AI in education

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Review

Artificial Intelligence in Educational Frameworks—A Critical Integrative Review of Conceptual Change and Empirical Evidence

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Abstract

Artificial intelligence (AI) is incorporated into frameworks for teaching, learning, assessment, and educational organization. This critical integrative review examines how these frameworks accommodate AI and the evidence associated with their use. The review used purposive web searches and included publications available by mid-October 2026. The synthesis distinguishes application, contextual specification, construct extension, relational reconfiguration, and AI-specific synthesis across professional knowledge, curriculum, learning, design, inclusion, assessment, and adoption. A source-to-entry crosswalk documents 120 analytical entries linked to 123 publications. Thirty empirical reports and one design case receive a structured access and appraisal record. All 31 selected records were examined in full text. Framework classifications based on partial material remain provisional. The comparison identifies tensions concerning ethical judgment, allocation of cognitive work, and attribution of understanding. Reported competence, AI-assisted products, and independent performance support different educational claims. A worked construct crosswalk shows how agency, regulation, and ethical judgment require distinct units and observations. Science, technology, engineering, and mathematics (STEM) provides disciplinary examples within a broader educational scope. The resulting research priorities connect proposed conceptual changes with the evidence needed to examine them.

Keywords: artificial intelligence; generative AI; educational frameworks; TPACK; STEM education; learning theories; assessment; teacher knowledge; critical integrative review

1. Introduction

Artificial intelligence (AI) is used to diagnose learning difficulties, provide feedback, generate instructional resources, and support educational decisions. Cognitive tutors connect computational models of knowledge with step-level assistance, while classroom orchestration systems connect information about learners with teachers' interventions (Anderson et al., 1995; Holstein et al., 2019). Generative artificial intelligence (GenAI) extends this range to the production of explanations, code, images, and lesson materials. These applications draw on educational frameworks to specify what teachers need to know, how learners engage with content, and how learning is assessed (Kasneci et al., 2023; Miao & Cukurova, 2024; Mishra et al., 2023).

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Frameworks serve different purposes. Technological pedagogical content knowledge (TPACK) describes professional knowledge for teaching with technology. Science, technology, engineering, and mathematics (STEM) identifies disciplinary fields and approaches to their integration; STEAM (science, technology, engineering, arts, and mathematics) incorporates the arts. Self-regulated learning describes processes through which learners direct their work. The Technology Acceptance Model concerns adoption. Treating these as equivalent theories obscures the questions each can answer. An account of teachers' perceived competence, for example, leaves open how their instructional decisions affect students' reasoning. An account of students' willingness to use AI leaves open whether the activity develops knowledge.

AI also enters these frameworks in different ways. Researchers may use existing categories to classify AI-supported activities, specify an established construct for an AI context, introduce an additional domain, or reconsider relationships among learners, teachers, and technological systems. These moves have different implications. Adding ethical knowledge to a teacher questionnaire changes its construct coverage. Positioning AI as a participant in collective inquiry changes the unit of analysis and the interpretation of discourse. Both deserve attention, but they require distinct forms of conceptual argument and empirical examination.

STEM education makes these differences particularly visible. An AI-generated solution can be mathematically correct while bypassing the reasoning a lesson is intended to develop. A scientific explanation can be fluent yet incompatible with experimental evidence. A technically functional design can conceal weak understanding of constraints. Integrated STEM introduces the further requirement that students connect disciplinary ideas through a meaningful problem (Kelley & Knowles, 2016; National Academy of Engineering & National Research Council, 2014). In primary and preschool education, research on educational robotics documents how teachers perceive its place in integrated STEM (Gavrilas & Kotsis, 2024). These demands provide a useful setting for examining the relationship between framework claims and educational evidence, while findings from language learning, management, and professional education extend the comparison beyond STEM.

This review examines how AI is incorporated into educational frameworks and how their concepts are used to study teaching and learning. It follows changes in professional knowledge, learner activity, social participation, and assessment, with particular attention to ethical judgment, the allocation of cognitive work, and the interpretation of AI-assisted products. The analysis connects these conceptual developments with the designs and outcomes of the studies in which they appear.

Three questions guide the review. How is AI incorporated into established and emerging educational frameworks? What changes in their constructs, relationships, and units of analysis? How closely does the available evidence match the educational claims made through these frameworks? The synthesis addresses these questions through an interpretive coding scheme, comparison of framework assumptions, and appraisal of selected empirical evidence.

2. Review Method

2.1. Review Design and Scope

The authors conducted a critical integrative review of conceptual arguments, empirical reports, research syntheses, and public competence frameworks (Snyder, 2019). The questions concern forms of AI incorporation, changes in constructs and units of analysis, and the relationship between framework claims and evidence. Sources were selected purposively to examine contrasting formulations and informative study designs. The five modes

are interpretive categories developed for this synthesis; they are not an independently validated taxonomy.

The focal publication period extended from 2019 through mid-October 2026. Earlier sources were retained for theoretical foundations and influential AI applications, including cognitive tutoring. Eligibility required an explicit educational role for predictive, adaptive, or generative AI in a framework, or evidence directly relevant to a framework claim. School, teacher, higher, and professional education were included. English-language full publications were eligible; an English abstract alone did not make a non-English publication eligible. Generic application lists and technical descriptions without a substantive educational rationale were excluded.

STEM was an analytical lens and a set of disciplinary examples, not an eligibility requirement. Its emphasis on explanation, evidence, and design constraints makes attribution of reasoning especially visible. Language education, design, management, special education, and institutional studies provide additional contexts. Claims about disciplinary inquiry are distinguished from broader propositions concerning teacher knowledge, assessment, and institutional adoption.

2.2. Search Sources and Dates

The authors assembled the literature through purposive, iterative web searches supported by the web-search functionality of ChatGPT (GPT-5.6 Sol, OpenAI, San Francisco, CA, USA). Publisher websites, institutional repositories, and digital object identifier (DOI) records from Crossref were consulted to check publication details and locate sources. The available search record consists of retained web queries and source locations. The underlying index and ranked-result version were not retained, which limits reproduction of the original result order.

The retained discovery and verification records date to October 2026. Supplementary Material S1 provides 344 retained exact queries and 621 source-location records representing 617 distinct URL strings (Figure 1). On 29 October 2026, after the publication eligibility cutoff, four targeted checks verified the identity or indexing of known publications using Education Resources Information Center (ERIC) and PubMed records and ScienceDirect metadata.

Discovery queries combined AI terminology with framework names, educational settings, or learning processes. Exact-title, author, DOI, numerical-result, and correction searches followed identified leads. The supplementary query register separates 159 discovery-oriented expressions from 29 verification expressions, 117 focused identification/verification expressions, and 39 audit follow-ups. These purposes were assigned retrospectively from the query text and its recorded batch. Focused searches can serve both identification and verification; that ambiguity is retained in the register.

References and framework names encountered in retrieved publications were followed through title or DOI searches and original publication records. Reference following was not separately enumerated. Selection was iterative: further queries addressed newly encountered frameworks, contrasting explanations, and uncertainties in an extraction. There was no prespecified saturation rule or fixed result-depth threshold. Total hits, all titles viewed, and all rejected records were not preserved and cannot be reconstructed reliably. Figure 1 therefore reports the documented corpus relationships without presenting an exhaustive screening census.

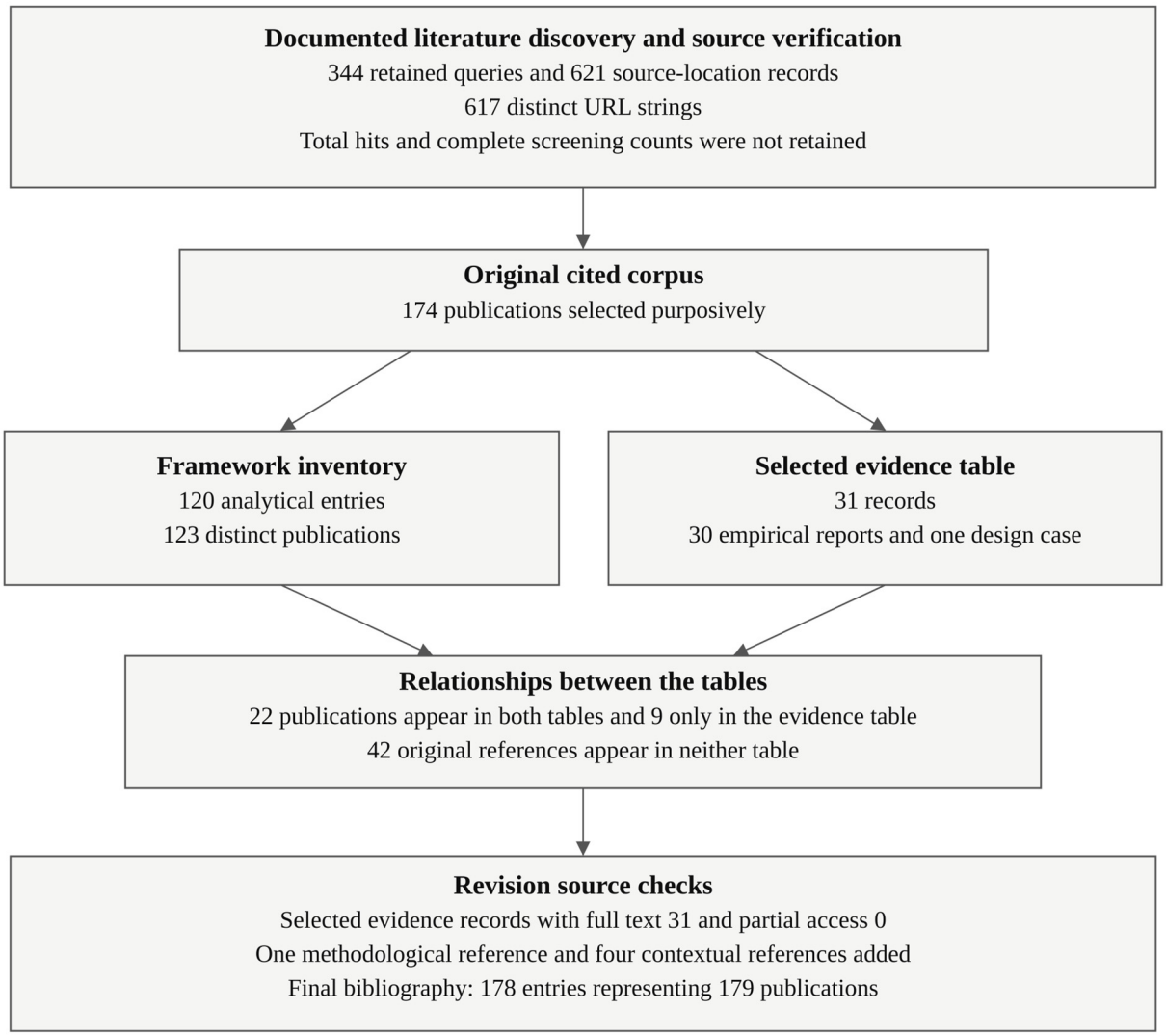


Figure 1. Documented corpus construction and source relationships. The diagram reports retained records and analytical organization; it is not an exhaustive screening flow. The final bibliography includes five references added after construction of the original 174-publication corpus.

