

AI in Education Moves From “Should We Use It?” to “What Learning Must Stay Human?”

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New school restrictions, Khan Academy’s proactive tutor, and district and higher-ed evidence point to a common shift: AI is being judged by preserved effort, visible thinking, and implementation capacity rather than novelty alone.

The week’s strongest signal is a shift in the unit of evaluation: education systems are beginning to judge AI less by model capability than by whether it preserves human learning, produces visible evidence of understanding, and fits the conditions of a real school. New York City is restricting student-facing AI and passive video access, while a Tech & Learning summary of UNESCO’s 2026 report frames AI as infrastructure that requires purpose, human agency, and governance. District evidence points to the same conclusion from the implementation side: the surrounding conditions often matter more than the tool. [1, 2, 3]

Policy is becoming selective, not simply anti-technology

New York City’s policy is a concrete example. Students cannot access YouTube on school-issued Chromebooks or iPads at school or home except through teacher-shared Google Classroom lessons. The broader policy generally bars individual screen use before third grade, recommends limits of 30 minutes in grades 3–5 and 45 minutes in grades 6–8, and bans student-facing generative AI from preschool through eighth grade. Schools are being told to use paper-and-pencil tests when possible, but required digital reading, math, and state assessments remain exceptions. [1]

The public signal is more nuanced than a wholesale retreat from technology. More than 80% of parents in one poll supported school laptops, 53% said it was important for students to learn AI tools for future careers, and 73% of registered

voters still viewed excessive reliance on devices, phones, and AI as a serious problem. Parent advocates described the desired balance as guardrails, secure data, and protection from low-quality material—not zero technology. Access also remains an equity issue: support for laptops was lower and uncertainty higher among low-income parents. [4]

UNESCO’s recommended operating model is purpose-first: identify what students or educators should be able to do better, inventory the algorithms already shaping decisions, preserve human questioning and reasoning, and redesign assessment rather than relying on detection. Its broader AI-literacy agenda includes training data, bias, hallucinations, missing perspectives, commercial incentives, privacy, consent, and human review of consequential decisions. [2]

District implementation is emerging as the differentiator. An analysis based on 100 district-leader conversations says the districts furthest along had staged change management, capacity-building, and explicit ROI practices. Denver Public Schools moved from 225 teachers in semester-long AI professional development to 4,000 teachers in two-tier training, followed by content-area work and planned governance involving educators, families, and community members. At KIPP Public Schools Northern California, short-cycle analysis found the strongest impact from an AI instructional tool in small-group settings for students well below grade level—and no observed benefit elsewhere. The source’s conclusion is unusually specific: the same tool produced strong results in one district and inconsistent results in another, with the difference usually residing in district conditions. [3]

The strongest product signal: preserve the learner’s work

Khan Academy is redesigning its classroom tutor around moments when learning is most at risk of becoming superficial. Sal Khan said the earlier version mostly waited for students to ask questions, even though many learners were embarrassed, could not articulate a question, or did not know what they did not understand. The newer classroom version appears after a wrong answer, asks the student to review it, and may award credit if the student demonstrates understanding. After a correct answer, it can ask for an explanation and potentially remove redundant practice. Teachers also receive narrative context—such as whether a student understood the method but made careless errors, memorized a formula, or moved unusually quickly—and Khan Academy’s planned interim assessments add prompts for students to explain their reasoning alongside conventional growth and proficiency measures. [5]



Khan Academy's founder on AI: "Hope isn't a strategy" / Sal Khan (32:59)

That is a more defensible design hypothesis than “give every learner a chatbot,” but it is still a hypothesis. KIPP’s finding that benefits appeared in one setting and subgroup, rather than everywhere, reinforces the need to measure unaided transfer, subgroup effects, and implementation fidelity. The EdTech Partnerships evidence framework reaches the same standard: credible evaluation must explain whether a tool works, why, for whom, under what conditions, and with what tradeoffs for privacy, equity, affordability, interoperability, and environment. [3, 6]

Google’s Gemini Notebook shows a parallel move toward traceability. The product is presented as working only from uploaded files and websites, generating study guides and other materials, and attaching inline citations that open and highlight the source passage. Google says uploaded files remain private. That can make checking easier and reduce ungrounded generation, but provenance is not the same as learning impact: a source-grounded study guide still needs a teacher or learner to inspect the source and test whether understanding survives after the tool is closed. [7, 6]

The scarce resource is practice—and apprenticeship

The assessment problem is becoming a learning-design problem. UNESCO describes a “classroom AI doom loop” in which AI generates the assignment, students use AI to complete it, AI evaluates the response, and an automated system

records the grade. Its proposed alternative is to make thinking visible through oral explanation, iterative drafts, authentic projects, reflection, in-class problem solving, and documentation of AI use. [2]

Ethan Mollick makes the same issue concrete for both education and work. He argues that learners can outsource repetitive practice because the work feels difficult, losing the basic skill they were supposed to build. He also warns that the entry-level apprenticeship pipeline can break when interns use AI to perform work they are still learning, managers route work around them, and companies prize efficiency over the inefficient periods in which novices receive human feedback. His proposed correction is to make teaching central and retain some assessments and work periods completed without AI. [8]



