning journey becomes the primary evidence of learning rather than any final polished output. It provides rich material for assessing distributed cognition (Pea, 1993), metacognitive regulation (Zhang et al., 2025), and disciplinary understanding.

Differentiating AFCL from Adjacent Assessment Approaches

While AFCL builds upon established traditions of authentic and process-oriented assessment, it is distinct in its specific adaptation to the challenges posed by generative AI. Unlike process-oriented portfolios, which can be curated and refined after the fact, the AFCL Interaction Trace provides a sequential audit trail of the student's critique process, making superficial compliance or post-hoc fabrication more difficult. Compared to AI-assisted co-creation approaches (common in many teaching-with-AI guides), AFCL explicitly centers the evaluation of AI output as the core learning objective, directly assessing critical interrogation skills rather than the quality of a co-created product. AFCL also complements emerging AI-integration frameworks that focus on teacher knowledge or policy-level classification (e.g., TPACK-oriented extensions for AI integration, AI-use/assessment scales, and teaching-with-AI playbooks), by specifying a concrete, assessable workflow that pairs context-locked prompts with disciplined critique scaffolds and verifiable interaction documentation. Furthermore, AFCL's systematic use of Classroom-Locked Prompts provides a more specific and scalable method for hardening assessments against AI completion than the general principles of authentic assessment alone. This combination—a mandated process log, a focus on critique over co-creation, and engineered contextual specificity—positions AFCL to address assessment validity and integrity concerns in a uniquely targeted and scalable manner for AI-ubiquitous environments.

Operationalizing Assessment: A Sample Rubric and Grading Feasibility

For instructors to evaluate AFCL Interaction Traces consistently and efficiently, a clear performance framework is essential. The core assessment dimensions and performance criteria are summarized in Table 1.

Table 1. AFCL Interaction Trace Assessment Rubric (100 points)

Dimension	Excellent (A Range)	Proficient (B Range)	Developing (C Range)	Inadequate (D/F Range)
Application of Thinking Lenses (40 pts)	Applies multiple relevant lenses systematically; critiques are specific, well-evidenced, and linked directly to course concepts.	Applies lenses correctly; critiques are clear but may lack depth or consistent connection to course specifics.	Applies lenses superficially; critiques are vague, general, or minimally connected to course material.	Fails to apply provided lenses; critique is absent or irrelevant.
Knowledge Integration & Correction (30 pts)	Effectively uses course knowledge to correct AI errors and add significant context; corrections are insightful and enhance the output.	Uses course knowledge to identify and correct main errors; additions are relevant but may lack depth or sophistication.	Identifies some errors but corrections are minimal, incomplete, or rely heavily on AI's original structure.	Fails to correct identifiable errors; adds no meaningful course-based knowledge or context.
Metacognitive Reflection (20 pts)	Reflection deeply analyzes the critique process, discusses strategy	Reflection describes the process and states some learnings; may lack detailed	Reflection is brief or generic, summarizing what was done without	Reflection is absent, purely descriptive of the task, or does not engage with

Dimension	Excellent (A Range)	Proficient (B Range)	Developing (C Range)	Inadequate (D/F Range)
	choices, and articulates clear insights about AI limits and personal learning.	analysis of strategy or self-evaluation.	meaningful analysis of thinking or learning.	the metacognitive prompt.
Process Documentation (10 pts)	Submission includes a complete, unedited Interaction Trace with all four required components clearly presented.	Submission includes the trace but may have minor omissions or formatting issues that slightly hinder readability.	Submission is incomplete (e.g., missing AI response or detailed annotations).	No shareable trace is provided, or the submitted document does not follow the required structure.

Grading Feasibility and Instructor Workload
A primary practical concern is the scalability of grading. The structured nature of the AFCL Interaction Trace can support more efficient evaluation than open-ended products, because the artifact is standardized and aligned to a small set of rubric dimensions. As an illustrative benchmark (not a universal guarantee), instructors may be able to use a brief grading routine—checking the trace for completeness, scanning for evidence of lens application, reading the reflective synthesis, and scoring with the rubric—in roughly 5–10 minutes per submission depending on class level, trace length, and instructor familiarity with the lens set. For a class of 30 students, this would suggest approximately 2.5–5 hours of grading per AFCL assignment. Institutions and instructors should treat these figures as planning estimates and validate them through local pilots, including norming sessions and sample calibration to ensure reliability across sections.

