ASCILITE 2026

The Future is Connection:

Collaboration, Creativity and Compassion in a Digital Society

How do we know students have learned? Rethinking evidence, assessment and assurance of learning in the Age of AI

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The rapid rise of artificial intelligence (AI) presents new challenges for educators striving to ensure learning can occur. Where higher education is making claims about graduate capability, we must ensure that our Assurance of Learning (AoL) architectures can support such claims. This symposium will introduce a systems-aware AoL architecture that aligns three interdependent layers: subject-level assessment design as evidence generation, program-level structures as mechanisms for longitudinal evidence integration, and institutional AoL frameworks as sites of interpretive judgement and capability claims. Through guided discussion the symposium will interrogate modes of learning, teaching and assessment that align with this model. We reframe AoL from a process of measurement and reporting to a system of evidencing. In doing so, it advances a future-focused agenda for institutional redesign, sector-wide reform, and research into evidence, inference, and capability in higher education environments where AI may now be fully embedded.

Keywords: assurance of learning, artificial intelligence, assessment, learning evidence

Background

The recent rise of artificial intelligence (AI) is fundamentally reshaping how knowledge is produced, applied and evidenced in higher education. As AI becomes increasingly embedded in learning, assessment and professional practice, long-held assumptions that assessment artefacts reliably represent individual learning are being challenged. Where there has always been vulnerability here, e.g., through contract cheating, AI has raised the spectre that all our non-invigilated tasks are at risk. Recent studies reveal that 88% of students use AI in their assessments (Rowsell, 2025), while 78% of educators feel underprepared to address this shift (Lee et al., 2024). Students are struggling with how to use AI without compromising learning and staff struggle to differentiate between student and AI generated writing (Murray & Tersigni, 2024). Universities are attempting to support both staff and students by introducing AI guidelines to add clarity around AI use, but it is unclear how effective these are. Where banning AI use is not plausible, detection is unreliable (Elkhatat et al., 2024) and learning may be compromised: How do we assure our students are learning?

This raises a critical question for higher education: if institutions claim that graduates have achieved capabilities, what evidence is sufficient to support those claims? We argue that this challenge extends beyond academic integrity or assessment redesign. It requires reconceptualisation of Assurance of Learning (AoL) as a systems-level architecture for generating, integrating and interpreting evidence of learning across subjects,

programs and institutions.

Until recent times, higher education systems have reasonably relied upon the relatively stable assumptions regarding the relationship between student performance, assessment artefacts, and capability. Assignments, examinations, portfolios, and performances have commonly been treated as sufficiently reliable indicators of individual learning, enabling institutions to aggregate results and make broader claims regarding graduate outcomes and educational quality. These assumptions underpin many contemporary AoL systems, where assessment evidence is sampled, mapped, aggregated, and translated into institutional claims regarding achievement of graduate attributes and standards. Institutional claims about learning therefore rely not merely on the existence of assessment artefacts, but on whether sufficient evidentiary justification exists to support those claims. As these claims are likely to be subject to regulations and laws this becomes paramount. We base the symposium on a three-layered model: (1) subject-level design, which generates observable and process-based evidence through structurally embedded integrity; (2) programmatic coherence, which integrates and triangulates longitudinal evidence (Schuwirth & van der Vleuten, 2011; van der Vleuten et al., 2012); and (3) institutional learning assurance architecture, which formalises the interpretive argument linking cumulative evidence to claims of graduate capability (Corbin et al., 2025).

The objective of this symposium is to stimulate in depth discussion around how we may be able to assure learning. Symposium speakers will discuss different perspectives on this, and the audience will discuss options and pose questions back to the speakers framed by the proposed model.

Symposium Plan

Discussions: (18 mins: 3 minutes per speaker)

Manisha Thakkar – Model of institutional/pedagogical approaches to AI
Jessica Marrington – Empirical results
Danielle Logan-Fleming – Process or Product and the role of oral tasks
Edward Palmer – Classroom approaches
Yali Chen – Student perspectives
Kerry Russo – Institution perspectives and exams

Symposium discussion activity (32 minutes including Q&A)

This will involve small group discussions within the audience, contemplating the proposed model and short presentations from the authors and identifying strengths and weaknesses in the approaches. Online interactive tools will be used to support discussion and aid dissemination of thoughts, which will be shared with all attendees.

Wrap-up (5 minutes)

What did you learn? How do we know?

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