



Neuroscience-Informed Theory and Strategies for AI-Enhanced Classrooms

Larry Wigger

University of Missouri – Kansas City

Artificial intelligence now sits at the center of both work and learning, challenging educators to strengthen, not surrender, human cognition. This article links economic change, cognitive neuroscience, and educational pedagogy to show how critical thinking becomes the decisive learning outcome in an AI age. Drawing from research on memory, feedback, and reinforcement, the author outlines how knowledge is built, not merely accessed. These principles are then applied in redesigning an undergraduate analytics course using an AI platform to individualize student challenge and feedback. The result is a model for teaching that uses AI to cultivate reasoning, adaptability, and ethical awareness.

Industrial organization and labor economics together illuminate how technological progress reshapes both work and cognition. The same forces that automate production also risk automating thought, widening gaps between technical proficiency and genuine understanding. To confront that tension, this article integrates economic theory's macro-level view of labor and institutional adjustments with micro-level insights into cognitive neuroscience. The former explains *why* critical thinking is now a survival skill in the labor market; the latter explains *how* such thinking develops through deliberate practice, memory reinforcement, and feedback loops. Bridging these disciplines, I examine my own application of these principles in an undergraduate analytics course redesigned around an artificial intelligence (AI) educational platform. There, the economic imperatives of re-skilling and the neuroscience of learning converge, demonstrating how structured, feedback-rich technology can cultivate the critical faculties essential to a human-centered AI collaboration.

Capturing the public's attention, OpenAI launched ChatGPT on November 30, 2022, and it has already evolved to ChatGPT-4 and beyond. Strong competition has since been fielded by Google, Baidu, Meta, and others. Common commercial uses already extend beyond large language models (LLMs) and large multimodal models (LMMs), with image generators and video processors, such as Midjourney and DALL-E, now beyond their third iteration. This algorithmic world of AI is the quintessential example of exponential change. According to Acemoglu and Johnson (2023), "A thousand years of history and contemporary evidence make one thing abundantly clear: there is nothing automatic about new technologies bringing widespread prosperity"

(p. 13). AI/automation trends suggest greater reliance on technology and automation relative to human labor, further de-skilling of labor, and increasing inequality in society (Wigger, 2024, 2025a). As Acemoglu and Johnson (2023) argue in *Power and Progress*, technological change often fails to deliver broad prosperity unless steered by inclusive institutions:

AI will continue to struggle with context and risk. And therein lies a clear role for humanity, as AI still requires humans to describe and recognize good ideas. (pp. 207-210)

This dehumanization of labor, combined with the growing concentration of private capital, also suggests a continued decline in the democratic coordination of work (Acemoglu & Johnson, 2023). And the exponential acceleration of technological change entails new ethical dilemmas. When humans encounter novel ethical dilemmas, they process them through their moral frameworks, perhaps tempered by the institutions involved. But an autonomous system cannot act ethically, because it is merely obeying its architects and managers. Sheffi (2023) states,

The pace of change raises questions about any curriculum designed to only impart specific facts. While shared knowledge binds societies—and technical knowledge will be required—it is the ability to continue to learn, think critically, and collaborate effectively that will be required in the technology-infused future societies. (p. 288)

Navigating work and society increasingly requires strong critical-thinking skills (Acemoglu & Johnson, 2023). This argument builds on earlier work outlining

AI's dehumanizing tendencies and the ethical imperative of cultivating critical reasoning as a counterbalance (Wigger, 2025a). Yet our educational models have tended to de-emphasize the foundational knowledge training and practice that critical thinking requires. We can leverage AI to provide students with individual development plans (IDP), one-to-one coaching/tutoring, immediate feedback, and cognitive challenges at the optimal level.

AI's Disruption of Work, Knowledge, and Learning

The proximate-ultimate distinction in social behavior analysis is useful when considering potential AI impacts on labor. Institutions must anticipate and adjust to both proximate and ultimate challenges, risks, and opportunities introduced by AI. Proximally, organizations must equip workers to engage AI ethically, minimizing negative externalities. The lack of moral agency in autonomous systems suggests that human ability to contextualize is key to expedient decisions and ethical judgments in novel proximate dilemmas. Regarding potentially lethal autonomous systems, "who's making the decision that will one day affect billions of people on our planet? And who's involved in that judgment process?" are unanswered questions that should terrify us (Metz, 2021, p. 244). Ultimately, stakeholder leadership must thoughtfully consider developing such technologies. The design and construction of autonomous systems, though capital intensive, scales readily, at a lower incremental cost, and potentially to the benefit of society (Wigger, 2024, 2025b).

As we increasingly embrace AI in our daily lives, we must continue to question who has trained these technologies and using what data were used. "Human beings do not enter the world as competent moral agents," according to Wallach and Allen (2009), "genes, development, and learning all contribute to the process of becoming a decent human being" (p. 99). Turing (1950) suggested that "instead of trying to produce a program to simulate the adult mind, why not rather try to produce one which simulates the child's? If this were then subjected to an appropriate course of education, one would obtain the adult brain" (p. 456). Seventy years later, we've surpassed Turing's suggestion that we train child-like programs to arrive at adult brains; adversarial machine learning networks now train themselves.