Ethan Mollick on Staying Human at Work / Dreamforce 2026 (4:53)

Justin Reich adds an important caution against premature certainty. He argues that educators know far less about effective practice with large language models than they do about established areas such as reading instruction, so the near-term response should be systematic experimentation rather than confident “best practices.” In his view, output evaluation depends heavily on domain knowledge, because users need to recognize when a model’s fluent answer is wrong. He also says school change spreads primarily through peer learning, not by distributing software or issuing a policy. [9]

AI literacy and higher education are moving toward guided practice

Experience AI, the free Raspberry Pi Foundation–Google DeepMind curriculum, offers a practical response that does not require teachers to become AI specialists. Its approach embeds AI literacy in existing work with data, prediction, context, research verification, critical thinking, and problem solving. One age-banded activity has 8- to 12-year-olds analyze misleading advertisements that anthropomorphize AI; the curriculum stresses that systems make predictions, are not people, and leave humans accountable. The program says it has been downloaded more than one million times, supports 22 languages, works with more than 40 international partners, and is being used by some schools in weekly seventh-grade advisory. [10]



AI Literacy for Teachers: Free Lessons, No Expertise Needed (1:45)

Higher education is confronting the same shift from content delivery to experience, judgment, and adaptability. Michael Horn argues that college may become more valuable when AI can teach information anywhere, because live interaction, research, relationships, experiential learning, networks, and knowing when knowledge applies become more important. A separate higher-ed analysis argues that policies, task forces, and isolated pilots do not create agility; institutions need the ability to move faculty, technology, curricula, pedagogy, assessment, and governance quickly. [11, 12]

There are early institutional versions of this model. Northeastern is scaling

faculty cohorts from roughly 20 participants to an estimated 100–200 across colleges, tying AI work to co-op and disciplinary conversations and distinguishing AI literacy from AI fluency. Its faculty-development discussion rejects formal AI detection because of privacy and false-accusation risks, emphasizing clear expectations and redesigned pedagogy instead. Khan described a proposed KNED Institute in similar terms: authentic, time-constrained work, global groups, peer review, AI-project portfolios, and learner-selected evidence for employers. The interest list exceeds 30,000, but that is demand for the model—not evidence that it works. [13, 5]

A global access example makes the same point without generative AI. In South Africa, Worldreader’s data-free BookSmart evaluation combined a four-group randomized trial with caregiver interviews: 812 caregivers enrolled and 519 completed both baseline and endline assessments. Completing more books was associated with stronger caregiver-reported expressive-language skills, while goal-setting messages increased completion of accompanying activities more than reminders. Engagement remained modest, families requested more home-language books and clearer routines, and the preliminary findings have not been peer reviewed. [14]

What This Means

- **For edtech buyers:** Treat every AI product as a learning hypothesis. Define the target capability, baseline, subgroup, implementation conditions, transfer task, and post-adoption review before counting usage as success. The relevant evidence standard is efficacy plus effectiveness, ethics, equity, and environmental viability. [6, 3]
- **For assessment leaders:** Separate practice from certification. Let AI support formative feedback, critique, or scaffolding where appropriate, but require students to explain, revise, solve unfamiliar problems, or demonstrate skills without the system when the goal is to certify competence. Do not make an imperfect detector the primary judge of authorship. [2, 13]
- **For K–12 leaders:** Replace blanket “AI” categories with age-, task-, and tool-specific rules. A ban on generic student-facing AI can coexist with narrow, purpose-built tools, but only if schools define the exception, protect access and privacy, and plan for the paper, device, accessibility, and assessment consequences of the transition. [1, 15]
- **For teachers and L&D teams:** Teach discernment inside subject learning. Ask whether AI is helping learners notice, question, practice, and defend their thinking—or merely removing the difficulty that builds the skill. Experience AI’s subject-embedded model and Mollick’s apprenticeship warning point in the same direction. [10, 8]
- **For higher education:** Build agility and applied experience as infrastructure, not as a one-off AI committee. Co-op, authentic projects, peer feedback, and portfolios can make learning visible, but they need outcome

evidence and employer validation rather than relying on novelty. [12, 11]

Watch This Space

- **Khan Academy’s classroom tutor and interim assessments:** The important next evidence is unaided performance, durable mastery, and subgroup results—not simply whether students engage with the tutor or complete more generated practice. [5]
- **New York City’s implementation:** Watch how schools reconcile paper-first guidance with required digital assessments, how exceptions are governed, and whether restrictions are accompanied by usable AI literacy rather than access control alone. [1, 2]
- **District evidence infrastructure:** The market is moving toward teacher coaching and institutional experimentation—McGraw Hill acquired TeachFX, while Cornell is launching faculty-led AI pilots and student fellows—but the meaningful test is whether these efforts produce comparable evidence across schools and learners. [3]
- **Higher-ed and workforce signals:** Follow whether portfolio-based, AI-enabled programs and co-op-linked faculty work become credible hiring signals while institutions preserve the human feedback and deliberate practice that entry-level workers need. [5, 8]
- **Global digital learning:** BookSmart’s peer-reviewed follow-up should clarify whether data-free access, local-language content, and goal-setting can turn availability into sustained family reading. [14]

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