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Designing for Complexity at Scale: Danielle McNamara on Learning Engineering and AI's Real Role in Education

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"Learning engineering does not center on a theory. It does not ever involve one theory. It's always centered on a challenge or a problem." — Danielle McNamara

"Improvement in post-secondary education will require converting teaching from a solo sport to a community-based research activity." — Herb Simon

Introduction

Over the past several years, this column series has explored artificial intelligence (AI) from multiple vantage points, including historical, cultural, ethical, creative, and pedagogical. In conversations with scholars across a range of disciplines, we have examined generative AI as an ecological force, creative collaborator, rhetorical technology, mirror, amplifier, and sometimes distorter of human intention (Mishra et al., 2024a, b). Across these discussions, a central concern has been whether we are asking the right questions about AI in education.

Much of the public conversation, both enthusiastic and alarmist, has centered on what AI can do. Can it be a tutor? Can it write? Can it personalize learning? Can it scale teaching? These are important questions, but they miss a step. These questions reflect how new technologies tend to impress us with their capabilities, before we even consider the context. As Neil Postman (1998) noted decades ago, technologies do not simply add tools to existing systems; they reshape the systems themselves. If this is true (and history suggests it is), then perhaps the more urgent question is not what AI *can* do—but rather, what problems are we trying to solve? Here, the field of learning engineering enters the conversation.

In this article, we speak with Dr. Danielle McNamara, Executive Director of the *Learning Engineering Institute* and Professor of Psychology at *Arizona State University*. Dr. McNamara's work sits at the intersection of cognitive science, linguistics, educational technology, and systems design. She is widely recognized for her pioneering work on intelligent tutoring systems and discourse comprehension, and for decades, has built technologies designed to improve reading, writing, and learning outcomes at scale. Yet, what makes her voice particularly important in this AI moment is not simply her technical expertise. It is her insistence on reframing the conversation.

Learning engineering, as McNamara describes it, does not begin with a theory, and it does not ask how we might test or refine an explanatory learning model. Instead, it begins with a challenge that asks us: what real-world learning problem are we trying to solve? What combination of disciplines, data, design, infrastructure, and importantly, technology, might help address it?

This shift may sound subtle, but its consequences are profound. Fields such as cognitive science and the learning sciences have long sought to understand how people learn, developing models of memory, comprehension, motivation, and transfer (Bransford et al., 2000). Their efforts have generated important insights and theoretical clarity. However, learning engineering operates differently. It is fundamentally

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problem-centered and embraces the complexities of authentic learning environments, like classrooms, online platforms, and institutional systems, and seeks to design solutions within those complexities. This act of embracing messiness, and aiming to design solutions from it, is also inherently creative.

Throughout this series, we have argued that creativity is not confined to the arts, nor reducible to flashes of individual genius (Henriksen et al., 2014). It is often found at the boundaries where disciplines intersect, where problems resist simple answers, and where integration becomes essential to understanding (Edwards, 2011). Learning engineering connects directly to this kind of transdisciplinary creativity in how it brings together linguists, cognitive psychologists, computer scientists, data engineers, faculty, administrators, and students to design better learning experiences.

Rather than asking whether AI can replace teachers or function as a "magic tutor," learning engineering asks what constraints currently shape learning, and whether technology meaningfully addresses those constraints. If the central barrier to personalized learning is not algorithmic sophistication but the time-bound structure of semesters and credentials, then building ever-smarter tutors may miss the point entirely.

As follows, we explore McNamara's articulation of learning engineering, her work on building data infrastructure for learning at scale, her critique of the "personalized tutor" narrative, and her vision of AI as an orchestrator that connects learners across time, space, and disciplines. Her reflections invite us to reconsider what counts as creativity and innovation in education. Perhaps the most transformative moves will not come from increasingly autonomous machines, but from reimagining systems within which learning occurs.

An Interdisciplinary Evolution

To understand learning engineering, we begin not with a definition, but with a trajectory.

