Generative AI and the Future of Teaching and Learning: Rethinking Pedagogy, Assessment and Teacher Roles.

ABSTRACT

Generative artificial intelligence (GenAI) lets learners and teachers obtain text, images, explanations, questions and feedback through ordinary language. That capability unsettles long-held assumptions about what students should produce unaided, how learning is evidenced and what teachers are for. This conceptual paper examines the educational opportunities and risks of GenAI and offers a human-centred framework for its use in schools and universities. It draws on UNESCO's guidance and competency frameworks, systematic and scoping reviews published between 2019 and 2025, and established learning theory. The analysis is organised around four connected themes: the nature of generative AI, pedagogy, assessment and the teacher's role. Four shifts are identified: from content delivery to learning design, from answer production to inquiry and critique, from product-focused to process-rich assessment, and from teacher-as-transmitter to teacher-as-designer, mentor and ethical decision-maker. A five-layer framework links human purpose, AI literacy and ethics, pedagogical integration, process-oriented assessment and institutional governance, and five testable propositions are derived from it. Hallucination, bias, privacy, unequal access, over-reliance and authorship receive particular attention. The paper argues that the educational value of GenAI depends less on the availability of tools than on task design, teacher agency, learner AI literacy and institutional safeguards.

Keywords*:* Generative artificial intelligence, pedagogy, assessment, teacher role, AI literacy, academic integrity, human-centred education

INTRODUCTION

Background and problem

Generative AI moved from a specialist research topic to an everyday classroom concern within a very short time. After conversational systems became freely available to the public in late 2022, students and teachers could ask for explanations, worked examples, lesson plans, quiz questions, summaries and first drafts, and receive them in seconds. Early scholarly commentary was quick to record both sides of this change. Kasneci et al. (2023) described how large language models might support personalised learning and reduce routine workload while warning about bias, inaccuracy and over-reliance. Baidoo-Anu and Owusu Ansah (2023) examined benefits such as tutoring-style support and formative feedback alongside limits on reliability and human interaction. Dwivedi et al. (2023), writing from many disciplinary standpoints, reached a similar conclusion: the opportunities are real, and so are the unresolved questions about integrity, ethics and policy.

Artificial intelligence in education is not new, but the present situation differs in one important respect. Earlier systematic work found that research on AI in higher education was driven mainly by technical fields, with limited involvement of educators and little critical reflection on risks (Zawacki-Richter et al. 2019). Generative systems reverse that arrangement. They sit directly in the hands of learners, so pedagogical decisions can no longer be left to developers or delayed until a body of settled evidence exists. A teacher may find that a class has already used a chatbot before the

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assignment was even explained. Education therefore needs working principles that are sturdy enough to survive rapid tool change.

International organisations have begun to supply such principles. UNESCO's guidance on generative AI calls for a human-centred approach built on ethical, safe, equitable and meaningful use, and pays specific attention to privacy, regulation and age-appropriate access (Miao and Holmes 2023). It complements UNESCO's prior ethical recommendation on artificial intelligence (UNESCO 2021) and its 2024 competency frameworks for students and teachers. The student framework defines four dimensions: a human-centred mindset, AI ethics, AI techniques and applications, and AI system design (Miao et al. 2024). The teacher framework includes five categories: human-centred mindset, AI ethics, AI foundations and applications, AI pedagogy, and AI for professional learning (Miao and Cukurova 2024). National policy contexts add further questions. In India, for example, the National Education Policy 2020 places weight on critical thinking, creativity and the purposeful use of technology (Ministry of Education 2020), which means that GenAI cannot be judged only by convenience; it has to be judged by whether it advances those goals.

The research record is growing quickly but remains uneven. A systematic review of school-level research located 197 relevant studies (Marzano 2025). A scoping review of assessment in higher education retained 32 articles and concluded that assessment must change to cultivate self-regulated learning, responsible learning and integrity (Xia et al. 2024). A systematic review of 41 studies on academic integrity reported gains in engagement and efficiency together with a significant risk of academic dishonesty (Bittle and El-Gayar 2025). Perhaps the most instructive result comes from a field experiment with nearly 1,000 high-school mathematics students. Unrestricted access to a GPT-4 interface improved performance during practice, yet students who later worked without the tool did worse than peers who had never had it, while a tutor-style version with built-in safeguards largely removed that harm (Bastani et al. 2025). The same technology, in other words, produced different learning outcomes depending on how it was designed into the task.

Much of the existing literature remains tool-centred or confined to one aspect of the problem, such as cheating, prompt skills or teacher workload. Fewer contributions show how generative AI, pedagogy, assessment, the teacher's role and institutional governance depend on one another. If pedagogy changes but assessment does not, students are rewarded for the wrong behaviour. If assessment changes but teachers are not supported, the redesign cannot be sustained. If policies are written without pedagogical reasoning, they tend to become lists of prohibitions. This paper addresses that gap by treating the five elements as one connected system.

Aim and research questions

The aim is to build a conceptual, evidence-informed account of how GenAI changes teaching and learning and to propose a framework that educators and institutions can use. Four questions guide the discussion:

- RQ1. What distinguishes generative AI from earlier educational technologies, and what does that imply for the relationship between learners, knowledge and tools?
- RQ2. How should pedagogy be redesigned so that GenAI strengthens, rather than replaces, learner thinking?
- RQ3. How can assessment remain valid and fair when learners have access to content-generating tools?
- RQ4. How does the teacher's role change, and what governance conditions allow that change to be sustained?