Humanity has a mere 200 years of photographic historical record, 130 years of film, and 70 years of television broadcasts. As Metz (2021) says, "Truthfulness, particularly when it comes to political questions, is very much in the eye of the beholder . . . many people would say that the technologists who built it were biased, and they would complain the data used to train it was biased and they just wouldn't accept it" (p. 260). Even with so brief an exposure to recorded media, many people seem to have lost the innate ability to reason critically

and determine credibility or even to recognize the need to develop these skills through education.

On their list of 12 skills deemed important to the top 20 in-demand jobs, the U.S. Government Accountability Office has included active learning, active listening, complex problem solving, critical thinking, and judgment/decision making (U.S. Government Accountability Office, 2022). Harvard Business Review and Accenture have identified five principles critical for AI and human collaboration, including reimagining business processes, embracing experimentation and employee involvement, actively directing AI strategy, responsibly collecting data, and redesigning work to include AI (Wilson & Daugherty, 2018). This human ability to contextualize is key to expediting decision trees and arriving at ethical judgments.

If society is to survive these challenges, we need to revisit our educational strategies. We must engender flexibility and adaptability in our students; now more than ever, the only thing constant will be change (Wigger, 2025b). We should recall from Charles Darwin that it is usually not the strongest or smartest, but the most responsive and adaptable, who thrives. Tomorrow's knowledge workforce will draw from three distinct categories: youth, who will need foundational skills to enter the workplace; existing workers, who will need ongoing re/up-skilling, with an estimated 40% needing just six months or less to contribute; and displaced workers, who will need substantial re-training. These three distinct categories of workers will require multiple approaches to educate and train, including updated degree programs, mid-length certifications, and on-demand learning (World Economic Forum, 2020).

Saenz et al. (2020) identify four capabilities that are critical for AI and human collaboration: interoperability for exchanging information, control, decisions, and feedback; authority balance, with clearly defined sequences and priorities in decision-making processes and rights; transparency in timely data on conditions for decisions, rationale, outcomes, and reliability; and mutual learning, with feedback loops to train AI and for humans to learn and trust.

Pedagogical Implications of Contemporary Neuroscience

Memory, Retrieval, and the Foundations of Learning

Meeting these societal and educational goals will benefit by leveraging Benjamin Bloom's combination of one-on-one tutoring with mastery techniques. Both Bloom's philosophy and B. F. Skinner's theories on operant conditioning are largely aligned with modern neuroscience, which shows that deliberate practice and timely, targeted feedback strengthen neural pathways. Bloom's taxonomy (Bloom, 1984) suggests a rigid hierarchy of cognitive skills, while, in reality, the brain operates through highly interconnected systems. Advanced

thinking, analysis, synthesis, and creativity emerge not from isolated faculties but from richly woven networks of knowledge and experience. Similarly, Bloom's division of learning into cognitive, affective, and psychomotor domains was, by his own admission, pedagogically useful but somewhat arbitrary/artificial. Neuroscience confirms that these dimensions are deeply intertwined. Emotion and cognition work in tandem to shape attention, reasoning, and memory.

While Bloom's tutoring research highlighted the extraordinary potential of personalized instruction, achieving such results requires elusive alignment of active retrieval, adaptive pacing, emotional engagement and feedback loops that are challenging to implement consistently, even in one-on-one settings. In a similar foundational contribution, Skinner (1954) argued that learning occurs through systematic reinforcement and immediate feedback (operant conditioning). Skinner's theories remain impactful and relevant today as they continue to inspire reinforcement learning techniques in AI, where algorithms improve through reward-based signals. Yet Skinner treated the mind as a "black box," focusing exclusively on observable behaviors while dismissing internal cognitive processes as irrelevant. Ironically, the very mechanisms Skinner disregarded are now recognized by neuroscience as central to how learning occurs and deep understanding develops (Oakley et al., 2025).

Existing research highlights that overreliance on AI during early learning stages can disrupt the natural development of procedural fluency and intuitive expertise. Effective collaboration between humans and AI, instead, requires learners, first, to cultivate the robust internal cognitive frameworks that empower them to critically assess and effectively utilize AI-generated results. Habitually relying on external searches rather than internalizing knowledge leads to superficial cognitive frameworks, constraining deep comprehension and the ability to transfer insights across contexts. Even amid abundant external information, true understanding remains fundamentally anchored in well-developed internal knowledge structures. Deeply internalized foundational knowledge is critical for synthesis and creative thought. Excessive dependence on external memory may produce accurate answers, but without the cohesive understanding and fluid mastery that distinguishes genuine expertise. Cognitive neuroscience underscores the necessity of actively training, rather than merely informing, during learning. Continuously outsourcing cognitive tasks risks cultivating only superficial competence (Oakley et al., 2025).

Recent studies in learning and memory caution that excessive dependence on external tools can impair the formation of deeper understanding. Compounding this challenge are certain pedagogical methods that are commonly employed alongside technology, especially heutagogical student-centered models where learners are expected to uncover key insights independently.

Instructors frequently interpret these approaches as discouraging formal guidance, corrections, and structured explanations. But explicit instruction, characterized by clear, structured explanations and deliberately scaffolded practice, remains indispensable when learners confront challenging new concepts. Humans readily acquire some skills, like language and facial recognition, through natural interactions. But mastering critical academic disciplines, including reading, mathematics, and science, typically necessitates explicit instruction and intentional practice (Sweller, 2008). Our cognitive architecture isn't inherently equipped to effortlessly assimilate these academic skills and concepts; instead, it requires deliberate training and repeated practice to solidify understanding. Excessively relying on external cognitive aids disrupts this crucial internalization process, ultimately resulting in superficial mental frameworks that undermine the deeper thinking and creative problem-solving capacities essential in complex tasks.