McNamara's intellectual path does not read like a conventional disciplinary progression. Her early academic life moved through linguistics, language teaching, clinical psychology, and experimental cognitive psychology. Although she began her undergraduate studies planning to follow her family into psychology (both her parents were clinical psychologists), she discovered linguistics while learning French. Over time, she began to integrate her interests: teaching English as a second language in France for five years; earning a master's in clinical psychology (discovering, in the process, that it was not an ideal fit for her); and then finding her calling in cognitive and experimental psychology. She noted that she had not necessarily moved between fields, as she had connected ideas across knowledge and experiences, saying, "I never switched, I integrated. Learning engineering is inherently transdisciplinary, and the development of this interdisciplinary mindset not only comes from working with others, but also how I evolved as a human being."

That phrasing is more than autobiographical, but also philosophical, signaling how ideas develop and a trajectory unfolds when disciplines are connected. This reflects the ways in which creativity often *feels* serendipitous, and ideas often *seem* to emerge in "ah ha" moments—yet research suggests that these moments are the result of a quietly unfolding process, where one connection leads to another and another (Kim, 2019). Such cross-pollination of ideas becomes possible when a person has many interests and experiences to draw upon and sees them as connected (Gilson & Litchfield, 2017).

McNamara found her current scholarly path through what felt like an "ah ha" moment, remarking on how she "discovered cognitive psychology and experimental psychology by accident. And I thought, oh my gosh, they pay you…to play games with people, and to answer questions. That's what you get to do, with questions that you're interested in." In retrospect, the field of linguistics sharpened her sensitivity to discourse and comprehension; experimental psychology provided methodological rigor; technology opened up possibilities for building systems to scale those insights. As the pieces accumulated and connected, it strengthened her background.

This integrative stance resonates with the concept of transdisciplinary creativity. Creativity is not simply novelty within a domain; it frequently emerges at the boundaries between domains, where ideas must be translated, reframed, and recombined (Henriksen, 2018). Learning engineering, as Dr. McNamara practices it, sits precisely at such intersections, requiring familiarity with theory, design, infrastructure, institutional constraints, human variability, and collaboration all at once. As McNamara emphasized, her career has been grounded in "collaborative interdisciplinary group work" focused on improving learning. Much of her research has been federally funded, particularly through the Institute of Education Sciences, and she noted the responsibility that accompanies that support as "my obligation and responsibility to write about what I'm doing. You don't get money from the federal government and then end up not sharing those results."

This ethic of openness extends beyond publishing her work. Technologies developed in her lab have been freely shared with educators, and data infrastructures are designed with dissemination in mind. The goal, as she put it, is not simply output, but communication about "what's working, what's not working, so that others don't keep recreating the same wheel."

Again, the creative dimension in learning engineering is subtle but significant. Creative systems, whether artistic, scientific, or educational, rarely emerge in isolation. They arise from networks, sustained iteration, and collective refinement (Sawyer, 2012). Learning engineering depends on precisely this kind of distributed expertise (Edwards, 2011), in bringing together diverse individuals not to defend disciplinary turf, but to address shared challenges.

Thus, McNamara's statement that she "integrated" rather than switched becomes emblematic of the field itself. Learning engineering is not a narrow specialization, but an orientation toward complexity. It assumes that learning problems do not fit neatly within a single theoretical frame but demand synthesis. This integrative stance is increasingly significant as AI becomes embedded within educational environments. If AI is to be more than a novelty or a shortcut, it should be understood within broader systems of language, cognition, design, equity, and institutional structure that shape learning. Integration is not incidental, but foundational.

Defining Learning Engineering: A Challenge-Centered Approach

While McNamara's intellectual journey helps us understand the origins of learning engineering, her articulation of the field's core distinction clarifies its significance. She situates the field of learning engineering alongside related traditions such as cognitive science and the learning sciences. Cognitive science, she explained, is an interdisciplinary field focused on understanding how humans think: how we solve problems, remember information, and process experiences. The learning sciences similarly aims to understand how people learn across contexts and developmental stages, often developing and testing theoretical models of learning processes. Learning engineering, however, she argues, begins somewhere else. As McNamara put it:

> Notice that cognitive science and the learning sciences are centered on a question to explain a phenomenon. You want to explain how it works. Learning engineering does not center on a theory, and it does not ever involve one theory. It's always centered on a challenge or a problem.