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Contribution and structure

The paper makes three contributions. First, it presents an integrated conceptual map linking the four themes of the title with governance (Figure 1). Second, it proposes a five-layer, recursive framework and derives five propositions that later empirical work can test. Third, it supplies practical tools in tabular form: an evidence base, a comparison with earlier technology, pedagogical and assessment redesign options, a teacher-role matrix, a risk register and a cross-layer connection matrix.

Section 2 explains the approach and the theoretical lenses. Sections 3 to 6 treat generative AI, pedagogy, assessment and the teacher's role as separate sections, each ending with links to the others. Section 7 covers risk, ethics and governance. Section 8 integrates the argument in the five-layer framework. Sections 9 to 10 set out implications and conclusion.

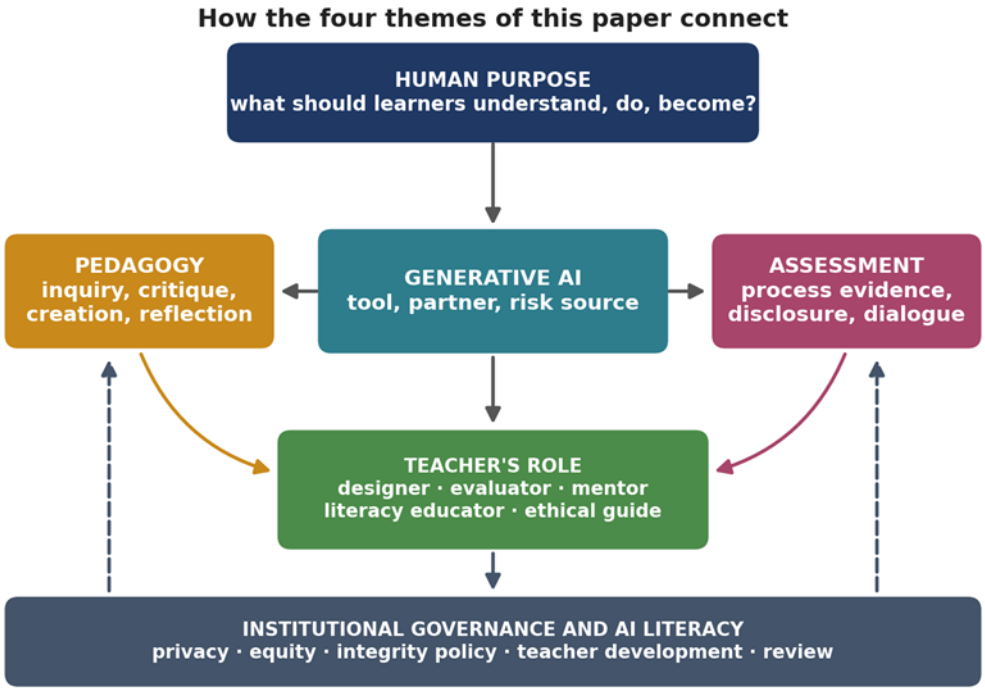


Figure 1. Conceptual map of the paper: how generative AI, pedagogy, assessment and teacher's role connect through purpose and governance.

Source: *Miao and Holmes (2023), Miao et al. (2024), Miao and Cukurova (2024) and Xia et al. (2024).*

APPROACH AND CONCEPTUAL FOUNDATIONS

Nature of the paper

This is a conceptual and descriptive paper. Sources were chosen purposively from three groups: policy and guidance documents issued by UNESCO; recent systematic reviews, scoping reviews and one large field experiment on GenAI in education; and foundational work in learning theory, assessment and teacher knowledge. Findings from the reviews are reported as their author's state them, and the interpretations built on them are the author's own. Table 1 lists the core evidence base and its use in this paper

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Table 1. Core evidence base and its use in this paper

Sources	Scope	Message its conveying
Miao and Holmes (2023)	UNESCO guidance on generative AI in education and research	Human-centred approach; privacy, regulation and age-appropriate use
Miao et al. (2024)	UNESCO AI competency framework for students	Four dimensions: human-centred mindset, AI ethics, AI techniques and applications, AI system design
Miao and Cukurova (2024)	UNESCO AI competency framework for teachers	Five dimensions and 15 competencies, from human-centred mindset to AI for professional learning
Xia et al. (2024)	Scoping review, 32 articles, assessment in higher education	Assessment should cultivate self-regulation, responsible learning and integrity; teacher development and policy review needed
Bittle and El-Gayar (2025)	Systematic review, 41 studies, 2021 to 2024	Engagement and efficiency gains alongside substantial academic-dishonesty risk
Marzano (2025)	Systematic review, K-12, 197 studies	Rapidly growing school-level evidence base
Qian (2025); Liu and Zhong (2025)	Systematic reviews on pedagogical applications and on TPACK-based integration	Pedagogical scaffolding, instructional guidance and effective assessment shape outcomes
Bastani et al. (2025)	Field experiment, nearly 1,000 high-school students	Unguarded GPT-4 access harmed later unaided performance; safeguards largely mitigated the harm
Weber-Wulff et al. (2023); Liang et al. (2023)	Evaluations of AI-text detectors	Detectors were unreliable and misclassified writing by non-native English speakers

Theoretical lenses

Five bodies of theory frame the analysis. Social-constructivist accounts of learning, including Vygotsky's (1978) zone of proximal development and the idea of scaffolding (Wood et al. 1976), suggest that help is educational when it is calibrated and gradually withdrawn. Cognitive load theory (Sweller 1988) and the notion of desirable difficulties (Bjork and Bjork 2011) explain why effort that feels inefficient can still produce durable learning, and why a tool that removes all effort may remove the learning as well. The TPACK framework (Mishra and Koehler 2006), which expands upon Shulman's (1987) account of pedagogical content knowledge, interprets teaching with technology as an amalgamation of technological, pedagogical, and content knowledge rather than a form of practical proficiency.

