

From Computational Literacy to Algorithmic Agency: Re-Envisioning Researcher Preparation in the Era of Generative Artificial Intelligence

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Abstract The emergence of generative artificial intelligence (GenAI) systems has fundamentally altered the epistemological conditions under which educational research is conducted, rendering existing faculty preparation frameworks necessary but insufficient. Building on a call for a computational mindset and subsequent work on educational data literacy, this article proposes a three-stage developmental progression culminating in algorithmic agency, which is the capacity to critically co-construct scientific knowledge with large language models and automated analytical pipelines while maintaining methodological rigor and preserving human epistemic authority. Unlike prior frameworks, which conceive of artificial intelligence as an analytical instrument under human direction, algorithmic agency addresses the qualitatively distinct challenge posed by GenAI systems that function as epistemic participants capable of synthesizing literature, constructing arguments, and producing knowledge claims that enter scholarly discourse alongside human-authored work. To operationalize this progression, we propose the Co-Intelligent Academic Practice (CAP) framework, a theoretically grounded developmental architecture comprising four cumulative competency domains organized across three developmental stages. A methodology integrating design and systems thinking provides the developmental process through which faculty build and sustain these competencies. We further argue that individual competency development is insufficient without commensurate institutional enablement, including

governed infrastructure, value-aligned policy, scholarly recognition, community-based developmental support, and equitable global participation. The article concludes by identifying empirical validation of the CAP staging model as the field's most urgent methodological priority and arguing that faculty development is the primary institutional lever through which epistemic norms for the co-intelligent era are established or abandoned.

Keywords artificial intelligence, educational data literacy, algorithmic agency, computational mindset, faculty development

1 Introduction

A decade ago, Gibson and Ifenthaler (2017) proposed that education researchers would need to employ “algorithms and algorithmic agents working alongside human thought and action” as “active, interactive co-producers of knowledge.” Written as an aspiration, this idea now describes reality: Faculty across disciplines routinely engage large language models (LLMs) to draft literature reviews, analyze datasets, and develop theoretical arguments (Bianchini et al., 2025). The prediction materialized, but faculty preparation has not kept pace (Raffaghelli et al., 2026). This transformation is fundamentally epistemological. When artificial intelligence (AI) systems generate, synthesize, and evaluate knowledge claims, what counts as research (e.g., who produces it; under what standards) is fundamentally altered. Faculty lacking frameworks for this shift risk ceding authority to systems whose workings they

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neither understand nor govern (Doshi-Velez & Kim, 2017). The urgency is not prospective but present.

The challenges identified in 2017 persist and have deepened. First, the qualitative–quantitative binary remains institutionally entrenched in graduate training, constraining researchable questions and methods (Ifenthaler, 2025a; Johnson & Onwuegbuzie, 2004). Second, data science methods, despite over a decade of advocacy, remain marginalized in flagship venues (Ifenthaler, 2025a). Recent bibliometric analyses reveal single-digit representation of machine learning and natural language processing in major educational journals (Samsul et al., 2023), reflecting a systemic failure to prepare scholars for current methodological realities. Therefore, we propose a developmental progression that extends our 2017 argument.

The idea of computational mindset we proposed was primarily epistemological; that is, researchers needed to grasp how computational methods produce knowledge differently from hypothesis-driven qualitative and quantitative methods and that this difference mattered for the integrity of their work (Gibson & Ifenthaler, 2017). This foundation was subsequently extended to educational data literacy (EDL)—a more fully specified competency profile addressing the concrete skills required to work with Big Data complexity, including its defining characteristics of volume, velocity, veracity, variety, variability, value, and visibility, as well as the organizational conditions under which these methods can be applied responsibly (Egloffstein et al., 2025; Ifenthaler, 2025a). However, these competencies, while necessary, proved insufficient in the generative artificial intelligence (GenAI) era, prompting our proposal for algorithmic agency, in which researchers must navigate systems that have evolved from analytical instruments into participants capable of synthesizing literature, constructing arguments, and generating knowledge claims, thus requiring the capacity to critically co-construct knowledge with AI while maintaining methodological rigor and human authority.

Accordingly, contemporary LLMs and related GenAI systems represent a qualitative shift from AI as a tool to AI as a co-intelligent collaborator (Hooshyar et al., 2025; Ifenthaler & Schumacher, 2023). This partnership model demands what Engelbart (1962) termed *executive capability*—that is, the human capacity to set an inquiry’s direction, goals, and standards rather than merely oversee automated execution. When researchers delegate not only pattern detection but also standard setting to AI, scholarship proceeds efficiently but without genuine epistemic direction. The core challenge is maintaining human authority in genuinely bidirectional human–AI collaboration (Azukas & Gibson, 2025; Seeber et al., 2020), not merely overseeing outputs after they are produced.

This article responds to the *Frontiers of Digital Education* special issue’s call for “Future Faculty Development.” It contributes to a global conversation that remains, in most institutions, dangerously under-resourced (Sun et al., 2026). In the following part of this paper, Section 2 traces conceptual evolution across the three stages and identifies where each falls short; Section 3 proposes the Co-Intelligent Academic Practice (CAP) framework for faculty competency development; Section 4 addresses enabling institutional conditions; Section 5 argues that faculty development is the primary lever for establishing or abandoning norms in the co-intelligent era.

2 From Computational Mindset to Algorithmic Agency

This section traces the conceptual evolution from a computational mindset to EDL and then to algorithmic agency, clarifying both the theoretical continuities and the qualitative breaches that necessitate each successive stage.

2.1 | Computational Mindset and Data Science

Gibson and Ifenthaler (2017) contended that the ascendance of algorithmic and data-intensive methods constituted not simply an expansion of the research toolkit but a transformation in how knowledge itself was produced in educational inquiry. The computational mindset reflected what was termed *awareness plus literacy*—that is, a professional orientation that enables researchers to recognize how computational methods generate knowledge through mechanisms qualitatively distinct from traditional hypothesis-driven approaches. This claim rested on a critical distinction between exploratory and confirmatory knowledge production (Gibson et al., 2019). As the authors argued, both approaches yield models, but exploratory analytics invents models through pattern discovery in complex data, while hypothesis testing validates prespecified theoretical propositions (Gibson & Ifenthaler, 2017). This distinction challenged the qualitative–quantitative binary that Johnson and Onwuegbuzie (2004) identified as a *simplistic view* constraining educational research. Researchers lacking a computational orientation faced a structural disadvantage not because they could not execute specific techniques but because they could not formulate or critically evaluate the questions that these methods made tractable.

The computational mindset framework addressed what Holland (1995) characterized as

complexity: educational phenomena as dynamically evolving systems with nonlinear relationships, nested hierarchies, feedback loops, and emergent properties irreducible to component analysis (Gibson & Ifenthaler, 2025). Traditional regression approaches, constrained by assumptions of linearity, independence, and homoscedasticity, proved inadequate for phenomena in which rules and data are fundamentally interdependent. Machine learning methods, such as support vector machines, clustering algorithms, and neural networks, offered alternatives for modeling nonlinear relationships among parameters without assuming predetermined functional forms (Gibson & Ifenthaler, 2017; McFarland et al., 2021). Ifenthaler's (2025a) data science paradigm extends this foundation into a comprehensive methodological program. Data science is defined as the application of statistics, computer science, information science, and educational theory to scientific phenomena (Piety et al., 2014), and the paradigm articulates both the scope and the institutional marginalization of data science methods in scientific research. The framework rests on four interlocking constructs: Big Data, which is characterized by seven dimensions, including volume, velocity, veracity, variety, variability, value, and visibility; machine learning, spanning supervised, unsupervised, semi-supervised, and reinforcement paradigms; data mining for pattern discovery; and data analytics, from descriptive through prescriptive approaches. These constructs have generated distinct research streams, such as educational data mining, learning analytics, social learning analytics, and curriculum analytics, each targeting different educational actors and decision scales.

What computational mindset and data science share is diagnostic precision: Both identify the epistemological inadequacy of the qualitative–quantitative binary as the organizing framework for educational inquiry, and both specify EDL as essential for the next generation of researchers. Current empirical evidence reveals a single-digit representation of machine learning and data analytics in major educational journals (Samsul et al., 2023), indicating a systemic failure to institutionalize methods appropriate to contemporary data realities. As McFarland et al. (2021) observed, data science represents not merely a technical innovation but a fundamental reorientation of the theory–data relationship—that most graduate programs have yet to enact. Both frameworks, however, conceive of algorithms as instruments employed by human agents. The researcher directs the inquiry, selects the methods, and interprets the results. Computational literacy and data science expertise describe increasingly sophisticated tool use, but agency remains unambiguously human. This instrumental framing, adequate for analytical AI, proves insufficient when AI systems transition from

analytical instruments to epistemic (e.g., knowledge-producing and interpretive) participants.

2.2 | Generative Rupture: Three Qualitative Shifts

Three characteristics of contemporary GenAI systems exceed the conceptual boundaries of computational mindset and data science frameworks, each representing transformational rather than incremental change.

2.2.1 Agency

LLMs and related GenAI systems do not merely process data according to prespecified instructions. They generate text, synthesize information across disciplinary boundaries, propose hypotheses, construct theoretical arguments, and engage in sustained, multiturn intellectual exchanges that exhibit contextual coherence (Grossmann et al., 2023). Thus, the relationship between researcher and system has shifted from unidirectional instrumentality to bidirectional collaboration. As Mollick (2024) demonstrated, treating LLMs as sophisticated search engines fundamentally misunderstands their operational nature and obscures the epistemological challenges they present. This shift problematizes the agent–instrument distinction central to both prior frameworks. When an AI system proposes theoretical interpretations, identifies gaps in the literature, or suggests analytical strategies, it performs functions previously reserved for human cognition (Ifenthaler, 2025b). The question becomes not whether AI can perform such functions—empirically, it does—but how researchers maintain authority as the boundary between human and machine contributions becomes permeable (Azukas & Gibson, 2025).

