AT A GLANCE

Assessment of Process of Learning

How might we design assessment approaches to focus on students' process of learning related to the developmental goal?

University of Pittsburgh
Learning Sciences + Emergent Technologies Hub

The Problem Landscape

For decades, submitted products — the essay, the lab report, the graded quiz — served as the primary window into student learning, on the assumption that the product reflected the student's own cognitive work. GenAI has disrupted that traceability. A submission of work created outside of class can no longer be assumed to reflect the thinking of the student who submitted it, forcing a more deliberate reckoning with what a given assessment was actually measuring in the first place.

Why does this problem exist?

- GenAI can now produce plausible, coherent text on demand. This decouples learning product from learning process and raises a fundamental question: are current assessments measuring whether learning truly happened, or only whether a competent-looking artifact was produced?
- Some tasks that could always have been completed through surface-level recall are now also completable by a language model — making the question of whether a task was measuring its intended learning goal newly urgent.

What makes it hard to address?

- Faculty responses have been reactive and highly variable: some keep the status quo, some revert to supervised assessment approaches, some try to circumnavigate AI capabilities through novel tasks, some embrace AI use directly. Each strategy carries its own risks, and decisions shaped by individual experience rather than shared frameworks produce inconsistent results.
- Process-centered assessments (oral defenses, revision logs, staged checkpoints, field-based observation) are more time-intensive to design, administer, and grade fairly than single-submission formats. Institutional systems — learning management platforms, grade books, accreditation rubrics — are largely built around product submission.

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What does promising practice look like?

- Building process artifacts into assessment design — prompt histories, revision rationales, reflection logs, interaction records — creates evidence of the thinking behind the work, tied to specific learning experiences that belong to a particular student in a particular context.

- The key move is from discursive to structural redesign: rather than adding rules about AI use to an unchanged task, changing the mechanics of the task itself so the desired behavior is built in. A policy that says "do not use AI" is discursive. An assignment that requires embodied observation, real-time dialogue, or explaining thinking aloud is structural — the meaningful evidence of learning can only come from the student.
- Assessments that increase student perceptions of authenticity, meaningfulness, and value show promise for increasing engagement and driving deeper learning.

Example Approaches

The approaches below are design sketches synthesized from research and inspired by documented classroom practice. They are starting points to adapt, combine, or set aside. All share a common logic: shifting the evidentiary basis of assessment from the polished product to the learning process itself. All would require careful adaptation to educational context, purpose, and student developmental level.

Example 1: The Embodied Learning Scavenger Hunt

Setting: High school and college

The instructor identifies a course concept with a real-world physical referent students can encounter in person. Each student documents a specific site — a neighborhood, institution, or public space — through photographs, field notes, and brief descriptions, and creates two to four trivia questions connecting their in-person observations to the course concept. The class plays the scavenger hunt together and convenes for a structured discussion comparing direct observations against what the data, text, or model predicted. The evidence of learning lives in the documentation students created, the questions they posed, and the quality of their comparative reflection. Requires a course concept with a real-world referent; instructors should build flexibility for students who face logistical barriers to site visits.

Example 2: AI-Mediated Argument Cycle

Setting: High school and college

Students work through a three-phase sequence on a contested course question. In Phase 1 (AI-free), students independently write a thesis and supporting argument; this is submitted before Phase 2 begins, putting the student's prior reasoning on the record. In Phase 2 (AI-engaged), students prompt an LLM to generate counterarguments to their own position, annotate the output for logical strengths, unsupported claims, and potential bias, and write a short response explaining which counterarguments they find compelling and which they reject. In Phase 3 (AI-free), students revise their original argument and reframe the question from a perspective underrepresented in the AI's response. Assessment targets the quality of reasoning across all three phases — not the polish of the final product. The rubric rewards depth of critique, intellectual honesty, and the coherence of the student's evolving argument.

Example 3: Oral Learning Checkpoint

Setting: High school and college

After a major assignment is submitted, the instructor holds a brief, unscripted conversation with the student about their work and thinking — not a scripted Q&A, but a real exchange in which the assessor can follow threads, probe deeper, and ask for elaboration. This can be implemented at different levels of intensity: a lightweight 5–10 minute checkpoint tied to any major assignment; a two-part contextualized assessment combining professional identity questions with course-specific content; a full 15–20 minute interactive oral as a standalone or capstone assessment; or a scalable group discussion variation in which the instructor circulates and engages each student with 2–3 direct questions about their own preparation. Equity considerations deserve direct attention — particularly for students with anxiety, multilingual learners, and students with disabilities for whom oral formats may introduce barriers that do not reflect actual understanding.

This is a summary of the full Resource Packet. The full packet is available on request. The packet contains an expanded description of potential approaches, limitations and contextual considerations, research citations, and a tools & templates section.