For assessment, the paper relies on constructive alignment (Biggs 1996), which requires that outcomes, teaching activities and assessment tasks reinforce one another, and on the formative assessment tradition (Black and Wiliam 1998). Finally, Biesta's (2010) distinction between the qualification, socialisation and subjectification purposes of education serves as a reminder that learning is not reducible to producing correct outputs: students also become members of a community and develop as independent persons. This broader view underlies the first layer of the framework in Section 8.

GENERATIVE AI IN EDUCATION

What generative AI is and why it differs

Generative AI refers to systems, usually built on large language or multimodal models trained on very large data sets that produce new content in response to prompts. Such models are sometimes described as foundation models because they can be adapted to many tasks (Bommasani et al. 2021). For education, three features matter most. The output is generated rather than retrieved, so it can be new but also wrong. The interaction is conversational and iterative, so the learner can ask follow-up questions, request a different level of difficulty or challenge an answer. And the output is probabilistic, which means the same prompt may not return the same result.

These features alter the pedagogical relationship. A learner using a textbook, search engine or earlier learning platform receives material that someone has already written or selected. A learner using a generative system enters a dialogue with a content-generating process whose reliability is uneven and often invisible. Table 2 summarises the main contrasts.

Table 2. Earlier educational technologies compared with generative AI

Dimension	Earlier educational technologies	Generative AI
Source of content	Authored, curated or retrieved material	Newly generated for each prompt
Interaction	Mostly fixed menus, search queries or pre-set pathways	Open-ended natural-language dialogue with iterative follow-up
Predictability	Content stable and checkable in advance	Output varies and may contain errors, invented references or bias
Learner's role	Access, practise, respond	Question, direct, evaluate, edit and decide what to trust
Main educational risk	Digital divide; shallow use of resources	Over-reliance, loss of productive struggle, unverified content, unclear authorship
Key question for the teacher	How do students reach this material?	What learning purpose is served by using AI on this task?

Source: *Holmes et al. (2019), Zawacki-Richter et al. (2019), Kasneci et al. (2023) and Miao and Holmes (2023).*

Educational affordances

For teachers, GenAI can help draft lesson ideas, differentiated examples, formative questions, discussion prompts, rubrics and first-pass feedback (Kasneci et al. 2023). Used critically, this may

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free time for interaction and instructional decisions. For learners, it offers conversational explanations, alternative examples, language support, brainstorming and the chance to keep questioning until an idea becomes clear (Baidoo-Anu and Owusu Ansah 2023). Students themselves tend to see value in these uses; a study of university students in Hong Kong found broad willingness to adopt the tools together with concern about accuracy, privacy and the effect on personal development (Chan and Hu 2023).

These benefits are conditional. They materialise when the learner stays intellectually active, comparing explanations, spotting gaps and testing ideas. When a student simply copies the answer, the technology can lower rather than raise cognitive engagement. The reviews by Qian (2025) and Liu and Zhong (2025) both point to the importance of instructional guidance, and the field evidence from Bastani et al. (2025) shows what can happen in its absence.

Limits that shape educational use

Three limits recur. First, generative systems can produce fluent but unsupported statements, a problem usually termed hallucination (Ji et al. 2023). Fabricated references and plausible but incorrect explanations are the most familiar educational examples. Fluency can be mistaken for authority, which is a particular hazard for novices who cannot yet judge correctness. Second, models learn from large text collections that carry social assumptions, so outputs may reproduce stereotypes or narrow cultural perspectives (Bender et al. 2021). Third, access is unequal: tools, devices, connectivity and adult guidance are distributed unevenly, and the gap affects who can benefit (UNESCO 2023; van Dijk 2005).

AI literacy as the enabling competence

Because of these constraints, AI literacy cannot be reduced to generating good commands. Long and Magerko (2020) describe AI literacy as a set of attributes that permit individuals critically analyze AI, interact and team up with it, and use it as a tool. Ng et al. (2021) break down the field into four sections: knowing and understanding AI, using it, evaluating it, and addressing moral dilemmas. The UNESCO student framework follows a similar logic (Miao et al. 2024). Taken together, these accounts imply that verification, source evaluation, recognition of uncertainty and ethical judgement belong at the centre of AI literacy for both learners and teachers.

Link to the next sections. If generated content must be checked, then pedagogy must give students tasks in which checking is the work (Section 4); if students may use the tools, then assessment must capture how they used them (Section 5); and if both are to happen, teachers need the knowledge and institutional backing to design for it (Section 6).

RETHINKING PEDAGOGY

From transmission to learning design

When explanations, examples and practice questions can be generated on demand, the scarce resource in a classroom is no longer information. It is well-designed experiences that lead students to think. Pedagogy therefore shifts from transmission toward learning design that emphasises inquiry, critique, creation and reflection. This is consistent with the revised taxonomy of educational objectives, in which evaluating and creating sit above remembering and understanding (Anderson and Krathwohl 2001). It also reframes the guiding contrast. The issue is not AI versus learning but AI-mediated learning, in which the learner’s agency is deliberately protected. The UNESCO student framework

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supports this view by positioning students as responsible users and co-creators who need ethical and critical judgement (Miao et al. 2024).