2.2.2 Language

Computational frameworks and data science methods operate primarily on structured data, requiring the translation of research questions into forms that computational systems could process—namely, mathematical notation, formal logic, and structured databases (Salganik, 2018). This translation barrier is real and consequential: It excludes researchers without programming expertise and marginalized questions resistant to formalization. Contemporary AI systems dissolve this barrier by operating through natural language, the primary medium of humanistic and qualitative scholarship (Bail, 2024). Researchers can now conduct literature synthesis, draft theoretical arguments, generate measurement instruments, or evaluate statistical outputs through conversational interaction that requires no specialized notation or coding skills. This

accessibility is epistemologically profound. It democratizes access to computational methods while simultaneously raising questions about what gets lost when scholarly work becomes too frictionless—when the effortful translation process that previously enforced conceptual precision vanishes.

2.2.3 Generativity

Data science tools analyze preexisting data, producing classifications, predictions, visualizations, and pattern identifications (Ifenthaler, 2025a). Their outputs are second-order representations of empirical phenomena. GenAI, by contrast, creates text, constructs arguments, synthesizes literature, and produces knowledge claims that enter scholarly discourse alongside human-generated work (Bender et al., 2021). When an AI system generates a literature review indistinguishable from human-authored work, traditional frameworks for attribution, evaluation, and validation become inadequate. This generative capacity raises what Doshi-Velez and Kim (2017) identified as the core interpretability problem: When AI systems cannot explain their reasoning in terms that permit human evaluation, how do we assess epistemic validity? The outputs may be fluent, coherent, and superficially plausible while embedding undetectable errors, biases inherited from training data, or reasoning chains that violate disciplinary standards. Neither a computational mindset nor EDL provides conceptual resources for addressing this challenge, as both frameworks assume a human capacity to inspect and validate computational processes—an assumption that GenAI's opacity violates.

2.3 | Definition of Algorithmic Agency

Algorithmic agency denotes a distinctively human capacity exercised in AI-mediated scholarly practice and not, as the term might otherwise be misread, a property or autonomy attributed to algorithms themselves. The agency in question resides with the researcher; as a qualifier, algorithmic specifies the conditions under which that agency is enacted—namely, inquiry conducted in and through algorithmic systems—rather than relocating agency to those systems. Accordingly, we define algorithmic agency as the capacity to critically co-construct knowledge with GenAI systems and automated analytical pipelines while maintaining methodological rigor and preserving human epistemic authority. This definition integrates three theoretically grounded components: critical co-construction, methodological rigor, and human epistemic authority.

The idea of critical co-construction draws on Vygotsky's (1978) concept of mediated action and Salomon's (1997) distributed cognition framework.

Intelligence is not an individual property but emerges through interaction with cultural tools, of which AI systems are currently a sophisticated example. Critical co-construction requires researchers to understand AI contributions deeply enough to evaluate them against disciplinary standards, much as they would evaluate the contributions of human collaborators. This is not passive acceptance of AI outputs but active interrogation: What data informed this synthesis? What assumptions structured this argument? What alternative interpretations were excluded? Critically, co-construction differs from mere oversight. Oversight implies human review of AI-generated output, constituting a retrospective quality check. Co-construction describes ongoing bidirectional engagement in which human judgment shapes the direction of inquiry, framing, and evaluative standards throughout the process (Azukas & Gibson, 2025). The researcher does not simply accept or reject AI contributions but actively negotiates their integration into the broader research program.

Maintaining methodological rigor addresses *automation temptation*: the tendency to treat AI-generated outputs as adequate substitutes for slower, more effortful human inquiry. GenAI's speed and fluency create pressure to lower epistemic standards, leading to the acceptance of outputs that appear scholarly without rigorous validation. Algorithmic agency resists this erosion by requiring AI-produced contributions to meet the same evidentiary standards, inferential validity criteria, and transparency requirements as human-produced scholarship. This requires what Schön (1983) termed reflective practice—that is, ongoing critical examination of methods, assumptions, and knowledge claims. For AI-mediated research, reflective practice extends to interrogating the provenance of training data, algorithmic bias, reproducibility, and the relationship between statistical patterns and causal mechanisms (Kitchin, 2014).

Preserving human epistemic authority engages the most fundamental risk that GenAI poses to research practice. Drawing on metacognition theory (Greene et al., 2008; Schraw & Dennison, 1994), we distinguish between monitoring and control functions in collaborative inquiry. Monitoring involves detecting patterns, synthesizing information, and tracking intermediate states. AI systems perform these functions with increasing efficiency. Control involves applying standards, setting goals, and directing the overall inquiry in accordance with disciplinary values and theoretical commitments (Lehmann et al., 2014). The critical danger emerges when control is delegated alongside monitoring, producing black-box methodologies that obscure rather than illuminate phenomena (Pasquale, 2015). Engelbart's (1962) concept of executive capability remains salient—namely, the human capacity to orchestrate subprocesses in an appropriate sequence and with appropriate timing toward coherent goals. In co-intelligent practice, AI systems augment specific

processes. However, executive capability—the authority to set research direction, establish evaluative criteria, and determine what counts as valid knowledge—must remain with human researchers. This is not a call for human supremacy but for appropriate role differentiation. As Pickering (1995) argues in his analysis of scientific practice, agency in knowledge production is distributed across human and nonhuman actors. The question is not whether AI systems have agency but how their agency is structured, constrained, and directed within systems of human governance (Ifenthaler et al., 2024).

Algorithmic agency thus represents the conceptual fulfillment of what the computational mindset and data science frameworks initiated, yet it must be distinguished from the adjacent constructs with which it is easily conflated. Where AI, algorithmic, and critical AI literacies emphasize comprehension and evaluation, where computational mindset and EDL specify methodological competencies, and where human–AI collaboration and co-intelligence describe the interactional configuration itself, algorithmic agency names the researcher’s normative capacity to retain epistemic authority when AI systems function as substantive knowledge producers rather than as sophisticated tools. Table 1 makes these distinctions explicit. Accordingly, each construct addresses a genuine dimension of AI-mediated inquiry, but only algorithmic agency foregrounds the preservation of human interpretive authority as its defining commitment.

3 A Framework for Faculty Preparation: CAP

The preceding sections establish the conceptual trajectory from a computational mindset through EDL to algorithmic agency and identify the precise

epistemological conditions that necessitate the third stage. Before turning to the practical question of faculty preparation, it is useful to consolidate that trajectory, since the competency architecture proposed below is the direct developmental consequence of the conceptual progression traced thus far. Table 2 summarizes the three foundational concepts along four analytic dimensions: their core focus, the role they assign to technology and algorithms in knowledge production, the characteristic limitation of each, and the implications each holds for the framework developed in this section. Read against this common set of criteria, the three stages are not interchangeable competencies but a cumulative sequence in which each stage resolves a limitation of its predecessor while introducing a qualitatively new demand that the next must address.

The practical questions that follow from the progression summarized in Table 2 are: What specifically must faculty know, be able to do, and commit to enacting to exercise algorithmic agency effectively in their scholarly work? We propose the CAP framework as this article’s central practical contribution. CAP is not a competency inventory in the conventional sense. It is a theoretically grounded developmental architecture specifying what faculty need across interdependent competency domains, how growth within those domains follows a recognizable trajectory, and what faculty development programs must do to support that trajectory. The framework builds directly on the foundation laid by Gibson and Ifenthaler (2017), Gibson et al. (2023), and Ifenthaler (2025a), extending their arguments from computational and data science preparation to the qualitatively different conditions created by contemporary AI systems.

3.1 | Competency Domains of CAP

The competency domains of CAP are neither parallel

Table 1 Algorithmic agency in relation to adjacent constructs

Construct	Primary focus	Relation to algorithmic agency
AI literacy	Understanding what AI systems are and how they function	Necessary foundation; not addressing epistemic authority in knowledge production
Algorithmic literacy	Recognizing how algorithms shape information and outcomes	Sensitizing to algorithmic mediation but stops short of agentic practice
Computational mindset	Problem decomposition, abstraction, and algorithmic reasoning	Supplies reasoning dispositions; not specific to AI-mediated inquiry
Educational data literacy	Competencies for working with complex data and analytical methods (in education)	Immediate predecessor; equipping practice but presupposes the researcher as principal analyst
Critical AI literacy	Interrogating the social, ethical, and political implications of AI	Providing an evaluative stance; oriented to critique rather than to enacting rigorous co-construction
Human–AI collaboration	The interaction between human and machine agents	Describing the setting in which agency is exercised, without specifying its epistemic conditions
Co-intelligence	Joint human–machine cognitive performance	Naming the collaborative product; does not adjudicate where interpretive authority resides