2.3. Corpus Construction and Empirical Selection

The original cited corpus comprised 174 publications. Its framework inventory contains 120 analytical entries linked to 123 distinct publications. An entry connects a framework or formulation with one or more sources; one publication may appear in several entries. For example, the same programming study informs cognitive-flexibility and social-learning entries, and a framework-development paper may contribute both a knowledge formulation and an integration model. Table S2 maps every cited source to all applicable entry and evidence-record identifiers. The final bibliography contains 178 entries representing 179 publications, with the Chiu (2026) article and its correction combined in one entry. These comprise the original 174 publications, one methodological reference for the Mixed Methods Appraisal Tool (MMAT), and four contextual references on STEM education and educational robotics. Table S2 distinguishes these five additions from the sources linked to the framework and selected evidence inventories.

Table S4 retains 31 selected evidence records, comprising 30 empirical reports and one faculty-development design case. Twenty-two of these sources also appear in the framework inventory and nine do not; 42 of the original 174 references occur in neither table. The empirical/design selection was made for contrasting evidence types: measurement,

teacher design, learner intervention, qualitative enactment, and institutional implementation. It was not a second exhaustive screen of all eligible empirical research. Table S2 identifies other empirical or design/evaluation reports retained elsewhere and gives their presentation role and reason for non-selection. Omission from Table S4 does not indicate methodological exclusion.

Eligibility was determined by the date of public availability, including online-first publication. Citations use the assigned issue year where available. Corrections and version differences were checked where identified. Numerical extractions preserve their outcome, comparison, timing, and reported uncertainty. Conflicting source descriptions are recorded explicitly, including inconsistent sample counts or intervention labels.

2.4. Coding Decisions and Interpretive Audit

Coding compared the stated parent framework with the role assigned to AI. The initial distinctions separated use of existing categories, AI-related specification of their content, and proposed changes to constructs or relationships. Iterative comparison clarified the boundary between an additional construct and a newly named combination of existing ideas. A separate AI-specific synthesis code was used for arrangements organizing established components around AI-related decisions. The final definitions and exclusion rules appear in Table 1; source-specific examples and boundary decisions are documented in Table S9.

Table 1. Coding the form of AI incorporation.

Mode	Coding Criterion	Illustration	Relevant Evidence
Application	Existing constructs organize an AI activity and the parent structure is retained. A technology change alone qualifies only as application.	5E lesson planning; Bloom-based outcome classification.	Links between framework constructs and the designed task, observation, or analysis.
Contextual specification	Existing constructs receive AI-related content or operational meaning. No separate additional domain is asserted.	TPACK technological knowledge includes prompting and model limitations.	AI-related construct content and its relationship with the parent framework.
Construct extension	The source proposes an additional distinguishable domain or dimension. A new name or new task alone is insufficient.	Ethical assessment in Intelligent-TPACK; collaboration knowledge in HCAP.	Evidence that the additional content is distinguishable; measurement or explanatory tests where available. Proposal and validation remain separate.
Relational reconfiguration	The source changes relationships, attribution, control, or the unit of analysis. The change must be stated beyond background discussion.	CoI presence as a sociotechnical accomplishment; distributed human–AI activity.	Specified changes in relationships, attribution, or the unit of analysis.
AI-specific synthesis	A new AI-focused arrangement combines existing constructs or organizes decisions. A new label does not by itself establish a new psychological construct.	IDEE; ASPIRE; five-dimensional institutional framework.	A clear account of the combined components and decisions; effectiveness requires a separate evaluation.

Note. Modes are non-exclusive and describe the type of incorporation. AI = artificial intelligence; TPACK = technological pedagogical content knowledge; HCAP = Human-Centric Artificial Intelligence Pedagogy; CoI = Community of Inquiry; 5E = engagement, exploration, explanation, elaboration, and evaluation. ASPIRE = Assess, Scaffold, Plan, Implement, Reflect, and Evaluate. AI-specific synthesis describes a newly named arrangement that combines established perspectives or organizes decisions around AI. IDEE—identifying desired outcomes, determining automation, ensuring ethical considerations, and evaluating effectiveness—illustrates this form alongside ASPIRE and the five-dimensional institutional framework (Altrabulsi et al., 2026; Mengesha et al., 2026; Su & Yang, 2023). These syntheses coordinate decisions about objectives, pedagogy, assessment, and institutional conditions. Their educational implications can be examined by tracing how the combined components shape activity and outcomes.

Each assignment followed four questions. Does the source retain the parent categories? Does it change their AI-related meaning? Does it propose a distinguishable additional construct or alter relationships or the unit of analysis? Does it assemble a new AI-focused

arrangement from existing components? More than one mode was assigned only when separate passages supported the respective changes. A new label, a new technology, or a favorable outcome alone was insufficient to establish construct extension. A framework mentioned only as background was not coded as directly applied.

The first author conducted the original framework coding. The register contains one set of assignments. Ambiguous cases were examined against the parent formulation and the decision rules in Table 1; Table S9 records the alternative reading and the passage or framework feature supporting the retained code. Examples include contextual specification in Mishra et al. (2023), construct extension in Celik (2023), and the relation between instructional function and cognitive activity in Inversion–Substitution–Augmentation–Redefinition (ISAR) (Bauer et al., 2025). The table also documents decisions for Technology–Organization–Environment (TOE) and AI-PACK. Coding was not independently duplicated. Classifications based on partial access remain provisional.

2.5. Source Access and MMAT Appraisal

Full text was consulted for all 31 selected evidence records. The complete faculty-development design case is distinguished from empirical outcome evaluation. Full-text checks also covered central TPACK, Intelligent-TPACK, AI-PACK, and ISAR arguments. Tables S3 and S7 identify the material consulted.

Scale for the Assessment of Narrative Review Articles (SANRA) was used as a checklist for the present review's rationale, aims, search description, referencing, reasoning, and presentation of findings (Baethge et al., 2019). It was not used to rate the primary studies or assign scores to included reviews. Primary empirical evidence was appraised with the Mixed Methods Appraisal Tool, version 2018 (MMAT; Hong et al., 2018). The applicable qualitative, randomized, non-randomized, descriptive, and mixed-methods criteria were recorded separately. Mixed-methods reports received component-specific and integration profiles. Ratings were Yes, No, or Cannot tell; no summed quality score was calculated.

The first author conducted the original MMAT appraisals. The register covers all 31 records, of which 30 have design-specific profiles. Fischer's (2026) design case is retained for its account of instructional design; its empirical screening information is insufficient for a design-specific MMAT profile. During source checks, each judgment was compared with the applicable criterion and the available methods or results. An identifiable supporting detail was required for Yes; insufficient reporting received Cannot tell. Table S6 reports design-specific profiles in criterion order and their main interpretive implications. Table S7 summarizes the study-level constraints informing evidential weighting. The appraisal was not independently duplicated.

2.6. Weighting and Access Sensitivity

Evidential weight followed the claim being made. Comparative outcomes informed only the intervention package, comparator, and assessment period actually studied. Uncontrolled pre/post changes, one-class-per-condition comparisons, and historical controls were given limited causal weight. Qualitative studies informed design processes and meanings; psychometric studies informed measurement within their populations. Neither supplied an intervention-effect estimate. Framework descriptions based on partial material were used provisionally and were not decisive evidence for causal or general effectiveness claims. Table S8 identifies the additional evidence and its implications for each central claim. This qualitative comparison assesses the argument's dependence on source access. The review does not estimate framework prevalence or pool intervention effects; entries and repeated appearances of a source are not treated as independent studies.

3. Forms of Conceptual Change

3.1. Framework Purposes and Units of Analysis

An educational framework can organize knowledge without explaining a causal process. Competence standards describe what people should be able to do. Design models structure decisions. Taxonomies distinguish categories of objectives or activities. Learning theories explain processes under specified conditions. These functions can be combined within a study, provided their contributions remain identifiable. AI integration brings them into contact because the same activity involves professional decisions, learner behavior, technological responses, and institutional rules.

Five purposes recur in the selected literature: specifying professional knowledge; defining curriculum and literacy; explaining learning and interaction; organizing design and assessment; and accounting for adoption and institutional conditions. Their units of analysis range from an individual teacher's judgments to a group's regulation and an institution's allocation of responsibilities. Figure 2 relates these purposes to the decisions, interactions, and assessments through which their connections can be investigated.

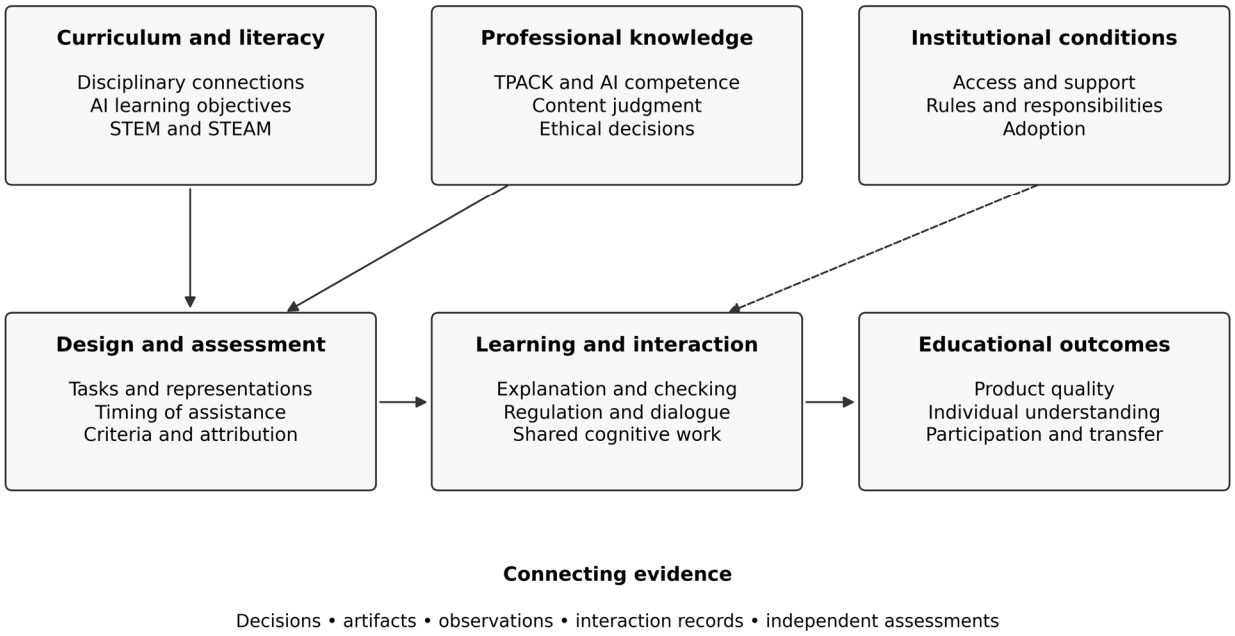


Figure 2. Framework purposes and the evidence needed to connect them. Solid arrows show proposed links from curriculum and professional knowledge through design and assessment to learning activity and educational outcomes. The dashed arrow indicates the contextual influence of institutional conditions on learning and interaction. These relationships are propositions for empirical investigation. The diagram relates curriculum, professional knowledge, institutional conditions, design, learning activity, and outcomes. AI = artificial intelligence; TPACK = technological pedagogical content knowledge; STEM = science, technology, engineering, and mathematics; STEAM = science, technology, engineering, arts, and mathematics.

