Generative AI as a Pedagogical Infrastructure in Higher Education

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Abstract

Generative artificial intelligence (GenAI) is rapidly reshaping higher education, yet instructors still lack practice-based guidance for integrating these tools into everyday teaching in ways that preserve accountability in the learning process. This paper examines the use of GenAI as *pedagogical infrastructure*: an embedded layer that supports—rather than replaces—core learning activities across multiple undergraduate and graduate applied-computing courses. Drawing on instructional artifacts, design iterations, and student reflections, we describe how structured GenAI interactions can scaffold problem formulation, surface intermediate reasoning, and support adaptive feedback during open-ended tasks.

We introduce the *AI-Mediated Instruction* (AIMI) framework to conceptualize three complementary roles for GenAI in instruction: *Cognitive Support*, *Mediated Instruction*, and *Learning Accountability*. We then present five instructional patterns—*Guided Decomposition*, *Contrastive Prompting*, *Error-as-Data*, *Reflective Explanation*, and *Boundary Setting*—illustrated with classroom examples from our undergraduate and graduate courses. The paper offers a design-oriented account intended to help instructors and curriculum designers embed GenAI responsibly, encourage iterative learning, and make student thinking more visible.

Keywords: Generative AI; higher education pedagogy; instructional patterns.

1. Introduction

Emerging trends and challenges. Generative AI (GenAI) has quickly transitioned from a novel technology to a common presence in higher education. Modern GenAI systems can generate humanlike text, explanations, and examples, and these tools are now widely accessible to students and instructors across disciplines. As a result, universities responded swiftly, framing GenAI primarily as a threat to academic integrity or as a productivity aid rather than an instructional resource [1-3]. These initial reactions address pressing concerns, but they risk overlooking deeper pedagogical questions about how GenAI might transform learning processes, instructional roles, and assessment practices. Overall, this highlights a gap in pedagogical strategy for leveraging GenAI effectively as a learning resource.

Existing research on AI in education has focused largely on intelligent tutoring systems, automated feedback, and adaptive learning platforms that provide structured guidance within well-defined instructional contexts [4,5]. These older systems emphasize efficiency and personalization in constrained environments. In contrast, modern GenAI systems enable open-ended, dynamic interaction, offering explanations and examples tailored to student input [6].

Recent studies have highlighted both the potential benefits and risks of applying GenAI in educational contexts, noting its ability to improve access to support alongside concerns about overreliance, accuracy, and academic integrity [7,8]. Despite this interest, concrete pedagogical guidance for integrating GenAI into course design remains limited. Current discourse has largely emphasized broad institutional policies and strategic responses, which leaves instructors without detailed guidance on classroom-level integration.

Open research questions. In practice, many instructors lack structured strategies for incorporating GenAI into instruction. Instead, they often make *ad hoc* decisions about if, when, and how students may use GenAI, leading to inconsistent expectations and uneven learning experiences. This *ad hoc* approach reflects the absence of a coherent pedagogical framework for GenAI: in most cases, the technology is treated as an optional shortcut rather than as an integrated element of the curriculum. As a result, the following research questions (RQs) remain unresolved to provide educators with effective and actionable guidance on:

- **RQ1**: How to align GenAI-assisted activities with specific learning objectives,
- **RQ2**: How to scaffold open-ended exploration with AI tools, and
- **RQ3**: How to reinforce student accountability when GenAI is used.

These research questions highlight the need for deliberate design principles and strategies that move beyond viewing GenAI solely as a threat or convenience.