Five design moves

Five practical design moves follow from this orientation. First, AI can serve as a brainstorming partner whose suggestions students must evaluate and improve. Second, students can compare several generated responses and identify factual, logical or ethical problems in each. Third, teachers can use AI to produce contrasting examples, one strong and one flawed, for students to critique. Fourth, learners can document how they revised an AI-generated draft and justify each change. Fifth, teachers can design tasks that rest on local evidence, personal reflection, practical performance or oral explanation, since these are hard to satisfy with a generic generated text. Table 3 sets these moves against the four shifts identified in this paper.

Table 3. Pedagogical shifts, classroom strategies and the learning purpose protected

From	To	Illustrative classroom strategy	Learning purpose protected
Content delivery	Learning design	Teacher generates alternative explanations with AI, then students choose the clearest and justify the choice	Understanding through comparison
Answer production	Inquiry and critique	Students compare three generated answers and mark factual, logical and ethical weaknesses	Evaluation and judgement
One-shot drafting	Documented revision	Students annotate how and why they changed an AI draft, keeping a short revision log	Metacognition and authorship
Generic tasks	Situated tasks	Assignments built on local data, personal reflection, oral explanation or practical performance	Evidence tied to the individual learner
AI as answer machine	AI as questioner or tutor	Tutor-style prompts that give hints and ask learners to explain their reasoning before showing a solution	Productive struggle

Source: *Anderson and Krathwohl (2001), Kasneci et al. (2023), Miao et al. (2024) and Bastani et al. (2025).*

What learning science and field evidence suggest

Learning theory explains why design details matter. Scaffolding works when help is matched to the learner and then withdrawn (Wood et al. 1976; Vygotsky 1978). Cognitive load theory distinguishes load that is merely burdensome from load that builds understanding (Sweller 1988), and the idea of desirable difficulties adds that certain kinds of struggle, such as retrieving information or generating an answer before seeing the solution, improve long-term retention (Bjork and Bjork 2011). A tool that always supplies the answer therefore risks removing the very effort from which learning grows.

The field experiment by Bastani et al. (2025) gives this concern empirical weight. Students with unrestricted access used the system as a crutch during practice and then performed worse on their own, whereas students using a version designed to give hints and withhold full solutions largely avoided that loss. The study was conducted in one school subject and context, so its size should not be generalised, but its logic is transferable: the educational value of GenAI depends on whether the interface and task keep the learner thinking. Educators can express this as a simple test for any proposed use. Does the learner still have to retrieve, reason, decide or create something before or after the tool responds?

Teacher knowledge and pedagogical coherence

Designing in this way requires integrated knowledge of the subject, of how students learn it and of what the technology can and cannot do, which is the core claim of TPACK (Mishra and Koehler 2006). A recent TPACK-based review of GenAI-supported student learning underlines the importance of instructional guidance and effective assessment (Liu and Zhong 2025). Pedagogical decisions about AI are consequently inseparable from decisions about assessment, which is the subject of the next section.

RETHINKING ASSESSMENT

Why assessment is disrupted

Assessment is probably the area most directly unsettled by GenAI. Take-home essays, generic reports and routine summaries have long served as proxies for individual learning. When students have unrestricted access to systems that can produce competent text in seconds, such products no longer provide strong evidence about what a particular student understands. Reviews of the field reach similar conclusions: Xia et al. (2024) argue that assessment should be transformed to cultivate self-regulated learning, responsible learning and integrity, and Bittle and El-Gayar (2025) find that the same tools that raise engagement and efficiency also create considerable risk of academic dishonesty.

Responding with greater surveillance is a weak strategy. It is costly, it damages trust, and, as discussed below, the technical tools on which it relies are unreliable. A stronger response treats assessment as an opportunity to capture reasoning, which is also what formative assessment research has long recommended (Black and Wiliam 1998). Bearman and Luckin (2020) make a related argument, suggesting that assessment tasks in a world with AI should concentrate on capabilities that are distinctively human.

Process-oriented assessment

Process-oriented assessment gathers evidence about how a learner thinks and works, not only about the final product. Staged assignments, research logs, drafts, annotated sources, oral discussions, project demonstrations, reflective commentaries and in-class application tasks all fit this pattern. Students may be asked to disclose whether and how AI was used and to evaluate the quality of its output, which turns the tool into an object of critical analysis. Feedback also remains central; its effect depends on whether it tells learners where they are, where they are going and how to proceed (Hattie and Timperley 2007). AI can help produce first-pass comments quickly, but teachers need to check their accuracy and tone before they reach students. Table 4 shows how common task types can be redesigned.