Pedagogical Mechanism and Cognitive Outcomes

The Four-Step Cognitive Workflow

AFCL structures a deliberate cognitive progression that transforms students from passive consumers of AI output to active, discerning evaluators. This pedagogical mechanism unfolds through four interconnected steps, each generating specific cognitive outcomes and assessable evidence captured by the AFCL rubric.

Step 1: Encounter with Engineered Imperfection

Students submit the context-locked prompt to an AI system and receive its generated response. Due to the prompt's design, the AI output contains predictable deficiencies—contextual misalignments, theoretical misapplications, omitted stakeholders, or generic formulations that fail to address course-specific nuances. This engineered imperfection creates productive cognitive dissonance (Festinger, 1957) between what the AI produces and what the student recognizes as necessary for the specific context, activating prior knowledge and establishing the motivational foundation for engaged critique.

Step 2: Disciplined Deconstruction via Thinking Lenses

Students systematically apply the provided Thinking Lenses to the AI output, moving from intuitive dissatisfaction to structured, evidence-based diagnosis. This analytical scaffolding prevents superficial critique while developing disciplinary-specific evaluation frameworks (Zhao et al., 2025). This step develops critical thinking as disciplined inquiry—the capacity to apply specific evaluative criteria consistently and rigorously.

Step 3: Knowledge Application and Constructive Correction

Drawing from lectures, readings, discussions, and their own insights, students actively use course-specific knowledge to correct identified errors, fill conceptual gaps, and contextualize generic AI output. This represents the core knowledge integration phase, where students must not only identify what's wrong but demonstrate how their disciplinary understanding provides superior alternatives. This step provides direct evidence of comprehension depth and knowledge application.

Step 4: Metacognitive Articulation in Reflective Synthesis

In the final component of the Interaction Trace, students articulate their overall process, strategy choices, challenges encountered, and insights gained. This reflective synthesis closes the metacognitive loop, requiring students to monitor and evaluate their own thinking about the AI critique process. Guiding questions may include: Which lenses proved most revealing? What was challenging about evaluating the AI output? How did this process change your understanding of the topic? This explicit metacognitive component develops reflection-on-action (Schön, 1983)—the capacity to think about one's thinking while engaged in complex tasks and to learn from those experiences.

Cognitive and Dispositional Outcomes

This structured workflow cultivates specific competencies essential for AI-augmented environments:

- Enhanced critical thinking and analytical precision develops through systematic application of evaluative criteria to complex artifacts (Lee et al., 2025; Zhao et al., 2025). Students learn to distinguish superficial from substantive flaws, identify implicit assumptions, evaluate evidence quality, and trace logical coherence—skills that transfer beyond AI evaluation to broader information literacy (Long & Magerko, 2020; Stewart & Rodgers, 2025).
- Deepened disciplinary understanding and knowledge integration occurs as the necessity to correct AI errors using course-specific knowledge creates adaptive expertise—the ability to apply knowledge flexibly to novel problems rather than merely reproducing learned information (Pea, 1993; Wiggins, 1990).
- Developed metacognitive regulation and learning strategy awareness emerges through explicit reflection on the critique process, cultivating self-regulated learning competencies including task analysis, strategy selection, monitoring, and adaptation (Flavell, 1979; Zhang et al., 2025).
- Cultivated critique literacy and intellectual humility develops through repeated structured engagement with AI limitations, building the capacity to evaluate AI-generated content with appropriate skepticism, methodological rigor, and constructive intent while recognizing the partial, constructed nature of all knowledge (Schön, 1983; Stewart & Rodgers, 2025).