Solution approach → Reframe GenAI as pedagogical infrastructure in higher education. Rather than treating GenAI as a shortcut or substitute for student work, we conceptualize it as a mediated element of the learning environment that can support cognition, structure instruction, and reinforce accountability when designed and applied intentionally. We explore this design problem through classroom-based observations. This reframing aligns with established learning theories that emphasize guided instruction, cognitive engagement, and self-regulated learning as essential for meaningful educational outcomes [9-11] and make the four contributions to research on responsible, human-centered uses of GenAI in higher education:

1. ***AI-Mediated Instruction (AIMI) framework.*** We introduce the AIMI framework, which conceptualizes GenAI as pedagogical infrastructure that mediates cognition, instruction, and accountability for learning in higher education. This framework is grounded in instructional design principles and cognitive learning theory, providing a structured basis for aligning GenAI use with learning objectives.
2. ***Instructional patterns for GenAI integration.*** We distill five actionable instructional patterns—*Guided Decomposition*, *Contrastive Prompting*, *Error-as-Data*, *Reflective Explanation*, and *Boundary Setting*—derived from our classroom experiences over the past three years. These patterns specify concrete design configurations for embedding GenAI into course activities intended to support learning rather than replace student effort.
3. ***Qualitative empirical grounding.*** We provide empirical grounding through qualitative observations drawn from teaching practice across higher education courses serving non–computer science, data-oriented student populations. These observations illustrate how different instructional patterns were associated with shifts in student reasoning, engagement, and instructional practice in applied computing contexts.
4. ***Design constraints and limitations.*** We articulate key design constraints and limitations that affect the responsible integration of GenAI into instructional settings. Rather than prescribing fixed solutions, these constraints offer practical guidance to help educators and curriculum designers make informed, context-sensitive design decisions.

Paper organization: The remainder of this paper is organized as follows: Section 2 examines existing research and learning theories shaping the use of AI in higher education; Section 3 introduces the AIMI framework and positions GenAI as pedagogical infrastructure; Section 4 discusses the methods and study design used to develop the framework; Section 5 describes instructional patterns we identified to operationalize the AIMI framework; Section 6 summarizes the findings, limitations, and implications for higher education practice of our study; and Section 7 presents concluding remarks and outlines future work.

2. Related Work and Theoretical Foundations

Research on AI in education has evolved over several decades, with early work primarily focused on intelligent tutoring systems, automated assessment and feedback, and adaptive learning environments. These systems are typically designed to operate within well-defined instructional contexts, providing learners with structured guidance, feedback, and sequencing based on predefined models of knowledge and performance [4,5]. Within this literature, AI is often conceptualized as a means of optimizing instructional efficiency and personalizing learning pathways, with success measured through task completion, accuracy, or time-on-task.

Beyond technical capability, scholars have emphasized the need to situate artificial intelligence in education within broader sociotechnical and institutional contexts. Research has highlighted how educational technologies often reshape power, authority, and learner identity in unintended ways, particularly when adoption outpaces pedagogical reflection [3]. Similarly, work on digital learning ecosystems emphasizes that learning technologies function as interconnected systems rather than isolated tools, with instructional design, assessment practices, and institutional norms jointly shaping learner experience [12]. These perspectives underscore the importance of examining GenAI not only as a technical innovation, but as an infrastructural component embedded within educational systems.

Recent advances in GenAI mark a fundamental departure from earlier educational AI systems. Rather than delivering predetermined instructional responses, GenAI engages learners through open-ended dialogue, explanation, and example generation. This shift has renewed scholarly attention to AI in higher education, particularly around pedagogical alignment, ethical use, and institutional readiness [3,7,8]. Recent syntheses highlight both expanded access to feedback and individualized support and persistent concerns about academic integrity, accuracy, and student dependence [13–15]. However, this literature largely treats GenAI as a tool or external intervention, rather than as an integrated component of instructional design.

A recurring theme in the literature is the tension between learner autonomy and instructional guidance when AI tools are introduced into educational settings. Cognitive load theory and related instructional design research emphasize that novice learners benefit most from structured guidance and scaffolding, particularly when engaging with complex or unfamiliar material [9]. Minimally guided instructional approaches may increase cognitive burden and hinder learning when learners lack sufficient prior knowledge. This insight is particularly relevant in the context of GenAI, which can produce fluent and persuasive responses that may obscure conceptual misunderstandings if not mediated properly by instructional constraints.