Knowledge versus skill is a false dichotomy, because the critical-thinking skills we seek to develop are built on a strong memory foundation. While embracing intelligent technologies and the vast information they provide, we must still actively cultivate our innate capacities for memory and sustained attention. By maintaining this critical balance, we avoid the false choice between having quick, flexible cognitive abilities and retaining deep, extensive knowledge: "In a world where we can look up almost everything, the ironic truth is that the knowledge we carry inside our heads is more valuable than ever" (Oakley et al., 2025, p. 4).

Actively recalling information involves more than mere access; it dynamically strengthens the underlying neural connections by stimulating the complete neural network associated with that memory. This active engagement not only fortifies those memory connections but also fosters integration with other concepts, far surpassing passive rereading or superficial review as an effective learning strategy (Wamsley, 2019). Through repeated retrieval and consistent practice, information that initially requires conscious effort gradually becomes embedded, making it intuitive and effortlessly accessible. From there, these memories become flexible, able to transfer knowledge across contexts and recombine familiar facts in novel configurations. This adaptability is the foundation for higher-order reasoning and sophisticated problem solving. When learners rely too heavily on technology aids, they risk short-circuiting the essential process by which knowledge becomes intuitive, never fully embedding the skills and understanding needed for fluency.

Cognitive Load, Prediction Error, and Productive Challenge

When humans encounter an unexpected situation, we react biologically with surprise that something is amiss. Perhaps you encounter a friend in an unexpect-

ed setting or a technology device does not operate as you expected. We call such dopamine- and norepinephrine-triggering reactions cognitive disequilibrium (Piaget, 1952). This lends support to Skinner's emphasis on reinforcement and timely feedback as core mechanisms in the learning process (Oakley et al., 2025). Just as positive reinforcement can strengthen desired behaviors, negative experiences also exert a powerful influence, often teaching lasting lessons through a single adverse event that conditions us to steer clear of repeating the same mistake. Neuroscience recognizes this sense of surprise at our experienced reality versus our expectation as a prediction error. Our highly effective error-detection systems rely on well-formed internal expectations, which are cultivated through memorization and repeated practice. A student who mastered multiplication tables in childhood has built a reliable mental framework that anticipates correct answers with ease. When a wrong answer appears, their brain instantly flags the inconsistency, triggering a cognitive alert that not only prompts correction but reinforces the learning process itself. Thus, internalized knowledge forms the mental scaffolding our brains rely on to swiftly detect and learn from errors.

Prediction errors serve a dual function, not only guiding us in correcting mistakes, but also helping focus our attention on what matters most in various contexts, reinforcing the development of adaptable mental frameworks. Each prediction error becomes a catalyst for deeper cognitive growth (Bein & Niv, 2025). And when excessive information is presented or is too heavily offloaded to external aids, it overwhelms working memory, disrupting a learner's ability to form meaningful associations and hindering the development of durable mental frameworks (Cowan, 2014). This common breakdown illustrates why externally stored knowledge, when not internalized, often falls short in our attempts to understand novel or complex situations and solve challenging problems. Without an existing framework to organize and simplify new information, our brains must handle each new challenge from square one, without the full benefit of our prior experiences. But if we instead develop a robust framework through memorization and practice, our brains will more readily predict the world around us and be receptive to prediction errors when they occur (Becker & Cabeza, 2024).

Neuroscience points to an optimal challenge threshold for effective learning, suggesting that learning is maximized when students perform at roughly 85% accuracy during practice. Often referred to as the "Eighty-Five Percent Rule," this principle aligns closely with Vygotsky's "zone of proximal development," the point where cognitive tasks are neither trivial nor overwhelming but instead calibrated to promote steady growth (Wilson et al., 2019). By maintaining this balance, educators can foster the formation and reinforcement of neural connections, building resilient cognitive frame-

works while avoiding the pitfalls of cognitive overload.

Technology, Cognitive Offloading, and the Risks of AI Over-Reliance

Proximate and ultimate considerations converged in education with the emergence of electronic calculators in the 1970s. This was followed by personal computers and the Internet in the 1980s and 1990s, which allowed for unprecedented levels of cognitive offloading. As a result, many educators began discouraging the memorization of facts that could be easily retrieved or computed externally, shifting the focus to "higher-order" thinking skills. Such arguments often gain traction, because research suggests that sustained, intentional thinking can feel uncomfortable or undesirable for many individuals (David et al., 2024). Unfortunately, this trend reflects a recurring pattern in education. Methods perceived as more abstract or intellectual, such as teaching "critical-thinking skills," are often valued above seemingly basic practices like memorization, regardless of their actual cognitive underpinnings or effectiveness. The move away from memorization was also shaped by the ongoing status struggles of colleges of education within the academic hierarchy. Often viewed as less rigorous, lacking direct authority over subject matter, post-secondary education sought to bolster its legitimacy by adopting seemingly sophisticated pedagogies. Progressive approaches that emphasized student-centered learning and higher-order thinking, rather than direct knowledge transmission, offered a way of distancing the field from its vocational training roots (Labaree, 2006).