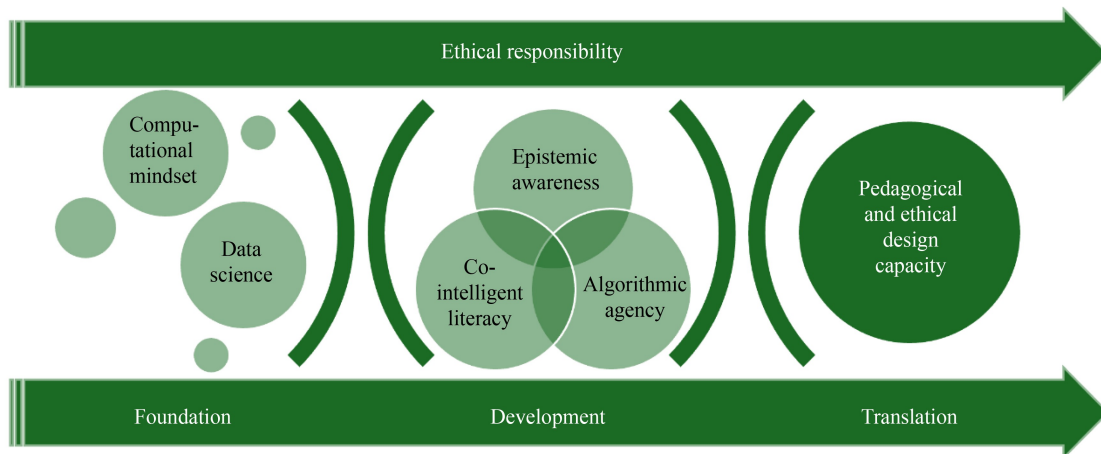
Table 2 Evolutionary relationship among the three foundational concepts

Analytic dimension	Computational mindset	Data science	Algorithmic agency
Core focus	Recognizing computation and algorithmic logic as constitutive of, rather than incidental to, contemporary inquiry	Acquiring the concrete competencies required to work rigorously with complex data, analytical methods, and modeling pipelines	Retaining human epistemic authority while critically co-constructing knowledge with GenAI systems
Role of technology and algorithms	Algorithms reframe the conditions of inquiry but remain external instruments applied by the researcher	Data-analytic systems become methodological infrastructure through which the researcher generates and interrogates evidence	AI systems function as substantive collaborators in knowledge production rather than as tools executing researcher-specified procedures
Characteristic limitation	Establishing that inquiry has changed without specifying the methodological competencies that changed inquiry demands	Presupposing the researcher as principal analyst and does not anticipate systems that themselves generate interpretations and claims	Cannot be exercised responsibly without the foundational mindset and analytic literacy on which its critical judgment depends
Implication for Co-Intelligent Academic Practice	Grounding the domain of epistemic awareness, the recognition that algorithmic mediation reshapes what counts as knowledge	Grounding the domain of co-intelligent literacy, the methodological capacity to work rigorously with data-intensive and AI-assisted analysis	Grounding the domains of algorithmic agency and pedagogical and ethical design capacity, in which interpretive responsibility remains irreducibly human

capacities to be developed independently nor stages on a single linear ladder. As [Figure 1](#) depicts, the framework is organized into three phases—foundation, development, and translation—within which the domains stand in distinct relations to one another. The foundation phase comprises computational mindset and data science. These are not themselves CAP competency domains but the antecedent preparation on which the framework rests. The development phase comprises the three core competencies of the CAP framework. A relation of logical dependency holds among them, since a faculty member lacking epistemic awareness cannot meaningfully exercise co-intelligent literacy, and one lacking co-intelligent literacy cannot responsibly practice algorithmic agency. Nevertheless, [Figure 1](#) represents these three as overlapping rather than sequentially stacked to signal that this dependency does not imply strict temporal succession. In practice, the three competencies develop in mutually reinforcing interaction, each deepening as the others mature. They are best understood as an integrated developmental core rather

than as discrete rungs acquired one at a time. The translation phase comprises the fourth domain, pedagogical and ethical design capacity, which occupies a categorically different position from the other three. It is not a terminal stage reached only after the developmental core is complete but the integrative capacity that translates epistemic awareness, co-intelligent literacy, and algorithmic agency into responsible research, teaching, and institutional practice.

Two features of the framework cut across this three-phase structure and are made explicit in [Figure 1](#). First, ethical responsibility is not confined to the translation phase or to any single domain; represented as an arrow spanning all three phases, it permeates the entire framework. Second, the progression across the three phases is developmental rather than merely additive, in that each phase both presupposes the preceding one and reconfigures its significance, so that foundation, development, and translation together constitute a single integrated architecture rather than a sequence of independent acquisitions.

**Figure 1** Co-Intelligent Academic Practice framework.

3.1.1 Epistemic Awareness

Epistemic awareness is an updated and extended form of the computational mindset (Gibson & Ifenthaler, 2017). Where the original competency called for general awareness that algorithms transform scientific inquiry, epistemic awareness in the CAP framework requires understanding how AI participates specifically in knowledge production—that is, what it can and cannot contribute at each stage of the research cycle, from raw data through information, knowledge, application, and theory to paradigm formation, and where validation responsibility remains irreducibly human. The data science taxonomy provides the technical foundation for this competency. Faculty equipped with knowledge of the core data science constructs—Big Data, machine learning, data mining, and data analytics—possess the conceptual vocabulary necessary to recognize AI operations within established methodological traditions and to identify when AI outputs require expert scrutiny (Ifenthaler, 2025a; McFarland et al., 2021). However, epistemic awareness is not reduced to technical knowledge of data science constructs. It requires an understanding of the epistemological implications of deploying those constructs—for instance, what assumptions are embedded in a supervised classifier, what inferential leap separates statistical clustering from pedagogically meaningful learner profiling, and what evidentiary standards must be met before descriptive patterns are converted into prescriptive interventions. The distinction between knowing that a method exists and understanding what it epistemically commits the researcher to recapitulates the central argument of Gibson and Ifenthaler (2017) that computational literacy is awareness plus literacy rather than mere technical execution.

3.1.2 Co-Intelligent Literacy

Co-intelligent literacy extends EDL (Papamitsiou et al., 2021) from proficiency in computational and statistical methods to competency in designing and conducting effective human–AI collaborative inquiry. The critical extension concerns the nature of the task: Whereas EDL equips faculty to work with AI as an analytical instrument, co-intelligent literacy equips them to work with AI as a collaborative participant whose contributions require active direction, evaluation, and integration. Three practical dimensions define this competency. First, effective prompt construction—ability to design prompts that activate AI capabilities within a disciplinarily bounded problem space, counteracting GenAI’s tendency toward plausible-sounding generality rather than domain-specific precision (Bail, 2024). Second, disciplinary output evaluation—capacity to assess AI-generated syntheses, arguments, and analyses

against the evidentiary standards of the researcher’s field, rather than accepting outputs on the basis of linguistic fluency, which bears no relationship to epistemic validity (Bender et al., 2021). Third, contribution regulation—ability to recognize when AI contributions require correction, supplementation, or rejection and to make those determinations on substantive rather than stylistic grounds.

Accordingly, the dependency relationship between co-intelligent literacy and epistemic awareness is not incidental. Faculty who cannot distinguish supervised from unsupervised learning, or who lack a foundational understanding of what a machine learning model does with educational data, are structurally unable to evaluate whether an AI system’s synthesis of that data is trustworthy. The technical substrate is not merely background knowledge. It is the prerequisite for informed critical judgment in human–AI collaboration (Hooshyar et al., 2025; Ifenthaler, 2025a, 2025b).

3.1.3 Algorithmic Agency

Building on the definition of algorithmic agency established in Subsection 2.3, we now specify its observable characteristics in academic practice, shifting from the conceptual distinction between monitoring and control to the behavioral forms through which this distinction becomes visible in scholarly work. Accordingly, algorithmic agency is a genuinely novel competency that neither the computational mindset nor EDL frameworks could fully anticipate or specify. It is also the competency most at risk of atrophy under conditions of unreflective AI adoption. Two features distinguish algorithmic agency from the preceding competencies. First, it is explicitly metacognitive in structure. Exercising algorithmic agency requires real-time monitoring of one’s own state of knowledge and understanding during AI collaboration. At each stage of inquiry, the faculty member must identify which knowledge claims derive from his own disciplinary understanding, which incorporate AI contributions, and whether the direction of the collaboration reflects the researcher’s own goals and standards or the AI system’s optimization pressures (Greene & Azevedo, 2007; Koriati, 2007). The fluency of AI outputs actively suppresses this metacognitive vigilance—what we term epistemic drift—because fluent, coherent prose does not signal reasoning errors, training data biases, or violations of disciplinary standards that less polished outputs would (Doshi-Velez & Kim, 2017). Second, algorithmic agency is discipline-sensitive in ways the prior domains are not. In computational fields where AI analytical outputs are relatively interpretable within established methodological conventions, the boundary between human and AI contributions is more illegible. In interpretive humanities or

qualitative social science, AI-generated prose may be formally indistinguishable from the researcher's own reasoned synthesis, making the monitoring-and-control distinction particularly difficult to maintain (Pasquale, 2015). These disciplinary variations require implementing the CAP framework with sensitivity to each field's epistemological standards, methodological traditions, and community validation practices. Generic AI literacy programs that proceed from tool capabilities rather than disciplinary contexts systematically fail to address this point.

3.1.4 Pedagogical and Ethical Design Capacity

Pedagogical and ethical design capacity is the competency that translates the three domains from the previous stage into responsible practice. It is the ability to design research workflows that integrate AI in ways that preserve faculty agency, maintain transparency with relevant audiences about AI's epistemic role, and actively counter the risks of bias propagation and epistemic overreliance that uncritical AI integration introduces (Hooshyar et al., 2025). This competency draws on design and systems-thinking methodologies, discussed further in Subsection 3.3, as its primary means of development. Effective co-intelligent practice is not adopted but designed iteratively, in response to evidence, and with attention to second-order effects in the broader system (Azukas & Gibson, 2025). Faculty development programs that treat AI integration as a technical adoption problem rather than a design research challenge will produce superficial competency that degrades under conditions of AI system change or increased epistemic complexity.