Cognitive engagement also shapes how GenAI supports or undermines learning. The *Interactive*, *Constructive, Active, and Passive* (ICAP) framework [10] characterizes engagement along a hierarchy, with deeper learning emerging as students generate, explain, and refine ideas through interaction. GenAI can promote higher levels of engagement by prompting explanation, comparison, and reflection; without intentional instructional design, however, it may instead encourage passive consumption of generated content and constrain constructive learning.

Self-regulated learning theory offers a useful lens for understanding GenAI in educational contexts. Effective learners monitor understanding, evaluate strategies, and adapt based on feedback [11]. GenAI can support these processes by providing immediate feedback and alternative explanations, but it can also erode self-regulation when learners outsource judgment or evaluation to the system. This tension highlights the need for instructional designs that emphasize transparency, reflection, and learner accountability.

Despite growing recognition of these theoretical considerations, existing literature offers limited guidance on how to operationalize them in classroom practice. Reviews of GenAI in higher education often call for clearer pedagogical strategies and instructional frameworks that move beyond general recommendations [7-8]. However, many studies stop short of articulating how instructors can deliberately structure AI participation in learning activities, assessments, and classroom norms.

The theoretical perspectives reviewed above inform the design of the AIMI framework.

Cognitive load theory motivates constraints for instruction mediation that structure when and how GenAI is used, limiting extraneous burden and solution substitution. The ICAP framework motivates patterns that promote constructive and interactive engagement, such as *Contrastive Prompting* and *Reflective Explanation* (see Section 5), rather than passive consumption of AI outputs. Self-regulated learning theory motivates accountability practices that require students to document, evaluate, and justify their GenAI use, preserving learner agency and metacognition. Together, these theories provide the conceptual foundation for AIMI's three roles—*Cognitive Support*, *Mediated Instruction*, and *Learning Accountability*—introduced in Section 3.

Building on this foundation, the paper synthesizes insights from AI in education, instructional design, and learning theory to propose the AIMI pedagogical framework for GenAI integration. Rather than evaluating tool performance or learner outcomes in isolation, our framework emphasizes the relational role of AI within the instructional system. By positioning GenAI as pedagogical infrastructure, our study extends existing literature toward a design-oriented perspective that foregrounds instructor mediation (addressing cognitive load), learner agency (fostering constructive engagement), and accountability (supporting self-regulation) as central to effective AI-enabled learning environments.

3. Generative Artificial Intelligence as Pedagogical Infrastructure

This paper conceptualizes GenAI as *pedagogical infrastructure* rather than as a discrete instructional tool or supplemental resource. In this context, infrastructure denotes GenAI systems that are embedded, persistent, and practice-shaping—often becoming most visible when they are poorly designed or misaligned with instructional goals. When treated merely as an optional aid, GenAI's influence on learning remains implicit and unmanaged. In contrast, framing GenAI as pedagogical infrastructure foregrounds instructional design as the primary mechanism through which AI meaningfully participates in learning, aligning with calls to emphasize its embedded role in educational practice [16].

We position GenAI across three interconnected pedagogical roles—*Cognitive Support*, *Mediated Instruction*, and *Learning Accountability*—that form the AIMI framework. As shown in Figure 1, their intersection represents balanced integration, where GenAI supports learning without undermining student agency or instructor control. *Cognitive Support* provides explanation and scaffolding; *Mediated Instruction* structures GenAI use through prompts, constraints, and task design; and *Learning Accountability* ensures reflection, attribution, and transparent assessment. Educational value thus emerges not from GenAI's presence alone, but from the intentional alignment of these roles. The remainder of this section explores each interconnected pedagogical role shown in Figure 1 in more depth.