This concern that critical thinking cannot function in the absence of domain knowledge is not new. A wide base of factual knowledge is what enables the effective application of skills, countering the false dichotomy between knowledge and skills. Without this background knowledge, students lack the ability to evaluate sources or even judge the plausibility of information. As E. D. Hirsch noted, "de-emphasizing factual knowledge actually hinders children from learning" (Hirsch, 2000, p. 5). Novices don't know what they don't know; without stored knowledge, they lack the scaffolding to ask meaningful questions or search for information effectively. Further empirical research reinforces this point. In a well-known study, children asked to look up unfamiliar words often produced nonsensical sentences because they misread definitions without the necessary vocabulary context, while the process of looking up words itself created cognitive overload (Miller & Gildea, 1987). Teaching the words in a meaningful context would have been far more effective. Thus, external resources are useful only to those who already possess a strong internal foundation of knowledge.

Unfortunately, these trends in education don't stop there but extend into society at large. Population-wide

IQ scores offer a compelling lens on how memory practices and broader cognitive habits influence intellectual development. For much of the 20th century, IQ scores rose consistently, a pattern known as the Flynn Effect, with major studies documenting gains of roughly three points per decade (Pietschnig & Voracek, 2015; Trahan et al., 2014). These IQ improvements were widely attributed to education, healthcare, nutrition, and increased social supports. Yet beginning with cohorts born after the mid-1970s, researchers identified a surprising reversal, particularly in developed economies. Studies revealed declines of up to seven points per generation in Norway, with similar downward trends showing in Britain, Denmark, France, and the Netherlands (Bratsberg & Rogeberg, 2018; Dutton et al., 2016; Teasdale & Owen, 2008).

Meanwhile, developing nations continue to see IQ gains as education and living standards improve. Perhaps most striking is that the IQ drop even appears within families, where younger siblings score lower than their older siblings, discounting simple demographic and/or genetic explanations. Researchers increasingly suspect that shifts in educational practices, technology use, and cognitive offloading may be driving this unexpected downturn. This research linking early heavy dependence on technology with weakened analytical reasoning underscores the need to “exercise” our cognitive “muscles” even as we leverage technological aids (Barr et al., 2015). To reverse this societal decline and build on past gains, we must renew emphasis on memory training, recognizing that the way we cultivate young minds shapes the collective intellectual capacity of society.

Overdependence on external tools risks eroding the internal mental frameworks that underpin deep thinking. Healthy learning requires balance, leveraging external aids as complements rather than substitutes for the rich, internalized knowledge that forms the foundation of genuine understanding (Fernando et al., 2024). When thoughtfully integrated, technology can enhance learning, offering rich feedback, varied examples, and opportunities for exploration. Yet when technology is used as a shortcut to bypass mental effort, it risks stunting cognitive growth and fostering mental complacency. Excessive reliance on external technology can strip away the lasting impact of discovery, hinder the development of fluid skills and intuition, and interrupt the mental formation necessary for efficient/critical thinking. If we continually offload too much mental work, we will increasingly fail to recognize blind spots in our own knowledge.

Toward a Neuroscience-Informed AI Pedagogy

Aside from the nuances of how we learn and how we should teach, it’s not a stretch to conceptualize AI-assisted IDPs:

More than four decades ago, Isaac Asimov noted the problem of our current system of education: “Today, what people call learning is forced on you. Everyone is forced to learn the same thing on the same day at the same speed in class. But everyone is different. For some, class goes too fast, for some too slow, for some in the wrong direction.” When Asimov wrote these words, his proposal for personalized teaching was purely aspirational. (Acemoglu & Johnson, 2023, p. 328)

Today, thanks to AI, such individualized teaching is entirely within our grasp.

While AI-driven educational tools hold much promise for one-to-one tutoring, immediate feedback, and individual development plans, emerging research highlights an ironic challenge. Because these systems are trained on existing instructional content, they often replicate the very pedagogical biases we now recognize as problematic. AI lesson-planning tools frequently favor minimally guided methods with few opportunities for deliberate knowledge-building or practice, the same approaches that neuroscience suggests undermine the development of strong cognitive schemas (Chen et al., 2025). This creates a troubling feedback loop where AI models absorb constructivist-influenced materials and, in turn, produce content that perpetuates such methods, all while presenting them as current/relevant. We need to critically assess not only how we deploy educational technologies, but also the pedagogical assumptions embedded within the tools themselves (Oakley et al., 2025).

The power of AI-driven educational tools and early empirical evidence on their use suggests they are worth the effort. AI has the potential to enhance, rather than erode, educational outcomes when thoughtfully implemented. A 2024 study in Ghana demonstrated that students using an AI-powered math tutor on WhatsApp for just one hour per week achieved significant gains in math performance compared to a control group (Henkel et al., 2024). This AI tool emphasized scaffolded practice and strategic hints rather than simply providing answers, encouraging active problem solving rather than passive consumption. Such evidence underscores that technology, when aligned with improved neuroscientific understanding of natural learning mechanisms, can deepen understanding instead of hindering it. The goal is not to reject technology or revert to rote drills, but to use tools in ways that complement human cognition. The “Eighty-Five Percent Rule” offers a guiding principle of finding the challenge level that stretches students without overwhelming them. Tools like calculators and AI that bypass this foundation risk undermining higher-level learning. Similarly, the well-intentioned push for “desirable difficulty” (Wilson et al., 2019) has, at times, overstepped, frustrating students and impeding the formation of coherent mental frameworks.