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Table 4. Redesigning common assessment tasks for the GenAI era

Task type	Vulnerability when AI is available	Process-oriented redesign	Evidence captured
Take-home essay	Complete text can be generated without engagement	Staged submission: proposal, annotated sources, draft, revision log and a short viva	Reasoning, source evaluation, revision decisions
Literature summary	Summaries and invented references are easy to generate	Students verify each source, correct an AI-generated summary and explain what it missed	Verification skill, critical reading
Problem set	Solutions can be copied without understanding	Part completed in class unaided; part with AI followed by an explanation of each step	Independent competence, explanation quality
Project or report	Generic content with little local grounding	Local data collection, interim presentations and a defence of design choices	Application, ownership, oral reasoning
Reflective journal	Reflection can be fabricated in plausible language	Reflection linked to dated class events, supported by short oral check-ins	Authentic metacognition

Source: *Black and Wiliam (1998), Bearman and Luckin (2020), Xia et al. (2024) and Bittle and El-Gayar (2025).*

The limits of AI-text detection

Institutions are often tempted to rely on software that claims to identify machine-written text. The evidence does not support treating such tools as arbiters. Weber-Wulff et al. (2023) tested a range of detection tools and found them neither accurate nor reliable enough for high-stakes decisions. Liang et al. (2023) showed that detectors disproportionately flagged writing by non-native English speakers as machine-generated, which raises a serious fairness concern in multilingual systems such as those in India. A more defensible approach is triangulation: process evidence, drafts, conversation with the student, source evaluation and demonstrated understanding. A detector score, if used at all, should prompt a conversation, not a penalty.

Academic integrity and authorship

GenAI complicates the line between original and assisted work. The central question is not simply whether AI was used, but whether its use fits the learning purpose of the task and whether the student remains answerable for what is submitted (Perkins 2023; Cotton et al. 2024). Institutions can therefore define transparent tiers of permitted use by task purpose, as set out in figure 2. Students should be taught to acknowledge substantive assistance and to verify what they use. Punitive rules alone are unlikely to be effective; they work best when combined with clear policy, AI literacy and assessment redesign (Bittle and El-Gayar 2025).

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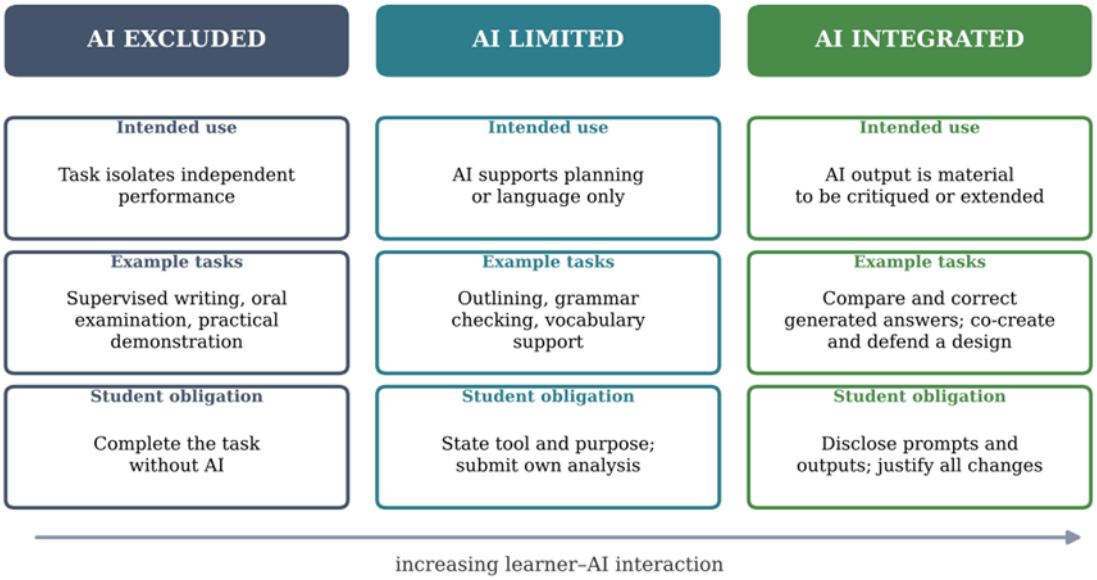


Figure 2. A tiered approach to AI use in assessed work

Source: Perkins (2023), Cotton et al. (2024), Xia et al. (2024) and Bittle and El-Gayar (2025).

Aligning pedagogy and assessment

Because assessment signals what counts, the alignment between teaching activities and assessment tasks is decisive (Biggs 1996). If classroom activities invite critique of AI output but the final assessment rewards polished text, students will rationally prioritise polish. Figure 3 depicts a six-step loop that keeps purpose, AI role, learner activity, and evidence and teacher judgement connected. The loop is intentionally cyclical: the teacher's feedback informs the next statement of purpose, so the same evidence serves both assessment and instructional improvement.

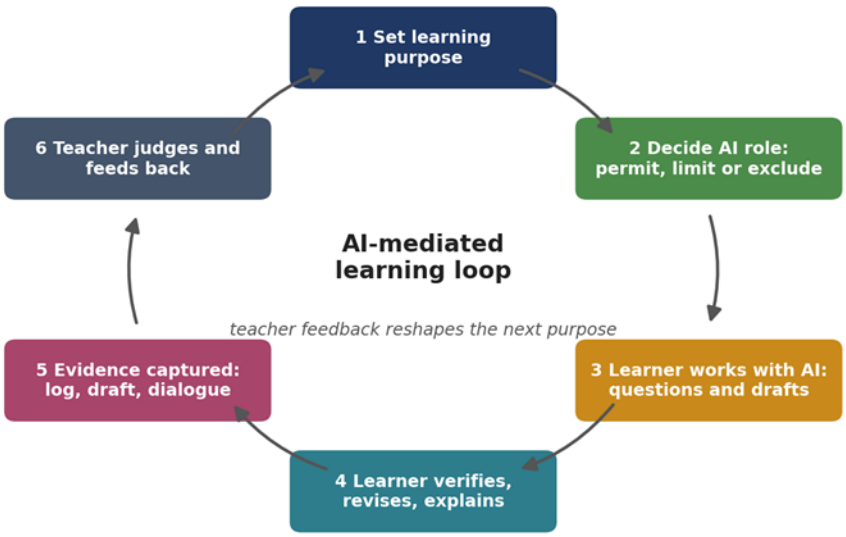


Figure 3. The AI-mediated learning loop linking pedagogy and process-oriented assessment.