The ethical dimension of this competency extends beyond individual research integrity to institutional responsibility. When AI systems trained on historically biased data produce discriminatory

classifications in high-stakes research contexts (Baker & Hawa, 2022), such as identifying at-risk students, allocating institutional resources, or evaluating scholarly quality, the faculty members who deploy those systems without interrogating their assumptions bear responsibility for the outcomes (Hooshyar et al., 2025). Pedagogical and ethical design capacity requires faculty to be equipped not only to recognize these risks but also to design workflows that structurally constrain them through bias auditing, outcome monitoring, and transparent reporting of AI's role in research decisions.

3.2 | Developmental Staging: A Trajectory for Faculty Growth

A framework that specifies which competencies faculty need but not how those competencies develop provides incomplete guidance for faculty development practice. The CAP framework draws on metacognitive developmental theory (Greene & Azevedo, 2007; Schraw & Dennison, 1994) to propose that CAP competency development follows a three-stage trajectory, with each stage characterized by distinctive patterns of AI engagement, epistemic risks, and intervention requirements. This developmental account directly challenges the institutional tendency to treat faculty AI development as a one-off training event. This tendency creates the appearance of preparation while leaving the underlying competency architecture undeveloped.

Table 3 cross-references the novice, developing, and expert stages (Ifenthaler, 2009, 2010; Le Maistre, 1998) with the CAP competency domains. The matrix includes indicative developmental emphases and illustrative behaviors for each domain at each stage. The matrix is deliberately not offered as an assessment instrument. Its behavioral descriptors are illustrative rather than exhaustive or psychometrically validated, and they make visible a point that holistic stage

Table 3 CAP developmental staging

CAP domain	Novice stage	Developing stage	Expert and adaptive stage
Epistemic awareness	Accepting AI outputs on the basis of linguistic fluency; does not distinguish surface plausibility from disciplinary adequacy	Recognizing that AI outputs can misrepresent sources or construct implausible arguments, but applies this recognition reactively and case by case	Holding a stable epistemological orientation; anticipates where and why AI mediation reshapes what counts as valid knowledge in the discipline
Co-intelligent literacy	Using AI as a convenience tool for drafting or summarizing, without evaluating disciplinary adequacy or monitoring the collaboration	Monitoring AI output quality competently but applies standards formulaically, without proactive, context-sensitive guidance of the collaboration	Fluidly allocating monitoring and control functions between self and AI; guides the collaboration proactively with calibrated disciplinary judgment
Algorithmic agency	Ceding interpretive direction to the AI by default; exercises little epistemic authority over the work's direction or evaluative standard	Retaining authority on familiar tasks but may relinquish it under unfamiliar tools, time pressure, or higher-stakes decisions	Maintaining clear epistemic authority as a matter of course; adapts collaborative practice as AI capabilities evolve rather than being led by them
Pedagogical and ethical design capacity	Not considering second-order effects of AI use on students, colleagues, or disciplinary norms; normalizes unreflective use	Designing AI-integrated research or teaching tasks with attention to some risks but addresses ethical and systemic effects partially or post hoc	Designing research, teaching, and institutional practice that translates the other three competencies into responsible use, anticipating systemic and second-order effects by design

Note. CAP: Co-Intelligent Academic Practice.

descriptions tend to obscure: Development across the four domains is domain-specific, task-sensitive, and frequently uneven. A faculty member may exhibit expert-level epistemic awareness in evaluating AI-generated literature syntheses within his own subfield while operating at a novice level of pedagogical and ethical design capacity when integrating AI into assessment or may display developing-stage co-intelligent literacy on a familiar analytical task yet regress to novice behaviors when confronting an unfamiliar tool or a higher-stakes decision. The stages should therefore be understood as descriptions of competency within a given domain and task context rather than as a single linear classification of a faculty member's overall standing.

3.2.1 Novice Stage

At the novice stage, faculty engage with AI primarily as a convenience tool—for example, drafting communications, summarizing documents, and generating preliminary text—without systematic attention to the quality of AI outputs, the monitoring and control dynamics of the collaboration, or the pedagogical implications of normalizing similar AI use among colleagues. The characteristic risk at this stage is unreflective adoption: accepting AI outputs as valid based on their linguistic surface features without the evaluative competency needed to assess their disciplinary adequacy (Bender et al., 2021).

The appropriate developmental intervention is structured comparative reflection—that is, asking faculty to evaluate AI-generated and human-generated analyses of the same disciplinary phenomenon side by side, identify where the AI synthesis is epistemically strong and where it fails, and articulate the disciplinary standards that ground those judgments. This kind of structured comparison develops epistemic awareness and begins to build the evaluative habits that co-intelligent literacy requires (Schön, 1983). However, this intervention faces a genuine bootstrapping problem. The evaluative capacities that make structured reflection productive are precisely what novice faculty have not yet developed. Faculty members who lack foundational EDL cannot meaningfully evaluate AI-generated analytical syntheses. This suggests that novice-stage interventions must be more externally scaffolded than reflection alone can provide—for instance, structured more like an apprenticeship in communities of practice (Lave & Wenger, 1991) than like self-directed professional learning (Stockwell, 2025). This has significant implications for faculty development program design. Novice-stage development requires expert facilitation, discipline-specific exemplars, and sustained engagement rather than a one-time workshop.

3.2.2 Developing Stage

At the developing stage, faculty have accumulated experience with AI collaboration and developed awareness of its limitations but have not yet achieved the fluent bidirectional integration that characterizes expert algorithmic agency. A characteristic pattern at this stage is asymmetric competency. For example, faculty may effectively monitor AI output quality by identifying when AI synthesis misrepresents sources or constructs implausible arguments without applying systematic disciplinary standards to guide the collaboration proactively. Alternatively, they may apply evaluative standards formulaically without the flexible, context-sensitive judgment that genuine expert practice requires (Hunter & Daw, 2021).

The appropriate developmental intervention at this stage is scaffolded co-design. In structured faculty development experiences, participants design, prototype, and test AI-integrated research workflows, receive substantive peer feedback grounded in disciplinary standards, and make revisions in response to evidence from their own practice. This is the stage at which design thinking methodology, organized around the cycle described in Subsection 3.3, operates most productively as a faculty development instrument. Moving faculty through the phases of empathizing with their knowledge limitations, defining specific co-intelligent practice problems, generating and testing design solutions, and iterating in response to evidence produces the kind of contextualized, evidence-responsive competency that algorithmic agency requires and that generic AI literacy workshops structurally cannot produce (Azukas & Gibson, 2025).

3.2.3 Expert and Adaptive Stage

At the expert and adaptive stage, faculty engage in genuine co-intelligent inquiry. They fluidly allocate monitoring and control functions between themselves and AI systems, maintain clear authority over the direction and evaluative standards of their work, assess AI contributions with calibrated disciplinary judgment, and adapt their collaborative practice as AI capabilities evolve. The defining characteristic of this stage is not technical mastery of AI tools, which are continuously changing, but a stable metacognitive and epistemological orientation that enables effective engagement with new tools as they emerge.

At this stage, appropriate institutional support is not instruction but structured community engagement. For instance, such support includes access to networks of advanced practitioners navigating analogous challenges in their disciplines, institutional recognition of co-intelligent practice as a legitimate form of

scholarly innovation, and opportunities to contribute to the field's developing evidence base by publishing and sharing co-intelligent research workflows, pedagogical designs, and evaluation frameworks. Without institutional recognition, expert practitioners have no structural incentive to invest in building collective capacity, and the regenerative pathway through which individual expertise becomes an institutional norm is broken (Steinert et al., 2016).

However, a critical gap in the developmental account presented here warrants explicit acknowledgment. The trajectory remains incomplete without specifying observable failure indicators at each stage. What does insufficient algorithmic agency look like in research outputs, classroom practice, or community-facing scholarship? How is it distinguishable by an external evaluator from competent co-intelligent practice? Developing empirically grounded behavioral indicators for each stage and validating the domain-specific, task-sensitive developmental pattern illustrated in Table 3 constitute a priority research task for the field—one that this article can identify and structure but not yet undertake.

3.3 | Design and Systems Thinking Cycle

The competency domains and developmental stages of CAP specify what faculty development must achieve. How it should proceed requires a methodological answer. We propose a design and systems thinking cycle, not merely as a workshop tool but as the primary process through which faculty develop CAP competencies. Hence, by practicing design thinking in relation to their own co-intelligent practice challenges, faculty simultaneously develop pedagogical and ethical design capacity and produce concrete artifacts—such as research workflows, teaching designs, and evaluation rubrics—that constitute the field's evidence base.

Consequently, if design thinking supplies the process, systems thinking supplies the frame within which this process must operate. Systems thinking is not an add-on to the process but its constitutive framework. Faculty, AI systems, students, disciplines, and institutions form a complex adaptive system with feedback loops, emergent behaviors, and unintended consequences that no single design intervention can fully control (Holland, 1995). The central discipline of systems thinking—asking not only whether a design works for the immediate problem but also what second-order effects it produces in the broader system—is essential for ensuring that co-intelligent practice development serves the epistemic and pedagogical goals of the CAP framework rather than inadvertently undermining them. The cycle includes: empathize, define, ideate and prototype, as well as test and iterate.

