Original Article

Generative AI as a Pedagogical-Cognitive Integration Agent: A Theoretical Model for Interdisciplinary, Multidisciplinary and Transdisciplinary Learning

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Abstract

Integrative learning requires learners and teachers to coordinate disciplinary concepts, methods and standards of evidence, yet such coordination is cognitively demanding and institutionally difficult. This conceptual article develops a model of generative artificial intelligence, particularly large language models, as a pedagogical-cognitive integration agent. The model was constructed through a structured, concept-driven synthesis of three literature domains: integrative learning, human-AI collaboration in education and generative AI. Concepts were compared according to the integrative demand addressed, the locus of activity, the division of human and computational labor, and the conditions required for epistemically defensible use. The resulting model comprises three interdependent axes: cognitive mediation, pedagogical co-orchestration, and systemic design alignment. Unlike a taxonomy of AI functions, the model specifies a recurrent process in which institutional conditions shape pedagogical design, teacher and learner interaction activates cognitive integration, and human evaluation feeds back into subsequent design. Generative AI contributes candidate connections, translations and syntheses, while teachers and learners retain responsibility for disciplinary grounding, verification, interpretation and judgment. Six revised vignettes illustrate both productive uses and predictable tensions, including misleading metaphors, superficial synthesis, bias and overreliance. The article defines the model's assumptions and boundaries and advances six propositions for empirical

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testing. Its contribution is therefore conditional: generative AI may support integrative learning when embedded in human-led cycles of inquiry, validation and revision, but fluent output alone does not constitute integration.

Keywords: generative artificial intelligence, human-AI collaboration, Integrative learning, interdisciplinary education, large language models, pedagogical co-orchestration, transdisciplinarity

1. Introduction

Over the past several decades, educational systems worldwide have gradually shifted from discipline-based instruction toward more integrative models of teaching and learning. Foundational work on curriculum integration, such as Beane's (1997) problem-centered approach, argues that meaningful learning emerges when students engage with real-life issues rather than isolated subject matter. Contemporary frameworks extend this view by highlighting how interdisciplinary and transdisciplinary learning cultivate deeper understanding, intellectual flexibility and the capacity to navigate complex domains of knowledge. For example, Drake and Reid (2018) demonstrate how integrated curriculum design promotes holistic learning experiences, while Kelley and Knowles (2016) show that inquiry-based STEM integration strengthens students' ability to construct explanations across disciplinary boundaries. Boix Mansilla and Duraisingh (2007) add evaluative clarity by identifying core criteria for high-quality interdisciplinary work, including disciplinary grounding, integrative purpose and advancement of understanding.

Despite this strong theoretical foundation, educators continue to encounter persistent obstacles when implementing interdisciplinary and transdisciplinary learning in practice. Research consistently shows that teachers often struggle to mediate between different disciplinary languages, identify meaningful conceptual bridges, and design coherent learning sequences that support students in synthesizing knowledge from multiple domains. Students, in turn, may experience cognitive overload as they attempt to link concepts, practices and epistemologies that originate in diverse disciplinary traditions. Additional challenges include planning cross-disciplinary units, coordinating among subject-area teachers, and providing the scaffolding necessary for learners to make deep, non-superficial connections. These difficulties reflect broader systemic tensions between traditional schooling structures and the demands of integrative learning.

At the same time, artificial intelligence has become increasingly embedded in educational environments. Earlier AIED research largely framed these technologies through personalization, assessment, automation and data analysis (Holmes et al., 2019; Zawacki-Richter et al., 2019). More recent human-AI collaboration frameworks move beyond a purely instrumental account, but they do not explicitly explain how generative systems might participate in constructing and validating cross-disciplinary relationships.

The technological object considered in this article is not artificial intelligence in general. The model primarily concerns generative AI systems based on large language models (LLMs), including multimodal systems that can produce and transform text, images and structured representations in response to natural-language prompts. Their relevance to integrative learning derives from their capacity to generate candidate analogies, summaries, mappings and cross-domain explanations. These capabilities differ from those of predictive analytics or conventional intelligent tutoring systems, which may classify, recommend or adapt content but do not ordinarily generate open-ended cross-disciplinary representations (Kasneci et al., 2023; UNESCO, 2023).

