AI’s Influence on Learning, Motivation, and Cognitive Processes

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Artificial intelligence (AI) is reshaping how people learn, stay motivated, and process information. Over the past five years, educational settings have increasingly incorporated AI-driven platforms to provide personalized instruction, adaptive assessment, and creative scaffolding. Tools such as generative language models, adaptive tutoring systems, and AI-powered feedback engines promise to democratize access to knowledge and reduce barriers for diverse learners. Early findings show that AI can help students manage workload, improve efficiency, and feel more confident in their learning experiences (Zhang et al., 2024; Sun et al., 2024).

Yet these same tools present new challenges. While AI may boost short-term outcomes, concerns are growing about how reliance on AI systems affects long-term learning, motivation, and cognitive health. Researchers have begun to document the emergence of "metacognitive laziness," in which students bypass effortful thinking by outsourcing reasoning to machines (Keller et al., 2025). Others point to evidence of "cognitive debt," where heavy use of AI reduces engagement in memory and critical thinking processes, leaving students less prepared to perform independently (Kosmyna et al., 2025). This tension highlights a paradox at the heart of AI in education: the technology can simultaneously scaffold learning while also undermining the very processes, attention, reflection, and deep reasoning, that education seeks to strengthen.
Motivation is central to this paradox. AI systems can personalize learning to match students' goals and abilities, potentially enhancing intrinsic motivation. At the same time, instant answers and pre-packaged solutions can diminish the value students place on effort and persistence, simply copying and pasting without even reading the response. Emotional and cognitive systems are deeply intertwined in this dynamic. Studies show that AI tools affect not just knowledge

acquisition but also the regulation of attention, memory, and emotion, which in turn shape motivation (Li et al., 2024; Köpeczi-Bócz, 2025).

Artificial intelligence influences learning in ways that are both promising and risky. Evidence across cognitive theory, instructional design, neuroscience, and human–AI interaction shows that AI can improve immediate performance and give students a stronger sense of progress when it is used within strong pedagogy. At the same time, AI tools often disrupt attention, reshape emotional engagement, and blur memory accuracy, which can undermine long-term learning and ownership of knowledge. The central argument of this review is that AI's benefits in motivation and short-term outcomes are real, but they come with cognitive trade-offs, including risks of metacognitive laziness, reduced critical thinking, and susceptibility to false memories. Managing these trade-offs requires theory-guided design and authentic assessment practices that keep learners actively engaged and cognitively responsible (Carney, 2020; Köpeczi-Bócz, 2025; Sirilertmekasakul et al., 2023; Wang & Fan, 2025).

Conceptual Foundations for AI Supported Learning and Motivation

Theories of learning and motivation provide essential context for understanding how AI interacts with cognition and educational outcomes. Each framework offers a unique lens for identifying both the benefits and risks of integrating AI into instructional design.

The 4E model of cognition: embodied, embedded, enacted, and extended positions cognition not as an isolated mental process but as one deeply integrated with environment, tools, and actions. From this perspective, AI tools are not simply external aids but potential extensions of a learner's cognitive system (Carney, 2020). This extension offers dual possibilities. On one hand, AI can enhance performance by offloading tasks such as retrieval or surface-level summarization, freeing learners to focus on deeper reasoning. On the other hand, over-extension may lead to dependence, where students neglect internal regulation strategies such as planning or self-monitoring. The 4E framework thus underscores the importance of balance: AI can augment cognition, but only when paired with intentional metacognitive practices that ensure learners remain active participants in their own thinking.

Cognitive dissonance methods add another layer to this discussion. According to Köpeczi-Bócz (2025), learning is strengthened when students confront contradictions between their prior beliefs and new information, creating discomfort that motivates resolution. When AI tools are designed to surface alternative perspectives or generate counterarguments, they can amplify this productive conflict, prompting learners to reflect and restructure their mental models. For example, an AI system that offers multiple explanations or challenges common misconceptions can encourage students to engage in self-explanation, a process strongly linked to deeper learning. At the same time, if AI delivers overly polished answers without room for dissonance, it may short-circuit the motivational benefits that arise from grappling with uncertainty.