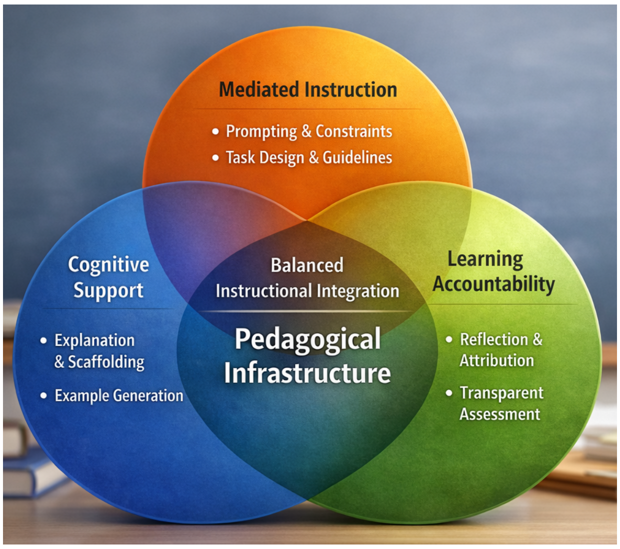

Figure 1: Elements in the AIMI Framework.

3.1 Cognitive Support

Cognitive Support assists learners with explanation, example generation, rephrasing of concepts, and exploration of alternative approaches. Such support can reduce extraneous cognitive load, particularly for novice learners who struggle to interpret complex material or unfamiliar terminology, effectively acting as a "thought partner" or explainer [17]. By providing immediate, responsive assistance, GenAI helps students focus attention on core ideas rather than procedural barriers.

However, *Cognitive Support* does not—and should not—imply cognitive replacement. Without instructional boundaries, students may rely on GenAI outputs as authoritative answers rather than as aids for understanding. The AIMI framework therefore distinguishes between support that scaffolds sense-making and use that substitutes for student reasoning. *Cognitive Support* is most effective pedagogically when GenAI outputs are positioned as provisional, explainable, and subject to student evaluation.

3.2 Learning Accountability

Learning Accountability ensures student learning remains visible, assessable, and attributable, even when GenAI is involved. This accountability includes transparency about GenAI use, reflective documentation of how outputs were incorporated, and assessment designs that prioritize reasoning and decision making over final products alone. *Learning Accountability* directly addresses concerns that GenAI obscures authorship or undermines evaluation.

Rather than prohibiting GenAI use, the AIMI framework emphasizes designing assignments that require students to articulate their understanding, explain their choices, and reflect on how GenAI contributed to their work. These practices foreground student reasoning and metacognition instead of treating outputs as self-evident evidence of learning. Accountability mechanisms therefore reinforce the idea that GenAI is a resource within the learning environment, not a proxy for learning itself.

3.3 Mediated Instruction

Mediated Instruction captures how instructors intentionally structure GenAI use within learning activities. Instructional mediation includes prompt design, constraints, task framing, and evaluation criteria that shift GenAI from generic use to pedagogically scaffolded interaction [16]. In this role, instructors mediate between the tool and the learner by determining when GenAI is appropriate, what forms of interaction are permitted, and how outputs should be interpreted.

Mediated Instruction transforms GenAI from an uncontrolled external resource into a guided participant in the learning process. For example, instructors may require students to compare GenAI-generated explanations with course materials, critique inaccuracies, or justify departures from suggested solutions. Such mediation preserves student agency while promoting deeper engagement and supports consistency across courses by making expectations for GenAI use explicit rather than implicit.

3.4 AIMI Framework Integration

Together, the AIMI framework elements form an integrated pedagogical system. These three roles correspond to key facets of learning theory: *Cognitive Support* helps manage extraneous cognitive load for novices [CITE], ensuring *Learning Accountability* fosters self-regulation and metacognition [CITE], and *Mediated Instruction* encourages active or contructive engagement in line with the ICAP framework [CITE]. The AIMI framework therefore emphasizes balance since effective integration of GenAI requires attention to all three roles simultaneously, as supported by design-oriented guidelines for AI integration [16].