This distinction also limits the meaning of the term integration agent. It denotes a functional role in a human-led educational process, not autonomous understanding, authorship or epistemic authority. LLM outputs are probabilistic constructions that may be fluent without being accurate, appropriately grounded or educationally valuable (Bender et al., 2021; Kasneci et al., 2023). Consequently, the model treats generative AI as a source of candidate relations that teachers and learners must interrogate, verify and revise.

This gap in the literature is increasingly consequential. According to the OECD Learning Compass (2019), future-oriented competencies such as systems thinking, complex problem solving and epistemic fluency require learners to move fluidly across domains, integrate diverse knowledge sources and construct multidimensional explanations. These competencies are central not only in interdisciplinary research but also in navigating the complex sociotechnical challenges that define the 21st century. Without a model that articulates how AI can support integrative cognitive processes, a critical opportunity remains unexplored.

The purpose of this article is to develop and delimit a theoretical model of generative AI as a pedagogical-cognitive integration agent. The article asks: under what conceptual and pedagogical conditions can generative AI contribute to multidisciplinary, interdisciplinary and transdisciplinary learning without displacing disciplinary rigor, teacher judgment or learner agency? The contribution is a structured model of three interdependent axes, a dynamic account of their relationships, explicit boundary conditions and propositions that can guide empirical testing.

2. Theoretical Background

2.1 Forms of Integrative Learning

Integrative learning has evolved significantly over the past several decades, reflecting a growing recognition that complex real-world challenges cannot be addressed through isolated disciplinary lenses. Within the scholarly literature, three major forms of integration are commonly distinguished: multidisciplinarity, interdisciplinarity and transdisciplinarity. Although often used interchangeably, these forms represent distinct conceptual and pedagogical approaches, each with unique implications for curriculum design, inquiry processes and knowledge construction.

Multidisciplinarity refers to the juxtaposition of multiple disciplines around a common theme or topic, while maintaining the internal logic and boundaries of each discipline. Knowledge remains largely parallel, and integration is not inherent but may be achieved by the learner. This approach is frequently used in school-based thematic units, where different subject-area teachers address a shared question or phenomenon from their respective disciplinary perspectives. Beane’s (1997) foundational model of curriculum integration rejects rigid disciplinary separation altogether and instead organizes learning around problems that matter in students' lives. Although Beane’s framework is often characterized as interdisciplinary, it also incorporates elements of multidisciplinarity by allowing disciplinary insights to be introduced when relevant to the problem under investigation.

Interdisciplinarity moves beyond mere juxtaposition by actively integrating concepts, methods or epistemologies from two or more disciplines to construct new understandings. Drake and Reid (2018) describe an interdisciplinary curriculum as a deliberate blending of disciplinary knowledge to foster deeper comprehension and more holistic learning experiences. Within STEM education, Kelley and Knowles (2016) emphasize that inquiry-based interdisciplinary learning requires students to coordinate scientific reasoning, mathematical modeling, engineering design and technological tools to solve authentic problems. Boix Mansilla and Duraisingh (2007) provide one of the most influential frameworks for evaluating interdisciplinary work, identifying three core criteria: appropriate disciplinary grounding, purposeful integration and the advancement of understanding beyond what each discipline could yield independently. Together, these contributions position interdisciplinarity as both a cognitive and epistemic process in which learners synthesize and transform disciplinary knowledge.

Transdisciplinarity represents the most expansive form of integration. Rather than combining existing disciplines, transdisciplinarity transcends disciplinary boundaries to address problems situated in complex real-world systems. Nicolescu (2014) conceptualizes transdisciplinarity as an approach that incorporates multiple levels of reality, integrates knowledge from academic and non-academic sources and seeks to generate new forms of inquiry that are not confined by traditional disciplinary structures. In this sense, transdisciplinarity not only crosses disciplinary lines but dissolves them, creating a space in which learners collaboratively investigate phenomena that require holistic, systemic and multi-perspective thinking.

Across these forms, scholars have identified several key integrative mechanisms essential to high-quality interdisciplinary and transdisciplinary learning. These mechanisms include conceptual bridging, in which learners connect ideas across domains; knowledge translation, involving the interpretation and re-expression of disciplinary concepts in ways that make them accessible to other fields; synthesis, the process of combining insights into coherent and novel understandings; and multi-perspective inquiry, through which learners analyze phenomena using diverse disciplinary, cultural or epistemic lenses. Each mechanism plays a critical role in enabling students to move flexibly across knowledge domains, construct complex explanations and engage with authentic problems that require integrated reasoning.

