

MIT Press • Open Encyclopedia of Cognitive Science

Active Learning

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MIT Press

Published on: Jun 17, 2026

DOI: <https://doi.org/10.21428/e2759450.703d687c>

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Active learning is the process by which learners actively seek, select, and organize information, shaping their own learning experiences rather than passively receiving information. It encompasses a wide range of behaviors, from making choices about what and how to learn to deciding which sources to consult, what questions to ask, and how to explore new environments, online or offline. Although it often involves information search, the defining feature is the learner's agency in making choices aimed at improving learning in terms of performance, competence, and understanding rather than merely making decisions. Using formal measures from information theory and computational psychology, contemporary research applies computational models like Bayesian frameworks to quantify the *efficiency* (informativeness of choices) and *effectiveness* (accuracy of outcomes) of active learning behaviors. These approaches make it possible to trace their development, capture individual differences and map them onto other cognitive or motivational factors, explore cross-cultural patterns, and measure gains from interventions.

History

The origins of active learning are deeply rooted in early 20th-century educational philosophy, particularly in the work of Maria [Montessori \(2008\)](#) and John [Dewey \(1916\)](#). Montessori's approach emphasized respect for the child's autonomy, hands-on engagement, and self-paced exploration within a carefully prepared environment, allowing children to choose activities and construct knowledge through direct experience. Dewey, in parallel, argued that education should center on "learning by doing," with students actively participating in problem-solving and reflection rather than passively absorbing information. Both Montessori and Dewey viewed learners as inherently curious and capable of directing their own development, laying the groundwork for modern emphases on agency and self-direction in education.

Building on these educational foundations, early constructivist theories in developmental psychology—most notably those of Jean [Piaget \(1952\)](#)—provided a psychological framework for understanding active learning. Piaget argued that children are not passive recipients of information but active explorers who construct knowledge through independent interaction with their environment. He theorized that learning is triggered by *cognitive disequilibrium*, a mismatch between expectations and observations that motivates children to seek new information, test hypotheses, and adapt their mental models. This perspective, later popularized as the "child as scientist" metaphor ([Gopnik et al., 1999](#)), inspired research showing that even very young children are systematic and purposeful in their information gathering and hypothesis testing (see [Bonawitz et al., 2012](#); [Gopnik et al., 2017](#); [Schulz & Bonawitz, 2007](#); [Stahl & Feigenson, 2015](#)).

As educational theory and developmental psychology evolved in parallel, the late 20th and early 21st centuries saw the emergence of more structured theories, formal models, and empirical research that bridged these traditions. Theories such as discovery learning ([Bruner, 1961](#)), inquiry-based learning, experiential learning ([Kolb, 1984](#)), and constructivism ([Steffe & Gale, 1995](#)) all advanced the idea that learning is most effective when learners are actively engaged in selecting, sequencing, and pacing their

experiences. Increasingly, these approaches have been supported by cognitive and developmental research as well as by advances in information theory, computational psychology, and machine learning. Theories such as George [Loewenstein's \(1994\)](#) “information gap” model formalized curiosity as a drive to close gaps in knowledge, providing a quantitative basis for understanding exploration and learning. Computational models—especially those based on Bayesian principles—enabled researchers to operationalize and measure the efficiency and effectiveness of active learning strategies by quantifying information gain and learning outcomes ([Gureckis & Markant, 2012](#); [Török et al., 2024](#)).

Most recently, ecological frameworks have emphasized that the efficiency of active learning strategies depends on the match between the learner’s characteristics, goals, and the structure of the environment ([Ruggeri, 2022](#)). This ecological active learning perspective highlights the multilayered adaptiveness of learners and has allowed researchers to capture the early emergence of active learning competencies, showing that even young children can flexibly tailor their strategies to context.

Core concepts

Agency, learner control, and choice

Active learning is fundamentally defined by the learner’s agency, the possibility and ability to direct and control the learning process by making choices about what, when, and how to learn. Control over learning—whether in selecting materials, setting goals, or pacing activities—distinguishes active learning from passive instruction and is linked to increased motivation, engagement, and improved outcomes ([Markant et al., 2016](#)). Empirical research using methods ranging from behavioral experimentation to eye tracking, computational modeling, and electroencephalogram studies has shown that even infants and young children are sensitive to the informativeness of different actions and environments ([Begus & Bonawitz, 2020](#); [Begus & Southgate, 2012](#); [Kidd et al., 2012](#); [Poli et al., 2020, 2024](#); [Ruggeri et al., 2024](#)) and that agency in learning—having control over choices—can enhance memory, task performance, cognitive engagement, and episodic memory across the lifespan ([Li et al., 2025](#); [Ruggeri et al., 2025](#); [Tullis & Benjamin, 2011](#); [Voss et al., 2011a, 2011b](#)). The mechanisms underlying these benefits are multifaceted, involving the formation of distinctive sensorimotor associations, goal-directed exploration, improved attentional coordination, adaptive selection of material, and metacognitive monitoring ([Markant et al., 2016](#)).

Motivation and curiosity

Motivation and curiosity are central drivers of active learning. Curiosity, often conceptualized as sensitivity to information gaps, motivates learners to seek out new information and experiences ([Loewenstein, 1994](#)). Both intrinsic motivation and the anticipation of resolving uncertainty enhance engagement and persistence, guiding learners toward opportunities for growth and deeper understanding ([Kidd & Hayden, 2015](#)) [see [Play](#)].