By positioning GenAI as pedagogical infrastructure, the AIMI framework provides a structured lens for evaluating and designing artificial intelligence enabled learning environments. It shifts the focus from whether GenAI should be used to how it can be responsibly embedded within instructional systems. This perspective enables educators and institutions to move beyond reactive policies toward intentional, theory informed adoption that aligns GenAI capabilities with educational values.

4. Methods and Study Design

This section outlines the qualitative, design-oriented methods used to develop the AIMI framework as pedagogical infrastructure for GenAI in higher education. It describes the instructional contexts, data sources, and analytic approach underlying the study, and clarifies the methodological scope, limitations, and ethical considerations shaping interpretation.

4.1 Research Approach and Study Context

Our study applies a qualitative, design-oriented research approach to examine how GenAI can be integrated into higher education as pedagogical infrastructure. Rather than evaluating the performance of specific GenAI tools or measuring learning outcomes through controlled experimentation, the study focuses on instructional design practices and classroom implementation as sites of analysis. This approach is appropriate given the exploratory nature of the research question and the rapidly evolving role of GenAI in educational settings.

Our study draws on instructional practice across seven course offerings between Fall 2023 and Spring 2026, spanning four undergraduate and three graduate courses in computer science and data science [6]. Undergraduate enrollments ranged from 50–100 students and graduate enrollments from 9–42 students. GenAI-mediated activities comprised varying proportions of graded work (~30–60%, with higher use in project-based graduate courses) and recurring in-class exercises emphasizing explanation, critique, and reflection. The courses served novice to advanced learners from diverse majors, with learning goals focused on conceptual reasoning, problem formulation, and applied analysis rather than programming proficiency alone. These contextual details indicate scope rather than statistical generalizability.

4.2 Data Sources and Analytic Process

Evidence consisted of (1) course artifacts like assignment prompts, rubrics, and student submissions; (2) structured student reflections describing how GenAI was used and evaluated; and (3) instructor field notes from class sessions and office hours. All materials were reviewed in de-identified form. Reflections were voluntary and not graded for content.

Analysis followed a three-stage iterative, inductive process. First, we open-coded artifacts and reflections to identify recurring forms of GenAI use, instructional friction, and mediation strategies. Second, these codes were clustered into candidate patterns representing recurring problem–solution pairs. Third, pattern names and descriptions were refined through comparison with learning-theory constructs (ICAP engagement, cognitive load, and self-regulation) to align design intent with observed enactment. Pattern definitions were iteratively validated against raw artifacts to ensure grounding in the data.

4.3 Methodological Scope, Rigor, and Ethics

Consistent with this design-oriented approach, findings are presented as observed tendencies and plausible mechanisms rather than measured learning gains. The aim is to articulate how particular configurations of GenAI use were enacted in classrooms and how students responded, not to establish causal effectiveness. Accordingly, Sections 5 and 6 are framed using observational language (e.g., “clearer questions,” “greater articulation of reasoning”) rather than outcome assertions.

All the activities described above occurred within normal course instruction and posed minimal risk. Student work was analyzed in de-identified form, and participation in reflections was voluntary. The study was reviewed under institutional procedures and deemed consistent with exempt educational research focused on improvement of teaching practice.

5. Instructional Patterns and Observations

This section presents the instructional patterns summarized in Table 1 that operationalize the AIMI framework (see Section 3). Distilled from repeated observations across seven undergrad and grad courses over three years (see Section 4.1), each pattern codifies an evidence-based design that captures a recurring pedagogical problem and a structured solution specifying how GenAI is used, how instructors mediate that use, and how student learning is made visible and accountable. Like software and prompt patterns [18,19], these patterns abstract successful practice rather than cataloging isolated tactics, making design intent explicit via coordinated use of *Cognitive Support*, *Mediated Instruction*, and *Learning Accountability*.