3.3.1 Empathize Phase

The cycle begins with the empathize phase, a genuine inquiry into the specific AI challenges and opportunities in each faculty member's disciplinary context. Generic AI literacy training fails at this point because it starts with AI capabilities rather than the specific epistemological standards, methodological traditions, and community validation practices of the disciplines in which faculty work. A historian evaluating AI-generated synthesis of archival sources faces epistemic challenges that differ from those faced by a statistician evaluating AI-generated model specifications or an educational psychologist evaluating the validity of AI-generated survey instruments. Faculty development that does not begin with this disciplinary specificity produces generic awareness rather than the domain-sensitive competency required by the CAP framework. The systems thinking question at this stage is as follows: Who else in the system is affected by how this faculty member currently practices AI-assisted inquiry? Early-career researchers inherit research norms from their supervisors; departments inherit methodological standards from their most visible practitioners; disciplines are shaped by what passes peer review. Empathizing with the full system, rather than only with individual faculty members' challenges, reveals the institutional leverage points at which developmental investment yields the broadest epistemic return.

3.3.2 Define Phase

The define phase translates the empathize phase's inquiry into specific, actionable problem statements. Rather than framing the challenge as AI adoption in general, faculty articulate the precise co-intelligent practice problems they face in their own disciplinary work: How to evaluate an AI-generated literature synthesis against the evidentiary standards of their field; what AI-integrated assessments would develop rather than bypass student metacognition; and how to maintain algorithmic agency when AI co-produces outputs for policy or community audiences. Problem statements at this level of specificity are the prerequisite for design work that generates genuine insight. The systems thinking question at this stage concerns causal depth: Is the identified problem a proximate symptom or a structural cause? A faculty member who defines the problem as ineffective prompt construction may be addressing surface behavior while leaving intact the institutional reward structures, curriculum gaps, or peer norms that produce it. A structurally sound problem definition is essential for designing interventions whose effects persist beyond the development context.

3.3.3 Ideate and Prototype Phase

The ideate and prototype phases move faculty from problem definition to the generation and testing of co-intelligent practice designs. In the research domain, this means designing and prototyping human–AI research workflows within actual disciplinary projects. In the teaching domain, it means generating and testing AI-integrated pedagogical designs against evidence of student metacognitive development and epistemic agency. The prototyping phase is epistemologically essential as co-intelligent practice is not improved by reflection alone but requires iterative engagement with actual AI systems in real disciplinary contexts (Schön, 1983). The systems thinking question here concerns feedback-loop activation: What second-order effects does this prototype generate? A design that improves individual research efficiency may simultaneously erode the collaborative peer review on which the validation of disciplinary knowledge depends. Identifying these system-level effects during prototyping, rather than discovering them post-deployment, is one of the primary contributions systems thinking makes to the design cycle.

3.3.4 Test and Iterate Phase

The test and iterate phase closes the cycle by evaluating faculty-produced designs against evidence from practice and revising them based on the findings. This phase transforms the cycle from a linear development process into a continuous improvement methodology appropriate for a domain in which AI capabilities are continually evolving. Co-intelligent practice is not a stable configuration that faculty achieve and maintain. It is a continuous design problem requiring ongoing evaluation and adaptation. Faculty development programs that treat it otherwise will produce competencies that are obsolete before they are fully operationalized. The systems thinking question during this phase concerns the definition of evidence: What counts as improvement in the full system, as distinct from optimization of a single component? Testing that focuses exclusively on individual faculty outcomes may miss the deterioration of student metacognition, the narrowing of methodological diversity, or the erosion of collegial knowledge-sharing norms. Systemic evaluation requires indicators drawn from multiple levels of the system and collected over time horizons sufficient for emergent effects to become observable.

The design and systems thinking cycle proposed here is not a prescriptive protocol but a generative methodology that is adaptable to disciplinary contexts, institutional conditions, and developmental stages. For instance, consider a faculty development program addressing an AI-assisted literature review

workflow. Participants empathize by examining how automated synthesis reshapes source discovery in their field. They define the problem as preserving evidentiary judgment rather than accelerating retrieval. They prototype a workflow in which AI proposes candidate literature while the researcher adjudicates inclusion against disciplinary standards. They test whether the design strengthens or erodes critical appraisal across a cohort. Consequently, the systems thinking discipline asks what second-order effects follow, such as narrowing citation diversity. What remains constant across these variations is the commitment to evidence-responsive iteration and systemic evaluation that extends beyond individual competency to community epistemic health.

4 Institutional Enablement

The CAP framework developed in Section 3 specifies what individual faculty members must know, be able to do, and commit to enacting to exercise algorithmic agency effectively. However, individual competency development is necessary but not sufficient for field-level adoption of CAP. Institutional and systemic conditions largely determine how faculty can practice co-intelligent inquiry. These conditions are driven by the available tools, the governance frameworks that regulate their use, the reward structures that define scholarly achievement, and the communities that provide the collegial infrastructure for iterative development. A faculty preparation framework that attends exclusively to individual capacity while leaving institutional conditions unaddressed will produce well-prepared faculty operating in environments structurally incapable of supporting what they have been prepared to do. This is precisely the mismatch that Gibson and Ifenthaler (2017) identified as characterizing the field's response to computational methods a decade ago and that Ifenthaler (2025a) documented as persisting into the present. This section specifies what institutions must provide across three interdependent domains: structural enablement, community-based developmental support, and equitable global participation.

4.1 | Structural Enablers: Infrastructure, Policy, and Recognition

Three distinct yet mutually reinforcing structural conditions are prerequisites for CAP at the institutional scale: infrastructure, policy, and recognition. Each represents a distinct institutional obligation; the absence of any one undermines the effectiveness of the others.

Infrastructure is the foundational precondition.

Faculty cannot exercise algorithmic agency without sustained, governed access to appropriate AI tools, yet such access is neither universal nor epistemically neutral. Data privacy concerns are a primary barrier to AI adoption across professional contexts (Hoel & Chen, 2018; Prinsloo & Slade, 2014; Schünemann & Baumann, 2017). This finding maps directly onto the academic setting, where student data are protected under frameworks such as the Family Educational Rights and Privacy Act in the United States and the General Data Protection Regulation in the European Union. AI tool use interacts with these protections in ways that most faculty are not equipped to evaluate independently. Institutions that encourage AI adoption without first resolving data governance questions effectively externalize compliance risk onto individual faculty, creating conditions in which the path of least resistance is unreflective adoption rather than the critically governed practice that algorithmic agency requires. Infrastructure provision, therefore, extends well beyond AI tool licensing: It encompasses data governance frameworks, privacy impact assessment processes, computational resource allocation, and the technical support capacity that makes responsible and reproducible AI-assisted research possible (Williamson, 2021).

Policy is the governance architecture that transforms access to infrastructure into legitimate practice. Institutions require clear, value-grounded policies covering AI use across research and teaching domains: in research, addressing AI authorship attribution, permissible uses of participant data in AI-assisted analysis, and standards for reporting AI's methodological role in published work; in teaching, addressing boundaries for student AI use, academic integrity standards calibrated to disciplinary and developmental contexts, and criteria for designing and assessing AI-integrated pedagogical tasks (Hawkins et al., 2026; Ifenthaler et al., 2024). The critical design principle is that such policies function as enabling frameworks rather than restrictive prohibitions. Policies that enumerate prohibited uses without specifying the conditions under which AI collaboration is methodologically legitimate and institutionally sanctioned will drive unreflective AI adoption underground rather than eliminate it, thereby generating precisely the epistemic risks the CAP framework is designed to address (Pasquale, 2015). We have argued elsewhere that institutional adoption of data analytics requires a fundamental shift from compliance-based to value-aligned governance frameworks (Gibson & Ifenthaler, 2020; Ifenthaler et al., 2021). This argument applies with greater urgency to GenAI systems, whose opacity and generativity create governance challenges that compliance checklists cannot adequately address.

Recognition is the institutional signal that co-intelligent practice constitutes legitimate scholarly work. Faculty development in algorithmic agency

demands sustained intellectual investment that most tenure and promotion systems do not currently reward. Where scholarship advancing co-intelligent practice—whether as peer-reviewed research on faculty development, designed and evaluated AI-integrated curricula, or developed and documented co-intelligent research workflows—does not count as recognized scholarly activity, only faculty with surplus capacity and intrinsic motivation will openly invest in it. The predictable result is an uneven distribution of co-intelligent competency concentrated in research-intensive institutional contexts capable of absorbing development costs, while teaching-focused institutions and contingent faculty, who bear the most risk from scholarly innovation and serve the most educationally underserved student populations, fall further behind. Consequently, the persistent marginalization of data science approaches in educational research publication venues reflects institutional failures of recognition and reward as much as individual competency gaps (Ifenthaler, 2025a). The remedy is the same in both cases: Institutional recognition must structurally precede, rather than retrospectively reward, the competency development it is meant to incentivize. We acknowledge the circularity embedded in this argument: Tenure systems conventionally reward demonstrated scholarly value, while co-intelligent practice has not yet generated the peer-reviewed evidentiary base that would justify systemic recognition. The most productive near-term institutional pathway therefore consists of pilot recognition programs tied to documented, externally evaluated co-intelligent practice portfolios, creating the evidentiary record on which broader policy revision can subsequently draw.

4.2 | Community-Based Developmental Support

Structural enablement provides the necessary conditions for co-intelligent practice; community provides the developmental environment in which those conditions become productive. Faculty developing algorithmic agency require sustained access to disciplinary peers navigating analogous challenges, shared repositories of tested co-intelligent workflows and pedagogical designs, and formalized learning communities that provide peer feedback, collective sense-making, and the institutional continuity that individually driven development initiatives cannot sustain. The evidence base for professional learning communities as a faculty development mechanism is well established (Lave & Wenger, 1991; Steinert et al., 2016), but the requirements of co-intelligent practice development extend beyond conventional collegial support. What is needed are communities that can generate, test, and iteratively refine practical knowledge about how human-AI collaboration functions in specific disciplinary and

institutional contexts. This knowledge does not yet exist in the published literature because the practice is too emergent to have been systematically studied.