These theoretical constructs form the foundation upon which the present article builds its proposed model of AI as a pedagogical-cognitive integration agent. Understanding how integration occurs—and the mechanisms that support it—provides essential groundwork for conceptualizing how AI might mediate, enhance or transform these processes in educational contexts.

2.2 21st Century Skills and Integrative Cognition

The demands of contemporary societies increasingly require learners to navigate complex, interconnected systems, work with rapidly expanding bodies of knowledge and engage with problems that cut across traditional disciplinary boundaries. The OECD Learning Compass (2019) provides one of the most influential frameworks for understanding these demands, identifying a set of future-oriented competencies that are essential for thriving in the 21st century. Among these competencies, four are particularly relevant to integrative learning: systems thinking, complex problem-solving, epistemic fluency, and multi-source knowledge work.

Systems thinking refers to the ability to understand phenomena as part of larger, dynamic and interdependent systems. It involves recognizing patterns, relationships and feedback loops rather than viewing issues through linear or isolated lenses. This form of cognition inherently transcends disciplinary boundaries, as systems—whether ecological, technological or social—cannot be adequately understood through a single disciplinary framework. Integrative learning environments provide opportunities for students to develop systems thinking by engaging with cross-cutting phenomena such as climate change, public health or technological ethics, each of which requires analysis at multiple levels and from multiple disciplinary perspectives.

Complex problem-solving is similarly rooted in the need to address real-world challenges that lack simple or predetermined solutions. According to the OECD (2019), such problems demand iterative inquiry, openness to uncertainty and the integration of diverse forms of knowledge. Interdisciplinary and transdisciplinary learning are particularly well-suited to cultivating these capacities, as they require learners to coordinate insights from different fields, evaluate competing explanations and construct solutions that account for interacting variables within multifaceted contexts.

Epistemic fluency—the ability to understand, compare and flexibly use different ways of knowing—plays a central role in integrative cognition. The OECD Learning Compass frames epistemic fluency as the capacity to draw on multiple epistemologies, whether scientific, mathematical, technological, historical or ethical, and to deploy them appropriately in relation to specific problems. This fluency is foundational to interdisciplinary work, which depends on learners' ability to recognize the strengths and limitations of each discipline and to integrate them into coherent, actionable understanding.

Finally, multi-source knowledge work highlights the need for learners to gather, evaluate and synthesize information from an increasingly diverse array of sources. In a knowledge environment shaped by digital tools, global information flows and expanding data sets, the ability to make sense of heterogeneous information is a core competency. Integrative learning frameworks purposefully design opportunities for students to work with varied forms of knowledge, ranging from empirical data to theoretical models, expert testimony, and lived experience.

Taken together, these competencies indicate that integrative learning is not merely an educational option, but a prerequisite for future-oriented education. The capacity to think systemically, solve complex problems, operate across epistemic frameworks and synthesize multi-source information aligns directly with the challenges of the 21st century. As the present article proposes, such competencies also underscore the need for new pedagogical models that leverage emerging tools—such as artificial intelligence—not simply to deliver or assess content, but to support the cognitive and epistemic processes at the heart of integrative learning.

2.3 Challenges in Implementing Integrative Pedagogy

Despite strong theoretical support for integrative learning, implementing interdisciplinary, multidisciplinary and transdisciplinary pedagogy remains challenging for educators and institutions. These challenges arise from both cognitive and structural factors documented in the literature.

A central difficulty involves teachers' capacity to maintain expertise across multiple disciplinary domains. Integrative learning requires educators to draw on diverse bodies of knowledge, coordinate multiple epistemic frameworks and guide students in constructing cross-disciplinary syntheses. Drake and Reid (2018) note that many teachers feel insufficiently prepared for cross-disciplinary curriculum design, and often lack confidence when navigating content beyond their primary disciplinary training. Similar concerns appear in STEM contexts, where Kelley and Knowles (2016) report that teachers struggle to integrate scientific inquiry, engineering design and mathematical modeling in coherent ways.

Learners face parallel cognitive challenges. Interdisciplinary and transdisciplinary tasks require students to process unfamiliar conceptual structures, compare differing disciplinary assumptions and integrate heterogeneous sources of information. According to the OECD (2019), these demands can generate high cognitive load, particularly when learners must simultaneously interpret multiple epistemic perspectives. Without adequate scaffolding, students may revert to monodisciplinary explanations, limiting the depth of integration they can achieve.