Table 1: Instructional Patterns and Observed Pedagogical Effects of GenAI Integration

Instructional Pattern	Core Function of GenAI	Mediated Instruction	Learning Accountability	Observed Effects
Guided Decomposition	Explain substeps and concepts	Prompts restrict solution generation	Students contextualize outputs via course materials	Clearer questions; reduced confusion
Contrastive Prompting	Provide alternative explanations	Students write first, then compare	Justification of accept/ revise/reject	Greater articulation of reasoning
Error-as-Data	Analyze mistakes	Tasks require critique of AI errors	Reflection on why outputs fail	Productive use of misconceptions
Reflective Explanation	Support metacognition	Prompts require explanation of process	Disclosure of GenAI influence	Increased self-regulation
Boundary Setting	Background support	Task-specific rules for use	Consistent documentation norms	Lower anxiety; aligned expectations

Each pattern in Table 1 represents a configuration of *Cognitive Support*, *Mediated Instruction*, and *Learning Accountability* that shapes student engagement and learning. As described in the remainder of this section, these patterns operationalize our AIMI framework by demonstrating how GenAI serves as pedagogical infrastructure when its role is designed intentionally rather than driven by AI model capabilities alone.

5.1 The *Guided Decomposition* Pattern

Context. Students often struggle with complex terminology and multi-step reasoning before they can meaningfully engage with problem solving.

Problem. Unconstrained GenAI use encourages solution-seeking behavior, reducing conceptual sense making and masking gaps in understanding.

Solution. *Guided Decomposition* positions GenAI as *Cognitive Support*, not a solver. Instructor-mediated prompts restrict outputs to explanations, rephrasings, or analogies using course language, explicitly prohibiting final answers. Accountability is maintained by requiring students to contextualize and evaluate explanations against course materials.

Classroom example. Students prompted GenAI to explain algorithmic substeps using textbook terminology, then annotated where the explanation aligned—or conflicted—with lecture notes before submitting their own solution.

Artifact snippet (prompt). Explain this concept using course terminology only. Provide (1) a definition, (2) one micro-example, and (3) one common misconception. Do not generate a final solution.

5.2 The *Contrastive Prompting* Pattern

Context. Advanced learning tasks require students to articulate reasoning and evaluate competing explanations.

Problem. When students consult GenAI before forming their own responses, opportunities for critique and metacognitive reflection are lost.

Solution. *Contrastive Prompting* requires students to produce an initial response independently, then compare it with GenAI output. Instructional mediation structures the comparison task, while *Learning Accountability* is enforced through justification of what was accepted, revised, or rejected.

Classroom example. Students drafted a design rationale, compared it to a GenAI-generated alternative, and submitted a short critique explaining which assumptions were valid and which were invalidated by course-specific constraints.

Artifact snippet (task). Submit your own response first and then (1) request an alternative explanation from GenAI and (2) write a brief critique comparing assumptions, structure, and constraints.

5.3 The *Error-as-Data* Pattern

Context. Novice learners benefit from immediate feedback but are vulnerable to overreliance on GenAI.

Problem. Early unrestricted access can replace student reasoning, while outright prohibition increases frustration and disengagement.

Solution. *Error-as-Data* introduces GenAI through progressive instructional mediation. Early tasks limit use to explanation and rephrasing; later tasks permit exploratory examples once baseline competence is demonstrated. *Cognitive Support* is framed around analyzing errors, and accountability emphasizes reflection on why outputs fail.

Classroom example. Students first used GenAI to interpret compiler errors; later, they evaluated flawed AI-generated code, identifying and correcting mistakes before submission.

Artifact snippet (task). Provide GenAI with your incorrect solution and ask it to identify possible errors. You must (1) verify each claim and (2) correct the work in your own words.

5.4 The *Reflective Explanation* Pattern

Context. As GenAI becomes embedded in coursework, instructors must ensure learning remains visible and attributable.