Cognitive Load Theory (CLT) offers a complementary explanation for how AI affects learning. CLT distinguishes between intrinsic load (inherent task difficulty), extraneous load (unnecessary cognitive effort), and germane load (mental effort invested in building schemas). AI can reduce extraneous load by providing clear explanations or targeted feedback, allowing students to focus more fully on germane processes (Sweller, 1988; Kosmyna et al., 2025).

However, when AI over-simplifies or provides answers too quickly, it may inadvertently reduce germane load, leading to surface learning rather than schema construction. In this way, CLT helps explain both the efficiency gains and potential depth losses that characterize AI-supported instruction.

Self-Determination Theory (SDT) adds a motivational dimension to these cognitive accounts. SDT emphasizes autonomy, competence, and relatedness as the core drivers of intrinsic motivation. AI systems can enhance these drivers by personalizing tasks to student ability levels, offering adaptive feedback that builds competence, and even simulating relational support through dialogue (Deci & Ryan, 2000). However, poorly designed AI risks undermining autonomy by over-directing learning or reducing competence by making success feel dependent on the tool rather than the student's own effort. The interplay between AI design and SDT principles may determine whether learners feel empowered or disempowered when working with these systems.

Taking together these frameworks suggest that the educational value of AI lies not in its raw computational power but in how it is embedded into pedagogy. The 4E model highlights the risks of over-extension, CLT shows the balance between efficiency and depth, SDT emphasizes motivational needs, and Cognitive Dissonance Theory (CDT) illustrates how challenge can drive conceptual change. Designing AI-supported instruction thus requires intentional integration: scaffolds must be paired with opportunities for planning, monitoring, and reflection to ensure that learners remain engaged in the active construction of knowledge rather than passive consumption.

Assessment and Measurement as Scaffolds for Learning

Reliable assessment is a precondition for effective adaptation in education. Without accurate measures of what students know, how they think, and how they feel, AI systems risk reinforcing misconceptions or creating misaligned learning paths. When done well, assessment not only evaluates performance but also provides scaffolding that guides learners toward deeper engagement and improvement.

AI-augmented neurocognitive screening exemplifies this shift. Traditional paper-based instruments often suffer from limitations such as infrequent administration, delayed feedback, and context constraints. By contrast, AI-supported systems enable remote, automated scoring that can deliver results in real time. These innovations increase accessibility and timeliness, making it possible to track learners' progress across diverse settings. Sirilertmekasakul et al. (2023) emphasize that neurocognitive screening tools enhanced by AI may provide early indicators of cognitive decline or changes in executive functioning, allowing for proactive interventions and personalized study plans. In instructional settings, this means learners can receive timely feedback aligned to their evolving strengths and weaknesses, enhancing self-regulated learning.

Psychometric research further strengthens this case. Mora-Romo et al. (2025) evaluated a brief cognitive function scale and found strong internal consistency and invariance across groups, supporting the feasibility of short instruments in authentic learning environments. This finding is significant because long and complex assessments often disrupt instruction, while shorter, reliable measures can integrate seamlessly into everyday educational practice. When coupled with AI, such measures can be continuously administered at scale, offering instructors a dynamic picture of student progress rather than static snapshots. The result is a shift from assessment as a one-time judgment to assessment as an ongoing scaffold that supports both learner growth and instructional design.