Another challenge concerns the mediation between disciplinary vocabularies and epistemologies. Each field operates with its own conceptual language, methodological norms and criteria for evidence. Boix Mansilla and Duraisingh (2007) emphasize that high-quality interdisciplinary work depends on learners' ability to translate and connect concepts across disciplines. However, such translation is rarely straightforward. Teachers frequently struggle to help learners navigate conflicting definitions, reconcile disciplinary assumptions or recognize conceptual shifts across domains.

Structural constraints within educational systems further complicate integrative practice. Traditional schooling organizes knowledge into separate subjects, each with its own independent schedule, assessments, and administrative structures. This organization creates barriers to cross-disciplinary collaboration and limits the potential for sustained integrative learning (Beane, 1997). Designing interdisciplinary units requires coordinated planning, flexible time structures and alignment of learning goals, yet many institutions lack these conditions. Nicolescu (2014) similarly argues that transdisciplinary learning demands institutional openness and structural flexibility, which are often absent in conventional educational settings.

Together, these challenges underscore the cognitive, pedagogical and systemic complexity involved in implementing integrative learning. They also highlight the need for supportive mechanisms that can facilitate conceptual translation, reduce cognitive overload and assist educators in designing cohesive inter and transdisciplinary experiences. These needs form an essential foundation for exploring how artificial intelligence might contribute to integrative pedagogy through new forms of cognitive and pedagogical mediation.

2.4 Generative AI and Human-AI Collaboration in Education

Earlier research on artificial intelligence in education focused on intelligent tutoring, prediction, personalization, automated assessment, and administrative support. A systematic review of higher education research found that these application-oriented categories dominated the field and that educator perspectives were comparatively underrepresented (Zawacki-Richter et al., 2019). Such systems remain relevant, but they do not by themselves explain the open-ended generative functions at issue in this model.

Generative AI and LLMs alter this landscape by transforming representations across domains and modalities. They can restate a concept for a different audience, propose analogies, generate contrasting explanations, organize heterogeneous material and suggest lines of inquiry. These are affordances, not guaranteed educational effects. An output becomes pedagogically useful only through a task structure that requires learners to interpret, compare, justify and revise it. The system does not independently determine whether a cross-disciplinary relation is valid or whether a synthesis preserves the standards of the contributing disciplines (Kasneci et al., 2023).

Human-AI collaboration frameworks provide an important foundation for this distinction. Ouyang and Jiao (2021) differentiate AI-directed, AI-supported and AI-empowered paradigms, with increasing learner control across the three. Molenaar

(2022) similarly proposes a hybrid intelligence perspective and levels of automation that distribute detection, diagnosis and action between humans and AI. These frameworks clarify control and the division of labor. The present model builds on them but addresses a more specific problem: how candidate connections among disciplinary concepts, methods and forms of evidence are generated, pedagogically staged, validated and incorporated into an integrative outcome.

2.5 Positioning the Model Among Existing Frameworks

Framework	Primary question	Human role	AI role	Unresolved issue addressed here
Traditional AIED applications	How can instruction, prediction or assessment be optimized?	Designer, instructor or recipient of system recommendations	Tutor, predictor, recommender or assessor	Does not specify how cross-disciplinary meaning is constructed and validated.
Ouyang and Jiao (2021)	Who directs learning across AI-directed, AI-supported and AI-empowered paradigms?	Ranges from recipient to leader	Ranges from director to collaborator	Clarifies agency, but not the mechanisms or quality criteria of disciplinary integration.
Molenaar (2022)	How should human and AI intelligence be combined at different levels of automation?	Shares detection, diagnosis and action with AI	Augments human regulation and decision making	Clarifies allocation of control, but not the pedagogical sequence of integrative knowledge work.
Integration Agent Model	How are cross-disciplinary relations proposed, enacted, checked and revised?	Frames inquiry, validates claims, preserves disciplinary rigor and authorizes use	Generates candidate mappings, translations, questions and syntheses	Specifies three linked axes, a feedback cycle, boundary conditions and testable propositions.