3.2. Applications, Extensions, and New Syntheses

Application uses established constructs to interpret an AI activity. Coding a chatbot-supported lesson with Bloom's taxonomy or the 5E model can reveal its objectives and sequence while leaving the framework's structure intact. Contextual specification gives an existing construct an AI-relevant meaning, such as technological knowledge involving model limitations, prompting, and output verification. Construct extension adds a distinguishable domain or dimension. Relational reconfiguration changes how the explanatory elements

interact or where the educational activity is located. Table 1 provides the coding criteria and examples.

The categories distinguish uses and adaptations of frameworks, including conceptual development. Their usefulness depends on the educational question and the clarity with which constructs inform observation. Applying an established theory can yield a precise account of an intervention. Revision becomes relevant when changing activity alters the interpretation of familiar indicators. AI-generated discussion posts, for example, complicate the attribution of cognitive presence to individual learners and prompt reconsideration of the evidence used to identify it.

Two distinctions help assess such proposals. First, an AI-specific task differs from an AI-specific psychological construct. Verifying a generated citation creates a new task context; the underlying evaluative judgment may already be represented in established accounts of assessment. Second, a change in operational control differs from a claim about human-like agency. Here, AI agency denotes the capacity of a system to select or generate actions within an educational arrangement. Responsibility for curricular purposes, assessment decisions, and safeguards remains a human and institutional concern (Holmes et al., 2022; Ouyang & Jiao, 2021).

3.3. Coverage Across Framework Families

The literature spans 11 framework families within the five educational purposes identified above. Table 2 maps their named formulations and corresponding entries in Table S3. STEM and STEAM organize disciplinary integration; TPACK describes teacher knowledge; cognitive load theory explains constraints on learning; and instructional-development models organize design decisions. These differences guide the interpretation of each framework's role in an AI-supported activity.

Table 2. Framework families and named formulations represented in the synthesis.

Framework Family	Frameworks and Formulations	Table S3 Entries
Professional knowledge and preparation	Technological pedagogical content knowledge (TPACK) and AI-TPACK variants and integrated i-TPACK; digitality-related pedagogical content knowledge (DPACK) and AI-PACK; Human-Centric Artificial Intelligence Pedagogy (HCAP); AI-agent pedagogical content ethical knowledge (AIA-PCEK); ethics-embedded AI-TPACK design (EE-AID); Teacher AI Competence Self-Efficacy Scale (TAICS).	B001–B017
Curriculum and literacy	Science, technology, engineering, and mathematics (STEM), with arts in STEAM; AI literacy and AI4K12; Digital Competence Framework for Citizens (DigComp); UNESCO and OECD competencies; Discipline-Specific AI Literacy (DiSAIL); D.I.V.E.R.S.E.; GenAI-Ped; AI Literacy Questionnaire (AILQ), Meta AI Literacy Scale (MAILS), and Scale for the Assessment of Non-Experts' AI Literacy (SNAIL). SCALE educational objectives.	B018–B030
Technology integration and human–AI roles	Substitution, Augmentation, Modification, Redefinition (SAMR); Passive, Interactive, Creative/Replacement, Amplification, Transformation (PICRAT); Replacement, Amplification, Transformation (RAT) with Co-Agency; Technology Integration Matrix (TIM); AI-directed, AI-supported, and AI-empowered education; hybrid intelligence. Inversion–Substitution–Augmentation–Redefinition (ISAR).	B031–B038
Cognition and scaffolding	Cognitive tutoring and apprenticeship; scaffolding; constructionism; Interactive–Constructive–Active–Passive (ICAP); cognitive load and load reduction; cognitive flexibility; multimedia learning; cognitive resilience. Knowledge Construction for prompting.	B039–B048
Regulation and motivation	Self-regulated and socially shared regulation; self-determination; Attention, Relevance, Confidence, Satisfaction (ARCS); task–technology fit; cognitive appraisal; control-value and achievement-goal theories; flow.	B049–B055
Social and adult learning	Community of Inquiry; communities of practice; knowledge building; social learning; connectivism; distributed cognition; activity and expansive learning; andragogy; heutagogy; transformative learning; posthumanist and critical accounts.	B056–B070

Table 2. *Cont.*

Framework Family	Frameworks and Formulations	Table S3 Entries
Instructional design	Analysis, Design, Development, Implementation, Evaluation (ADDIE); 5E and 7E learning cycles; Prediction–Observation–Explanation–Evaluation (POEE); Gagné; Adaptive Control of Thought–Rational (ACT-R); First Principles; four-component instructional design (4C/ID); Understanding by Design (UbD); Activity-Centred Analysis and Design (ACAD); Conversational Framework; IDEE; LLM-Ed.	B071–B083
Projects and experiential learning	Problem-based, project-based, experiential, and service-learning; Conceive–Design–Implement–Operate (CDIO) and Project-work AI Integration Framework (PAIIF); Double Diamond; Mechanics–Dynamics–Aesthetics (MDA); educational games; mastery learning; Interactive Design Process Framework (IDPF) for STEAM.	B084–B092
Inclusion and sociocultural participation	Universal Design for Learning (UDL) and UDL-AI-TPACK; challenge-based learning through MIIA-R; culturally responsive assessment; environmental science agency (ESA); social-emotional learning (SEL); SCALE arts-based pedagogy; embodied and rhizomatic learning.	B093–B100
Assessment	Revised Bloom taxonomy; Structure of the Observed Learning Outcome (SOLO); constructive alignment; evidence-centred design; feedback literacy and evaluative judgment; AI Assessment Scale (AIAS), including its 2025 revision; Generative AI Assessment Literacy Scale (GAA-LS); ASPIRE; Structured AI-Guided Education (SAGE).	B101–B111
Adoption and governance	Technology Acceptance Model (TAM); Unified Theory of Acceptance and Use of Technology (UTAUT); expectancy-value and social cognitive theories; diffusion of innovation; planned behavior; Concerns-Based Adoption Model (CBAM); Technology–Organization–Environment (TOE) as an organizational-model antecedent; Innovation Resistance Theory; Plan–Do–Check–Act (PDCA); five-dimensional institutional synthesis. Community-wide ethics of AI in education. Information Systems Success; Technology Readiness and Acceptance Model (TRAM).	B112–B120

Note. The families group related educational purposes and units of analysis. Each range identifies the corresponding entries in Table S3. Parent frameworks, AI-related formulations, and measurement instruments are named separately within the relevant family. A named antecedent indicates conceptual use within a proposal; direct operationalization is identified in Table S3. UNESCO = United Nations Educational, Scientific and Cultural Organization; OECD = Organisation for Economic Co-operation and Development; SCALE = Scientific Literacy, Computational Thinking, AI Literacy, Learning to Learn, and Engineering and Design Thinking; D.I.V.E.R.S.E. = Digital Integrated Vertical and Ethically Responsible Syllabus for Education; MIIA-R = Integrated Inclusive AI Challenge Model.

The family map identifies the scope of the selected literature. Table S3 provides 120 analytical entries linking 123 publications; Table S2 supplies the source-to-entry crosswalk. Related formulations can share a publication, and the same study can inform several frameworks. These counts describe the organization of this review and do not estimate framework prevalence.

4. Teacher Knowledge and Professional Competence

4.1. TPACK and Professional Judgment

TPACK builds on pedagogical content knowledge, which connects understanding of subject matter with its representation for learners (Mishra & Koehler, 2006; Shulman, 1986). Its original formulation treats teaching with technology as situated and complex. AI-related developments address the knowledge involved in selecting, interpreting, and supervising systems that can generate educational content. A central issue is how this knowledge appears in instructional decisions and students' opportunities to learn. A broader STEM educator framework situates TPACK alongside disciplinary literacy, collaboration, and professional development (Gavrilas & Kotsis, 2025a).

Mishra and colleagues interpret generative AI through TPACK while emphasizing its generative and social properties and the importance of contextual knowledge (Mishra et al., 2023). This is principally a contextual specification of the framework. The practical question is how teachers judge an output in relation to a subject, a learning goal, and particular learners. Chemistry examples developed by Feldman-Maggor and colleagues show why prompting involves content and pedagogical reasoning (Feldman-Maggor et al., 2025).

Peikos and Stavrou examine science planning through pedagogical content knowledge, while Cooper's exploratory work exposes the need to scrutinize generated science resources (Cooper, 2023; Peikos & Stavrou, 2025). These studies make disciplinary judgment visible through examples and products.

4.2. AI-Related Forms of Teacher Knowledge

Celik's Intelligent-TPACK combines AI-related technological knowledge, technological pedagogical knowledge, technological content knowledge, integrated TPACK, and ethical assessment. Scale development used 428 teachers and produced 27 items. In the reported structural model, ethical assessment and technological pedagogical knowledge were associated with integrated TPACK, whereas technological knowledge had no significant direct association with that outcome (Celik, 2023). The instrument combines contextual specification with an added ethical-assessment domain and measures teachers' reported knowledge.

Later AI-TPACK studies examine relationships with digital proficiency and across subject contexts (Hava & Babayiğit, 2025; Karataş & Ataç, 2025; Ning et al., 2024). Chen and colleagues' survey of 454 Chinese university teachers reports a negative direct association between AI-technological knowledge and AI-TPACK alongside positive indirect associations through other knowledge domains (X. Chen et al., 2026). The authors interpret this as a suppression pattern within the joint model. The available abstract of Younas and Noor's (2026) survey of 455 university instructors in Pakistan reports mixed support for relationships among AI-related knowledge and ethics. Taken together, these findings concern model-dependent associations among reported knowledge domains; the use of a shared AI-TPACK label does not establish equivalent constructs or relationships across instruments.

Lorenz and Romeike locate AI-PACK within digitality-related pedagogical content knowledge (DPACK). AI-related knowledge (AI-K) is examined through user-oriented, technological, and sociocultural perspectives and connected with pedagogy and subject content through AI-related pedagogical knowledge (AI-PK), AI-related content knowledge (AI-CK), and AI-related pedagogical content knowledge (AI-PCK) (Lorenz & Romeike, 2023). The framework consequently addresses understanding and interpreting AI phenomena as well as their educational use. Its competency examples illustrate how teachers can connect system operation, disciplinary representation, and social consequences.

The Human-Centric Artificial Intelligence Pedagogy (HCAP) framework distinguishes AI-technological, AI-content, AI-pedagogical, human–AI collaborative, and ethical knowledge. Chiu's three-round Delphi with 30 teachers yielded 25 knowledge items (Chiu, 2026). Human–AI collaboration becomes an explicit domain, encompassing decisions about how to organize productive interaction. The corrected HCAP terminology separates this formulation from Celik's Intelligent-TPACK. The naming history includes an earlier editorial and a correction to the 2026 article (Chiu, 2025, 2026). The Delphi specifies the content of the five domains through teacher consensus.

The Artificial Intelligence Agent–Pedagogical Content Ethical Knowledge framework (AIA-PCEK) emphasizes AI-agent knowledge and ethical oversight alongside pedagogy and content. Mimoudi and Mokhtari illustrate its rationale through teacher-training material, and Mimoudi and Bouabid develop the account further (Mimoudi & Bouabid, 2026; Mimoudi & Mokhtari, 2025). The publications provide a conceptual account of the knowledge teachers use when selecting AI roles and supervising their educational consequences.