Our ultimate aim should be deep learning by ensuring that students actively engage their own memory and reasoning, working within that optimal zone where tasks are challenging but attainable. When designed and implemented thoughtfully, AI tools can augment resource-strained educators in doing just that.

Learners should be encouraged to attempt solutions and wrestle with problems independently before seeking assistance, keeping in mind the optimal success rate of roughly 85%. Productive struggle activates the brain's natural learning processes, yet excessive difficulty can disrupt the formation of strong cognitive frameworks. In practical terms, this calls for careful timing of instructional support; instructors should resist the urge to provide immediate answers while also avoiding leaving students adrift with tasks well beyond their current skill level. By fostering persistence while ensuring frequent moments of success, instructors help students build both confidence and effective cognitive frameworks. Technology should be deliberately integrated as a supplement rather than a replacement for thinking. When employing AI tutors or search tools, their use should be structured to keep students cognitively engaged, such as leveraging AI for hints or verification rather than generating complete answers. Research indicates that learning outcomes improve when AI operates under guided conditions, such as posing questions or prompting reflection, rather than functioning as a passive source for solutions (Oakley et al., 2025).

Early Pedagogical Application of AI

I have long been a proponent of student-led heuristical learning, seeking to activate latent curiosity through my courses. But the rapid growth of AI use in my students' future workplaces, coupled with a noticeable decline in their critical-thinking skills, has led me to revisit the pedagogies I use and more intentionally explore educational use of technology. In this article I've provided evidence of both the enduring need for critical-thinking skills and the neuroscience for how we lay the foundation for those skills. In my course syllabi, I frequently quote Seneca's *docendo discimus* "By teaching, we learn." I do so to emphasize my logic in assigning weekly student group presentations, where they teach each other the week's material, followed by active discussion. And at this interesting nexus of technology and society, perhaps we as educators need to embrace that philosophy ourselves, teaching the very things we are still actively learning, in this case, including the responsible integration of AI into our daily lives and work.

To this end, I utilized an AI platform in spring 2025 for an undergrad elective course. We are in the midst of an explosion in AI educational tools on top of an already robust technology landscape. The particular course I in question, DSOM 346: Service Sector Analytics, had presented me with multiple challenges, including

exponential growth in enrollment, an analytic subject in an online asynchronous modality, stale video lecture content, my desire for greater differentiation between my various courses, and the university requirement to renew its five-year online quality certification. Figure 1 illustrates steady growth across semesters, with a notable increase in recent years to 50 students in spring 2025. This upward trend suggests growing student interest in the subject of analytics, but it also may somewhat validate the appeal of the innovative teaching methods piloted in this course.

Given the plethora of tools available, rebuilding an online course with alternate technologies could be daunting. However, I opted to utilize new edutech start-up Edvisor.ai for a holistic solution for content creation of immersive/searchable text and weekly podcasts, coaching/tutoring, discussion moderation, and grading/assessment. With minimal guidance from me, followed by iterative feedback, Edvisor.ai generated fully immersive readings on my subject matter and friendly, dynamic podcasts to introduce each weekly module. Students' listening and reading were followed by Edvisor.ai-generated quizzes, discussion forums, and case studies for deeper individual reflection. Each of these three assessments was layered with AI hints to maintain the desired 85% difficulty level, without disclosing full answers, and each was graded immediately with comments for timely, reinforcing feedback.

According to Edvisor.ai, of the students in their spring 2025 launch courses, 77% agree or strongly agree that "Edvisor.ai improved my learning," and 56% agree or strongly agree that "My grades likely improved." Additionally, 49% of students rated "Instant feedback" as their top valued feature, and 65% were willing to refer Edvisor.ai to another professor. Interestingly, only 33% of students claimed to use other AI tools, mainly ChatGPT. Qualitative sentiments ranked highly included "Ease of use/UI" (user interface), "Instant feedback/auto-grader," and "Learning improvement." Figure 2 highlights a consistent trend of strong university student evaluations for DSOM 346, with scores largely remaining in the upper 4.0 range on a 5-point scale. However, the data suggests the need to monitor pedagogical enhancements, including the integration of Edvisor.ai, which, in the pilot offering, reduced perceived instructional quality from the prior year. This rating should not be allowed to trend down.

Figure 3 compares DSOM 346 students' grades against the relevant instructor's average across all courses. While grades for DSOM 346 generally align with or slightly trail the broader average, the upward trend toward the mid-90s highlights improved student outcomes, likely tied to active engagement and targeted feedback strategies.

Figure 4 tracks performance across four benchmark exams, all consistently achieving high percentages (mid-80s to 90s). The data indicates not only student