Problem. Without structured reflection, GenAI obscures authorship and shifts assessment toward outputs rather than reasoning.

Solution. *Reflective Explanation* embeds *Learning Accountability* by requiring students to document how GenAI was used, which outputs influenced their work, and how those outputs were evaluated or modified, emphasizing metacognition over compliance.

Classroom example. Project submissions included a short reflection describing GenAI interactions, validation steps, and how final reasoning diverged from initial AI suggestions.

Artifact snippet (reflection). Describe how GenAI influenced your reasoning—what you kept, changed, or rejected, and why.

5.5 The *Boundary Setting* Pattern

Context. Ambiguous expectations around GenAI use generate anxiety, inconsistency, and integrity disputes.

Problem. Implicit or course-by-course norms force students to infer acceptable use, undermining fairness and alignment with learning objectives.

Solution. The *Boundary Setting* pattern establishes GenAI as pedagogical infrastructure through explicit, task-specific rules governing when and how GenAI may be used and documented. Instructional mediation operates at the course level, while accountability is normalized rather than policed.

Classroom example. Across multiple courses, instructors adopted shared rules allowing GenAI for explanation and post-draft critique only, with brief documentation of use, resulting in fewer disputes and clearer alignment with instructional goals.

Artifact snippet (course rule). GenAI is allowed for explanation and post-draft critique only; not for producing final answers.

6. Discussion and Implications

Our analysis of the instructional patterns in Section 5 advances a practice-driven view of GenAI integration by positioning it as pedagogical infrastructure embedded in instructional systems. These patterns show that educational value arises from design configurations rather than model capabilities alone. When applied through balanced structures of *Cognitive Support*, *Mediated Instruction*, and *Learning Accountability*, GenAI can support conceptual engagement while preserving student agency. The remainder of this section synthesizes the interpretations, limitations, and implications of these findings for higher education practice.

6.1 Cross-Pattern Findings

Across the five instructional patterns, we consistently observed three recurring effects in student artifacts, reflections, and field notes. First, *Guided Decomposition* activities with constrained prompting shifted help-seeking toward task-specific questions about criteria and intermediate reasoning, rather than requests for completed solutions. Second, *Contrasted Prompting* and *Error-as-Data* activities made reasoning more visible, as students explicitly annotated points of alignment and divergence between their work and GenAI outputs. Third, explicit *Boundary Setting* activities reduced ambiguity around acceptable use, evidenced by more consistent disclosure practices and fewer clarification requests.

However, these instructional patterns were not uniformly successful. For example, decomposition prompts sometimes led students to bypass intermediate reasoning under time pressure; contrastive tasks produced superficial comparisons when rubrics did not require justification; and error-as-data activities occasionally increased overconfidence when students trusted model explanations over compiler feedback. These cases indicate that the AIMI framework depends on sustained instructional mediation and highlight the importance of continuous scaffolding and clear rubrics to fully realize the patterns' benefits.

6.2 Implications for Instructional Practice

Our observations and design insights highlight the need for educators to shift from reactive policies toward proactive instructional design. Rather than debating if GenAI should be permitted, instructors can specify how it may be used, for what purposes, and under what constraints. For example, our study found that when students were given structured prompt rules, they asked more on-topic, intermediate questions rather than simply seeking answers

The instructional patterns identified in our study show how guided prompting, comparison and critique, scaffolded exploration, and structured reflection can reframe GenAI from a source of concern into a pedagogical asset—particularly in courses serving novice or non-technical learners, where unmanaged use may otherwise increase confusion or dependence. For example, guided prompting (*Guided Decomposition*) helped students unpack complex tasks, comparison and critique (*Contrastive Prompting*) made their reasoning visible. Likewise, scaffolded exploration (*Error-as-Data*) let novices safely learn from mistakes and structured reflection (*Reflective Explanation*) ensured students remained aware of their own thought processes.