Emotion quantification represents another promising but controversial frontier. Advances in multimodal sensing allow AI systems to integrate data from facial expressions, vocal tone, text sentiment, gestures, and even physiological signals to infer student engagement levels. In theory, such systems can tailor pacing, adjust challenge levels, or offer supportive feedback when frustration is detected (Martínez-Prieto et al., 2025). By making motivation and emotion visible to instructors, AI has the potential to create more responsive classrooms that address not only cognitive needs but also affective dimensions of learning. However, these tools raise critical ethical issues. Privacy concerns loom large when systems track sensitive biometric or behavioral data. Moreover, the interpretation of signals is far from straightforward: a furrowed brow may reflect confusion, concentration, or disengagement, depending on context. Liu (2024) warns that misinterpretations could lead to harmful interventions, making instructor oversight and governance essential.

The integration of AI into assessment thus presents a double-edged sword. On the one hand, it enables continuous, personalized feedback that scaffolds learning and strengthens motivation. On the other hand, it raises pressing questions about accuracy, fairness, and data governance. To maximize benefits, educators must ensure that assessment systems are validated, context-sensitive, and guided by clear ethical frameworks. While measurement provides the scaffolding to adapt instruction, its ultimate value depends on how AI shapes actual learning outcomes and higher-order thinking. In this way, measurement becomes more than evaluation — it becomes an active partner in fostering motivation, supporting cognition, and preserving student autonomy. However, these systems must be governed carefully, particularly in how outcomes are interpreted (Liu, 2024).

Effects of AI on Learning Outcomes and Higher Order Thinking

The impact of AI on student performance and higher-order thinking is one of the most congested areas of current research. A recent meta-analysis of 51 studies reports a large positive average effect of ChatGPT on learning performance, with an age range from 18-42, that consisted of a wide range of uses, both personal and in the workplace, with moderate gains in both perceived learning and higher-order thinking skills (Wang & Fan, 2025). These effects, however, are not uniform. Stronger gains appear in contexts where AI is embedded into structured pedagogical models such as problem-based learning, where students are required to apply AI outputs in authentic problem-solving, and when use is sustained over several weeks rather than in one-off assignments. By contrast, short-term or unstructured use of AI often produces weaker effects, suggesting that benefits depend heavily on instructional design.

Complementary research by Lin and Chen (2024) illustrates this nuance. Their study of AI-integrated educational applications in secondary classrooms found that thoughtfully implemented tools enhanced creativity and fostered positive academic emotions, such as interest and enjoyment. Students using AI reported higher engagement in brainstorming and problem-solving tasks, with measurable improvements in creative outcomes. However, the same study also revealed a darker side: for some learners, reliance on AI increased anxiety and reduced enjoyment, especially when they felt they were no longer in control of the learning process. This aligns with Self-Determination Theory's emphasis on autonomy and competence. When AI enhanced feelings of capability, students flourished; when it undermined their sense of ownership, motivation and emotion suffered.

At the cognitive level, emerging evidence points to potential trade-offs. Kosmyna et al. (2025) combined EEG recordings with behavioral assessments in an essay-writing study, finding that extended reliance on ChatGPT led to what they termed "cognitive debt." Students who heavily leaned on AI exhibited reduced neural connectivity in regions linked to memory and executive control, weaker immediate recall of content, and lower perceived authorship when later asked to write without assistance. These results highlight a tension: AI may boost immediate task performance, but it risks reducing cognitive engagement in processes that support long-term learning.

Other findings echo this concern. Zheng et al. (2024) documented that over-reliance on AI dialogue systems can erode students' cognitive abilities, particularly critical reasoning and memory retention. Similarly, Keller et al. (2025) warned of "metacognitive laziness," where students adopt surface-level strategies when AI is available, avoiding the deeper reflection necessary for higher-order thinking. In contrast, Zhou et al. (2024) demonstrated that when AI is framed as a partner rather than a replacement providing scaffolds, explanations, and counterexamples it can encourage deeper elaboration and strengthen analytical reasoning.

These findings suggest, that this body of work suggests a guiding design principle: AI is most effective when used as a scaffold for learning within explicit instructional frameworks. For example, requiring students to generate explanations, practice retrieval, or apply AI suggestions to authentic tasks helps ensure that AI enhances rather than replaces cognitive effort. Embedding AI into structured, active learning models leverages its strengths while mitigating risks of dependency. Ultimately, the evidence supports a balanced approach: AI should augment, not substitute, the processes of reasoning, reflection, and creative problem-solving that define higher-order thinking.