Illustrative Application: Cross-Disciplinary Case Studies

The following case studies demonstrate how the core AFCL elements—Classroom-Locked Prompts, Thinking Lenses, and the Interaction Trace—are applied and adapted across different disciplines. These vignettes are illustrative rather than empirical reports; they are intended to make the design logic concrete while highlighting conditions under which AFCL may succeed or fail. In practice, AI outputs may be largely correct, student background knowledge may be insufficient to identify subtle errors, and "engineered imperfection" can yield responses that are either trivially flawed (making critique shallow) or deceptively plausible (making critique demanding). The examples below should therefore be read alongside the framework's boundary conditions and the need for iterative prompt/lens refinement within specific institutional and accommodation contexts.

Sociology Case Study: Spatial Justice and Urban Development

Course Context: "Urban Inequality and Spatial Justice," an upper-division sociology course examining how power relations shape urban spaces, using spatial justice concepts discussed explicitly in recent class sessions.

AFCL Implementation:

Classroom-Locked Prompt: "Using the spatial justice framework—particularly the concepts of 'thirdspace' and 'right to the city' as we defined and debated them in our Weeks 3-4 seminars—critique the hypothetical proposal to relocate our city's main public library from its current downtown location to the new Riverfront Luxury Mall development. Consider specifically: accessibility for homeless populations, the symbolic politics of placing a public institution in a privatized space, and the implications for spatial democracy. Reference our case study of the Downtown Eastside redevelopment controversy from last week's class."

Thinking Lenses Provided: Theoretical Fidelity Lens (evaluate alignment with spatial justice concepts as discussed in class); Stakeholder Geography Lens (identify which community perspectives are represented/absent); Spatial-Power Analysis Lens (examine how the proposal redistributes spatial access and control).

The structural differences between traditional source-cited prompts and AFCL's Classroom-Locked Prompts are summarized in Table 2.

Table 2. Pedagogical Impact Comparison of Prompt Design Strategies

Aspect	Traditional: Source-Cited Prompt	AFCL: Classroom-Locked Prompt
AI Resistance	Low: AI can retrieve and summarize cited sources	High: AI lacks access to in-class discourse and materials
Ghostwriting Resistance	Low: Task can be outsourced using provided citations	High: Requires knowledge of specific class events and discussions
Attendance Incentive	None: Success independent of participation	Strong: Engagement necessary to understand referenced concepts
Cognitive Demand	Passive retrieval: Relies on AI synthesis of public knowledge	Active recall and application: Requires retrieval of in situ learning
Equity Consideration	Favors strong independent researchers or AI users	Favors engaged participants: Values classroom contribution
Assessment Authenticity	Tests AI access and synthesis skill	Tests actual learning, integration, and critical application

Note. Adapted from Dawson, P. (2020). *Defending Assessment Security in a Digital World*. Routledge.

AI Limitations and Student Response: The AI produces a generic critique focusing on physical accessibility (distance, transportation) but misses the politicized understanding of space as produced through power relations discussed in class. It fails to connect the mall's private security policies to concepts of "spatial injustice" and overlooks the symbolic dimension of placing a public institution in commercial space. In their Interaction Trace, the student uses the Theoretical Fidelity Lens to identify where the AI's analysis depoliticizes space, correcting it by explaining how spatial justice understands space as "socially produced" through power relations. Using the Stakeholder Geography Lens, they incorporate details from the class case study about how mall security policies effectively criminalize homelessness. Their corrected analysis frames the library relocation not as a neutral administrative decision but as an act of "spatial privatization" reinforcing urban inequalities. The reflective synthesis articulates how this exercise deepened their understanding of spatial theory while developing capacity to recognize when AI outputs lack necessary critical-political dimensions (Stewart & Rodgers, 2025).

Creative Writing Case Study: Human-First AFCL Adaptation

Course Context: "Advanced Fiction Writing," a workshop-based course where developing distinctive narrative voice through iterative revision represents the primary learning objective.

Human-First AFCL Implementation:

Phase 1: Unmediated Human Creation — Students write original short stories without AI assistance, engaging in the cognitive struggle essential to creative development.