3. Conceptual Development Method

This article uses structured conceptual synthesis rather than a systematic review or empirical grounded theory study. Conceptual articles develop relationships among constructs by integrating previously disconnected domains, making assumptions explicit and producing propositions that can orient later research (Jaakkola, 2020). The procedure was informed by conceptual framework analysis, which treats a framework as a network of related concepts and recommends iterative comparison, categorization, synthesis and validation across multidisciplinary literatures (Jabareen, 2009).

The development process comprised five stages. First, the focal phenomenon was bounded as LLM-based generative AI used to support integrative learning, rather than AI in education as a whole. Second, three concept domains were purposively selected: theories and quality criteria for multidisciplinary, interdisciplinary, and transdisciplinary learning; research on the cognitive, pedagogical, and organizational challenges of integration; and frameworks for AIED, generative AI, and hybrid human-AI collaboration. Foundational works and major peer-reviewed frameworks were prioritized because the purpose was construct development, not exhaustive coverage or effect estimation.

Third, concepts were entered into an analytical matrix using four questions: what integrative demand is addressed; where the activity is located, within learner cognition, pedagogical interaction or curricular organization; what contribution can generative AI make; and which human responsibility cannot be delegated. Fourth, concepts were compared iteratively. Functions concerned with translation, mapping and synthesis converged around cognitive mediation; functions concerned with task framing, scaffolding, dialogue and assessment converged around pedagogical co-orchestration; and functions concerned with standards, sequencing, time, resources and institutional feasibility converged around systemic-design alignment. These categories were retained because they describe distinct loci of activity while also forming a temporal and recursive process.

Fifth, the emerging model underwent two conceptual checks. A comparison check distinguished it from existing AIED and human-AI collaboration frameworks. A boundary check identified conditions under which the proposed mechanism should not be expected to work, including absence of disciplinary grounding, passive acceptance of generated text, lack of teacher validation and institutional arrangements that preclude sustained inquiry. The resulting model is therefore analytic and provisional. The vignettes illustrate its mechanisms and tensions; they do not constitute validation.

4. Rationale for the Integration Agent Model

The model connects three problems that are often treated separately. Integrative learning theory specifies the need for disciplinary grounding, purposeful combination and an advance in understanding (Boix Mansilla & Duraisingh, 2007). Classroom and curriculum research identifies the cognitive load, coordination demands and structural barriers that make these outcomes difficult to achieve (Beane, 1997; Brassler & Dettmers, 2017; Drake & Reid, 2018). Generative AI research identifies systems capable of rapidly producing candidate representations across multiple knowledge domains, but also documents problems of fabrication, bias, opacity and uncritical reliance (Bender et al., 2021; Kasneci et al., 2023; UNESCO, 2023).

The theoretical problem is therefore not whether an LLM can produce interdisciplinary-sounding text. It can. The problem is how such output becomes part of a defensible learning process. The model answers by locating AI contributions within a human-governed cycle. Systemic conditions enable or constrain pedagogical design; teachers and learners co-orchestrate inquiry; generative AI offers candidate bridges and representations; learners perform the cognitive work of comparison and synthesis; and human evaluation determines whether the result is accurate, appropriately integrated and educationally meaningful.

5. The Dynamic Integration Agent Model

The model consists of three interdependent constructs: cognitive mediation, pedagogical co-orchestration, and systemic design alignment. They are axes in an analytic sense, but they also operate as a recurrent process. Systemic design alignment establishes goals, constraints, and resources. Pedagogical co-orchestration translates these conditions into tasks, roles and dialogue. Cognitive mediation occurs as learners work with disciplinary representations and AI-generated candidates. Human epistemic validation evaluates the result and feeds revisions back into all three axes.

Construct	Unit of analysis	Generative AI contribution	Non-delegable human work	Proximal output
Cognitive mediation	Learner meaning making across disciplinary representations	Candidate mappings, translations, analogies, contrasts and syntheses	Interpretation, comparison, justification, source checking and revision	A reasoned cross-disciplinary representation
Pedagogical co-orchestration	Teacher-learner-AI activity during inquiry	Questions, alternative routes, examples, feedback prompts and draft criteria	Framing purposes, allocating roles, diagnosing misconceptions and moderating dialogue	A structured inquiry that elicits active integrative work
Systemic-design alignment	Curriculum and organizational conditions	Candidate sequences, standards mappings, resource groupings and assessment drafts	Priority setting, contextual adaptation, fairness decisions and institutional accountability	A feasible and coherent integrative design

5.1 Cognitive Mediation

Cognitive mediation is the learner's work of relating disciplinary representations without collapsing their differences. Generative AI can accelerate the production of candidate relations by translating vocabulary, offering analogies, contrasting explanations and organizing information into maps or provisional syntheses. The construct is not equivalent to cognitive offloading. Its educational value depends on whether learners actively compare the generated relation with disciplinary sources and explain why the relation is useful, limited or misleading. This requirement is consistent with the distinction between passive exposure and constructive or interactive engagement (Chi & Wylie, 2014).