Source: *Biggs (1996), Black and Wiliam (1998) and Xia et al. (2024).*

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THE CHANGING ROLE OF THE TEACHER

Redistribution rather than replacement

GenAI does not remove the need for teachers; it redistributes their work. Routine generation of materials can increasingly be assisted by technology, while human judgement becomes more important in setting learning goals, choosing tasks, interpreting evidence, building relationships and responding to individual students. Selwyn (2019) cautions against assuming that the relational and judgement-based aspects of teaching can simply be automated. The earlier finding that educators were rarely at the centre of AI-in-education research (Zawacki-Richter et al. 2019) also suggests that teacher voice has to be built into this transition deliberately rather than assumed.

Five evolving roles

Five roles describe this change (Figure 4 and Table 5). As a learning designer, the teacher decides when AI adds genuine educational value. As a critical evaluator, the teacher checks generated content for accuracy, bias and fit. As an AI-literacy educator, the teacher helps students understand limitations and responsible use. As a mentor, the teacher supports motivation, identity, collaboration and wellbeing, areas where human presence is central. As an ethical decision-maker, the teacher protects privacy, fairness and learner agency. These roles correspond closely to the dimensions of the UNESCO teacher framework, which identifies 15 competencies across five dimensions (Miao and Cukurova 2024).

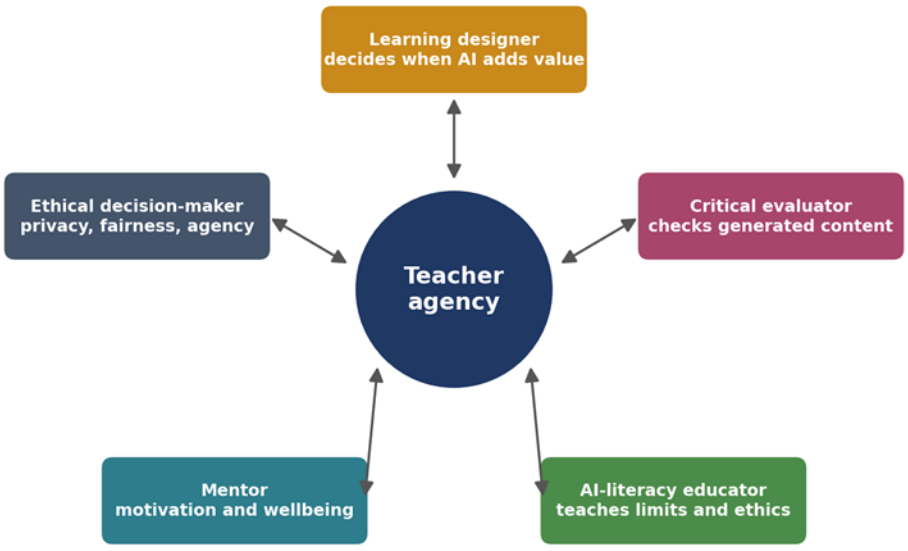


Figure 4. Five evolving roles of the teacher in AI-mediated education.

Source: *Miao and Cukurova (2024), Mishra and Koehler (2006) and Selwyn (2019).*

Table 5. Teacher roles, UNESCO framework links and support needed

Role	What it involves	Related UNESCO teacher dimension	Support needed

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Role	What it involves	Related UNESCO teacher dimension	Support needed
Learning designer	Choosing tasks, deciding when AI is permitted, limited or excluded, aligning activities with assessment	AI pedagogy	Time, exemplar designs, collaborative planning
Critical evaluator	Checking generated content for errors, bias and suitability before classroom use	AI foundations and applications	Subject-specific guidance on common failure modes
AI-literacy educator	Teaching verification, source evaluation and responsible use	Human-centred mindset; AI foundations and applications	Curriculum resources; student-facing materials
Mentor	Sustaining motivation, belonging, identity and wellbeing	Human-centred mindset	Workload relief for relational work
Ethical decision-maker	Protecting privacy, fairness and learner agency; choosing tools responsibly	Ethics of AI	Clear data-protection rules and approval processes
Reflective professional learner	Experimenting, sharing practice and updating methods as tools change	AI for professional learning	Communities of practice; sustained professional development

Source: *Miao and Cukurova (2024).*

Teacher education and professional learning

Teacher education must therefore move beyond generic digital literacy. Future teachers need practice in designing AI-supported lessons, critiquing generated material, constructing AI-aware assessments and discussing ethical dilemmas. They also need experience with AI-free activities, because responsible use includes knowing when not to use AI. Professional development can be organised around progressive competence: understanding AI, applying it to selected tasks, evaluating its outputs, redesigning pedagogy and creating context-specific practice. Xia et al.'s (2024) scoping discussion strengthens this agenda by proposing development activities in assessment, AI, and digital literacy, in addition to paying attention to teachers' convictions about human and AI assessment.

Emotional and professional dimensions matter as well. Rapid technological change can unsettle professional identity, and teachers need institutional permission to experiment, share what works and exercise judgement rather than being expected to adopt every new tool at once. Support for teachers is thus not an add-on to the pedagogical and assessment changes described above; it is a condition for them.