Phase 2: Strategic AI Engagement — Students submit selected passages to a generative AI tool with the prompt: "Suggest three alternative phrasings for these descriptive paragraphs that maintain the narrator's melancholic tone but vary sentence structure."

Phase 3: Metacognitive Synthesis — Students write a critique explaining why they would reject certain AI suggestions (e.g., they dilute voice, impose generic conventions), what they learn about their own stylistic choices through this contrast, and how recognizing "AI-typical" phrasing helps them avoid generic writing (Stewart & Rodgers, 2025). This reflective critique engages metacognitive synthesis (Flavell, 1979), essential for self-regulated learning.

Phase 4: Final Revision — Students revise their stories, informed by this analysis but guided by their original artistic voice.

This adaptation preserves what Greene (1995) termed "the space of personal becoming"—the educational territory where students develop their distinctive voices. The AI serves as a contrasting mirror rather than a creative partner, helping students see their own stylistic choices more clearly through comparison with computational alternatives.

Theatre Studies Case Study: Preserving Experiential Learning

Course Context: Writing Intensive Theatre course where developing nuanced interpretation of dramatic texts through close reading represents a core competency.

Adapted AFCL Sequence:

1. Students write detailed analyses of a play scene based on multiple close readings and live performance observations.

2. They submit their key interpretive claims to an AI tool with the prompt: "What alternative interpretations might other readers propose for these claims about character motivation?"
3. Students write a reflection addressing what the AI's alternatives miss about their original analysis, how considering these alternatives strengthens their interpretation, and what this process reveals about the difference between computational text analysis and human literary interpretation (Selwyn, 2024).
4. Students develop their final analysis, enriched by this reflective process but grounded in their original interpretive work.

This approach recognizes that some learning objectives—developing unique interpretative voice (Greene, 1995), cultivating observational acuity (Wolf, 2018), learning to sit with creative uncertainty—represent "AI-resistant competencies" that cannot be developed through interaction with synthetic intelligence. AFCL serves here as a framework for transparent conversation about AI's appropriate boundaries within a course. The broader disciplinary adaptability of AFCL is summarized in Table 3.

Table 3. AFCL Adaptation Spectrum Across Disciplines

Discipline Type	Primary Learning Goals	AFCL Adaptation	AI's Role	Assessment Focus
Data-Driven Fields (STEM, Social Sciences)	Analytical rigor, methodological competence, evidence evaluation	Standard AFCL	Generative partner for critique	Quality of analytical critique, methodological correction
Interpretive Humanities (Literature, Philosophy, History)	Textual interpretation, argument development, historical contextualization	Modified AFCL	Contrasting interpreter	Depth of original interpretation, quality of comparative analysis

Discipline Type	Primary Learning Goals	AFCL Adaptation	AI's Role	Assessment Focus
Creative Arts (Creative Writing, Theatre, Studio Art)	Original voice, personal expression, artistic innovation	Human-First AFCL	Limited reader/respondent	Development of distinctive voice, reflective insight about artistic choices
Experiential Fields (Performance, Clinical Practice, Field Research)	Embodied knowledge, situational judgment, adaptive response	Optional AFCL	Post-experience analytical tool	Quality of experiential reflection, insight about human vs. AI perception

Note. Adapted from Selwyn (2024) and Stewart & Rodgers (2025). Core components—context-specific prompts, structured lenses, and documented process—remain central but adapt to disciplinary needs.

AFCL Beyond AI Imperfection: Grading Judgment in an Era of AI Accuracy

A legitimate critique of AFCL is that its pedagogical leverage depends on current AI limitations—that if AI tools become perfectly accurate and context-aware, the need for student correction vanishes. This critique misunderstands AFCL's core assessment mechanism. AFCL does not grade correctness; it grades *judgment, context, and critique*—cognitive and ethical capacities that AI does not replace, even when its outputs are factually accurate (Selwyn, 2024).