That distinction may appear small at first glance, but it reframes the enterprise entirely. Rather than asking how learning works to refine theory, learning engineering asks how we might address a concrete learning challenge in the real world. The goal is not explanatory clarity but solving a practical problem. For example, research in discourse comprehension might investigate how text cohesion affects understanding. Learning engineering might ask a different question: How do we address the problem of first-year students entering college unable to meaningfully engage with academic texts? That problem cannot be solved by discourse theory alone. It may require attention to motivation, belongingness, institutional policies, financial pressures, course design, and technological affordances, among other influences.

This orientation toward problem-solving echoes distinctions long drawn between science and engineering. Herbert Simon (1996), often credited for developing design as a field of inquiry, famously described the sciences as concerned with what *is*, while engineering is concerned with *what ought to be* constructed. Design, in Simon's (1969) formulation, is about devising courses of action aimed at changing existing situations into preferred ones, and learning engineering operates squarely within this design-oriented tradition. It is less about isolating variables under controlled conditions and more about iteratively building and refining interventions within complex systems.

Importantly, this does not imply a rejection of rigor. McNamara was clear that learning engineering relies on evidence, experimentation, and systematic comparison. "You would still do pre-test, post-test," she noted. "Data are fundamental because learning is messy. You need strong evidence, multiple data sources, and careful planning for the comparisons you will make."

The difference lies not in abandoning experimental logic, but in situating it within iterative cycles of design and implementation. This aligns with traditions of design-based research (Brown, 1992), where theory and practice inform one another through repeated refinement in authentic settings. Yet, learning engineering extends this orientation toward larger infrastructures and institutional systems.

The embrace of "messiness" is particularly significant in its divergence from traditional experimental paradigms that often aim to minimize contextual variability to isolate causal mechanisms (Berliner, 2002). Learning engineering, by contrast, assumes that variability is inherent to learning environments. Students differ in prior knowledge, goals, identities, and constraints. Institutions differ in policies, schedules, and resources. Technology interacts with all of these factors in dynamic ways.

In this sense, learning engineering embodies a creative stance toward complexity. Creativity research has long suggested that innovation often arises when individuals or teams engage with ill-defined problems that resist straightforward solutions (Runco & Jaeger, 2012). Ill-structured challenges demand synthesis, iteration, and flexibility. By centering challenges rather than theories, learning engineering accepts that educational problems are rarely tidy. They are layered, systemic, and deeply human.

This shift from theory-centered to challenge-centered inquiry is particularly relevant in the current AI-centered landscape. Many AI applications in education are built around demonstrating capability, for instance, showing that a model can generate explanations, answer questions, or simulate tutoring behaviors (Liu et al., 2025). Learning engineering asks instead: What specific learning constraint are we addressing? Is time the barrier or motivation? Is it inequitable access? And does technological intervention meaningfully engage that constraint? By reframing the conversation in this way, learning engineering invites us to move beyond fascination with tools and toward a clearer articulation of purpose.

Building Infrastructure: Learning at Scale

If learning engineering begins with a challenge, it must also confront the realities of scale. Educational problems do not unfold in tidy laboratory settings. They emerge across institutions, platforms, policies, and populations that are large, heterogeneous, and constantly shifting. Addressing such challenges requires more than an elegant intervention. It requires infrastructure.

For McNamara, this realization led to a pivotal move. In 2021, rather than waiting for external digital platforms to open their data to researchers, she asked a more ambitious question: "I decided to ask ASU if they wanted to become an open digital learning platform for researchers." The reasoning, she explained, was foundational: "A data infrastructure is the foundation for a tutoring system. If I'm going to build an intelligent tutoring system, I need that infrastructure. I was envisioning ASU as a very large tutoring system where we could explore what works."

That reframing is striking. Rather than building a standalone AI tutor and inserting it into existing systems, she imagined the university itself as a learning system that could be studied, understood, and iteratively improved. This move reflects the learning engineering stance we discussed earlier: begin with the challenge, and design within the complexity rather than outside of it.