A successful cognitive bridge preserves relevant features of the source disciplines and advances understanding of the focal problem. A fluent association that cannot be justified does not meet this criterion. The learner must therefore remain the agent of integration, while the LLM serves as a generator of objects for inquiry.

5.2 Pedagogical Co-orchestration

Pedagogical co-orchestration refers to the intentional coordination of teacher, learner and AI activity. The teacher frames an integrative purpose, selects the disciplines that must be represented, specifies quality criteria and determines when AI should generate, critique or remain absent. Learners ask questions, test alternatives and justify revisions. Generative AI can widen the space of possibilities, but it does not set the educational purpose or decide which connections merit acceptance.

This construct incorporates the teacher's cognitive labor directly into the model. Teachers are not merely final reviewers. They design the epistemic conditions of the interaction, interrupt misleading trajectories, require evidence, surface disagreement and decide when disciplinary expertise or external sources are necessary. Co-orchestration therefore converts AI output from an answer into a revisable contribution to dialogue. Student-centered design principles similarly emphasize learner ownership, scaffolding and an authentic purpose rather than mere exposure to generated content (Lee & Hannafin, 2016).

5.3 Systemic-Design Alignment

Systemic-design alignment concerns the fit between an integrative activity and the curriculum, timetable, assessment system, available expertise, data governance rules and institutional priorities. Generative AI can propose sequences, identify apparent overlaps among standards and draft rubrics, but these outputs require contextual authorization. A technically plausible unit may still be infeasible, inequitable or misaligned with local learning goals. This axis is not a background condition. It shapes the time available for verification, the disciplinary expertise accessible to learners and the incentives created by assessment. It also receives feedback from classroom enactment. Recurrent misconceptions may indicate a need for new scaffolds; inequitable access may require a different design; and workload effects may alter the allocation of human and computational tasks. Its concern with feasible curricular coordination builds on longstanding work in interdisciplinary curriculum design (Jacobs, 1989).

5.4 Relationships, Assumptions and Boundaries

The three axes are related through enablement and feedback. Systemic alignment enables and constrains pedagogical co-orchestration. Co-orchestration creates the conditions under which cognitive mediation can be productive. Teachers and learners evaluate the quality of cognitive outcomes, and this evaluation feeds back into task design and institutional arrangements. Generative AI can intervene at each stage, but human validation crosses all stages.

The model assumes access to relevant disciplinary sources, sufficient teacher knowledge or access to expertise, learner participation in evaluation, and an institutional environment that permits revision rather than rewarding rapid output alone. It applies primarily to open-ended learning tasks that require relationships among domains. It is less applicable to routine practice, closed-answer tutoring or high-stakes decisions in which unverifiable generation is inappropriate. It should not be used to characterize an LLM as an autonomous knower, moral agent or substitute for disciplinary communities.