As AI capabilities improve, AFCL's function evolves from error-correction to nuance-amplification and ethical framing (Stewart & Rodgers, 2025). A perfectly accurate AI might generate a factually correct policy analysis, but it cannot inherently weigh competing stakeholder values, interrogate its own political assumptions, or adapt its reasoning to the specific ethical commitments of a course. These are acts of judgment—situated, values-informed, and disciplinary—that remain uniquely human. The Classroom-Locked Prompt ensures this by design: it requires students to connect AI output to localized discussions and course contexts that no public AI can access. The Thinking Lenses then scaffold evaluation of that output not for factual errors, but for depth, bias, framing, and ethical alignment. In essence, AFCL replaces the directive to "show your work" with the imperative to "show your judgment" (Wiggins, 1990)—making student thinking visible and assessable precisely because it focuses on the cognitive layer above factual recall where human insight becomes indispensable.

Preserving Space for Unmediated Experience and Creative Struggle

This focus on judgment necessitates careful consideration of when AI integration is appropriate. A legitimate concern is that AI-integrated frameworks might inadvertently diminish the cognitive capacities that distinguish human creativity and experiential learning. Research demonstrates that originality often emerges from "productive struggle"—the cognitive friction when learners wrestle with ambiguity and generate ideas without external assistance (Hennessey, 2019). Similarly, artistic voice develops through iterative refinement of personal expression, not through critique of external outputs (Sibanda & Busby, 2024).

AFCL addresses this concern through two design features. First, the framework explicitly does not prescribe when or whether to use AI—this remains a pedagogical decision based on learning outcomes. Second, for disciplines where unmediated experience is paramount, AFCL offers adaptation rather than prescription. In creative writing, students might complete multiple drafts before using AI for comparative analysis; in theatre studies, students might document embodied responses before examining how AI would describe the same experience. This preserves what Greene (1995) termed "the space of personal becoming"—the territory where students develop distinctive voices.

The framework acknowledges that some learning objectives are fundamentally incompatible with AI mediation. Developing unique writing voice, cultivating observational acuity, or learning to sit with creative uncertainty represent "AI-resistant competencies" that cannot be developed through interaction with synthetic intelligence. In such cases, AFCL serves as a framework for transparent conversation about AI's appropriate boundaries rather than a template for assignment design.

Rapid-Response Implementation Pathway

The Urgency of Implementation
Translating the AFCL conceptual framework into practice requires a structured yet agile implementation pathway. Given reported growth in student AI use in many contexts (Al Mashagbeh et al., 2025; Pearson, 2025), institutions face pressure to respond quickly while avoiding brittle, enforcement-only approaches (Selwyn, 2024). The four-month sequence below is presented as an illustrative rapid-response checklist (not a rigid or universally appropriate timeline): institutions may move faster or slower depending on governance processes, labor agreements, procurement, privacy review, instructional design capacity, and existing AI infrastructure. The intent is to surface the major implementation components that typically require coordination, so readers can adapt sequencing to local constraints.

Month 1: Foundation and Emergency Piloting
Weeks 1-2: Rapid-Response Task Force Formation involves assembling a small, empowered

team with representatives from faculty innovators, instructional design specialists, academic integrity office, IT support, and student representatives. This task force should have decision-making authority and a clear mandate: develop immediately usable resources and launch pilot implementations within the month. Weeks 2-3: Development of "AFCL Emergency Toolkit" creates lightweight, actionable resources including a 2-page explainer document, "clone-and-go" assignment template with examples across disciplines, brief instructor video, and FAQs for students and faculty. Weeks 3-4: Launch of "Quick-Start" Pilot Program recruits faculty volunteers from diverse departments through a call emphasizing urgency and support, offers modest stipend or teaching credit for participation, conducts a single workshop introducing the framework and toolkit, and establishes a dedicated support channel for just-in-time assistance.

Month 2: Pilot Execution and Policy Clarification
Concurrent Activities include pilot faculty running their AFCL assignments with ongoing task force support, academic integrity office issuing clear interim guidance distinguishing between prohibited AI use (undisclosed AI generation for traditional assignments) and required AI use (documented critique as part of AFCL assignments), and recommending specific, accessible AI tools with instructions for students on account creation and conversation saving.