Attention, Prediction, and Emotion as Mechanisms of Impact

Learning with AI unfolds in dynamic environments where attentional control, predictive processing, and emotional regulation shape outcomes as much as content delivery itself. Unlike traditional classroom settings, AI-based instructional systems continuously adjust pacing, salience, and challenge levels, creating conditions where cognitive mechanisms are either enhanced or undermined depending on design choices.

Attention is a particularly important mechanism. Experimental evidence shows that learners become more efficient at identifying targets that are likely to appear at specific times, a process known as temporal regularity learning. Williams et al. (2025) demonstrated that people not only anticipate when targets will appear but also exhibit greater susceptibility to feature-matched distractors and anticipatory motor tuning aligned with temporal expectations. This suggests that instructional systems can guide attentional allocation by controlling timing and salience cues. AI tools that direct attention toward relevant stimuli may reduce extraneous cognitive load, supporting deeper processing. However, if salience is poorly calibrated, such systems risk amplifying distraction, splitting attention across irrelevant cues, and ultimately undermining comprehension.

Prediction also plays a role in how AI influences learning. Predictive processing theories suggest that the brain constantly anticipates incoming information, minimizing effort when expectations align with outcomes. Well-designed AI systems can scaffold these predictive processes by introducing patterns that learners gradually internalize, creating efficiencies in how they process information. For example, adaptive tutoring platforms that pace material according to learner performance help align expectations with achievable challenges, sustaining engagement without overwhelming the student. Yet there is a danger in over-optimization. If predictive scaffolds remove too much uncertainty, learners may miss opportunities to grapple with desirable difficulties those productive challenges that strengthen memory and higher-order thinking (Wang & Fan, 2025). Thus, prediction mechanisms highlight the need to calibrate AI's support so that learners remain engaged in effortful processing rather than coasting on easy patterns.

Emotion is the third mechanism through which AI shapes learning. Advances in emotion quantification research have enabled systems to infer affective states from multimodal signals, including facial expressions, vocal tone, text sentiment, gestures, and physiological indicators (Liu, 2024). Appropriate use of these data streams can sustain motivation by detecting disengagement early, adjusting task difficulty, or offering encouragement when frustration arises. For example, systems that identify signs of boredom may increase task variety, while those detecting anxiety may reduce task load until confidence improves. Such responsive designs align with Self-Determination Theory, which emphasizes the need to support competence and autonomy for intrinsic motivation.

Yet emotion quantification also introduces risks. If misused, it can optimize for comfort over growth, removing the kinds of cognitive and emotional challenges that promote deeper learning. Overly “protective” AI may reduce exposure to dissonance, stunting conceptual change (Köpeczi-Bócz, 2025). Moreover, the surveillance implications of emotion detection are nontrivial: students aware of being monitored may alter their behavior, experience stress, or disengage entirely. This tension reflects the broader ethical paradox of AI in education: the same systems that can foster motivation and focus can also undermine autonomy and trust.

Together these results point to, attention, prediction, and emotion function as key mechanisms of AI’s educational impact. These findings rest on lab-based studies with limited ecological validity, which raises questions about how they generalize to real classrooms. They explain why AI can raise immediate performance without necessarily building durable understanding, particularly if the systems lower desirable difficulty too far. When calibrated well, AI can harness these mechanisms to create focused, engaged, and motivated learners. These mechanisms help explain why some outcomes are enhanced while others suffer, which brings memory integrity and ownership into sharper focus. When misapplied, it risks creating environments of distraction, over-comfort, or surveillance that erode both cognitive and motivational foundations for long-term learning.