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RISKS, ETHICS, EQUITY AND GOVERNANCE

A risk register

Human-centred integration requires attention to risks that go beyond cheating. Table 6 summarises the main risks, their educational consequences and measures that educators and institutions can take. Students may enter private or confidential information into third-party systems, so UNESCO's guidelines highlights information security and regulation (Miao and Holmes 2023). In India, the Digital Personal Data Protection Act 2023, adds a legal dimension by including provisions for children's personal data. Bias requires teachers and students to ask whose knowledge is represented, what sources underlie an answer and whose perspectives are absent. Unequal access means that if AI becomes a hidden prerequisite for good performance, existing inequalities may widen, so accessible alternatives and institutional support are required (UNESCO 2023; van Dijk 2005). Over-reliance can erode learner agency by removing opportunities to struggle productively and learn from error (Bastani et al. 2025).

Table 6. Principal risks of GenAI in education, consequences and mitigation

Risk	Educational consequence	Supporting literature	Mitigation
Hallucination	Learners absorb unsupported claims or invented references	Ji et al. (2023); Kasneci et al. (2023)	Teach verification; require source checks; treat output as a draft
Bias	Stereotyped or culturally narrow content	Bender et al. (2021)	Examine whose perspectives are missing; compare multiple sources
Privacy	Personal or sensitive data exposed to external systems	Miao and Holmes (2023); Government of India (2023)	Approved tools only; no personal data in prompts; age-appropriate access
Unequal access	Advantage for students with better tools and guidance	UNESCO (2023); van Dijk (2005)	Provide institutional access and non-AI alternatives
Over-reliance	Reduced retrieval, reasoning and persistence	Bastani et al. (2025); Bjork and Bjork (2011)	Tutor-style design; unaided practice; reflection on use
Integrity and authorship	Unclear ownership and unfair advantage	Bittle and El-Gayar (2025); Perkins (2023)	Tiered AI-use policy; disclosure; process evidence
Detector misuse	False accusations; bias against non-native writers	Weber-Wulff et al. (2023); Liang et al. (2023)	Triangulate evidence; never rely on a score alone

Ethical principles

The risks above sit within broader ethical frameworks. Floridi and Cowls (2019) propose five principles for AI in society, namely beneficence, non-maleficence, autonomy, justice and explicability, while Jobin et al. (2019) found convergence across published AI ethics guidelines on transparency, justice, non-maleficence, responsibility and privacy. UNESCO’s (2021)

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recommendation offers a global normative basis. For education, these principles translate into practical questions: does a given use benefit the learner, could it harm, does it preserve the learner's autonomy, is it fair across groups, and can teachers and students understand how it works well enough to question it?

Institutional governance

Institutions need flexible policies that distinguish acceptable assistance from inappropriate substitution and that are revised regularly because capabilities change quickly. Chan (2023) proposes a policy framework for universities with pedagogical, governance and operational dimensions, an arrangement that fits the cross-layer logic of this paper. Governance should cover data protection, tool approval, accessibility, academic integrity, assessment design, teacher training and student support. Procurement should weigh evidence of educational value rather than novelty; the Global Education Monitoring Report makes the wider point that technology should be adopted on educational terms and that robust evidence of added value is often limited (UNESCO 2023). Participation by students and teachers in policy development can improve clarity and legitimacy and let policies reflect disciplinary differences.

AN INTEGRATED HUMAN-CENTRED FRAMEWORK

The five layers

Drawing the previous sections together, the paper proposes a five-layer framework (Figure 5). Layer 1, human purpose, means that every AI use begins with a defined educational objective: what should learners understand, practise or create? This layer reflects Biesta's (2010) wider purposes of education. Layer 2, AI literacy and ethics, equips learners and teachers with knowledge of capabilities, limits, bias, privacy, intellectual property, verification and responsible use. Layer 3, pedagogical integration, embeds AI through inquiry, dialogue, critique, personalisation, creativity and collaboration rather than answer automation. Layer 4, process-oriented assessment, gathers evidence in the form of drafts, reasoning, reflection, performance, dialogue, source evaluation and disclosure of AI use. Layer 5, institutional governance, provides policies on privacy, age appropriateness, integrity, procurement, accessibility, teacher development and review.

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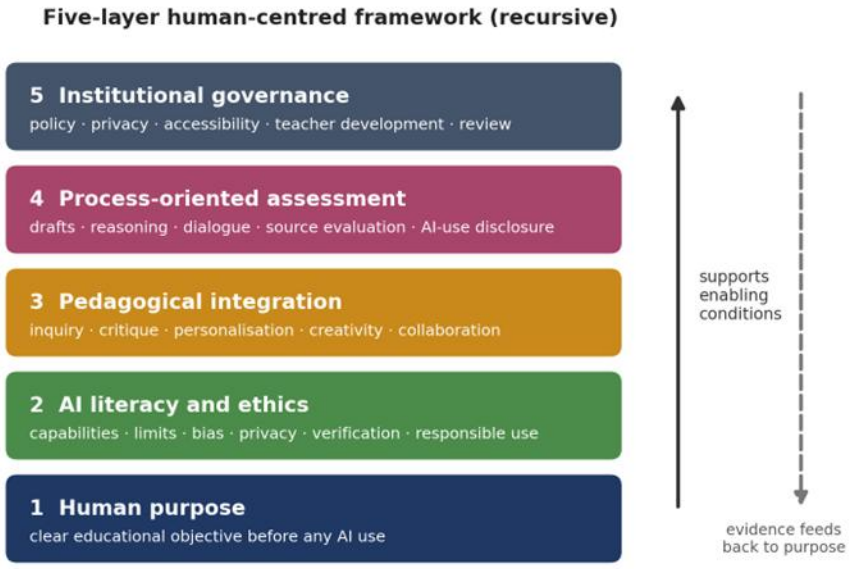


Figure 5. The five-layer human-centred framework for GenAI in education.