Month 2.5: Ethical and Policy Safeguards
Concurrent with ongoing pilots, the institution must address key governance and ethical constraints to ensure responsible scaling. This involves: (1) Privacy and Data Governance: Formalizing the use of an enterprise AI tool (e.g., ChatGPT Edu) with institutional data agreements that comply with relevant privacy regulations (e.g., FERPA). Clear policies must be communicated to students regarding data collection, usage, and retention within the AI interaction environment. (2) Accessibility and Equity: Ensuring equitable student access to required technology and AI tool licenses; providing onboarding for digital/AI literacy; and coordinating with disability services to offer accommodations when the standard interaction or documentation process presents barriers (e.g., alternative formats for interaction traces, extended time, assistive technology compatibility). Equity planning should explicitly consider multilingual learners, first-generation students, and students at under-resourced institutions or in low-bandwidth contexts. (3) Policy Alignment: Reviewing and revising academic integrity policies to explicitly differentiate between unauthorized AI use and pedagogically structured, documented AI engagement as part of AFCL assignments. This proactive step mitigates later conflicts and supports faculty implementation.

Month 3: Analysis, Adaptation, and Amplification
Week 9-10: Sprint Review and Resource Refinement conducts a "lessons learned" session with pilot faculty, focusing on what worked well in prompt design and lens selection, student stumbling points, grading challenges, and technological issues. Using this feedback and exemplary student logs, the Emergency Toolkit is refined into a more robust "AFCL Design Playbook" including discipline-specific prompt examples, expanded lens options, sample graded logs, and strategies for efficient grading. Week 11-12: Amplification Campaign hosts a campus-wide webinar featuring pilot faculty presenting their implementations, student work examples, and impact on assessment practice and student learning, launches broader faculty adoption initiative, and develops and distributes student-facing guide explaining authorized versus prohibited AI use and the pedagogical value of critique assignments.

Month 4 and Beyond: Scaling and Institutional Integration
Ongoing Activities include integrating AFCL resources and workshops into regular Center for Teaching and Learning programming, formalizing policy revisions based on pilot evidence, conducting informed evaluations of enterprise AI solutions with appropriate privacy, accessibility, and logging features, showcasing exemplary student work in department meetings and teaching showcases, and incorporating AFCL logs into program-level assessment of critical thinking, written communication, and information literacy outcomes. This implementation pathway enables institutions to respond with necessary urgency while building toward sustainable, integrated practice. It represents bottom-up, top-down change—leveraging faculty innovation while providing institutional support and policy alignment.

Faculty Development for Disciplinary Adaptation

Successful AFCL implementation requires faculty development that addresses both technological competence and pedagogical judgment about when and how to integrate AI. Training should include:

Module 1: Disciplinary Self-Assessment — Faculty analyze their course learning objectives to determine which competencies require unmediated human experience (Hennessey, 2019), where AI might serve as a useful reflective tool, and how to sequence human and AI activities to preserve core learning.

Module 2: Adaptation Design — Faculty learn to modify AFCL components for their discipline, including designing Classroom-Locked Prompts that reference experiential learning, creating Thinking Lenses for evaluating AI's handling of subjective experience or creative expression, and developing rubrics that assess human insight development alongside AI critique.

Module 3: Ethical and Epistemological Reflection (Stewart & Rodgers, 2025) — Faculty engage with questions such as what forms of knowledge are fundamentally human and should remain AI-free, how to teach students to recognize when AI use enhances vs. undermines their learning, and what are the environmental and ethical costs of AI use in their discipline.

This development approach recognizes that effective AI integration requires more than technical skill—it demands pedagogical wisdom about what should and should not be technologically mediated. The implementation model should include just-in-time support resources, peer mentoring networks among early adopters, and recognition systems for faculty innovation in assessment redesign.