Our AIMI framework reframes instructors as mediators of learning rather than gatekeepers of technology. By making expectations explicit and embedding accountability mechanisms, educators can preserve assessment integrity while supporting exploratory learning.

This design shift appears to reduce instructional friction and student anxiety by aligning GenAI use with clear learning objectives. These implications reflect practice-based interpretations from course enactments rather than demonstrated learning gains and are intended to inform instructional design decisions that others can adapt and examine in their own contexts.

6.3 Institutional and Policy Implications

Our interpretations support the view that broad prohibitions or generic policy statements are insufficient to address the pedagogical implications of GenAI. Institutions may benefit from supporting faculty development initiatives that emphasize instructional design and learning theory alongside technological literacy. Policies that recognize GenAI as part of the instructional infrastructure, rather than as an external threat, can better align governance with classroom realities.

In addition, institutional assessment frameworks may need to evolve to account for learning processes alongside final products. Encouraging reflective and process-oriented assessment practices can help ensure that student learning remains visible and attributable in GenAI-enabled environments. Such alignment has the potential to support equity by reducing disparities in how students interpret and navigate ambiguous GenAI policies.

From a broader perspective, our findings align with calls for human-centered approaches to artificial intelligence that emphasize transparency, user agency, and meaningful human control [20]. Treating GenAI as pedagogical infrastructure reinforces the view that educational technologies should augment—not replace—human judgment and instructional expertise. International policy discussions have similarly emphasized the importance of aligning artificial intelligence adoption with educational values, equity considerations, and long-term societal goals [21,22]. These perspectives suggest that sustainable GenAI integration requires coordinated attention to pedagogy, governance, and institutional culture.

6.4 Limitations and Threats to Validity

Our study has several limitations. The findings in Section 5 are based on qualitative observations from a limited set of higher education courses and are not intended to generalize across disciplines or institutional contexts. Our study contains no controlled comparisons or longitudinal measures of learning outcomes. Accordingly, the AIMI framework and instructional patterns should be interpreted as design insights rather than prescriptive solutions. In addition, no inter-rater coding was conducted; themes were refined through author discussion and consideration of negative cases.

The rapidly evolving nature of GenAI further constrains interpretation. Although the framework is intended to be tool-agnostic, changes in GenAI capabilities may necessitate ongoing refinement of instructional strategies and governance. Taken together, these limitations position our findings as exploratory and context-dependent, offering conceptual guidance rather than definitive evidence of instructional effectiveness.

7. Concluding Remarks

The rapid integration of GenAI into higher education has outpaced the development of pedagogical frameworks capable of guiding its responsible and effective use. This paper contributes to addressing this gap by proposing and refining a model of GenAI as embedded pedagogical infrastructure through analysis of teaching practice and iterative instructional design. Through an analysis of teaching practice, our study suggests that the educational impact of GenAI depends fundamentally on how instructors deliberately structure its use.

The AIMI framework we present provides educators with a structured lens for this design work, moving the conversation from whether to use AI to how to integrate it to support conceptual engagement, mediate learning, and ensure accountability. The instructional patterns we identify offer practical starting points for this integration. Ultimately, this perspective underscores the need to move beyond reactive policies. When treated as a designed component of the learning environment, GenAI can enhance transparency and reduce cognitive barriers. As these technologies evolve, this infrastructure view offers a sustainable path for aligning emerging tools with enduring educational values.

Our future research will build on the work presented in this paper by examining the application of the AIMI framework across diverse disciplines and institutional settings. Empirical studies that investigate how specific instructional patterns influence learning outcomes, engagement, or equity would further strengthen the evidence base. Longitudinal research may also explore how sustained GenAI integration shapes student learning strategies and instructor practices over time.

Our future work will also examine the interaction between GenAI and emerging assessment models, as well as the implications of GenAI integration for curriculum design at the program level. Investigating student perceptions of agency, trust, and responsibility in GenAI enabled learning environments may provide further insight into how pedagogical infrastructure influences educational experience.

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