Exploration and hypothesis testing

Active learners engage in exploration and hypothesis testing, seeking out evidence and experimenting with different actions to reduce uncertainty. This process supports flexible problem solving and adaptive learning, with learners systematically generating and evaluating hypotheses about their environment ([Bonawitz et al., 2012](#); [Jirout & Klahr, 2012](#)) [see [Causal Learning](#); [Causal Reasoning](#)].

Constructivist knowledge building and computational models

Active learning has been fruitfully modeled in computational terms, formalizing it as a process of maximizing information gain. Bayesian frameworks conceptualize learners as agents who update their beliefs by integrating new evidence to reduce uncertainty, thereby constructing knowledge through probabilistic inference ([Tenenbaum et al., 2011](#)). This Bayesian approach builds on traditional constructivist ideas by providing a quantitative account of how learners select actions that optimize learning efficiency and effectiveness ([Török et al., 2024](#)). Computational models further explain how learners balance exploration and exploitation—guiding hypothesis testing and information search in a principled manner ([Markant & Gureckis, 2014](#)). Developmental studies highlight intriguing differences; unlike adults, children often rely less on generalization and more on directed exploration when searching for information or rewards ([Schulz et al., 2019](#)) [see [Bayesian Models of Cognition](#)].

Metacognition and self-regulation

Active learning involves metacognitive processes that enable learners to identify and monitor information gaps, guiding their decisions about what to learn next. This self-monitoring supports strategic allocation of cognitive resources and adaptive learning behaviors ([Metcalfe, 2009](#)). Such metacognitive monitoring enhances learning efficiency by focusing attention and effort on areas of greatest need, facilitating deeper understanding and retention ([Koriat, 2007](#)) [see [Metacognition](#); [Self](#)].

Adaptiveness and flexibility

A hallmark of active learning is adaptiveness; learners adjust their strategies in response to feedback, task demands, and environmental constraints ([Gigerenzer et al., 1999](#); [Simon, 1990](#)). This flexibility is essential for effective learning in complex, real-world situations and is central to ecological approaches to active learning ([Ruggeri, 2022](#)).

Questions, controversies, and new developments

Key open questions in active learning concern the developmental origins and mechanisms that allow learners—especially children—to flexibly adapt their strategies across environments. A central issue is how learners become increasingly efficient and adaptive: recognizing abstract structures, developing verbal competence, and learning when to stop exploring (see [Ruggeri, 2022](#)) [see [Cognitive Development](#)].

Motivation remains critical for understanding how individuals engage with learning. Elements such as intrinsic curiosity, the desire for autonomy, and control over choice shape engagement, persistence, and

exploration (see [Kidd & Hayden, 2015](#); [Loewenstein, 1994](#)). Yet, the dynamic interplay between motivational and cognitive processes—particularly how motivation influences exploration and learning outcomes—remains insufficiently understood [see [Affective Neuroscience](#)].

Another key question concerns how mechanisms such as directed exploration, generalization, and sensitivity to uncertainty develop across the lifespan. Researchers are investigating whether active learning follows a “cooling-off” process—early randomness giving way to focused, uncertainty-guided strategies—or whether it reflects a more direct shift toward efficient, goal-directed exploration (see [Schulz et al., 2019](#); [Török et al., 2024](#)) [see [Reinforcement Learning](#)].

Disentangling the roles of cognitive resources, prior knowledge, motivation, and environmental structure requires longitudinal, cross-cultural, and computational approaches to capture how learning operates across diverse contexts and populations (see [Ruggeri et al., 2024](#)) [see [Cognitive Variability](#)]. Ultimately, a major goal is to identify effective interventions that foster adaptive, lifelong active learning while clarifying how human strategies align with—or diverge from—those used by artificial intelligence systems ([Markant & Gureckis, 2014](#)) [see [Bayesian Models of Cognition](#)].

Broader connections

Rather than a topic bounded by any one field, active learning serves as a conceptual bridge—bringing together domains to reveal shared mechanisms of adaptive behavior and opening up new directions for understanding both natural and artificial intelligence [see [Cognitive Development](#)]. Active learning integrates perspectives and methods from cognitive science, artificial intelligence, biology, and education, offering a unifying lens on how agents—from insects to robots—engage with uncertainty to guide their own learning [see [Bayesian Models of Cognition](#); [Reinforcement Learning](#)]. In cognitive science, it connects with curiosity, metacognition, and self-directed exploration, revealing how learners tailor their behavior in response to evolving environments [see [Metacognition](#)]. These insights directly inform artificial intelligence systems that emulate human-like exploration and adaptive querying [see [Large Language Models](#)]. Biological research further enriches this picture, showing that the ability to actively select and refine learning strategies is evolutionarily conserved across species, from tool-using birds to problem-solving primates [see [Animal Cognition](#)]. In education, digital platforms have transformed learning into a more social, participatory process, amplifying opportunities for active engagement while also introducing challenges related to distraction and information quality [see [Attention](#); [Social Learning](#)]. Understanding how learners navigate and evaluate such environments requires insights from developmental psychology, attention research, and media studies [see [Cognitive Variability](#)].

Acknowledgements

Grammarly was used to check grammar and improve phrasing, and OpenAI’s ChatGPT (GPT-5.3) was used to assist with text trimming. All suggestions were carefully reviewed and revised by the author to ensure

that the final text reflected the author's original ideas.

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