Minds at School: Advancing cognitive science by measuring and modeling human learning *in situ*

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Introduction

Unlike in other animals that might reach full maturity within a few months or years, human cognitive development follows an unusually protracted timeline. In many contemporary societies, people might require several years of scaffolded learning opportunities to develop the full suite of cognitive skills and abilities they are expected to have as adults. This extended period of development reflects our species' unique capacity for cumulative cultural learning: humans have evolved specialized cognitive mechanisms that enable us to learn from, communicate with, and teach others across the lifespan (Csibra & Gergely, 2009; Tomasello, 2016).

Schools are one of the most iconic and impactful manifestations of this cultural transmission of knowledge. While access to education is now nearly universal, its benefits remain unevenly distributed (Darling-Hammond, 2001). Many students, especially in under-resourced communities, do not develop essential competencies (Bachman et al., 2015; Rittle-Johnson et al., 2024). Thus there remains a critical need to develop educational experiences that are both effective and well adapted to a wide range of learning conditions.

Traditional approaches to studying learning in cognitive psychology have focused on controlled laboratory tasks over short timescales. This strategy offers certain practical advantages, including the ability to formulate theories in terms of relatively simple cognitive models that are testable in small samples. However, this approach offers limited predictive value when challenged to account for the dynamics of human learning in complex and varied real-world contexts over longer timescales.

Recent methodological advances offer promising solutions to these challenges. New digital learning infrastructure enables longitudinal tracking of authentic learning behaviors in larger and more diverse populations of learners, thus providing stronger experimental tests of any given hypothesis (Stigler et al., 2020; Motz et al., 2024). At the same time, advances in machine learning have potential to enable formulation of mechanistic theories of learning that account for more complex interactions between sources of variation across individuals and groups. These developments can jointly advance scientific understanding of human cognition while improving teaching and learning (Bassen et al., 2020). This symposium will convene researchers at the forefront of these efforts to share insights from their own work, and perspectives on opportunities and challenges that lie ahead.

Judith Fan & Kristine Zheng (Moderators): What's in it for cognitive science?

Why should cognitive scientists care about what happens at school? Of course, one reason is social responsibility: cognitive scientists should translate our understanding about how human learning works to make schools work better, for the benefit of society. But in these opening remarks, we will primarily emphasize the benefits for cognitive science. We will outline several ways that studying human learning in situ— in authentic educational settings — could offer payoffs for advancing fundamental understanding of how the mind works. In particular, research conducted in schools, particularly by using student-facing educational technologies, compels us to use more diverse samples, more complex stimuli, longer timescales, and new measures of behavior and performance. These allow us to advance theory beyond what could be achieved in the lab.

Ji Y. Son: The Better Book Approach: Understanding and improving complex learning through collaborative improvement science

The Better Book approach (Stigler et al., 2020) integrates measurement and experimentation directly into student-facing educational materials, enabling cross-disciplinary teams to advance scientific understanding of complex learning while producing actionable insights that drive iterative improvements. CourseKata, a technology platform implementing the Better Book approach, features interactive introductory statistics textbooks used at over 100 institutions. Data from diverse students reveals how

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understanding of introductory statistics unfolds over weeks or months, under realistic learning conditions. For example, data collected through CourseKata shows how psychological constructs such as growth mindset predict both long-term learning outcomes and day-to-day engagement (Sutter et al., in preparation). A separate line of investigation on students' struggles with abstract notation revealed that symbols are more meaningful when grounded in data visualizations (Zhang et al., 2024), an approach particularly impactful for racially marginalized students (Sutter et al., 2024).

Ben Motz: Casting a wider net and building more robust theory with ManyClasses

The core feature of the ManyClasses approach is the execution of many independent replications of an experiment in parallel across diverse classes (de Leeuw et al., 2022; Fyfe et al., 2021). A ManyClasses study examines the same experimental contrast in dozens of courses, spanning learning materials and student populations. In doing so, we address both "What works?" and "For whom and in what contexts?" For example, the second ManyClasses study (Motz et al., preprint) examined the benefits of prequestions across 30 different classes, finding that the effect is moderated by prior knowledge and that more difficult prequestions cause disengagement. By outlining the boundary conditions of learning strategies in practice, the ManyClasses model enables cognitive scientists to build more robust and practically relevant theories.

Candace Thille: Two decades of leveraging digital infrastructure to advance scientific understanding of human cognition and improve the way people teach and learn.

The Open Learning Initiative (OLI) began in 2002 at Carnegie Mellon University to develop web-based learning environments grounded in cognitive science principles. OLI collected learner interaction data, used knowledge modeling algorithms to estimate learner states, and provided feedback to learners, instructors, and course designers. Learning theory informed the first version of each OLI course, with subsequent versions refined based on empirical data. The 2004 Pittsburgh Science of Learning Center used OLI courses as research environments combining classroom field studies' realism with laboratory studies' rigor. This talk will discuss the continuation and expansion of that approach over two decades and highlight current work leveraging generative AI.

Shayan Doroudi: Reviving the interdisciplinary study of learning in humans and machines

In cognitive science's early days, human cognition and artificial intelligence were studied alongside efforts to understand and improve education. AI-based theories provided insights on real-world learning (Carley, 1986) and educational technologies (Anderson et al., 1995; Papert, 1980), while observations of children informed AI theories (Minsky, 1988). This mode of thinking has declined as methods have diverged. While large-scale educational technologies and modern machine learning methods offer new opportunities for studying learning *in situ*, I focus on another entry point: AI theories and computational models rooted in cognitive science. I will discuss how agent-based models can be used to study learning dynamics (Rismanchian & Doroudi, 2023) and how theoretical machine learning frameworks offer novel insights into human learning (Doroudi & Rastegar, 2023).

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