The theoretical basis for investing in these communities is Engelbart's (1962) regenerative bootstrap principle, which holds that the most powerful developmental strategy is to build augmentation capacity first among those who are actively doing the work. Applied to institutional co-intelligence development, this principle generates a compounding logic. Faculty members who develop advanced algorithmic agency within structured communities of practice help refine institutional AI governance and infrastructure, which in turn enable more sophisticated faculty practice and generate further institutional learning and policy development. Institutions that invest earliest in these communities will not simply precede those that delay—they will operate within a qualitatively different developmental ecology, where individual competency and institutional capacity develop in recursive, mutually reinforcing relations rather than in isolation. This compounding dynamic is consistent with the organizational transformation patterns documented in prior work on institutional learning analytics adoption (Chatterjee & Bhattacharjee, 2020; Egetenmeier & Hommel, 2020; Gašević et al., 2019; Gibson & Ifenthaler, 2020; Hilliger et al., 2020), in which technological infrastructure and staff capabilities were found to develop most effectively through structured communities of practice centered on current institutional cases rather than through sequential, top-down implementation (Gibson & Ifenthaler, 2020; Ifenthaler, 2020).

These communities must be designed to reflect the developmental stages proposed in Subsection 3.2. Novice-stage faculty require externally scaffolded, discipline-specific communities that offer structured comparative reflection and expert facilitation, analogous to apprenticeship (Lave & Wenger, 1991). Developing-stage faculty require peer co-design communities structured around the iterative cycle described in Subsection 3.3. Expert-stage faculty require boundary-spanning networks that connect advanced practitioners across disciplines and institutions, providing collegial infrastructure for publishing, sharing, and collectively evaluating innovations in co-intelligent practice. Failing to differentiate community design by developmental stage—that is, treating all faculty as equivalently positioned relative to AI collaboration—is a structural error that generic faculty AI training programs systematically make and that the CAP framework is explicitly designed to correct.

4.3 | Equity and Global Participation

The structural enablers and community support specified in the preceding subsections are unequally

distributed across national, linguistic, and institutional contexts in ways that the CAP framework must explicitly confront. Access to advanced GenAI systems is concentrated in well-resourced institutions in high-income countries, a structural inequality that defines the current global digital divide. Data governance expertise, legal infrastructure for student data protection, technical support capacity, and faculty development funding are similarly skewed. A framework for co-intelligent faculty preparation that proceeds as though these inequalities are external to its theoretical scope will, in practice, accelerate them: Institutions with resources will rapidly develop algorithmic agency, while those serving the most educationally underserved student populations fall progressively further behind, producing a global competency divide that reproduces and deepens existing inequalities in educational quality and access (Miao & Cukurova, 2024; UNESCO, 2016).

Addressing this challenge requires international collaborative models of faculty development explicitly designed to share frameworks, expertise, and institutional learning across resource contexts (Ifenthaler et al., 2024)—not to replicate high-resource models in low-resource settings but to develop contextually appropriate pathways through the three-stage progression from a computational mindset through EDL to algorithmic agency. The critical distinction here is between international collaboration and international standardization. The CAP framework must be adapted rather than uniformly applied across diverse national, linguistic, disciplinary, and institutional contexts. Appropriate AI integration in a research-intensive doctoral program at an institution in a high-income country is epistemologically and practically distinct from appropriate integration in an undergraduate teaching institution in a resource-constrained context (Wisker et al., 2007). Frameworks that do not build in this contextual sensitivity generate superficial compliance rather than genuine competency development—an outcome that serves institutional performance metrics while leaving the underlying epistemic preparation gap intact.

Effective international collaboration models must address both capacity sequencing and content sharing: building a foundational computational mindset, then EDL, and then algorithmic agency in a sequence responsive to each institutional context's starting point rather than imposing a uniform implementation timeline. This sequencing principle follows directly from the CAP framework's developmental logic and the bootstrapping argument of Gibson and Ifenthaler (2017). Accordingly, a global ecosystem of co-intelligent faculty practice cannot be constructed by transferring advanced competency frameworks to contexts lacking the foundational infrastructure to

support them. It must be built iteratively and collaboratively from the conditions that actually exist in each context—precisely the open, collaborative, and inclusive approach called for by UNESCO’s Sustainable Development Goal 4 (Miao & Cukurova, 2024; Sabzalieva & Valentini, 2023; UNESCO, 2016).

The institutional enablement conditions set out in this section are not supplementary to the CAP framework; they constitute it. Individual algorithmic agency, developed in institutional environments that lack adequate infrastructure, governance, recognition, community, and equitable access, will remain episodic, precarious, and inequitably distributed. Hence, transforming researcher preparation from computational literacy to algorithmic agency requires not only a new competency framework but also the institutional architecture within which that framework can take root, develop, and become the normative standard for co-intelligent scholarly practice.

4.4 | Implementation Pathways

The preceding subsections establish the institutional conditions that CAP presupposes, but specifying necessary conditions is not the same as specifying how to realize them. A framework that identifies infrastructure, policy, recognition, community, and equity as constitutive requirements while remaining silent on the mechanisms for their institutional realization risks the very theory–practice mismatch that Section 4 diagnoses. This subsection therefore sets out five concrete pathways for translating the CAP framework from a normative specification into institutional practice.

The first pathway is institutional readiness assessment (Ifenthaler, 2020). Because the framework’s developmental progression must respond to each institution’s starting point (Subsection 4.3), implementation must diagnose where an institution stands across the domains of Subsection 4.1, identifying not a ranking but the binding constraint, since the absence of any one condition undermines the others. This aligns with learning analytics adoption, where capability develops through engagement with current institutional cases rather than top-down rollout (Buckingham Shum & McKay, 2018; Gibson & Ifenthaler, 2020). The second pathway bootstraps exemplary practice through targeted pilots (Buckingham Shum, 2023). Given the circularity acknowledged in Subsection 4.1, initial investment should focus on faculty already engaged in co-intelligent inquiry within structured communities. Such pilots produce the externally evaluated portfolios that break the circularity and the situated knowledge that Subsection 4.2 identifies as absent from the literature, provided they are instrumented for evidence generation from the outset. The third pathway scales community infrastructure by developmental stage

(Caskurlu et al., 2021). Since undifferentiated design is a characteristic error of generic AI training, novice communities must be established first, followed by peer co-design communities, and then boundary-spanning expert networks, because each stage’s capacity is the precondition for facilitating the next. The fourth pathway co-evolves policy and recognition with demonstrated practice. Provisional recognition through pilot portfolios and interim enabling policy generates evidence that subsequently informs durable revisions to governance and promotion criteria, operationalizing the shift from compliance-based to value-aligned governance (Ifenthaler et al., 2021). The fifth pathway builds cross-institutional collaboration from the outset, since unmediated diffusion would accelerate the inequalities of Subsection 4.3. Instruments should be documented for contextual adaptation rather than uniform transfer, with sequencing beginning from the computational mindset (Ifenthaler et al., 2024).

Accordingly, these pathways remain testable propositions rather than validated procedures and are interdependent: When only partially enacted, they reproduce precisely the unsustainable adoption that Section 4 seeks to prevent.

4.5 | Risk Management Related to AI Ethics and Dependency

Institutional enablement must also guard against the risks that co-intelligent practice itself introduces, since the same systems that extend scholarly capacity can, under conditions of uncritical use, diminish it. Sustained delegation of analytical and interpretive labor to AI systems threatens cognitive dependency (Jacobowitz, 2026; Tian & Zhang, 2026), progressive deskilling of researchers (Bareither & Griessl, 2026), diminished critical thinking (Jain et al., in press), erosion of scholarly originality (Dai & Chan, 2026), and overreliance on AI-generated reasoning (Sætra, 2026). These risks are not incidental effects of misuse but predictable consequences of efficiency pressures on faculty who are rewarded for output. Each corrodes the human epistemic authority that algorithmic agency is expressly designed to preserve. The danger is compounded by its gradualism, since the atrophy of core scholarly capacities seldom announces itself until well advanced. These risks, in turn, raise questions of accountability that institutions cannot leave unresolved. Because GenAI systems cannot bear responsibility, accountability for AI-generated errors must remain unambiguously with the human scholar. Institutions must establish oversight mechanisms that make this locus explicit, including transparent authorship and contribution standards, disclosure requirements specifying AI’s methodological role, and review processes that treat undisclosed or unverified AI use as a matter of research integrity (Hawkins et al., 2026). Treating

such accountability structures as constitutive of responsible enablement distinguishes the critically governed practice the CAP framework demands from unreflective adoption.

5 Conclusions

This article has developed a single, cumulative argument: The transformation of educational research practice by GenAI demands not an incremental update to existing faculty preparation frameworks but a qualitative reconceptualization of what researcher competency means and what institutions must provide to develop it. We began with the observation that the call for a computational mindset now characterizes faculty working conditions across all disciplines. The prediction has been empirically realized; however, the preparatory infrastructure has not.