Memory Integrity, Authenticity, and Ownership of Learning

Human memory is inherently malleable, and the integration of AI into educational environments magnifies this vulnerability. Pataranutaporn et al. (2025) demonstrated in a controlled experiment that AI-edited media can implant false recollections and even increase participants' confidence in those inaccuracies. The most striking effects occurred when static edits were animated into realistic videos, suggesting that the more vivid and convincing the stimulus, the stronger its ability to distort memory. While this study focused on manipulated media, the findings carry direct implications for educational contexts. If students repeatedly encounter AI-generated content that blends fact and fabrication, they may unknowingly encode false information as true.

Beyond factual accuracy, issues of ownership and authorship also arise. Kosmyna et al. (2025) found that students who relied heavily on AI writing assistants exhibited weaker immediate recall of their own essays, as well as reduced perceptions of authorship. Learners often reported feeling that the final product was not truly their own work. This diminished sense of ownership is critical: when students perceive learning outputs as externally generated, their motivation to engage deeply declines, and long-term retention weakens. Such outcomes align with concerns about "cognitive debt," where convenience-driven reliance on AI erodes the effortful encoding processes required for durable memory formation.

The 4E cognition framework helps explain why memory integrity is so susceptible in AI-supported environments. When learners extend their cognitive systems into tools, they risk shallow encoding if metacognitive control is weak. Carney (2020) argues that extension without reflection produces traces that are fragile or even misaligned with the learner's intended meaning. In practice, this means that AI may help students produce polished artifacts without ensuring that the underlying knowledge is personally encoded.

Educators can mitigate these risks through intentional design. Transparent media provenance, such as watermarking or metadata, can help students distinguish original from generated materials. Version control systems that preserve drafts can highlight the evolution of learners' own thinking, reinforcing ownership. Finally, retrieval practices asking students to reconstruct arguments or explanations without AI assistance, strengthens encoding and ensure that knowledge is not outsourced entirely to the tool. These safeguards preserve authenticity and align with pedagogical goals of building resilient memory and personal accountability in learning.

Synthesis and Open Questions

Across the literature, a consistent pattern emerges: AI can raise scores, accelerate feedback, and enhance perceived learning when thoughtfully embedded in pedagogy. At the same time, risks cluster in three areas. First, attention shaping that favors speed over depth weakens transfer and higher-order reasoning. Second, emotion adaptation without clear instructional goals may trade short-term comfort for long-term growth. Third, memory integrity is threatened by both manipulated media and over-reliance on AI-generated text, which undermine ownership and encoding.

These findings lead to several open questions. How much AI use is too much, what dose and schedule optimize durable learning rather than shortcutting it? What are the most effective ways to embed cognitive dissonance into AI-supported tasks to sustain motivation? How can emotion-sensing technologies be deployed in ways that foster engagement without creating surveillance cultures? And critically, how do learner characteristics such as self-efficacy, prior knowledge, and cultural context shape the balance of AI's benefits and harms?

From these gaps, testable hypotheses emerge. For example:

H1: Students who frequently rely on AI tools will report higher short-term efficiency but demonstrate lower long-term retention and critical thinking compared to students with limited reliance.

H2: Learners with higher academic self-efficacy will use AI more selectively and exhibit stronger motivation and performance outcomes than those with lower self-efficacy.

H3: Instructional designs that integrate AI with retrieval practice and self-explanation tasks will produce stronger long-term memory than designs emphasizing AI-generated outputs alone.

Future research must combine validated measures, transparent media controls, and authentic assessments that require planning, explanation, and transfer without tool outputs visible during evaluation (Sirilertmekasakul et al., 2023; Mora-Romo et al., 2025; Liu, 2024; Williams et al., 2025; Wang & Fan, 2025; Kosmyna et al., 2025; Pataranutaporn et al., 2025; Carney, 2020; Köpeczi-Bócz, 2025). These steps will ensure that AI serves as a scaffold rather than a substitute, empowering learners to grow as autonomous, motivated, and reflective thinkers.

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