Figure 1
10-Year Enrollment Trend

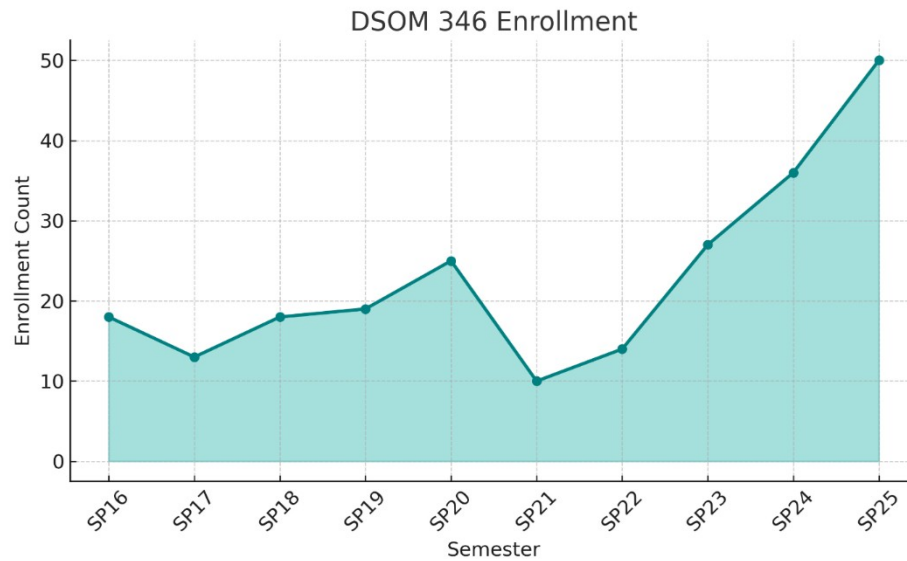
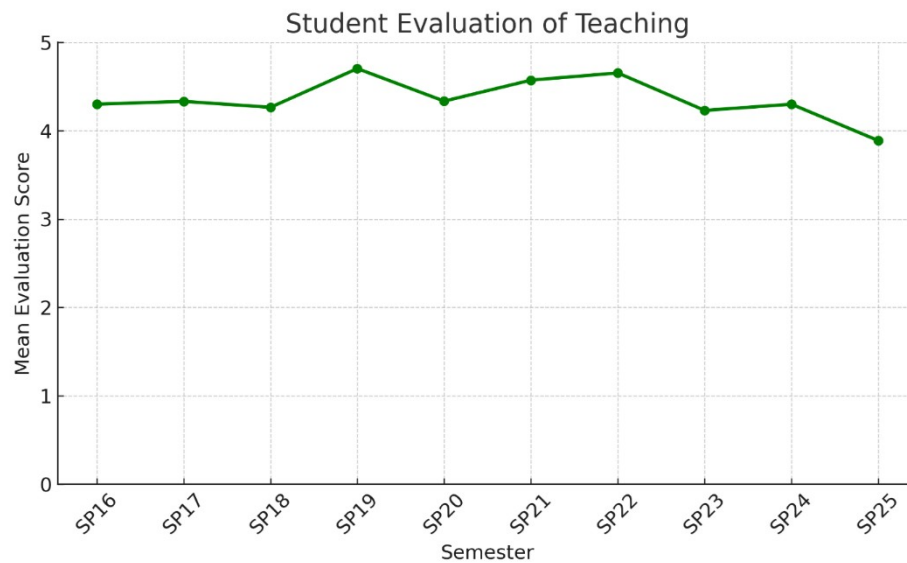


Figure 2
10-Year Quality Metric



mastery of course concepts but also the effectiveness of structured practice and AI-supported scaffolding to reinforce foundational skills. No persistent trends have developed across the most recent four years of online asynchronous modality or the transition from traditional textbook and publisher's platform to the new Edvisor.ai model. Utilizing consistent benchmark exams in the

university's LMS independent of the Edvisor.ai platform, has allowed me to calibrate pedagogical difficulty while tracking student outcomes across changes in pedagogy, modality, LMS, and content. It ensures my students are not penalized by my real-time pedagogical trials, as I am able to adjust grades when benchmark exams clearly show a student learning outcome has not been