Generative AI variants also differ internally. Belkina and colleagues derive a GenAI-TPACK representation from implementation cases interpreted through Substitution, Augmentation, Modification, and Redefinition (SAMR) and Laurillard's Conversational Framework (Belkina et al., 2025). Demir and colleagues organize an extended formulation around technology, theoretical framework, and AI agency. Five additional domains address critical

evaluation, prompting, ethical judgment, role sharing, and student–AI interaction, with practical judgment represented through a phronesis axis (Demir et al., 2026). The formulations address implementation categories and professional knowledge, respectively. Table 3 summarizes their architectures, forms of incorporation, and evidence.

Table 3. AI-related teacher knowledge frameworks.

Formulation	Knowledge Architecture	Form of Incorporation	Evidence and Scope
Intelligent-TPACK (Celik, 2023)	AI-specific TK, TPK, TCK, TPACK, and ethical assessment.	Contextual specification; construct extension.	Survey-based knowledge structure and associations; self-report measures.
AI-PACK (Lorenz & Romeike, 2023)	AI-K, AI-PK, AI-CK, and AI-PCK within DPACK; user-oriented, technological, and sociocultural perspectives.	Contextual specification.	Theoretical derivation with teaching examples.
HCAP (Chiu, 2026)	AI-technological, content, pedagogical, collaborative, and ethical knowledge.	Contextual specification; construct extension.	Three-round Delphi defining knowledge content.
AIA-PCEK (Mimoudi & Bouabid, 2026; Mimoudi & Mokhtari, 2025)	AI-agent, pedagogical, content, and ethical knowledge.	Construct extension; relational reconfiguration.	Conceptual development with teacher-training illustrations.
Integrated i-TPACK (Aldemir et al., 2025)	AI-related TK, TPK, TCK, CK, professional development, and integrated TPACK; ethics across domains.	Contextual specification; construct extension.	Three-week module; 25 matched self-reports and instructional artifacts; no concurrent comparison group.
GenAI-TPACK (Belkina et al., 2025)	Teacher integration represented through synthesis of implementation cases.	Contextual specification.	Representation developed through synthesis of implementation cases.
Extended GenAI-TPACK (Demir et al., 2026)	Technology, theory, and AI agency; five additional domains and practical judgment.	Construct extension; relational reconfiguration.	Conceptual model specifying additional domains and relationships.
Artifact assessment (Eyal, 2025)	AI knowledge, AI pedagogical knowledge, AI content knowledge, and integration.	Contextual specification.	Scored instructional artifacts and expert appraisal.

Note. AI = artificial intelligence; AI-K = AI-related knowledge; AI-PK = AI-related pedagogical knowledge; AI-CK = AI-related content knowledge; AI-PCK = AI-related pedagogical content knowledge; TK = technological knowledge; CK = content knowledge; TPK = technological pedagogical knowledge; TCK = technological content knowledge; TPACK = technological pedagogical content knowledge; DPACK = digitality-related pedagogical content knowledge; HCAP = Human-Centric Artificial Intelligence Pedagogy; AIA-PCEK = Artificial Intelligence Agent–Pedagogical Content Ethical Knowledge; GenAI-TPACK = TPACK for generative artificial intelligence.

4.3. Ethics as a Domain and as a Practice

These models differ in how they represent ethical knowledge and judgment. Celik measures ethical assessment as a distinguishable factor. HCAP makes ethical knowledge an explicit domain with implications throughout professional activity. Aldemir and colleagues' integrated i-TPACK distributes ethics across six domains, adding AI as curriculum content and AI for professional development to the knowledge architecture. Their three-week module involved 29 preservice teachers, with 25 matched survey pairs. Gains in self-assessed knowledge were accompanied by examples of ethical reasoning in instructional artifacts and micro-teaching (Aldemir et al., 2025). The single-cohort design leaves the causes of the reported change unresolved.

These representations locate ethical judgment at different points in teaching. A separate domain makes ethical knowledge available for direct assessment. A distributed account examines its expression across subject content, pedagogical decisions, and professional

learning. A sequence of checkpoints locates ethical deliberation in the design process. These approaches suggest complementary observations: what teachers recognize as an ethical issue, how they respond in a particular task, and whether that response influences subsequent instructional decisions.

4.4. Linking Competence to Instructional Decisions

Some formulations connect previously separate areas of professional practice. The UDL-AI-TPACK model combines Universal Design for Learning (UDL) with AI-related teacher knowledge (Cersosimo, 2026). The Ethics-Embedded AI-TPACK Design model (EE-AID) translates ethical considerations into checkpoints during planning, prompting, verification, and revision (Nguyen & Nguyen, 2026). These proposals operate at different levels. One organizes the knowledge relevant to inclusion; the other specifies a sequence of professional actions.

4.5. Measuring Professional Capability

Eyal develops an artifact-based AI-TPACK assessment with four principal components, 14 criteria, and 65 indicators. Sixty teacher-educator artifacts were evaluated, with five experts independently rating a 20-artifact subset; the reported overall intraclass correlation was 0.84 (Eyal, 2025). This supports agreement in scoring the selected artifacts. Generalization to new tasks, raters, or pupil learning requires separate evidence. In educational robotics, the Attitude, Knowledge, and Application of Educational Robotics (AKAER) questionnaire illustrates a survey-based approach to assessing educators' attitudes, knowledge, and reported application (Gavrilas & Kotsis, 2025b).

Celik and colleagues studied 120 Finnish preservice teachers completing an AI-assisted lesson-planning task. Prompts were interpreted through a Knowledge Construction framework and plans assessed for student agency, adaptive strategies, and flexible tools. Higher prompting phases were associated with more adaptive plans (Celik et al., 2026). The contemporaneous design supports a relationship among knowledge, prompting, and plan quality; it does not establish a temporal mediation mechanism.

Two course reports illustrate AI-focused preparation for preservice teachers. Antonio (2025) followed a cohort of 84 preservice science teachers. Aldemir et al. (2025) examined perceived knowledge and instructional artifacts within a three-week module. In both studies, the absence of a concurrent comparison group limits attribution of change. Dogan organizes professional development around Intelligent-TPACK, while TAICS measures perceived capability across six domains (Chiu et al., 2025; Dogan, 2026). These contributions address preparation and measurement at different levels.

5. Curriculum, AI Literacy, and STEM Integration

5.1. Learning with and About AI

STEM and STEAM identify curricular relationships; STEAM explicitly includes the arts. Their use in an AI study requires an account of the disciplinary work. AI-supported mathematics lessons and engineering projects may address one discipline or connect several. A claim of integrated STEM requires those connections to be visible in the problem, representations, decisions, and assessment (Kelley & Knowles, 2016; National Academy of Engineering & National Research Council, 2014). AI can support the work of a discipline, become an object of study, or do both within the same project.

Research in STEM encompasses AI-supported disciplinary learning, education about AI, and integrated projects combining both purposes (Chasanidou et al., 2026; Niri et al., 2026; Xu & Ouyang, 2022). Studies examine tutoring, feedback, modeling, and the allocation of agency during human–AI interaction (M. Wu & Ouyang, 2026; Zhu et al., 2026). Inter-

pretation depends on the curricular objective and on the disciplinary reasoning expected of learners. A study of AI concepts and a study using AI to investigate a scientific problem therefore address different aspects of the curriculum.

Arts integration also needs an educational rationale. Producing an illustration may support communication, while critique of representation, cultural assumptions, or aesthetic choices can contribute distinct knowledge. Leon and colleagues' transdisciplinary account brings agency, assessment, and ethics into this wider curricular discussion (Leon et al., 2025). Sotiropoulos and colleagues' Interactive Design Process Framework proposes iterative co-design and review for STEAM projects (Sotiropoulos et al., 2026). These proposals help organize curricular decisions; their value can be examined through the quality of disciplinary connections in student reasoning and products.

Environmental science agency (ESA) connects inquiry, students' positioning as experts, and participation in community change. Kim studied 23 teachers using GenAI to design lessons intended to support this form of student agency. Lesson documents, chat logs, and surveys recorded teachers' design choices and difficulties aligning AI outputs with their goals (W. J. Kim, 2026). The observed outcomes concerned teacher design work; students' development of ESA was not measured.

5.2. Literacy, Competence, and Progression

AI literacy frameworks articulate what learners should understand and do in relation to AI. Long and Magerko specify competencies for interaction and critical evaluation; Ng and colleagues distinguish understanding, application, evaluation and creation, and ethical issues (Long & Magerko, 2020; Ng et al., 2021). The AI4K12 initiative organizes curriculum through perception, representation and reasoning, learning, natural interaction, and societal impact (Touretzky et al., 2019). Computational thinking contributes to problem formulation and computational representation (Wing, 2006). A learner's ability to program a deterministic sequence and their understanding of how a trained classifier generalizes remain distinct learning objectives.

The PopBots curriculum illustrates learning about AI through developmentally situated, embodied activities (Williams et al., 2019). Constructionist approaches extend this principle through creating and revising artifacts. Lin and colleagues' review of 34 studies identifies practices including experimentation, making, and optimization, alongside persistent conceptual and ethical misunderstandings (Lin et al., 2025). This evidence connects AI literacy with learning processes. The production of a working artifact becomes educationally informative when learners can explain its behavior, test its limitations, and revise it on the basis of evidence.

The United Nations Educational, Scientific and Cultural Organization (UNESCO) teacher framework sets out 15 competencies across five dimensions, and its student framework 12 across four dimensions (Miao & Cukurova, 2024; Miao et al., 2024). The teacher dimensions cover a human-centered mindset, ethics, foundations and applications, pedagogy, and professional learning. The student framework covers a human-centered mindset, ethics, techniques and applications, and system design. These public frameworks organize educational aims and proposed progression for curriculum and professional learning. Ng and colleagues' account of teachers' AI-related digital competence connects these concerns with the Digital Competence Framework for Educators (DigCompEdu) and wider professional responsibilities (Ng et al., 2023).

5.3. Public Competence Frameworks and Situated Literacy

Digital competence frameworks provide a further route for AI incorporation. The Digital Competence Framework for Citizens (DigComp) 2.2 introduced examples addressing

interaction with AI systems; DigComp 3.0 subsequently integrated AI competence across its structure and supplied more detailed learning outcomes (Cosgrove & Cachia, 2025; Vuorikari et al., 2022). The Organisation for Economic Co-operation and Development (OECD) and European Commission's 2026 AI literacy framework addresses primary and secondary education through engagement with, creation with, management of, and shaping of AI (OECD & European Commission, 2026). These public frameworks organize curricular expectations and provide reference points for program design and assessment.

Discipline-Specific AI Literacy (DiSAIL) gives disciplinary language and epistemic practice a more explicit role. Stolpe and colleagues distinguish the potential for participation, including disciplinary literacy, AI competence, and acceptance, from the enactment of that participation in problem articulation and disciplinary reasoning (Stolpe et al., 2026). Marzano and colleagues' D.I.V.E.R.S.E model similarly connects teacher preparation with a progressive K–12 digital curriculum, informed by a survey of 898 teachers (Marzano et al., 2026). The survey describes perceptions that informed the proposal; evaluation of the curriculum itself remains a separate question. Together, these contributions show why a general AI literacy score provides incomplete information about competent participation in a specific subject.