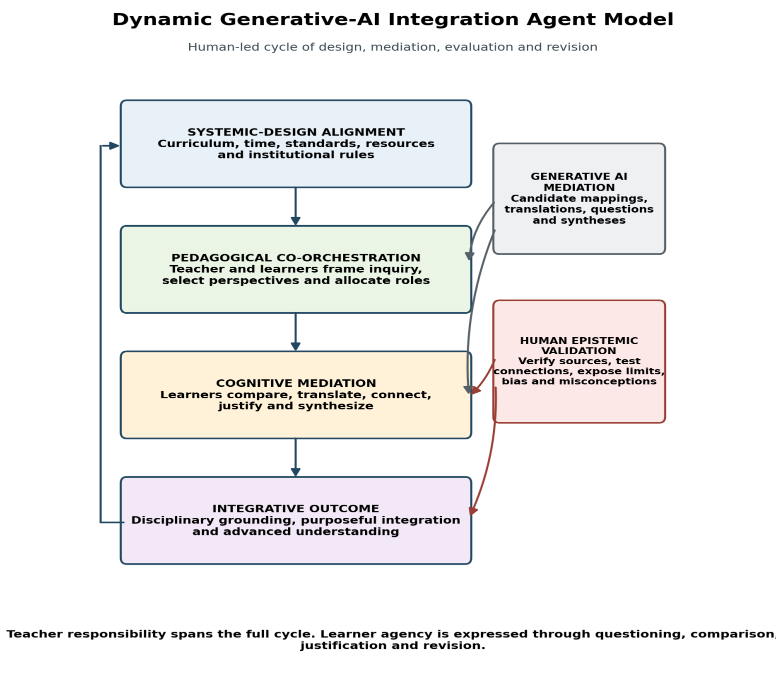

Figure 1. Dynamic generative-AI integration agent model.

5.5 Propositions for Empirical Testing

- P1. Generative-AI-supported integration will produce higher-quality interdisciplinary outcomes than unsupported use only when learners are required to compare and justify AI-generated connections against disciplinary sources.
- P2. Pedagogical co-orchestration will mediate the relationship between generative AI affordances and the quality of integrative learning.
- P3. Teacher-led epistemic validation will reduce conceptual error and superficial integration relative to conditions in which generated syntheses are accepted without structured review.
- P4. Learner-generative engagement, expressed through explanation, critique, and revision, will moderate the effect of AI support; passive acceptance will weaken or reverse the expected benefits.
- P5. Systemic design alignment, including time, expertise, assessment, and access, will moderate the model's feasibility and sustainability.
- P6. Iterative feedback from evaluated learner outcomes to pedagogical and systemic design will improve subsequent integrative task quality more than one-way generation workflows.

6. Practical Applications: Tension-Rich Illustrative Vignettes

The following vignettes illustrate mechanisms and failure points. They are hypothetical and are not presented as evidence that the model is effective.

Vignette 1. Sustainable energy, climate science and mathematical modeling. An LLM proposes a relation among household energy data, carbon emissions and climate models. Students initially treat the generated equation as a direct causal model. The teacher requires them to identify assumptions, units and data sources, then compare the proposal with an authoritative climate dataset. They discover that the model omits grid composition and temporal variation. The revised product preserves the AI-generated bridge but makes its boundary conditions explicit. Cognitive mediation is productive because pedagogical validation prevents a convenient relationship from becoming a false one.

Vignette 2. Biological processes and literary metaphor. To explain protein synthesis, the LLM describes the ribosome as a craftsman and mRNA as instructions. The metaphor improves initial accessibility but implies intention and central control. The teacher asks students to mark where the analogy maps accurately and where it fails. Students then rewrite the metaphor to include molecular interaction, probability and error. The exercise demonstrates that disciplinary translation is not the replacement of scientific explanation by a memorable story.

Vignette 3. Justice across history and philosophy. The LLM groups primary sources under themes such as authority, rights and civic duty, but it reads later liberal concepts into earlier legal texts. Students compare the generated categories with the language and historical setting of each source. The teacher introduces a competing philosophical interpretation and asks which evidence each account excludes. The final synthesis retains disagreement instead of manufacturing a single transhistorical definition of justice.

Vignette 4. Water scarcity inquiry. The LLM drafts a route that combines environmental science, geography, economics, and ethics. Its first version prioritizes technical efficiency and underrepresents local knowledge and distributional justice. The teaching team adds community testimony, defines evidentiary standards for each discipline and assigns learners to challenge the assumptions of another group. Systemic design alignment is evident in the time allocated to field data, source verification, and stakeholder perspectives.

Vignette 5. Integrative assessment rubric. An LLM generates a rubric for disciplinary grounding, integration and synthesis. The descriptors appear polished but reward the number of disciplines mentioned rather than the quality of their relationship. Teachers test the rubric on contrasting student samples and revise it to penalize unsupported connections and to recognize justified limits. AI reduces drafting time, while professional judgment determines what counts as quality.

Vignette 6. Urban resilience pathways, The LLM proposes pathways based on student interests, local data and curricular standards. A review shows that students with fewer digital resources are channeled toward less complex tasks and that the local data omit informal communities. Teachers reject automated pathway assignment, offer learners meaningful choice and supplement the dataset. The episode shows that adaptation is not neutral and that decisions about systemic fairness cannot be delegated.