Discussion: Implications and Future Directions

Transformative Implications for Educational Practice

Widespread adoption of AFCL necessitates significant evolution in faculty practice, shifting from content transmission and product evaluation toward cognitive experience design and reasoning process assessment. Faculty expertise becomes expressed not primarily through content delivery but through designing context-rich learning environments where AI's limitations create opportunities for knowledge application. For students, AFCL represents a shift from information consumption to critical evaluation, from product creation to process articulation, and from individual cognition to distributed intelligence. Students learn to coordinate their own thinking with AI capabilities while maintaining appropriate trust calibration and human oversight (Stewart & Rodgers, 2025)—precisely the competencies essential for AI-augmented workplaces (World Economic Forum, 2025; Zhao et al., 2025).

Toward a Balanced Educational Ecosystem

AFCL represents one component within a balanced pedagogical ecosystem that includes AI-Enhanced Learning Spaces (where frameworks like AFCL apply), AI-Free Learning Spaces (for developing unmediated cognitive capacities), and Transitional Learning Spaces (where students learn to move between mediated and unmediated thinking). The framework contributes to "AI literacy across the curriculum" (Long & Magerko, 2020)—not meaning every course uses AI, but that every course helps students develop intentionality about when and how to engage with AI tools. This aligns with emerging models of "thoughtful technology integration" (Selwyn, 2024) emphasizing pedagogical purpose over technological novelty.

Future innovation must address the complementary challenge: designing learning experiences that develop precisely those capacities AI cannot replicate—sustained attention (Wolf, 2018), embodied observation, personal voice (Greene, 1995), creative struggle, and ethical judgment (Sibanda & Busby, 2024). By creating structured spaces for transparent AI engagement, AFCL helps preserve room for these essential human capacities.

Critical Challenges, Limitations, and Research Agenda

Practical implementation challenges include faculty capacity, student readiness, and grading efficiency—addressed through the provided rubric and workload estimates. Equity considerations are paramount; institutions must provide equitable access to AI tools, offer digital literacy support, and ensure assessments do not disproportionately advantage students with prior AI experience.

Ethical considerations requiring institutional governance include: surveillance and data privacy (use of privacy-preserving, institutionally governed AI platforms); commercial dependencies (risks of vendor lock-in); epistemological concerns (avoiding reinforcement of positivist views that marginalize experiential knowing); and labor implications (whether replacing writing with critique constitutes meaningful innovation).

Technological evolution presents additional challenges: rapid obsolescence of locking strategies as AI improves, differential access creating second-level digital divides (Al Mashagbeh et al., 2025), and the need to adapt AFCL to multimodal AI beyond text generation.

A robust research agenda is essential to validate the framework:

1. Comparative Effectiveness Studies: Measuring learning outcomes (critical thinking, metacognitive gains) between AFCL-implemented courses and those using traditional or other AI-integrated approaches (Lee et al., 2025).

2. Implementation and Equity Studies: Investigating barriers to faculty adoption across disciplines and examining how AFCL affects students from different demographic and socioeconomic backgrounds (Al Mashagbeh et al., 2025).
3. Longitudinal and Transfer Studies: Tracking critique literacy development across programs and investigating transfer to professional, civic, or personal contexts (World Economic Forum, 2025).
4. Ethics and Perception Studies: Exploring student and faculty perceptions regarding documentation requirements, privacy, and pedagogical value of structured AI critique (Selwyn, 2024).

A comparative overview of AFCL and adjacent AI-integrated assessment approaches is provided in Table 4.

Table 4. Comparison of AI-Integrated Assessment Approaches

Approach	Core Strategy	AI Resistance	Key Pedagogical Focus	Implementation Complexity	Primary Assessment Evidence
AFCL (This Framework)	Structured critique of AI outputs	High (through classroom-locking & process trace)	Critical thinking, metacognition, judgment	Moderate	Documented Interaction Trace & Reflection
AI-Augmented Co-creation	Transparent collaboration with AI on output generation	Low to Medium	Creative synthesis, ethical AI use, product quality	Low to Moderate	Quality of co-created final product
Process Portfolio	Comprehensive, curated logs of AI	Medium	Reflective practice, learning	High	Curated portfolio of

Approach	Core Strategy	AI Resistance	Key Pedagogical Focus	Implementation Complexity	Primary Assessment Evidence
Documentation	use & process		journey, self-regulation		process artifacts
Competency-Based AI Use	Focus on demonstrated outcomes regardless of tools used	Medium	Skill demonstration, practical application	High	Performance on authentic tasks
AI-Detection & Prohibition	Identify and penalize undisclosed AI use	Variable (evolving)	Traditional academic integrity, rule compliance	High	Forensic analysis of student submission

Note. Adapted from Dawson (2020) and Liang et al. (2023).