5.4. What Literacy Scores Represent

Literacy measures encode different constructs. The AI Literacy Questionnaire (AILQ) includes affective, behavioral, cognitive, and ethical dimensions (Ng et al., 2024b). The Meta AI Literacy Scale (MAILS) combines AI literacy with related psychological competencies and was examined with 300 German-speaking adults (Carolus et al., 2023). The Scale for the Assessment of Non-Experts' AI Literacy (SNAIL) organizes 31 self-report items around technical understanding, critical appraisal, and practical application (Laupichler et al., 2023). Their scores describe perceptions within specified measurement models and populations.

6. Learning Processes and Human–AI Interaction

6.1. Constructivism, Constructionism, and Scaffolding

Constructivist accounts concern how learners interpret information through existing understanding. Generated explanations can become material for that activity, with their educational value depending on how learners examine and use them. Scaffolding additionally requires assistance calibrated to developing capability and its eventual reduction (Wood et al., 1976).

Bai and colleagues operationalize scaffolding through shared task understanding, ongoing diagnosis and calibrated support, and fading in a postgraduate coding and computational-thinking course. The supported cohort comprised 31 students and the historical comparison cohort 36. Prompting and algorithm-product scores favored the supported cohort, including during fading (Bai et al., 2026). The reported direction persisted after adjustment for measured cohort differences. Historical controls and inconsistencies in the reported test statistics limit causal and quantitative interpretation. The design nevertheless specifies how assistance can be adjusted and withdrawn.

Constructionism adds emphasis on learning through making personally or socially meaningful artifacts. With generative AI, the division of work within making becomes consequential. Students may design and test an artifact while AI helps produce a component; they may also obtain a finished artifact with limited understanding of its construction. Fischer's faculty-development design case describes experimentation, peer interaction, and the production of locally relevant resources, including differing participant needs for conceptual guidance (Fischer, 2026). Lee and Budwig develop a process-relational interpretation of constructionism in which agency and meaning emerge through interaction

over time (Lee & Budwig, 2026). The first documents a design; the second proposes a change in the theoretical description of learning.

Constructionist work makes revision histories, explanations of choices, and artifact testing relevant evidence of learning. A completed product can document participation without showing how understanding developed.

6.2. Cognitive Tutoring and Apprenticeship

The connection between AI and learning frameworks has a substantial history. Cognitive tutors operationalized an account of skill acquisition through explicit cognitive models, step-level assistance, and estimates of developing knowledge (Anderson et al., 1995). This tradition is relevant to current work because the instructional assumptions were expressed in the system's representation of the task. Analysis of a conversational system likewise depends on specifying the learning processes represented in its responses.

Cognitive apprenticeship specifies modeling, coaching, scaffolding, articulation, reflection, and exploration. Exploration gives learners responsibility for framing and investigating problems as support is reduced. Its recent applications include a hybrid teacher-education course supporting instruction for self-regulated learning, a biochemistry problem-based intervention, and a simulation-based science agent (Adler & Shani, 2026; Chao et al., 2026; Sheng et al., 2026). These applications differ in who supplies expert modeling and how the system responds to learner activity. The quality of coaching depends on the correspondence between the agent's diagnosis and the learner's difficulty.

Chao et al. (2026) compared 22 high-school students using a proactive apprenticeship agent with 31 using a reactive question-answer agent during a simulation task. Allocation followed availability. Application gains favored the apprenticeship agent, although the between-group comparison was non-significant ($p = 0.07$); conceptual gains also did not differ significantly. Process analyses identified both scientific modeling and dependence on AI contributions. These observations direct attention to the correspondence between the agent's guidance, the learner's observation, and the reasoning subsequently performed. In Sheng and colleagues' study, the proposed interaction between AI questioning and instructor modeling was an interpretation of the intervention; that interaction was not directly tested (Sheng et al., 2026).

6.3. Cognitive Engagement and Cognitive Load

The Interactive–Constructive–Active–Passive (ICAP) framework relates modes of engagement to the cognitive processes implied by learner activity (Chi & Wylie, 2014). Its application to AI requires attribution of the activity. An explanation generated by a chatbot and read by a student differs from an explanation generated by the student, even when both appear in a lengthy conversation. Interactive engagement requires contributions that develop reasoning through reciprocal exchange; message volume alone is an inadequate indicator. Zhang and colleagues' ICAP GenAI scale offers a measure of reported engagement in academic research (J. Zhang et al., 2025). Process analysis can examine whether those reported modes correspond to learners' explanations and revisions.

Cognitive load theory addresses demands on limited working memory during learning (Sweller, 1988). AI can reduce search demands or organize an explanation, but it can also introduce irrelevant material and additional verification work. The consequences depend on prior knowledge and the instructional objective. Martin and colleagues connect generative AI with load reduction instruction, emphasizing structured support and learner expertise (Martin et al., 2025). This yields a more precise question than whether AI reduces effort overall: which demands are removed, and which learning-relevant operations remain with the learner?

The two perspectives are complementary. ICAP describes the character of the learner's activity; cognitive load theory helps explain when the demands of that activity become productive or excessive. Their joint application draws attention to the relationship between the depth of engagement and the demands of a task. A request to critique several AI-generated solutions may prompt constructive activity while placing excessive demands on novices. A worked example may lower immediate demands and prepare students for subsequent explanation. Studies can examine this interaction by varying prior knowledge and the timing of support, while assessing both process and subsequent independent performance.

The Inversion–Substitution–Augmentation–Redefinition (ISAR) model connects technology integration with cognitive learning (Bauer et al., 2025). Inversion describes reduced cognitive engagement or learning, for example through overreliance on AI. Substitution preserves the instructional function and depth of cognitive processing. Augmentation adds support within the existing task and processing level. Redefinition involves a shift toward constructive or interactive processing when the comparison activity is passive or active. These categories describe changes relative to an instructional condition without AI. This makes the learner's activity central to the interpretation of an AI intervention and connects the model with ICAP. The categories express proposed relationships between instructional support, cognitive activity, and learning; classifying an intervention requires an explicit comparison condition.

6.4. Multimedia, Embodied, and Arts-Based Learning

The cognitive theory of multimedia learning has informed the design of an AI video assistant combining transcription, engagement, and reinforcement functions. AlShaikh and colleagues evaluated the system through nine educational experts and automated content metrics (AlShaikh et al., 2024). The evaluation concerns generated content and expert judgments of usability; learner performance was outside the reported evaluation.

The SCALE taxonomy organizes Scientific Literacy, Computational Thinking, AI Literacy, Learning to Learn, and Engineering and Design Thinking (W. Yang, 2025). Zhang and Yang connect these objectives with arts-based pedagogy and embodied cognition (L.-X. Zhang & Yang, 2026). The taxonomy specifies educational objectives; the later formulation proposes processes for their enactment. Their effectiveness remains an empirical question.

Cognitive flexibility and social learning also inform AI-supported instructional design. Zheng and colleagues organized introductory programming through lab rotation, generative AI, and peer code review (W. Zheng et al., 2026). The design offered multiple representations of related content and opportunities to examine peers' code. The six-week comparison involved two intact classes comprising 83 students and reported higher post-test critical-thinking and academic-resilience scores for the combined design. With one class per condition and several instructional components changing together, the study supports evaluation of the combined arrangement while leaving the separate contribution of AI unresolved. Nathaniel et al. (2025) proposed the GenAI-Ped framework to guide the use of generative AI while developing foundational programming skills.

6.5. Regulation, Motivation, and Shared Control

Self-regulated learning (SRL) concerns how learners set goals, select strategies, monitor progress, and adapt their actions (Zimmerman, 2002). Self-determination theory (SDT) addresses motivation through autonomy, competence, and relatedness (Ryan & Deci, 2000). These perspectives overlap in educational practice but describe different constructs. Choice among AI prompts is one feature of an interface; autonomy concerns the learner's experience of volition. Accurate answers may improve perceived competence while providing limited opportunity to regulate a learning process.

Chiu's three-round Delphi with 36 teachers maps 20 ChatGPT activities to psychological needs and self-regulation phases. Kong and Yang connect subject learning with the development of regulation in K–12 education (Chiu, 2024; Kong & Yang, 2024). Ng, Tan, and Leung compare a generative SRL chatbot with a rule-based chatbot over three weeks of secondary science learning with 74 students. They report gains in science knowledge, behavioral engagement, and motivation (Ng et al., 2024a). This comparison locates the contribution of generative AI within an existing design for self-regulated learning.

Socially shared regulation of learning (SSRL) shifts attention to how groups jointly establish goals, monitor work, and reflect. Kim and colleagues used nine AI scenarios and paper prototypes in focus groups with 30 undergraduate and graduate students to identify perceived pedagogical requirements for supporting SSRL (J. Kim et al., 2025). This provides design requirements from anticipated use. Zheng and colleagues compared reflection reports, short-answer prompts, and an AI agent among 97 students across three semesters. Reflection in the AI cohort showed more connected and critical content, with further analyses of selected higher- and lower-performing teams (Y. Zheng et al., 2026). The reflection method coincided with the semester, and the reported analysis denominators were not fully reconciled. The findings inform the design and analysis of reflection within that setting.

Learner regulation and shared regulation require different observations. Individual questionnaires can describe reported strategies, while a claim about a group's regulation requires evidence of jointly established goals, monitoring, and revision.

6.6. Motivational Mechanisms and Adult Learning

Motivational frameworks identify different reasons for participation in AI-supported activity. Research on STEM teachers combines task–technology fit, cognitive appraisal, and control-value theory to examine professional learning, while achievement-goal theory has been used to study engagement in AI-supported language learning (Y. Zhang & Zhou, 2026; Zhu et al., 2025). Gao et al. (2026) developed a 25-item AI-flow measure covering seven experiential dimensions using 448 valid survey responses from preservice teachers. These studies connect AI use with the motivational processes and perceived experiences represented in their survey measures.

Adult learning introduces questions of relevance and control over learning purposes. Adarkwah connects institutional conditions with a GenAI-supported adult learning ecology, and Song and colleagues examine an AI-supported heutagogical design (Adarkwah, 2025; R. Song et al., 2026). The proposed freedom to define goals must be distinguished from the instructional support provided to pursue them.

Transformative learning offers a further interpretation of professional change. Raju and colleagues analyzed two cross-sectional cohorts of university personnel, with 104 responses from 2023 and 313 from 2024. Their analysis describes patterns of reflection and pedagogical experimentation. Differences in the reported theme proportions were non-significant (Raju et al., 2026). The findings characterize differences in the accounts given by two cohorts.

6.7. Communities of Practice and Knowledge Building

Communities of practice foreground participation in shared professional activity. Jin and colleagues applied this perspective to knowledge co-construction among generative AI, novice teachers, and experienced teachers in an online learning community. Their mixed-methods analysis identified different patterns of contribution and engagement (Jin et al., 2025). This focus differs from the presences specified by Community of Inquiry: it concerns how participation, experience, and professional knowledge are organized within a community.

Knowledge-building research concerns the collective improvement of ideas. B. Chen et al. (2023) documented classroom uses of ChatGPT through interviews with 10 consenting students and classroom artifacts. The study did not measure prior AI literacy or track subject-knowledge gains. Falloon and Jones propose overlapping zones of human–machine cognitive work (Falloon & Jones, 2026). The empirical and conceptual accounts can be connected through evidence that AI contributions become objects of collective examination and revision.