At an institution serving over 180,000 students across modalities, the scope of this effort is significant. Learning@Scale, as the initiative became known, brings together demographic data, longitudinal performance records, course characteristics, Canvas interaction logs, discussion boards, and assignments into an integrated structure. But integration, as it turns out, is rarely straightforward. As McNamara described the process:

> One step toward this was developing a data warehouse to bring everything together. But you can imagine the challenges. There might be 10 versions of a name or five entries for gender, all pulled from different sources — Salesforce and other systems. Much of that data simply isn't suitable for inclusion in Learning@Scale.

What appears initially as "data" quickly reveals itself as a sociotechnical puzzle. Different systems encode information differently. Identifiers do not align. Language data introduces additional ethical complexity. The work of infrastructure building is as much about governance, privacy, and coherence as it is about analytics.

Perhaps the most telling moment came when McNamara reflected on timeline expectations. "I thought I could get it done in six months," she said, with a pause that carried its own meaning. "So, three years later…" She went on to describe the painstaking work of the project:

> We have a procedure for de-identifying discussion boards and taking out names, etc. And one thing we did was to create a static database, one that can be eventually released to the public so that they can have learning scientists and linguists be able to do studies to better understand language and learning within those platforms.

This reflects more than a technical aside, but something central to the philosophy of learning engineering. Infrastructure is not glamorous—it is iterative, slow, and often invisible. Yet without it, high-quality, large-scale inquiry becomes impossible. Small experimental studies can demonstrate mechanisms, but they cannot reveal patterns that emerge only across tens of thousands of learners interacting with real systems over time.

This kind of infrastructure also reframes what we mean by "intelligent" systems. Intelligence, in this view, does not reside solely in a model generating responses. It emerges from the interplay between data pipelines, institutional design, privacy protections, and human interpretation. Sociotechnical research has long emphasized that technologies are embedded within networks of policy, power, and practice rather than operating independently (Sovacool & Hess, 2017). Learning@Scale makes this embedding explicit.

Importantly, McNamara does not see this work as surveillance or optimization for its own sake. The purpose of building such a system is to ask better questions. Which students are struggling and when? How do different course structures shape engagement? What patterns emerge across disciplines or modalities? Infrastructure enables those inquiries, but it does not predetermine the answers.

Thus, building infrastructure requires imagining new ways of seeing learning, designing systems that make those perspectives visible, and accepting that the process will be slower and more complex than anticipated. The six-month timeline becoming three years is evidence of what it means to design within real systems.

As AI tools become more tightly woven into educational environments, this groundwork becomes more consequential. Without robust infrastructure, AI can start to operate as a layer on top of opaque systems. With the right infrastructure, however, there is potential for principled, evidence-informed integration. McNamara remains cautious about what AI should aspire to become, reframing the issue to focus on not if we can build intelligent tutors at scale, but whether the structure of formal education constrains what such tutors could meaningfully accomplish.

Questioning the "Magic Tutor" Narrative

As conversations about AI in education accelerate, one vision tends to dominate public imagination: the personalized tutor. From Bloom's (1984) "two-sigma problem" to contemporary large language models capable of generating tailored explanations, the dream of one-to-one instruction at scale has long been framed as a kind of educational holy grail (Beale, 2025).

For her part, McNamara does not reject personalization. In fact, she affirms it quite directly. "I do fundamentally believe that learning should be personalized," she told us. "You need something very different for this goal or that goal, for your goal, than I do." The assumption that learners differ in needs, motivations, and trajectories is not controversial. What she questions, however, is whether current educational structures allow meaningful personalization.

Her concern is less about the technical sophistication of AI systems and more about the temporal logic of schooling itself. As she put it:

> The real obstacle to a "magic tutor" and truly personalized learning is time. Our system is currently organized around fixed terms and semesters, where a student is expected to learn all of calculus in seven weeks, regardless of prior knowledge.

This observation shifts the focus away from algorithmic capability and toward institutional constraint. Even the most advanced adaptive system must operate within the fixed boundaries of semesters, credit hours, and seat-time expectations. Students who need more time are rarely granted it. Students who could move more quickly are often held back. The structure is calibrated to an imagined "average" learner, even as personalization rhetoric suggests otherwise.