Future Research Directions

The proposed research agenda addresses both practical implementation questions and broader theoretical issues. Important directions include comparative effectiveness studies, longitudinal tracking of critique literacy development, transfer studies, faculty adoption studies, equity impact studies, privacy and surveillance studies, research on adaptive AFCL systems, and studies of collaborative AFCL environments. This research is necessary to move the conceptual framework presented here toward evidence-based practice.

Conclusion: Toward Trustworthy Learning in AI-Augmented Education

In many institutional contexts, a majority of students report using AI for academic work (Al Mashagbeh et al., 2025), while usage patterns vary across disciplines and regions; meanwhile, detection-based responses have proven both technically unreliable and pedagogically counterproductive (Liang et al., 2023), underscoring the need for principled and practical pathways for innovation. This article has presented the AI-First Critique Learning (AFCL) framework as a three-part contribution: a theoretically grounded conceptual model, actionable implementation guidance, and a defined agenda for necessary empirical research.

The AFCL framework addresses this disruption by fundamentally reimagining the relationship between assessment and AI—shifting focus from product generation to process critique. By making student thinking visible through documented critique of AI outputs, AFCL seeks to restore evaluative validity while developing precisely those higher-order cognitive competencies that distinguish human expertise in an AI-augmented age.

AFCL's theoretical foundations in distributed cognition, metacognition, and authentic assessment provide principled guidance for its three core elements: Classroom-Locked Prompts that ensure contextual specificity, Thinking Lenses that scaffold analytical rigor, and Standardized Interaction Environments that generate verifiable reasoning traces. The framework's rapid four-month implementation pathway acknowledges the urgency of the challenge while providing structured guidance for institutional adoption, including addressing ethical and governance considerations. By beginning with faculty innovation and scaling through evidence-based refinement, this pathway enables timely response without sacrificing pedagogical quality or institutional coherence.

For faculty, AFCL offers a path from the unsustainable role of AI detective back to the essential roles of learning designer and intellectual guide. For institutions, it provides a strategy for maintaining credential credibility and demonstrating adaptive leadership. For students, it cultivates the critical judgment, metacognitive agility, and collaborative capacity needed to thrive in professional and civic contexts where AI mediation is increasingly normative. The critique that AFCL might diminish certain forms of human cognition represents a crucial reminder of its appropriate application. AFCL is designed for contexts where AI use is widespread or justified—not as a replacement for pedagogies centered on unmediated experience or personal voice development. Its value lies in creating structured spaces for AI engagement so that other spaces can remain intentionally technology-free.

As higher education navigates the AI transformation, we face dual challenges: designing effective AI-integrated learning while preserving and enhancing the human cognitive capacities that distinguish us from machines. AFCL addresses the first challenge, making it an essential but not sufficient component of educational adaptation. Its greatest contribution may be in helping institutions create clear boundaries between mediated and unmediated learning—ensuring that as AI becomes ubiquitous in some educational spaces, we intentionally preserve others for the slow, difficult, beautiful work of becoming fully human thinkers, creators, and knowers.

This pedagogical shift does not merely adapt to AI but reasserts the core mission of higher education: to develop discerning, ethical, and agile thinkers. In doing so, AFCL responds to the urgent call from accreditors and employers for graduates who can navigate complex, AI-mediated information landscapes with critical integrity. The framework thus serves as both a conceptual model for immediate adaptation and a long-term investment in the kinds of human cognition that will remain indispensable—human judgment, ethical reasoning, and creative critique—even as AI capabilities continue to advance (World Economic Forum, 2025).

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