6.8. Inquiry, Presence, and Distributed Cognition

The Community of Inquiry (CoI) framework relates cognitive, social, and teaching presence in educational communication (Garrison et al., 1999). AI complicates the evidence used to infer those presences. Stenbom and Garrison consider collaborative inquiry and shared metacognition, while Ba and colleagues conceptualize generative AI as an epistemic condition affecting the production and interpretation of contributions (Ba et al., 2026; Stenbom & Garrison, 2026). This is a relational reconfiguration: the same fluent message can emerge through different combinations of human and machine activity. Dong and colleagues use CoI in an empirical model of AI-supported analytics and engagement (Dong et al., 2026), illustrating a more conventional application of established constructs.

Connectivist accounts examine participation in networks of people and resources. Bui develops a framework for student–AI knowledge co-creation, and Crimmins and colleagues draw on connectivism alongside cognitive offloading and critical pedagogy (Bui, 2026; Crimmins et al., 2026). Distributed-cognition approaches similarly examine how thinking is organized across people, artifacts, and environments. Samuel's Epistemic Entanglement Framework proposes epistemic co-agency through critical engagement with AI contributions (Samuel, 2026). Westerbeek develops cognitive resilience as the capacity to sustain attention, reasoning, and judgment within a distributed cognitive environment (Westerbeek, 2026). These conceptual proposals change the object of analysis while retaining an educational concern with human development.

6.9. Activity Systems and Hybrid Intelligence

Activity theory examines relations among subjects, objects, tools, rules, communities, and divisions of labor, with attention to development and contradictions (Engeström, 2001). AI enters an existing activity system. Assessment policies, curriculum expectations, access, and professional roles shape what teachers and students can do. Lee and Granziera operationalize an activity-theory perspective in a study of teachers' adoption intentions (Lee & Granziera, 2026). Survey relationships capture perceived conditions; longitudinal observation is needed to examine how tensions change practice and the object of teaching.

Hybrid-intelligence accounts make the allocation of functions explicit. Molenaar describes AI through detection, diagnosis, and action and distinguishes six levels of automation according to the distribution of control and monitoring (Molenaar, 2022). Ouyang and Jiao distinguish AI-directed, AI-supported, and AI-empowered education, while Cukurova develops the implications of hybrid intelligence for human learning (Cukurova, 2025; Ouyang & Jiao, 2021). These accounts support analysis of when computational assistance and human judgment complement one another. The amount of automation is a design characteristic whose educational value depends on the task and learner.

Holstein and colleagues' co-design work on classroom orchestration brings this issue into teachers' real-time decisions (Holstein et al., 2019). Useful information must be interpretable and actionable within a classroom. A dashboard that detects difficulty can support intervention, yet its value also depends on what the teacher can do in response. These concerns connect teacher knowledge to institutional conditions and to the timing of assistance.

They also show why general descriptions of AI as a collaborator need specification of roles, information, authority, and opportunities for intervention.

Expansive learning examines how participants collectively reconsider the object and organization of their activity. Yang and Markauskaite used a formative intervention to study student teachers' transformative agency in responding to generative AI (H. Yang & Markauskaite, 2025). This extends the activity-system perspective from perceived adoption conditions to the actions through which professional practice can be reconsidered. The unit of analysis is the developing collective activity, which requires evidence across episodes of questioning, modeling, experimentation, and consolidation.

Rhizomatic and posthumanist proposals also reconsider the boundaries of educational participation. Rhizomatic AI for Language Education (RAiLE) connects rhizomatic learning with the distribution of epistemic authority, language legitimacy, and institutional governance (Khodi & Curle, 2026). Pedagogical Symbiosis conceptualizes learning through hybrid human–AI cognition (Elsayed, 2026). Both proposals locate learning within relations among people, technologies, and institutions, extending the discussion of agency beyond control over individual tool use.

7. Instructional Design and Assessment

7.1. Inquiry, Problem Solving, and Experiential Learning

Inquiry sequences make the placement of AI assistance explicit. Choi's four-week qualitative study with eight preservice Earth science teachers examines AI-supported 5E planning; Moundridou and colleagues investigate assistance with inquiry-based lesson design and implementation (Choi, 2025; Moundridou et al., 2024). These studies concern teachers' translation of an instructional sequence into materials and decisions.

InquiryGPT structures prediction, observation, explanation, and evaluation. P.-H. Li et al. (2025) describe InquiryGPT as a ChatGPT-based inquiry assistant and leave the underlying model version unspecified. Its framework description and Table 2 label the final stage Evaluate, although a methods sentence also calls it Experiment. The eight-week study involved 62 engineering students working in pairs, with a week-6 knowledge test and a week-8 delayed test. Reported knowledge and thinking outcomes favored the structured condition, while acceptance differences were non-significant (P.-H. Li et al., 2025). PA-GPT compared structured peer assessment with conventional ChatGPT among 61 engineering students over eight weeks. A knowledge test and self-reported thinking skills supplied distinct outcomes (T. T. Wu et al., 2025). The complete report describes computer-generated allocation, but inconsistent analysis denominators constrain interpretation of the knowledge comparison.

Problem-based learning (PBL) provides a related application in professional education. Ergezen Sahin and colleagues randomized 40 physiotherapy students to AI-supported or conventional PBL. Knowledge scores favored the AI-supported condition at the end of the two-week intervention, while between-group differences on the Mini Clinical Evaluation Exercise were non-significant (Ergezen Sahin et al., 2025). Baseline knowledge differed between groups and the study reports incomplete outcome data. The findings concern short-term learning. The different patterns for knowledge and clinical performance show the importance of matching an outcome measure to the capability under investigation.

Experiential learning organizes movement among concrete experience, reflective observation, abstract conceptualization, and active experimentation (Kolb & Kolb, 2005). Salinas-Navarro and colleagues apply this cycle to an operations-management live case with 86 postgraduate students. AI supported exploration and reflection alongside contact with a real organization. Feedback was favorable but uneven: the targeted live-case survey had 16 respondents, and 69% rated AI reasonably or very helpful (Salinas-Navarro et al.,

2026). The case documents curricular enactment with substantial participation variation; AI assistance formed part of the wider live-case design.

A mechanism can be examined by varying when comparable support is supplied within the same sequence, such as before a prediction or after an initial explanation, while keeping the learning objective stable.

7.2. Sequencing Instruction and Supporting Complex Tasks

Abdikayumova and Madybekova compared three intact Grade 10 chemistry classes comprising 93 students over a 12-week intervention. The combined arrangement included contextual activities, a 7E sequence, ChatGPT tutoring, and PhET simulations (Abdikayumova & Madybekova, 2026). Several components changed together. PhET was a simulation component; the comparison does not identify a separate AI effect.

Other frameworks organize more complex tasks. Lu and colleagues used Gagné's events, ACT-R, and problem-chain guidance to generate and assess lesson plans (Lu et al., 2026). Niu and colleagues combined 4C/ID, cognitive-load principles, and AI in a 12-week immunology package with 177 students and a reported four-week delayed assessment (Niu et al., 2026). Random-number-table allocation is described alongside a quasi-experimental label; the appraisal retains that reporting discrepancy and limits attribution to the package.

Cimen and Bolatli (2026) compared traditional instruction, ARCS, and ARCS with a chatbot among 75 first-year nursing students in a university physiology course (25 assigned per group). The combined group showed the largest immediate achievement gain. The group-by-time comparison for cognitive load was non-significant. The reported analysis degrees of freedom leave the outcome denominator unclear. In Y. Li et al. (2026), emotional and agentic engagement differed between two language classes using the same AI chatbot with or without teacher presence. Differences in behavioral and cognitive engagement were non-significant.

7.3. Design Models, Dialogue, and Accessibility

The Analysis, Design, Development, Implementation, and Evaluation (ADDIE) model structures instructional development. Chai and colleagues examine generative AI across its stages (Chai et al., 2025). Su and Yang's IDEE framework specifies identifying desired outcomes, determining automation, ensuring ethical considerations, and evaluating effectiveness (Su & Yang, 2023). These models organize professional decisions. Their explanatory value for learning depends on the instructional processes selected within those decisions.

Laurillard's Conversational Framework links conceptual discussion, practical activity, feedback, and adaptation. Bakharia and Corrin illustrate how generative tools can produce interactive applications embodying these relationships (Bakharia & Corrin, 2025). Such work extends the means available for learning design while retaining a recognizable pedagogical architecture. Belkina and colleagues combine this framework with Substitution, Augmentation, Modification, and Redefinition (SAMR) when examining higher-education implementations (Belkina et al., 2025). SAMR can categorize task changes, although its categories provide an incomplete basis for evaluating educational quality, as Hamilton and colleagues' critique makes clear (Hamilton et al., 2016). Mehta et al. (2025) applied PICRAT to Google NotebookLM in medical education. Philbin and Sentance (2025) used the same framework to map student activity and teacher practice in computing education.

Universal Design for Learning (UDL) addresses learner variability through options for engagement, representation, and action and expression. Evmenova and colleagues consider generative AI in this context, and Sakowicz and Hamidi examine special educators' content development (Evmenova et al., 2024; Sakowicz & Hamidi, 2025). AI can help generate alternative representations and entry points. Their adequacy requires examina-

tion of both accessibility and disciplinary meaning. Simplifying vocabulary can improve access to a science problem, while simplifying away the relation being investigated changes the objective.

7.4. Backward Design, Learning Environments, and Project Work

Understanding by Design has informed a human–AI co-design model for linking transfer goals, performance tasks, and learning activities (Dogan, 2025). This application locates AI support within the relationship between intended learning and the evidence required to assess it.

The Activity-Centred Analysis and Design (ACAD) framework has been used to examine relations among tasks, material settings, and social arrangements in an architectural activity involving DALL-E (Leibowitz et al., 2025). At the program-design level, the ADMIT project's LLM-Ed report draws on ABC Learning Design, Carpe Diem, Iceberg, enABLe, and ELDeR to identify design activities that large language models can support (Guardia Ortiz et al., 2025). These approaches enter the report as antecedents of a combined learning-design framework.

Project and design frameworks place assistance within problem framing and development. PAIIF adapts CDIO to decisions about AI in project work (Nikolic et al., 2025). A four-week Double Diamond study reported favorable design and perception outcomes among 120 animation students (F. Song & Xu, 2026). Its Table 1 means, standard deviations, and sample sizes do not reproduce the reported omnibus F statistic, so the reported magnitude is not used to support a strong comparative claim.

Game design extends this range of arrangements. Wen and Chu map AI functions onto Mechanics–Dynamics–Aesthetics (Wen & Chu, 2026). Ngu et al. (2025) compared an AI-supported game with video-supported game activity and text support. Learning and flow comparisons favored the AI-game group over text, while fidelity was compared with the video-game group. Service-learning and mastery-learning applications address game creation and quiz generation (Hutt & Hieb, 2024; Wan et al., 2025). These contributions concern distinct design purposes; source-specific evidence and access limits appear in the supplementary inventory.