The three-stage progression we have traced through this article is not a rhetorical device but a theoretical claim about logical dependency. The computational mindset established that algorithms transform the epistemological character of inquiry, not merely its technical apparatus. EDL specifies what this transformation demands in concrete methodological terms, including competency in Big Data complexity, machine learning paradigms, data mining, and the full spectrum of analytics approaches. Both frameworks, however, were designed for a research environment in which AI served as an analytical instrument under human direction. The arrival of GenAI systems capable of synthesizing literature, constructing arguments, generating hypotheses, and producing knowledge claims that enter scholarly discourse alongside human-authored work renders both frameworks necessary but insufficient. Algorithmic agency—the capacity to critically co-construct knowledge with AI while maintaining methodological rigor and preserving human epistemic authority—is the stage that the logic of the first two demands but that neither could fully anticipate until the emergence of LLMs made the need empirically undeniable.

The CAP framework proposed in Section 3 translates this theoretical progression into a practical architecture for faculty preparation. Its four competency domains are organized as a cumulative developmental progression because genuine co-intelligent practice is structurally hierarchical. Each domain presupposes the preceding ones, and skipping stages produces fragile competencies that degrade under conditions of increased epistemic complexity or AI system change. The three developmental stages resist the institutional tendency to treat faculty AI development as a discrete training event, insisting instead that co-intelligent practice is a trajectory requiring sustained investment,

iterative design, and community-based support. To illustrate, consider a department piloting CAP through an AI-assisted qualitative coding initiative. At the novice-stage, faculty first examine how automated coding reshapes interpretive judgment within their tradition. At the developing stage, faculty co-design a workflow in which AI proposes provisional codes that researchers adjudicate against the study's analytic framework. At the expert stage, faculty convene a cross-disciplinary review of the resulting artifacts, evaluating whether interrater reliability improves without flattening interpretive nuance. The design and systems thinking cycle provides both the developmental process and the evaluative discipline through which this trajectory is navigated, surfacing second-order effects such as premature analytic closure and keeping the practice current as AI capabilities continue to evolve.

Individual competency, however well developed, may be institutionally insufficient. The structural conditions for CAP, including infrastructure, governance policies, recognition frameworks, and community-based developmental support, are established at the institutional and systemic levels. Institutions that encourage AI adoption without resolving data governance issues, establishing enabling policy frameworks, or recognizing co-intelligent practice as legitimate scholarly work will foster unreflective adoption rather than the critically governed practice that algorithmic agency requires. The parallel with the adoption of institutional learning analytics is instructive: Organizational conditions, governance frameworks, and staff capability have consistently been the binding constraints on the productive use of educational data. The same logic applies with greater consequences to GenAI, whose opacity and generativity create governance challenges that no individual faculty member can responsibly navigate without institutional support. The equity dimension is inseparable from this institutional argument: A global faculty development framework that proceeds as though AI infrastructure, training resources, and institutional support are equitably distributed will accelerate rather than ameliorate the global digital divide, undermining educational equity commitments.

The most consequential limitation of the framework presented here is its predominantly theoretical character. The CAP developmental staging model is grounded in metacognitive theory and organizational learning research, but it has not yet been empirically validated against observed faculty AI use patterns. As a conceptual contribution, it articulates relationships that remain analytically derived rather than empirically demonstrated, and its staging logic should accordingly be read as a hypothesis to be tested rather than an established trajectory. Three further limitations qualify its scope. First, the framework is presented as largely

discipline-general, yet the epistemic cultures, data practices, and evidentiary standards of different fields may require substantially different articulations of algorithmic agency, such that a single staging model may obscure consequential disciplinary variation. Second, the GenAI systems that the framework addresses are evolving faster than the tools and policies that govern them, so specific competency descriptions risk partial obsolescence and require periodic revision. Third, the institutional enablement conditions specified in Section 4 presuppose unequally distributed resources, and the framework cannot, on its own, remedy the structural inequalities that will shape its uptake.

Studies employing think-aloud protocols during AI-assisted research tasks, longitudinal workflow documentation across developmental stages, and comparative outcome analyses between CAP-informed and conventionally trained cohorts could confirm, substantially revise, or falsify the staging model and the competency architecture it organizes. We issue this agenda not as a conventional acknowledgment of limitations but as a substantive research priority, since the field cannot responsibly scale co-intelligent faculty development without an empirical grounding that renders its claims falsifiable. These limitations define a concrete empirical agenda comprising four priorities: validating the developmental staging model through think-aloud and longitudinal workflow studies of faculty AI use; testing the domain-specific and uneven developmental pattern proposed in Table 3 against observed practice; developing and calibrating behavioral indicators that distinguish competent co-intelligent practice from its failure modes at each stage; and evaluating, through comparative designs, whether CAP-informed faculty development yields stronger epistemic outcomes than conventional training.

To sum up, the most productive developmental strategy is for researchers to use and iteratively refine the augmentation tools themselves, generating institutional knowledge through practice before generalizing to broader implementation. Applied here, this means that scholars studying co-intelligent faculty development bear a reflexive obligation to practice algorithmic agency in their own inquiry. This demands that researchers model CAP competencies in their research design, exercise genuine epistemic authority over AI-assisted analytical processes, and document co-intelligent workflows transparently alongside the findings those workflows produce. This is not epistemological self-congratulation but methodological consistency. Accordingly, a framework for co-intelligent practice that is not itself practiced in its production lacks the reflexive integrity that scholarly credibility requires.

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Declaration on the Use of AI AI tools, including Claude, ChatGPT, Gemini, Keenious, SciSpace, and Grammarly, were used in preparing this manuscript. Consistent with the concept of co-intelligence, the authors took the lead in conceptualization, organization, interpretation, drafting, editing, and critical review, while the AI tools were used in a limited fashion across a range of cross-checks, validation, resource finding, pattern recognition, text generation, reference checking, formatting, grammar checking, and writing style. The core conclusions were independently completed by the authors, who assume full accountability for the entire manuscript.

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References

- Azukas, M. E., & Gibson, D. C. (2025). Co-intelligence in the classroom: The DOT framework for AI-enhanced teaching and learning. *AI Enhanced Learning*, 1(2), 269–293.
- Bail, C. A. (2024). Can generative AI improve social science? *Proceedings of the National Academy of Sciences of the United States of America*, 121(21), e2314021121.
- Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education.

- International Journal of Artificial Intelligence in Education*, 32(4), 1052–1092.
- Bareither, C., & Griessl, L. (2026). Hybrid epistemic practices and the transformation of academic assemblages: Generative AI and epistemic messiness in the qualitative social sciences and humanities. *AI & Society*, 41(7), 6459–6475.
- Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? In: *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*. New York: ACM, 610–623.
- Bianchini, S., Müller, M., & Pelletier, P. (2025). Drivers and barriers of AI adoption and use in scientific research. *Technological Forecasting and Social Change*, 220, 124303.
- Buckingham Shum, S. (2023). Embedding learning analytics in a university: Boardroom, staff room, server room, classroom. In: Viberg, O., & Grönlund, Å., eds. *Practicable learning analytics*. Springer, 7–33.
- Buckingham Shum, S., & McKay, T. (2018, March 12). Architecting for learning analytics: Innovating for sustainable impact. Available from EDUCAUSE Review website.
- Caskurlu, S., Richardson, J. C., Maeda, Y., & Kozan, K. (2021). The qualitative evidence behind the factors impacting online learning experiences as informed by the community of inquiry framework: A thematic synthesis. *Computers & Education*, 165, 104111.
- Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, 25(5), 3443–3463.
- Dai, W., & Chan, C. K. Y. (2026). Shaping responsible GenAI use in research through AI literacy-oriented guidelines: Insights from postgraduate students. *International Journal of Educational Technology in Higher Education*, 23(1), 33.
- Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. *arXiv Preprint*, arXiv:1702.08608.
- Egetenmeier, A. C., & Hommel, M. (2020). “Trust the process!”: Implementing learning analytics in higher education institutions. In: Ifenthaler, D., & Gibson, D. C., eds. *Adoption of data analytics in higher education learning and teaching*. Springer, 113–134.
- Egloffstein, M., Delcker, J., & Ifenthaler, D. (2025). Developing educational data literacy: From online course design to classroom practice. In: Schumacher, C., & Ifenthaler, D., eds. *International perspectives on educational data literacy*. Routledge, 214–238.
- Engelbart, D. C. (1962). *Augmenting human intellect: A conceptual framework*. Defense Technical Information Center.
- Gašević, D., Tsai, Y., Dawson, S., & Pardo, A. (2019). How do we start? An approach to learning analytics adoption in higher education. *The International Journal of Information and Learning Technology*, 36(4), 342–353.
- Gibson, D. C., & Ifenthaler, D. (2017). Preparing the next generation of education researchers for Big Data in higher education. In: Kei Daniel, B., ed. *Big Data and learning analytics in higher education: Current theory and practice*. Springer, 29–42.
- Gibson, D. C., & Ifenthaler, D. (2020). Adoption of learning analytics. In: Ifenthaler, D., & Gibson, D. C., eds. *Adoption of data analytics in higher education learning and teaching*. Springer, 3–20.
- Gibson, D. C., & Ifenthaler, D. (2025). Computational learning theories: A mixed-methods framework for AI enhanced educational research. *International Journal of Technology in Teaching and Learning*, 21(1), 1–26.
- Gibson, D. C., Kovanovic, V., Ifenthaler, D., Dexter, S., & Feng, S. H. (2023). Learning theories for artificial intelligence promoting learning processes. *British Journal of Educational Technology*, 54(5), 1125–1146.
- Gibson, D. C., Webb, M. E., & Ifenthaler, D. (2019). Measurement challenges of interactive educational assessment. In: Sampson, D., Spector, J. M., Ifenthaler, D., Isaías, P., & Sergis, S., eds. *Learning technologies for transforming large-scale teaching, learning, and assessment*. Springer, 19–33.
- Greene, J. A., & Azevedo, R. (2007). A theoretical review of Winne and Hadwin’s model of self-regulated learning: New perspectives and directions. *Review of Educational Research*, 77(3), 334–372.
- Greene, J. A., Azevedo, R., & Torney-Purta, J. (2008). Modeling epistemic and ontological cognition: Philosophical perspectives and methodological directions. *Educational Psychologist*, 43(3), 142–160.
- Grossmann, I., Feinberg, M., Parker, D. C., Christakis, N. A., Tetlock, P. E., & Cunningham, W. A. (2023). AI and the transformation of social science research. *Science*, 380(6650), 1108–1109.
- Hawkins, B., Taylor-Griffiths, D., & Lodge, J. M. (2026). Summarise, elaborate, try again: Exploring the effect of feedback literacy on AI-enhanced essay writing. *Assessment & Evaluation in Higher Education*, 51(5), 879–891.
- Hilliger, I., Ortiz-Rojas, M., Pesántez-Cabrera, P., Scheihing, E., Tsai, Y. S., Muñoz-Merino, P. J., Broos, T., Whitelock-Wainwright, A., & Pérez-Sanagustín, M. (2020). Identifying needs for learning analytics adoption in Latin American universities: A mixed-methods approach. *The Internet and Higher Education*, 45, 100726.
- Hoel, T., & Chen, W. (2018). Privacy and data protection in learning analytics should be motivated by an educational maxim—Towards a proposal. *Research and Practice in Technology Enhanced Learning*, 13(1), 20.
- Holland, J. H. (1995). *Hidden order: How adaptation builds complexity*. Perseus Books.
- Hooshyar, D., Šir, G., Yang, Y., Kikas, E., Hämäläinen, R., Kärkkäinen, T., Gašević, D., & Azevedo, R. (2025). Towards responsible AI for education: Hybrid human–AI to confront the elephant in the room. *Computers and Education: Artificial Intelligence*, 9, 100524.
- Hunter, L. E., & Daw, N. D. (2021). Context-sensitive valuation and learning. *Current Opinion in Behavioral Sciences*, 41, 122–127.
- Ifenthaler, D. (2009). Model-based feedback for improving