Figure 3
10-Year Student Outcomes

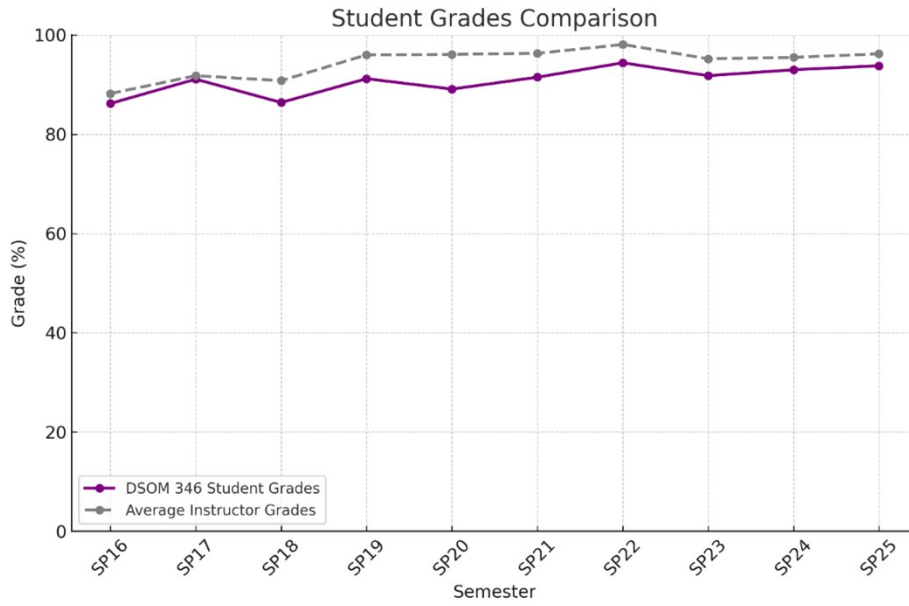
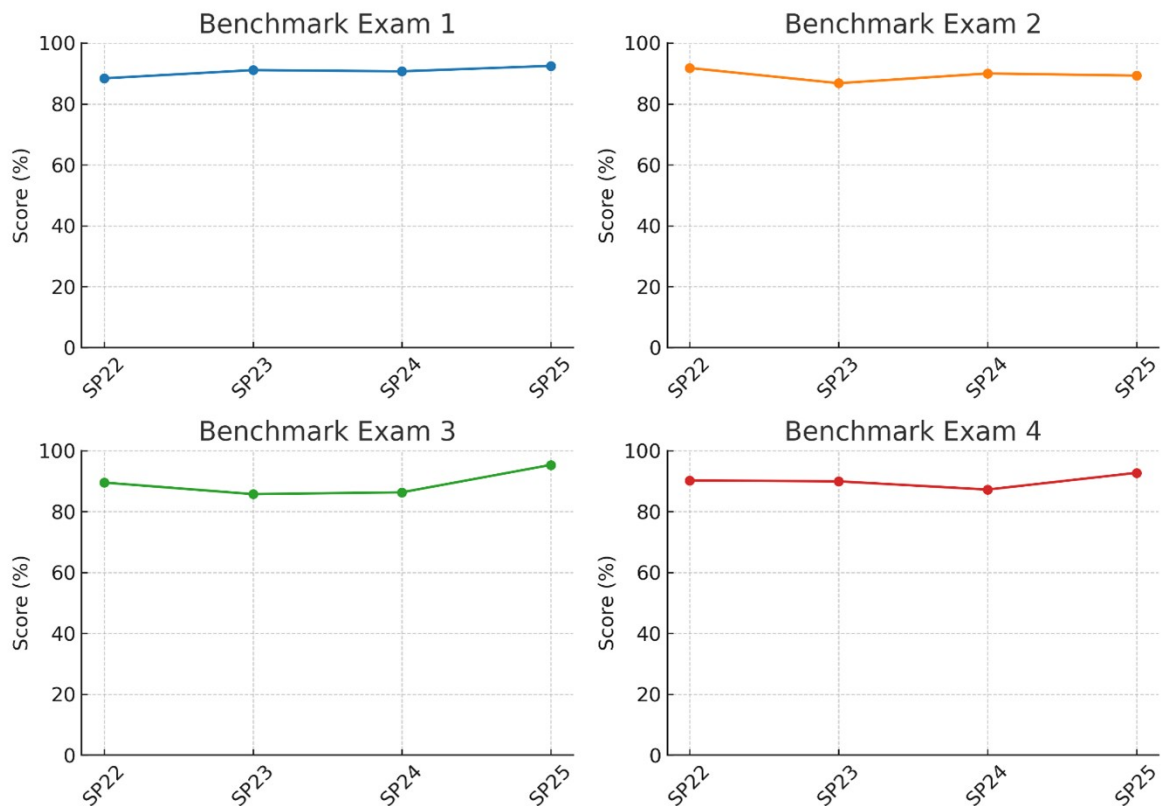


Figure 4
4-Year Course Exam Scores



taught as effectively as it was prior to any change. This study has of course been fully vetted and approved by my university's Institutional Review Board, with only summary data retained, fully de-identified/anonymized.

Closing Thoughts

Following the successful outcome from my spring 2025 trial use of Edvisor.ai for an undergrad elective course with 50 students, I have pursued the same plan for a fall 2025 graduate elective course, which has now also received university online quality certification. The University of Missouri – Kansas City's Center for Advancing Faculty Excellence is piloting an Edvisor.ai course online asynchronously to tutor faculty in teaching large enrollment courses. And for spring 2026, an interdisciplinary teaching team is planning to use Edvisor.ai for course content and deeper engagement in an undergraduate elective course on AI, Entrepreneurship, and History, in which we equip non-STEM students with marketable skills.

The exponential acceleration of technological change is a hallmark of industrial revolutions. Each occurrence forces disruptive institutional adjustments, with increasing capital intensity, de-skilling of existing labor, while also providing expansive entrepreneurial opportunities (Wigger, 2025a). Past revolutions pale in comparison to today's breakneck implementation, with AI able to disrupt in mere months. Of particular concern is the tendency for automation to displace the lowest-skilled workers. While AI technologies have a great deal of promise to improve the speed, accuracy, and efficiency of decision-making processes, their application must be done ethically, taking into account the ramifications for society at large as well as the moral issues that arise in their use. And therein lies a clear role for humanity: AI requires humans to describe and recognize good ideas. The human ability to contextualize is key to navigating decision trees and efficiently arriving at ethical judgments. Thus, we must equip workers with critical-thinking skills to employ AI ethically, minimizing negative externalities.

This article argues that work and society increasingly require strong critical thinkers; that such cognitive ability depends on a robust foundation of knowledge built through memorization and practice; and that AI, when thoughtfully implemented, can strengthen rather than further displace human cognition. Ultimately, AI-enabled education tools can provide individual development plans for which educators frequently do not have time, energy, or longitudinal access. Proximally, individual AI tools or holistic platforms like Edvisor.ai can facilitate courses designed to leverage the 85% rule to deliver optimal challenge, provide one-to-one coaching, and give timely feedback for immediate reinforcement, all of which collectively build the stronger mental frameworks critical thinking requires.

