

A Predictive Learning Engineering Framework for Modeling Active Learning

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Active Learning

learning engineering

predictive analytics

Active Learning has been consistently linked to improved learning outcomes, persistence, and equity, yet it remains difficult to operationalize in digital and large-scale learning environments. While theory emphasizes internal cognitive processes such as sense-making, reflection, and strategic adaptation, learning-at-scale systems primarily capture observable behaviors. This disconnect has led to analytic approaches that equate engagement with behavioral presence, limiting the ability of learning analytics to represent meaningful learning activity. We present a predictive learning engineering framework that models Active Learning as an emergent, theory-aligned construct inferred from large-scale learner interaction data. Grounded in experiential, constructivist, sociocultural, and metacognitive theory, the framework conceptualizes Active Learning as patterns of generative, evaluative, and adaptive engagement. Using a human-centered, heuristics-guided construct specification process, predictive modeling, and iterative validation, the framework supports actionable and scalable active learning analytics in authentic learning-at-scale environments.

Introduction

Active Learning has been consistently linked to improved learning outcomes, persistence, and equity across instructional contexts. Despite broad consensus on its importance, Active Learning remains challenging to operationalize in digital and large-scale learning environments. This disconnect has led to analytic approaches that equate engagement with behavioral presence rather than meaningful learning activity. As a result, many dashboards and early warning systems struggle to distinguish productive struggle from disengagement, or strategic persistence from superficial activity. Learning engineering provides an opportunity to address this gap by systematically integrating theory, data, and iterative validation to produce actionable representations of learning processes.

Theoretical and Pedagogical Foundations

Active Learning is conceptualized as an instructional and cognitive process in which learners engage through purposeful activity, reflection, and feedback to construct and apply knowledge. This view traces to Dewey's principle of learning through reflective experience rather than passive reception (Bot et al., 2005). Piaget's theory of cognitive development situates learning as the active construction of knowledge (Barrouillet, 2015), while Vygotsky's sociocultural theory emphasizes learning through social interaction and scaffolding within the Zone of Proximal Development (McLeod, 2012). Kolb's experiential learning cycle

further articulates learning as an iterative process of experience, reflection, conceptualization, and experimentation. Within higher-education contexts, these theoretical commitments translate into pedagogical practices that intentionally engage learners in cognitive and social activity.

Predictive Learning Engineering Framework

Human-Centered Learning Engineering Orientation

The Predictive Learning Engineering Framework is grounded in the view that learning engineering is fundamentally human-centered, emphasizing deep understanding of learners, contexts, and systems rather than purely technical optimization. Consistent with Thai et al. (2022), learning engineering is conceptualized as an integrative discipline that draws on user-centered design, learning experience design, human–systems integration, design thinking, and universal design for learning to ensure that educational innovations meaningfully serve diverse learners. From this perspective, predictive analytics are not treated as abstract performance estimators, but as learning engineering instruments embedded within a broader instructional ecosystem. The framework begins with understanding the instructional challenge, the learner populations being served, and the contexts in which learning occurs. Empathy with learners, including recognition of their prior knowledge, strategies, needs, and constraints, guides construct specification and indicator design. This human-centered orientation helps ensure that operationalizations of Active Learning are theoretically anchored in experiential, constructivist, sociocultural, and metacognitive perspectives, reflect authentic learner experience rather than narrow behavioral proxies, and remain grounded in observable behavioral and cognitive processes that can be quantified at scale using multimodal educational data.

Construct Specification, Modeling, and Predictive Validation

To operationalize this structure at scale, we introduce the Learning Engineering Institute’s Predictive Analytics Framework, which models Active Learning as it emerges from authentic Learning-at-Scale (L@S) data through three interrelated stages:

- (1) Construct specification and indicator design. Grounded in learning theory and human-centered learning engineering principles, this stage identifies the core cognitive and behavioral processes underlying Active Learning and maps each construct onto feasible indicators supported by ASU’s L@S data environment. Because learning-at-scale data are inherently noisy and context-dependent, analytic heuristics guide indicator selection by prioritizing purposeful learner action over passive exposure, emphasizing temporal patterns rather than isolated events, ensuring interpretability for instructors and designers, and accounting for learner variability to avoid deficit-oriented assumptions.
- (2) Data-driven modeling of Active Learning signals. Using L@S datasets, we apply predictive and behavioral modeling techniques appropriate to the structure and granularity of available data to represent how students engage with courses at scale. Models leverage interaction patterns, submission behaviors, attempt trajectories, and participation indicators to capture meaningful variation in student learning journeys through composite and temporally sensitive signals.
- (3) Predictive validation. Modeled indicators are evaluated for coherence, predictive utility, and generalizability across courses and learner subgroups. Treating prediction as a form of empirical validation, this stage assesses whether emergent behavioral patterns correspond to meaningful learning processes and outcomes beyond what is captured by basic engagement metrics.

This framework exemplifies a learning engineering approach (Schatz et al., 2022). Construct specification functions as a design phase grounded in cognitive theory and heuristic guidance; data-driven modeling serves as iterative prototyping using real learner traces; and predictive validation provides continuous evidence for refinement and generalizability. Through this

engineering cycle, the framework produces actionable, theory-aligned indicators of Active Learning that can inform analytics, guide instruction, and support equitable, system-level decision-making.

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