Source: *Miao and Holmes (2023), Miao et al. (2024), Miao and Cukurova (2024), Biesta (2010) and Chan (2023).*

The layers are recursive rather than strictly sequential. Governance supports ethical use; ethical literacy supports pedagogical integration; pedagogical integration reshapes assessment; assessment yields evidence of learning; and that evidence returns to the first layer, since learning purposes ultimately decide whether AI should be used at all. Table 7 shows how the layers connect to the four themes discussed in Sections 3 to 6.

Table 7. Cross-layer connection matrix: how framework layers link generative AI, pedagogy, assessment and teacher's role

Layer	Generative AI	Pedagogy	Assessment	Teacher's role	Governance
1. Human purpose	Used only where it serves a stated objective	Objectives set before tool choice	Outcomes define what counts as evidence	Learning designer	Policy references educational purpose
2. AI literacy and ethics	Limits and biases made explicit	Verification built into tasks	Students evaluate AI output	AI-literacy educator; ethical decision-maker	Training and guidance for staff and students
3. Pedagogical integration	Positioned as questioner, partner or object of critique	Inquiry, comparison, revision	Tasks align with activities	Learning designer; mentor	Time and resources for redesign

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Layer	Generative AI	Pedagogy	Assessment	Teacher's role	Governance
4. Process-oriented assessment	Use disclosed and evaluated	Learning activities produce visible process evidence	Drafts, logs, dialogue, tiered AI use	Critical evaluator	Integrity procedures based on triangulation
5. Institutional governance	Tools approved, data protected	Flexible policy by discipline	Fair, transparent rules	Reflective professional learner	Review cycle; participation of staff and students

Propositions for future testing

Five propositions follow from the framework and are offered as hypotheses for empirical work rather than established findings.

- P1 (Technology vs. Purpose Focus): Student learning outcomes and conceptual mastery are significantly higher when tool selection is dictated by pre-defined behavioral learning objectives (Purpose-Driven) compared to when lesson structures are adapted around the capabilities of a specific software tool (Technology-Driven).
- P2 (The Mediation of AI Literacy): The effect of raw access to GenAI applications on a student's critical thinking performance is fully mediated by the student's baseline level of AI literacy, specifically their measured competence in source verification and output evaluation.
- P3 (Scaffolded vs. Open Interfaces): GenAI integration patterns using tutor-style scaffolding (which provide incremental hints and demand active user retrieval) yield higher independent post-test performance than open, guardrail-free text generation interfaces (which automate complete solutions).
- P4 (Assessment Validity Factors): The predictive validity of take-home academic evaluations in the GenAI era is positively correlated with the volume of process-based evidence collected (e.g., version histories, change logs, and oral defences) relative to the final product submission.
- P5 (Dual-Engine Sustainability): Long-term, stable adoption of AI-aware pedagogical integration within educational departments cannot be sustained by institutional policy mandates alone, requiring a positive, symbiotic interaction between explicit administrative support systems and individual teacher agency.

IMPLICATIONS FOR PRACTICE, TEACHER EDUCATION AND POLICY

Classroom practice. Teachers can begin with small changes: add a verification step whenever generated content is used; ask students to explain a solution in their own words; and keep a short log of how AI contributed. Each of these preserves learner effort and yields visible evidence. Where the aim is independent performance, tasks can be completed in class without AI, and where the aim is critical evaluation, AI output can be the material under study.

Teacher education. Programmes should give future teachers repeated opportunities to design, test and critique AI-supported lessons and assessments, and should include deliberate AI-free practice. The UNESCO teacher framework offers a reference for sequencing such learning (Miao and

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Cukurova 2024), and the review evidence suggests that development on assessment and AI literacy is especially needed (Xia et al. 2024).

Institutional policy. Policies are most effective when they are transparent, flexible, regularly reviewed and developed with those who must apply them. Tiered statements of acceptable use (Table 5) give clarity without blanket prohibition. Procurement decisions should rest on evidence of educational benefit and on data-protection compliance.

CONCLUSION

Generative AI is more than another digital resource. It changes the relationship among knowledge, production, assessment and teaching, and its educational significance depends on how institutions redesign learning around human purposes. The future of teaching is unlikely to be settled by a choice between human teachers and AI systems. A more productive direction is a human–AI partnership in which technology supports selected cognitive and administrative tasks while teachers retain responsibility for educational purpose, relationships, judgement, ethics and learner development.

The analysis in this paper shows that generative AI, pedagogy, assessment and the teacher's role cannot be treated in isolation. Changing one without the others produces misalignment: tasks that reward the wrong behaviour, assessments that cannot be trusted, or teachers asked to carry changes they have not been prepared for. The five-layer framework, comprising human purpose, AI literacy and ethics, pedagogical integration, process-oriented assessment and institutional governance, offers a way to keep these elements coherent. Its central principle is simple. AI should be used when it strengthens learning, not merely because it can perform a task. Future-ready education will need not only students who can use AI but also learners and teachers who can question it, evaluate it, govern it and recognise when human judgement must remain in charge.

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