This tension is not new, as educational scholars have long critiqued the Carnegie Unit and time-based credentialing for prioritizing duration over demonstrated competence (Silva et al., 2015). While competency-based education movements have tried to address this imbalance, most institutions are still anchored to semester rhythms. Within the constraints of such systems, personalization often becomes superficial, adjusting content or pacing while leaving underlying constraints intact.

McNamara pointed to a troubling implication of this structure. For instance, a student may spend years engaged in coursework, developing skills and knowledge, yet leave without a credential if they do not complete the prescribed sequence. "A student who has been completing these courses can walk away in their third year with nothing. With absolutely nothing," she observed. Therefore, the problem is not necessarily a lack of learning, but a lack of recognition. This point complicates the promise of AI tutors because if the primary barrier to personalization is structural time rather than insufficient feedback, then increasingly capable tutoring agents may address only part of the problem. In this sense, the constraint could be less about pedagogy than the system itself.

At the same time, McNamara highlighted another paradox within AI enabled personalization, where many adaptive tools assume a level of subject matter understanding that novices simply do not possess. "It's a paradox," she explained. "You get a new learning technology, which is 'adaptive' and 'personalized,' and all those fancy words. But to drive it properly, you already need to know what you're doing in the subject that you're trying to learn." Her observation is also supported by emerging research on AI literacy and domain expertise (McCaleb et al., 2025). Such tools can amplify the thinking of knowledgeable users, yet they may mislead those without sufficient grounding to evaluate outputs (Rudolph et al., 2023). Personalization, in this context, risks becoming stratified, disproportionately benefiting those already advantaged.

Taken together, these observations suggest that the "magic tutor" narrative may oversimplify the challenge. AI can generate explanations, scaffold problems, and simulate dialogue, yet without structural flexibility and foundational knowledge, such capabilities may only partially address deeper inequities. For McNamara, the question is not whether AI can tutor. It is whether tutoring, as currently imagined, is the most generative role for AI within educational systems. If time-bound credentials and institutional logics constrain personalization, then perhaps the opportunity lies elsewhere. It is at this juncture that her vision of AI as orchestrator begins to take shape.

AI as Orchestrator: Rethinking What Technology Is For

If AI is not best understood as a "magic tutor," then what might its most generative role be?

For McNamara, the answer lies not in replacing teachers or simulating one-to-one instruction, but in orchestrating richer forms of social learning. She was explicit about this distinction. "I don't actually believe that we need personalized tutors as defined," she told us. Instead, she described what she sees as a more promising direction, saying, "The wonderful role of AI that I envision is as an orchestrator of these experiences of knowing. So, for example, orchestrating social experiences." This shift in metaphor is pivotal in that a tutor implies dyadic interaction: one learner, one guide; while an orchestrator implies coordination across many actors, roles, and perspectives. The image is less about substitution and more about arrangement.

McNamara pointed to the Oxford tutorial model as an example of deeply engaging, dialogic learning. Small groups of students working closely with faculty, engaging in sustained conversation, and building understanding through interaction. “This is how people learn,” she observed. The challenge, however, is scale. That kind of experience is resource-intensive and historically reserved for a small segment of learners. “We cannot serve all of the people who need to learn at home, at midnight, in different countries,” she said. Refugees, working adults, single parents, first-generation students, and in fact, most contemporary learners, do not fit the traditional residential model, yet they still benefit from dialogue, collaboration, and community.

Here, “AI as orchestrator” becomes compelling. Rather than delivering isolated content to individuals sitting alone in kitchens or dorm rooms, AI could help coordinate connections across time zones, disciplines, and levels of expertise. McNamara offered a vivid example:

> What if a physics student were working on a question that also connects to music, where physics and mathematics are deeply embedded? Students from different perspectives could collaborate on a shared project, with AI helping to coordinate their work across time, space, disciplines, and levels of understanding.

This vision reframes personalization as connection rather than isolation. Instead of tailoring content narrowly to individual pathways, AI might help surface complementary perspectives, align collaborative projects, and scaffold group inquiry. In creativity research, such cross-disciplinary encounters are often where new ideas emerge, as innovation frequently arises when diverse forms of expertise intersect and challenge one another (Sawyer & Henriksen, 2024).