7. Discussion

7.1 Theoretical Contribution

The revised model contributes a domain-specific account of human-AI collaboration for integrative learning. Existing AIED paradigms clarify who directs activity, while hybrid intelligence frameworks clarify how control may be distributed (Molenaar, 2022; Ouyang & Jiao, 2021). Integrative learning scholarship, in turn, specifies the epistemic quality of the desired outcome (Boix Mansilla & Duraisingh, 2007). The Integration Agent Model connects these insights by explaining how candidate disciplinary relations move through design, learner cognition and human validation.

The contribution is narrower than the original claim that AI constitutes an entirely new epistemic partner. The term agent identifies a role in a process, not an autonomous status. What is theoretically distinctive is the configuration of three interdependent axes and the claim that human epistemic validation is a constitutive mechanism rather than an external safeguard. Without validation, the process may generate interdisciplinary language but does not meet established criteria for interdisciplinary understanding.

7.2 Practical Implications

For teachers, the model suggests designing activities in which AI outputs are intermediate objects. Prompts should request alternatives, assumptions and uncertainties, while tasks should require learners to compare generated content with disciplinary sources and explain revisions. Assessment should value justified connections and recognition of limits rather than surface breadth. Professional development should combine generative AI literacy with practice in disciplinary validation, analogy analysis and integrative assessment.

For institutions, adoption decisions should consider the time required for verification, access to disciplinary expertise, data protection, equitable access, and the incentives created by assessment. Claims of workload reduction should be evaluated empirically because time saved in drafting may be replaced by time needed for checking, contextualization and correction.

7.3 Limitations and Risks

The model is conceptual and has not been empirically validated. Its literature base was selected purposively for theory development and is not an exhaustive systematic review. The three axes should therefore be tested against alternative categorizations and across different educational levels, disciplines, languages and institutional contexts.

Generative AI creates several epistemic risks. LLMs may fabricate sources, reproduce bias, flatten disagreement and generate fluent but shallow syntheses (Bender et al., 2021; Kasneci et al., 2023). Translation across disciplines may erase differences in method or evidence. Metaphors may introduce misconceptions. Personalization may reproduce inequity when data are incomplete or when learners have unequal access to paid systems and expert support. Privacy and intellectual property concerns also limit which learner data and curricular materials can appropriately be processed (UNESCO, 2023).

There are also pedagogical risks. If learners outsource comparison and synthesis, AI support may reduce the very epistemic fluency the activity is intended to develop. Teachers may lack the disciplinary breadth needed to validate every connection, particularly in transdisciplinary work. The model therefore does not assume that teacher oversight is automatically sufficient; it may require collaboration among subject specialists, librarians, community experts and students.

7.4 Research Agenda

The six propositions can be examined through design-based studies, classroom experiments and longitudinal research. Outcomes should include disciplinary accuracy, quality of integration, learner explanation and revision behavior, teacher workload, equity and transfer to new problems. Process data could examine how learners accept, reject or transform AI-generated connections. Comparative studies should vary the level of automation, teacher validation protocols and assessment incentives. Research should also identify domains in which generative mediation is counterproductive or unsafe.

8. Conclusion

Generative AI can rapidly produce cross-disciplinary explanations, metaphors, mappings and inquiry routes, but the production of connected language is not equivalent to integrative learning. This article has developed a dynamic model that situates generative AI along three interdependent axes: cognitive mediation, pedagogical co-orchestration, and systemic design alignment. Institutional conditions shape pedagogical design; pedagogical design elicits learner cognitive work; and human evaluation feeds revisions back into the cycle. The model assigns generative AI a bounded role. It proposes candidate relations and representations. Teachers and learners determine whether those candidates are accurate, appropriately grounded, ethically defensible and useful for the problem under study. Teacher judgment and learner agency are therefore not residual safeguards but core mechanisms of the model. The model's value now depends on empirical testing. Studies should examine when structured human-AI interaction improves disciplinary grounding and integrative understanding, when it produces superficial coherence or dependency, and how outcomes vary with expertise, task design and institutional support. The appropriate conclusion is conditional: generative AI may expand the possibilities of integrative pedagogy, but only when educational design turns its outputs into objects of inquiry, verification and revision.

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Conflict of Interest Statement

The authors declare no financial or non-financial conflicts of interest related to the conduct, analysis, interpretation, or publication of this study.

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