- expertise and expert performance. *Technology, Instruction, Cognition and Learning*, 7(2), 83–101.
- Ifenthaler, D. (2010). Bridging the gap between expert–novice differences: The model-based feedback approach. *Journal of Research on Technology in Education*, 43(2), 103–117.
- Ifenthaler, D. (2020). Change management for learning analytics. In: Pinkwart, N., & Liu, S., eds. *Artificial intelligence supported educational technologies*. Springer, 261–272.
- Ifenthaler, D. (2025a). Educational data science: A paradigm shift for the methodology of educational science? *Educational Science*, 36(70), 35–45. (in German).
- Ifenthaler, D. (2025b). Information processing re-visited: Reciprocal perspectives on artificial intelligence and human-centered systems. *AI Enhanced Learning*, 1(1), 229–243.
- Ifenthaler, D., Gibson, D., Prasse, D., Shimada, A., & Yamada, M. (2021). Putting learning back into learning analytics: Actions for policy makers, researchers, and practitioners. *Educational Technology Research and Development*, 69(4), 2131–2150.
- Ifenthaler, D., Majumdar, R., Gorissen, P., Judge, M., Mishra, S., Raffaghelli, J., & Shimada, A. (2024). Artificial intelligence in education: Implications for policymakers, researchers, and practitioners. *Technology, Knowledge and Learning*, 29(4), 1693–1710.
- Ifenthaler, D., & Schumacher, C. (2023). Reciprocal issues of artificial and human intelligence in education. *Journal of Research on Technology in Education*, 55(1), 1–6.
- Jacobowitz, S. (2026). The hidden functions of sycophancy in AI systems: Steering, consistency, and cognitive dependency. *AI & Society*, 41(7), 6573–6588.
- Jain, P., Shajit, D., Maini, A., Shahin, Y., & Panda, A. (in press). Cognitive offloading, critical thinking and attitudes towards artificial intelligence in the era of ChatGPT: A comparative study of artificial intelligence-assisted and manual task performance in young adults. *Cognitive Processing*.
- Johnson, R. B., & Onwuegbuzie, A. J. (2004). Mixed methods research: A research paradigm whose time has come. *Educational Researcher*, 33(7), 14–26.
- Kitchin, R. (2014). *The data revolution: Big Data, open data, data infrastructures & their consequences*. Sage Publications.
- Koriat, A. (2007). Metacognition and consciousness. In: Zelazo, P. D., Moscovitch, M., & Thompson, E., eds. *The Cambridge handbook of consciousness*. Cambridge University Press, 289–325.
- Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge University Press.
- Le Maistre, C. (1998). What is an expert instructional designer? Evidence of expert performance during formative evaluation. *Educational Technology Research and Development*, 46(3), 21–36.
- Lehmann, T., Hähnlein, I., & Ifenthaler, D. (2014). Cognitive, metacognitive and motivational perspectives on preflexion in self-regulated online learning. *Computers in Human Behavior*, 32, 313–323.
- McFarland, D. A., Khanna, S., Domingue, B. W., & Pardos, Z. A. (2021). Education data science: Past, present, future. *AERA Open*, 7(1), 1–12.
- Miao, F., & Cukurova, M. (2024). *AI competency framework for teachers*. UNESCO.
- Mollick, E. (2024). *Co-intelligence: Living and working with AI*. Portfolio.
- Papamitsiou, Z., Filippakis, M. E., Poulou, M., Sampson, D. G., Ifenthaler, D., & Giannakos, M. (2021). Towards an educational data literacy framework: Enhancing the profiles of instructional designers and e-tutors of online and blended courses with new competences. *Smart Learning Environments*, 8(1), 18.
- Pasquale, F. (2015). *The black box society: The secret algorithms that control money and information*. Harvard University Press.
- Pickering, A. (1995). *The mangle of practice: Time, agency, and science*. The University of Chicago Press.
- Piety, P. J., Hickey, D. T., & Bishop, M. J. (2014). Educational data sciences: Framing emergent practices for analytics of learning, organizations, and systems. In: *Proceedings of the Fourth International Conference on Learning Analytics and Knowledge*. Kyoto: ACM, 193–202.
- Prinsloo, P., & Slade, S. (2014). Student data privacy and institutional accountability in an age of surveillance. In: Menon, M. E., Terkla, D. G., & Gibbs, P., eds. *Using data to improve higher education: Research, policy and practice*. Sense Publishers, 197–214.
- Raffaghelli, J. E., De Rossi, M., & Ferrarelli, M. (2026). AI in higher education through complex lenses: Bridging knowledge management and faculty development. In: Bolisani, E., Nakash, M., Bratianu, C., & Bejinariu, R., eds. *Managing human and artificial knowledge: New horizons in AI-supported knowledge management*. Springer, 175–197.
- Sabzalieva, E., & Valentini, A. (2023). *ChatGPT and artificial intelligence in higher education: Quick start guide*. UNESCO.
- Salganik, M. J. (2018). *Bit by bit: Social research in the digital age*. Princeton University Press.
- Salomon, G. (1997). *Distributed cognitions: Psychological and educational considerations*. Cambridge University Press.
- Samsul, S. A., Yahaya, N., & Abuhassna, H. (2023). Education Big Data and learning analytics: A bibliometric analysis. *Humanities and Social Sciences Communications*, 10(1), 709.
- Schön, D. A. (1983). *The reflective practitioner: How professionals think in action*. Basic Books.
- Schraw, G., & Dennison, R. S. (1994). Assessing metacognitive awareness. *Contemporary Educational Psychology*, 19(4), 460–475.
- Schünemann, W. J., & Baumann, M.-O. (2017). *Privacy, data protection and cybersecurity in Europe*. Springer.
- Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G.-J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., ... Söllner, M. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information & Management*, 57(2), 103174.
- Steinert, Y., Mann, K., Anderson, B., Barnett, B. M., Centeno, A., Naismith, L., Prideaux, D., Spencer, J., Tullo, E., ... Dolmans, D. (2016). A systematic review of faculty development initiatives designed to enhance teaching effectiveness: A 10-year

- update: BEME Guide No. 40. *Medical Teacher*, 38(8), 769–786.
- Stockwell, G. (2025). Self-directed professional development. In: Tafazoli, D., ed. *The Palgrave encyclopedia of computer-assisted language learning*. Palgrave Macmillan, 1–6.
- Sun, D., Ba, S., Cha, Y., Yu, J., Chiang, F.-K., Dai, H. M., & Lim, C. P. (2026). Empowering university teachers in higher education: A generative AI-responsive competency framework. *Computers and Education: Artificial Intelligence*, 10, 100542.
- Sætra, H. S. (2026). The rise of the research automaton: Science as process or product in the era of generative AI. *AI & Society*, 41(3), 1865–1879.
- Tian, J., & Zhang, R. (2026). Outsourcing thinking to AI? Focused immersion, AI dependency, and the double-edged impact on critical thinking. *Humanities and Social Sciences Communications*, 13(1), 1015.
- UNESCO. (2016). *Education 2030: Incheon declaration and framework for action for the implementation of Sustainable Development Goal 4: Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all*. UNESCO.
- Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.
- Williamson, B. (2021). Making markets through digital platforms: Pearson, edu-business, and the (e)valuation of higher education. *Critical Studies in Education*, 62(1), 50–66.
- Wisker, G., Robinson, G., & Shacham, M. (2007). Postgraduate research success: Communities of practice involving cohorts, guardian supervisors and online communities. *Innovations in Education and Teaching International*, 44(3), 301–320.