7.5. Inclusion, Cultural Responsiveness, and Social-Emotional Learning

Inclusion can be examined through the opportunities offered by the materials and activities that teachers design. Padrón Alvarez and Estrada-Molina's participatory study combined UDL, challenge-based learning, and generative AI. It included 83 students, 80 assessed proposals, and 178 artifacts. Proposal feasibility and curricular coherence were stronger than the integration of UDL and pedagogical AI use (Padrón Alvarez & Estrada-Molina, 2026). The results identify accommodation of learner variability as an area requiring further development within the designs.

Culturally responsive science assessment provides a related case. Nyaaba and colleagues developed a framework linking cultural contexts and identities with AI-supported item generation (Nyaaba et al., 2024). The educational question concerns the authenticity and relevance of those representations, as well as the science being assessed. Social-emotional learning adds another dimension. Henriksen and colleagues' framework for teacher education addresses the possible use of AI alongside human oversight, cultural sensitivity, and the risks of depersonalization (Henriksen et al., 2025). These contributions give inclusion a substantive role in educational judgment, extending the analysis beyond the availability of personalized content.

7.6. Objectives, Feedback, and Assessment Literacy

Bloom's revised taxonomy distinguishes cognitive processes and types of knowledge (Krathwohl, 2002). AI-supported activities can be classified within it, and Xia and colleagues use it to organize a meta-analysis of learning outcomes (Xia et al., 2025). The assessment question is whose cognitive activity a product demonstrates. A generated argument may meet surface criteria for analysis or creation while the student's contribution consists mainly of selection. The objective, task, and evidence of achievement need to remain aligned when AI participates in production.

Feedback literacy provides a complementary account. Carless and Boud emphasize understanding feedback, judging quality, managing affect, and taking action; Tai and colleagues examine evaluative judgment as the capacity to assess the quality of work (Carless & Boud, 2018; Tai et al., 2018). AI increases the availability of comments and alternatives, making selection and use of feedback particularly consequential. An appropriate outcome is whether learners identify relevant advice, reject misleading suggestions, justify revisions, and apply the underlying principle in subsequent work. The amount of generated feedback captures supply, while these measures capture learning activity.

The Artificial Intelligence Assessment Scale (AIAS) organizes the role of AI in assessment tasks (Perkins et al., 2024). Furze and colleagues' institutional pilot reports changes in assessment practice, engagement, and detected misconduct during implementation (Furze et al., 2024). The 2025 revision gives the framework an explicit social-constructivist basis and develops its use in assessment redesign, including AI exploration (Perkins et al., 2025). These versions should be distinguished when interpreting implementations: the pilot examined the earlier formulation, while the later paper specifies a revised relationship between permitted assistance, task design, and assessment validity.

The AIAS versions organize assessment permissions and task design. GAA-LS instead measures students' perceived assessment-related capabilities; its exploratory and confirmatory samples of 486 and 798 were randomly divided from one recruitment pool of 1284 responses (Nie et al., 2026). These instruments operate at institutional-design and individual-measurement levels, respectively.

Evaluative judgment offers a more explicit account of the capability involved in judging quality. Bearman and colleagues distinguish judgment of AI outputs, judgment of AI processes, and AI assessment of students' evaluative judgments (Bearman et al., 2024). Zhan and colleagues connect feedback literacy with the AI feedback environment through a cycle of forethought, control, and retrospect (Zhan et al., 2025). These conceptual contributions explain why receiving feedback and acting on it are separate educational processes. Evidence of development would need to show how learners interpret criteria, evaluate suggestions, and improve their own decisions across tasks.

7.7. Alignment, Evidence, and AI-Specific Assessment Designs

Constructive alignment connects intended learning, teaching activities, and assessment evidence. Its application to AI-assisted work focuses attention on the relationship between the assessed product and the learner's contribution (Klapproth, 2026). The Structure of the Observed Learning Outcome (SOLO) taxonomy provides a complementary account of the structure of understanding. Brunnström and Palmqvist use it to interpret an illustrative learner–AI dialogue and develop the idea of AI-interaction literacy (Brunnström & Palmqvist, 2026). Their analysis relates structural complexity to the learner's direction and evaluation of the exchange.

Evidence-centred design makes the inferential chain explicit. Cheng and colleagues connect claims about human–AI writing with interaction traces and epistemic network analysis (Cheng et al., 2024). This provides a concrete route for examining process evidence

in addition to the final text. ASPIRE and SAGE organize wider design and assessment decisions: the former develops a cycle in public-health education, while the latter connects supported production with documented judgments and a task-appropriate demonstration of understanding (Elkhodr & Gide, 2026; Mengesha et al., 2026). They coordinate the decisions through which AI-assisted work is produced, documented, and assessed.

8. Adoption and Institutional Conditions

The Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) examine why people intend to adopt and use technologies (Davis, 1989; Venkatesh et al., 2003). In educational AI research, perceived usefulness, effort, social influence, and facilitating conditions interact with trust, risk, and competence. Zhao and colleagues combine UTAUT with expectancy-value theory, adding innovation expectations, costs and benefits, and perceived risk. Their study involves surveys of 338 K–12 computer science teachers and 12 interviews (Zhao et al., 2026). Its educational relevance concerns conditions for adoption within a particular teaching context.

Foroughi and colleagues connect TAM with the Information Systems Success model in a survey of 406 Malaysian university students. Their model relates system quality to perceived usefulness and ease of use and examines trust as a moderator of the relationships with attitude (Foroughi et al., 2025). This formulation connects an adoption framework with perceived qualities of the system.

The Technology Readiness and Acceptance Model (TRAM) combines readiness dispositions with TAM. Wei and colleagues extend it through trust in a study of 331 learners of Chinese as a second language (Wei et al., 2026). The reported relationships differ across optimism, innovativeness, discomfort, and insecurity. Trust is positively associated with perceived usefulness and ease of use. These studies concern acceptance and intention; their findings locate conditions under which learners may engage with AI.

Social cognitive theory and diffusion-of-innovation perspectives broaden this account. Malago and colleagues' survey of 403 higher-education students relates self-efficacy, observational learning, and relative advantage to attitudes toward generative AI, with attitudes mediating several reported relationships with use (Malago et al., 2026). These associations help explain perceived engagement conditions. Learning outcomes provide a complementary basis for examining these adoption conditions. The non-significant acceptance differences in InquiryGPT, alongside differences in other outcomes, provide a concrete example of why adoption and learning should be measured separately (P.-H. Li et al., 2025).

Institutional conditions also shape the meaning of competence. Teachers may know how to evaluate a generated resource yet lack time for review or access to an appropriate system. A policy may encourage AI use while leaving responsibility for errors unclear. UNESCO's guidance addresses capacity, human agency, and institutional preparation in this wider setting (Miao & Holmes, 2023). Holmes and Tuomi similarly place educational AI within broader educational and societal arrangements (Holmes & Tuomi, 2022). These conditions help explain why technically similar systems can produce different practices across institutions.

Adoption can be examined over time through teachers' decisions, available support, and the learning opportunities created by use. Positive intention alone leaves several subsequent trajectories possible, including sustained practice, superficial compliance, and abandonment.

The Concerns-Based Adoption Model offers a developmental lens on adoption. The available abstract of Hur's (2025) mixed-methods study reports increased AI awareness and confidence alongside continuing concerns about teachers' roles and students' learning. Such findings show that positive expectations and consequential reservations can coexist.

The Theory of Planned Behavior has been extended to examine preservice teachers' intentions to learn AI (Sanusi et al., 2024). Ahmad and colleagues' organizational adoption proposal discusses the Technology–Organization–Environment (TOE) framework alongside other adoption models. Their proposed procedure addresses organizational needs, strategic fit, user preparation, and monitoring (Ahmad et al., 2023). A five-dimensional framework for ChatGPT combines readiness, pedagogical integration, resistance, governance, and continuing improvement, drawing on the Technology Integration Matrix, Innovation Resistance Theory, and Plan–Do–Check–Act (Altrabulsi et al., 2026). These approaches connect individual intentions with organizational resources and procedures. Longitudinal studies can examine how these conditions develop into sustained instructional practice.

9. Empirical Findings

The selected evidence records cover measurement, teacher design, learner intervention, qualitative enactment, and institutional implementation. Table 4 compares representative claims; all studies in the table were consulted in full text. Tables S4, S6 and S7 provide source details, MMAT profiles, and the evidence used to interpret the findings. Confidence depends on the outcome and comparison, the assessment period, and the limitations identified in appraisal.

Table 4. Empirical contrasts relevant to framework claims.

Study	Comparison or Material	Outcome Pattern	Consequence for Interpretation
(Celik et al., 2026)	Knowledge, prompts, and adaptive plans.	Higher prompting phases associated with more adaptive plans.	A plausible intermediate process; direction remains uncertain.
(Ng et al., 2024a)	Generative versus rule-based SRL chatbot.	Science knowledge and engagement favored the generative condition.	Two classes, inconsistent sample/group descriptions, and short-term outcomes constrain causal interpretation.
(T. T. Wu et al., 2025)	Structured peer assessment versus conventional ChatGPT.	At eight weeks, knowledge-test scores and several self-report ratings favored structured use.	Knowledge and perceived thinking are distinct outcomes; inconsistent analysis denominators limit quantitative interpretation.
(P.-H. Li et al., 2025)	POEE-guided inquiry versus ChatGPT.	Knowledge and thinking outcomes favored structured inquiry; knowledge tests occurred in weeks 6 and 8. Acceptance differences were non-significant.	Guidance and reflection reports change together; paired allocation and analysis require caution.
(Bastani et al., 2025)	Base and safeguarded tutors versus control.	Practice gains; subsequent unaided examination harm in GPT Base, with no significant advantage in GPT Tutor.	Safeguards and assessment conditions change the conclusion.
(Kestin et al., 2025)	Designed AI tutor versus active-learning lessons.	Immediate physics post-tests favored the tutor; pooled observations were repeated across two lessons.	A specific pedagogical package; durability was not established.
(Ergezen Sahin et al., 2025)	AI-supported versus conventional PBL.	Knowledge advantage at the two-week module endpoint; Mini-CEX difference non-significant.	Baseline knowledge imbalance and incomplete outcomes limit interpretation.
(Salinas-Navarro et al., 2026)	AI-supported live case without a control.	Positive but uneven feedback and participation.	Implementation evidence with selection and engagement constraints.
(Bai et al., 2026)	Scaffolded versus historical course cohort.	Prompting and algorithm-product scores favored the supported cohort; adjusted models reported the same direction.	Historical controls and inconsistent test statistics limit causal and quantitative interpretation.

Note. All studies in this table were consulted in full text. Table S4 supplies sample and duration information; Tables S6 and S7 provide appraisal, access history, and weighting. SRL = self-regulated learning; POEE = Prediction–Observation–Explanation–Evaluation, following the operational stages in P.-H. Li et al. (2025), Table 2; PBL = problem-based learning.

Bastani and colleagues' school-mathematics experiment reports 48% higher practice performance with GPT Base and 127% with safeguarded GPT Tutor relative to the no-AI control. On subsequent unaided examinations, GPT Base performed 17% worse; the safe-

guarded condition did not show a statistically significant advantage over control (Bastani et al., 2025). These are relative changes in particular assessment conditions, not standardized effect sizes. Their direction supports a distinction between supported practice and subsequent unaided learning.