Importantly, this is not an argument for technological determinism. McNamara does not imagine AI spontaneously generating meaningful communities. Orchestration still demands human intentionality, pedagogical design, and institutional support. However, AI may lower the coordination costs, making certain forms of distributed collaboration more feasible.

This orchestration metaphor also aligns with long-standing sociocultural theories of learning. Knowledge is not merely transmitted; it is co-constructed through interaction (Vygotsky, 1978; Wenger, 1998). If learning is fundamentally social, then the goal of technology should not be to bypass that social dimension, but to amplify and structure it in productive ways. Seen in this light, AI becomes less a substitute for teachers and more a facilitator of networks. It might identify shared interests across courses, surface students wrestling with similar conceptual challenges, or support dialogue across disciplines. It might help educators coordinate projects that extend beyond the boundaries of a single classroom. These possibilities do not eliminate human judgment but seek to extend it.

This also brings us back to creativity and the fact that creativity is often relational and contextual, emerging within communities of practice rather than in isolation (Sawyer, 2012). If AI is designed primarily to optimize individual performance metrics, it is likely to limit and narrow creative possibilities. However, if it is designed to orchestrate collaboration and cross-pollination, it has the potential to expand them.

Such a shift requires rethinking what counts as educational success. Is the goal efficiency and speed, or is it depth and connection? Is it individual mastery in a fixed timeframe, or collective problem-solving across flexible boundaries? AI as orchestrator pushes us toward the latter questions.

And yet, even this more expansive vision must contend with structural realities. Institutions are governed by credentialing systems, assessment regimes, and accountability pressures that shape what is possible. As McNamara reminded us earlier, time remains a stubborn constraint.

If AI is to function as an orchestrator of learning rather than a superficial personalization engine, it must be embedded within systems willing to value collaboration, process, and distributed expertise. Without such shifts, orchestration risks being layered atop unchanged structures. The promise, then, lies not in intelligence alone, but in alignment between technological capability and institutional imagination.

Systemic Constraints, Power, and the Limits of Technology

McNamara’s vision of AI as an orchestrator of learning is expansive, but it is not naïve. Throughout our conversation, she returned to a simple but often overlooked reality: educational technologies do not operate in a vacuum. They are embedded within systems of credentialing, governance, and power that shape what learning is recognized, valued, and rewarded. Any serious conversation about AI in education must contend with those systems rather than imagining technology as a workaround.

One of the most persistent constraints, in her view, is the way credentials function as invisible boundaries on educational imagination. When students are asked to rethink higher education, even in speculative exercises, they often struggle to move beyond familiar structures—exhibiting perhaps a kind of ‘functional fixedness’ (McCaffrey, 2012). As McNamara observed, “Students’ inability to imagine alternatives is striking. It always comes back to: how do you get the paper?” Here, the degree rather than the learning becomes the organizing principle, and learning which does not neatly culminate in a recognized endpoint often goes unacknowledged. The issue, then, is not whether learning occurred, but whether the system has a way to value it.

These questions become even more consequential as AI systems grow more powerful. McNamara was clear that her concerns are less about the technology itself than about where power resides. “AI has no power unless somebody is running it,” she reminded us. The risks thus emerge not from intelligence in the abstract, but from who controls systems, whose values are encoded, and whose interests are prioritized. This is why she is careful about the lane in which she works, emphasizing institutional responsibility, data governance, and education as a public good.

Conclusion

Taken together, Dr. McNamara’s perspective brings us back to the central theme of learning engineering. It does not promise clean solutions, a single theory, or a universal tool. Instead, it asks us to seriously engage with the systems within which learning happens and to design within their constraints while remaining attentive to their limits. AI, in this framing, is neither simply a savior or a threat. Its value depends entirely on how thoughtfully it is used and embedded in education contexts.

Throughout this series, we have argued that technological change reshapes not just practices, but values. Learning engineering offers a way to navigate that reshaping with intention, shifting the conversation from what AI can do to what education ought to become, foregrounding challenges rather than capabilities, systems rather than tools, and integration rather than optimization. In a moment saturated with hype and fear, that reframing feels not only refreshing, but necessary.

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