Kestin and colleagues compared two undergraduate physics lessons in a randomized crossover arrangement. Among 194 eligible students, pooled post-tests contained 142 AI-condition and 174 classroom-condition observations, with median scores of 4.5 and 3.5. The reported standardized-effect range of 0.73–1.30 reflects modeling choices and ceiling effects; it is not a confidence interval (Kestin et al., 2025). Outcomes were immediate, and the AI and classroom conditions differed in location and pacing. Repeated observations are not unique participants.

These experiments support claims about specified tutors and assessment conditions. The broader intelligent-tutoring literature likewise aggregates systems with particular instructional functions and comparators (Ma et al., 2014). Their findings do not validate every educational framework used to describe AI.

Boolzen and colleagues included 85 studies in their STEM synthesis; 49 studies contributed 59 effect sizes to the meta-analysis. The random-effects estimate was Hedges' $g = 0.84$ (95% confidence interval 0.53–1.15), with $I^2 = 96.32\%$ and a prediction interval of −1.52 to 3.20. Robust Bayesian adjustment for publication bias yielded a posterior mean of 0.076 (95% credible interval −0.37 to 0.79) (Boolzen et al., 2026). Their use of the Inversion–Substitution–Augmentation–Redefinition (ISAR) model connects this heterogeneity with differences in the cognitive activity of intervention and comparison conditions. The moderator analysis supplies an empirical application of the model, while substantial residual heterogeneity limits a single interpretation of AI-supported STEM learning.

The access sensitivity comparison yields three conclusions. Artifact and questionnaire studies support different claims from learner outcome comparisons. Multicomponent interventions do not identify each component's contribution. Assessment conditions can change the inference about learning.

10. Cross-Framework Synthesis

10.1. Frameworks and Educational Activity

The five modes locate the kind of claim an AI-related formulation makes. Applying an existing sequence, redefining its content for AI, adding a construct, relocating the unit of analysis, and assembling a new design arrangement require different evidence. This comparison prevents a newly named model or a favorable intervention result from serving automatically as evidence that an established theory has changed. This distinction draws on Whetten's (1989) account of theoretical contribution, which distinguishes changes in the factors a theory considers from changes in how and why those factors are related.

The modes also expose competing explanations within an instructional arrangement. A reduction in task demands can be consistent with cognitive-load accounts, while ICAP directs attention to whether learners generate explanations or only receive them. Faster completion can therefore accompany either more efficient learning or reduced learner contribution. A comparison must assess which processes occurred and what students can subsequently do (Bauer et al., 2025; Chi & Wylie, 2014; Sweller, 1988).

10.2. Three Tensions That Organize the Evidence

Ethical judgment is organized differently across teacher-knowledge models, AI literacy measures, assessment design, and institutional guidance. Celik's (2023) framework identifies an ethics domain; Aldemir et al. (2025) distribute ethical deliberation across domains and activities. These representations imply different measurements and predictive

questions. A common design task could test whether a separate ethics score or observed ethical decisions better explains revisions after controlling for prior professional knowledge.

Control and cognitive responsibility also generate competing predictions. Self-determination concerns experienced volition, self-regulation concerns management of learning, and hybrid-intelligence accounts describe allocation of functions (Molenaar, 2022; Ryan & Deci, 2000; Zimmerman, 2002). More freedom to delegate does not by itself predict stronger self-regulation. The tutor comparisons show why task completion and later unaided performance must be related to the actual distribution of cognitive work (Bastani et al., 2025).

Individual and distributed accounts locate accomplishment at different levels. A group's successful human–AI product can be an appropriate measure of joint performance. The operational assumptions conflict when that same product is treated as sufficient evidence for an outcome defined as unaided individual mastery. CoI reinterpretations and evidence-centred assessment help specify the contributions needed for each inference (Ba et al., 2026; Cheng et al., 2024; Eyal, 2025). Each assessment claim therefore requires evidence of the relevant contributions and performance conditions.

A construct crosswalk makes these relationships inspectable by linking each term to its unit, mechanism, observable evidence, and rival interpretation. Similar vocabulary alone does not establish measurement equivalence.

10.3. A Worked Construct Crosswalk

Table 5 applies the crosswalk to agency, regulation, and ethical judgment using reviewed publications. Celik et al. (2026) evaluated features of teacher-generated plans, whereas W. J. Kim (2026) examined design for pupils' environmental science agency. Both concern agency, but the observed unit and intended educational outcome differ. The crosswalk keeps that distinction visible and identifies what an additional study would need to observe.

Table 5. A worked crosswalk for agency, regulation, and ethical judgment.

Construct and Unit	Framework Interpretation	Evidence in the Reviewed Sources	Discriminating Observation
Agency: teacher design and pupil participation	Teacher authorship of a plan, pupils' disciplinary agency, and system control locate agency in different actors and activities.	Celik et al. (2026) assessed planned opportunities for student agency. W. J. Kim (2026) examined 23 teachers designing for ESA; pupil ESA was unmeasured.	Observe pupils identifying a relevant problem, using disciplinary evidence, and acting on it. A plan or a teacher's favorable perception alone cannot establish these outcomes.
Regulation: individual and group activity	SRL concerns learners' planning and monitoring. SSRL concerns shared regulation. Automated sequencing describes a system function.	Ng et al. (2024a) compared chatbot-supported science learning. J. Kim et al. (2025) elicited anticipated requirements for group regulation.	Trace who initiates goals and revisions, whether the group negotiates them, and what persists when prompts are reduced. Compare system compliance with learner-initiated regulation.
Ethical judgment: knowledge and enacted decisions	A separate ethics domain and ethics distributed across design routines imply different indicators and predictive questions.	Celik (2023) specifies an ethics domain. Aldemir et al. (2025) embed ethics across domains; the single-cohort design limits attribution of the reported changes.	Use the same problematic AI output to compare an ethics score with justified identification and correction of bias, while accounting for prior subject and pedagogical knowledge.

Note. The crosswalk is an analytical demonstration using the reviewed studies. Proposed discriminating observations are research suggestions, not additional findings. ESA = environmental science agency; SRL = self-regulated learning; SSRL = socially shared regulation of learning.

The crosswalk separates an overlap in educational purpose from equivalence of constructs. It also makes a research comparison possible: hold the task and participants constant, specify the competing explanations, and collect the observations that would favor one interpretation. This procedure connects framework selection with measurement and avoids combining individual, group, and institutional constructs into an unexplained global integration score.

10.4. Disciplinary Reasoning Across Framework Levels

STEM-specific evidence concerns disciplinary inquiry, explanation, and design. The chemistry and science-planning studies connect professional knowledge with the selection and evaluation of explanations (Feldman-Maggor et al., 2025; Peikos & Stavrou, 2025). Research in educational robotics identifies implementation barriers perceived by preschool and primary educators (Gavrilas et al., 2025). InquiryGPT organizes prediction, observation, explanation, and evaluation within an engineering course (P.-H. Li et al., 2025). These examples support examination of disciplinary reasoning; they do not establish equivalent outcomes in all subjects.

Broader propositions receive different support. Teacher-design evidence also comes from special education, experiential-learning evidence from operations management, and institutional sensemaking from faculty across disciplines (Raju et al., 2026; Sakowicz & Hamidi, 2025; Salinas-Navarro et al., 2026). These contexts support a broad distinction among constructs, products, and outcomes. The curricular contribution of integrated STEM, STEAM, or SCALE remains tied to the disciplinary relationships specified in the particular design (Leon et al., 2025; Sotiropoulos et al., 2026; W. Yang, 2025).

11. Research Priorities

Further progress requires studies that discriminate among explanations. Teacher-framework research can compare whether new AI-specific domains predict performance beyond established TPACK measures. Learning research can test whether the timing and reduction in assistance affect later independent performance. Assessment research can examine how accurately product scores identify individual understanding under different permitted AI contributions. Institutional research can follow how policies and professional support influence enacted practice over time.

Table 6 translates these priorities into research propositions, measures, and designs. Samples should include variation in subject, expertise, language, and access, with sufficient description of the AI system and instructional arrangement to support comparison. Model version, available context, feedback rules, and permitted forms of use can materially alter an intervention.

Table 6. Testable propositions and discriminating research designs.

Proposition	Measures	Design and Rival Explanation
AI-specific verification and ethical judgment predict instructional decisions after accounting for subject knowledge and general digital competence.	Subject knowledge; digital competence; AI-related knowledge; independently scored verification and design tasks.	Compare predictive models on held-out observations; examine the added contribution of AI-related constructs.
Assistance supports independent learning when learners retain explanation and verification and support can be reduced.	Origin of explanations; hint use; verification; delayed unaided performance.	Vary assistance timing and fading within comparable tasks; distinguish reduced effort from improved understanding.
Distributed ethical practice and a separate ethical-knowledge domain make distinguishable predictions.	Ethics scale; observed decisions; justifications across repeated tasks.	Compare domain-focused instruction with embedded decision routines; examine shared-method effects.
A group's AI-supported performance and members' individual learning can develop differently.	Group product; shared-regulation episodes; individual explanation and transfer.	Collect group and individual outcomes over time; examine unequal participation.
Process information improves the interpretation of AI-assisted assessment products.	Product ratings; contribution records; oral explanation; new-task performance.	Blind raters to process information in one condition; test added agreement with independent capability.
Institutional support affects enactment through specific resources and practices.	Access, review time, policy clarity, professional collaboration, observed use.	Longitudinal multi-site study; distinguish intention from implementation and local leadership effects.

Note. Research propositions derived from the synthesis, with suggested measures and designs for empirical investigation.

Measurement development is equally important. Studies need evidence that instruments distinguish adjacent constructs and function comparably across intended groups.

Performance assessments can examine the detection of plausible errors, justification of revisions, and transfer of a principle. Process data can establish when these actions occur, although logs require interpretation and appropriate handling of participant information. Independent explanation after support is removed is especially useful when the educational claim concerns durable capability.

12. Limitations

The corpus was assembled through purposive web discovery, with incomplete preservation of total hits and screening decisions. The supplementary register makes retained queries and source relationships inspectable, but search ranking and the original result depth cannot be reproduced. Selection and reference following may have missed relevant frameworks, and the English-language restriction limits linguistic coverage. The empirical/design table illustrates contrasting evidence and does not enumerate all eligible empirical research.

Coding and appraisal were not independently duplicated. The five modes remain an interpretive analytical scheme, and framework classifications based on partial material are provisional. Full-text checks covered all 31 selected records, but complete access does not resolve confounding, inconsistent reporting, or short assessment periods. The review estimates neither pooled effects nor framework prevalence.

13. Conclusions

For the first review question, the selected literature demonstrates several forms of AI incorporation, organized here as application, contextual specification, construct extension, relational reconfiguration, and AI-specific synthesis. These modes identify the change a source proposes and the evidence that would support it. Their usefulness is analytical; independent evaluation of the coding scheme remains necessary.

For the second question, the principal changes concern ethical judgment, allocation of cognitive responsibility, and the unit to which knowledge or agency is attributed. The worked crosswalk shows why these changes require explicit definitions and observations. For the third question, the empirical evidence supports bounded claims about particular measures, designs, and instructional arrangements. Comparative learning evidence is strongest when outcomes, comparators, timing, and limitations are explicit. Incremental validity of new domains, long-term transfer, and cross-context generalization remain research propositions.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/aieduc2040037/s1. Supplementary Material S1. Search register, source-to-entry crosswalk, framework and evidence inventories, access and appraisal records, sensitivity analysis, and coding examples.

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