References

- Acemoglu, D., & Johnson, S. (2023). *Power and progress: Our thousand-year struggle over technology and prosperity*. PublicAffairs.
- Barr, N., Pennycook, G., Stolz, J. A., & Fugelsang, J. A. (2015). The brain in your pocket: Evidence that smart-phones are used to supplant thinking. *Computers in Human Behavior, 48*, 473-480. <https://dl.acm.org/doi/10.1016/j.chb.2015.02.029>
- Becker, M., & Cabeza, R. (2024). Prediction error minimization as a common computational principle for curiosity and creativity. *Behavioral and Brain Sciences, 47*, e93. 10.1017/s0140525x23003540
- Bein, O., & Niv, Y. (2025). Schemas, reinforcement learning and the medial prefrontal cortex. *Nature Reviews Neuroscience, 26*, 1-17.
- Bloom, B. S. (1984). The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring. *Educational Researcher, 13*(6), 4-16.
- Bratsberg, B., & Rogeberg, O. (2018). Flynn effect and its reversal are both environmentally caused. *Proceedings of the National Academy of Sciences, 115*(26), 6674-6678. <https://doi.org/10.1073/pnas.1718793115>
- Chen, B., Cheng, J., Wang, C., & Leung, V. (2025). Pedagogical biases in AI-powered educational tools: The case of lesson plan generators. *Social Innovations Journal, 30*(2). <https://socialinnovationsjournal.com/index.php/sij/article/view/10004>
- Cowan, N. (2014). Working memory underpins cognitive development, learning, and education. *Educational Psychology Review, 26*(2), 197-223.
- David, L., Vassena, E., & Bijleveld, E. (2024). The unpleasantness of thinking: A meta-analytic review of the association between mental effort and negative affect. *Psychological Bulletin, 150*(9), 1070-1093. <https://doi.org/10.1037/bul0000443>.
- Dutton, E., van der Linden, D., & Lynn, R. (2016). The negative Flynn Effect: A systematic literature review. *Intelligence, 59*, 163-169.
- Fernando, C., Osindero, S., & Banarse, D. (2024). The origin and function of external representations. *Adaptive Behavior, 32*(6), 515-549. <https://doi.org/10.1177/10597123241262534>
- Henkel, O., Horne-Robinson, H., Kozhakhmetova, N., & Lee, A. (2024). Effective and scalable math support: Evidence on the impact of an AI-tutor on math achievement in Ghana. <https://doi.org/10.48550/arXiv.2402.09809>
- Hirsch, E. D. (2000). You can always look it up—or can you? *American Educator, 24*(1), 4-9.
- Labaree, D. F. (2006). *The trouble with Ed schools*. Yale University Press.
- Lee, K., & Qiufan, C. (2021). *AI 2041: Ten visions for our future*. Currency.
- Metz, C. (2021). *Genius makers: The mavericks who brought AI to Google, Facebook, and the World*. Dutton.

- Miller, G. A., & Gildea, P. M. (1987). How children learn words. *Scientific American*, 257(3), 94-99.
- Oakley, B., Johnston, M., Chen, K.-Z., Jung, E., & Sejnowski, T. (2025). The memory paradox: Why our brains need knowledge in an age of AI. In M. Rangeley & N. Fairfax (Eds.), *The artificial intelligence revolution: Challenges and opportunities*. Springer Nature (forthcoming).
- Piaget, J. (1952). *The origins of intelligence in children* (originally published in 1936). International Universities Press.
- Pietschnig, J., & Voracek, M. (2015). One century of global IQ gains: A formal meta-analysis of the Flynn effect (1909–2013). *Perspectives on Psychological Science*, 10(3), 282-306.
- Rimol, M. (2021, June 14). Gartner says the majority of technology products and services will be built by professionals outside of I.T. by 2024. *Gartner*. www.gartner.com/en/newsroom/press-releases/2021-06-10-gartner-says-the-majority-of-technology-products-and-services-will-be-built-by-professionals-outside-of-it-by-2024
- Saenz, M., Revilla, E., & Simon, C. (2020, March 18). Designing AI systems with human-machine teams. *MIT Sloan Management Review*. <https://sloanreview.mit.edu/article/designing-ai-systems-with-human-machine-teams/>, Accessed March 4, 2024.
- Sheffi, Y. (2023). *The magic conveyor belt: Supply chains, AI, and the future of work*. MIT CTL Media.
- Skinner, B. F. (1954). The science of learning and the art of teaching. *Harvard Educational Review*, 24(2), 86-97.
- Sweller, J. (2008). Instructional implications of David C. Geary's evolutionary educational psychology. *Educational Psychologist*, 43(4), 214-216.
- Turing, A. (1950). Computing machinery and intelligence. *Mind*, 59, 433-460. doi: 10.1093/mind/LIX.236.433.
- Teasdale, T. W., & Owen, D. R. (2008) Secular declines in cognitive test scores: A reversal of the Flynn Effect. *Intelligence*, 36(2), 121-126. <https://doi.org/10.1016/j.intell.2007.01.007>
- Trahan, L., Stuebing, K. K., Hiscock, M. K., & Fletcher, J. M. (2014). The Flynn Effect: A meta-analysis. *Psychological Bulletin*, 140(5), 1332-1360. <https://psycnet.apa.org/doi/10.1037/a0037173>
- Turing, A. (1950). Computing machinery and intelligence. *Mind*, 59, 433-460. <https://doi.org/10.1093/mind/LIX.236.433>
- U.S. Government Accountability Office. (2022, August). *Workforce automation: Insights into skills and training programs for impacted workers* (Report to Congressional Committees). https://www3.weforum.org/docs/WEF_Future_of_Jobs_2020.pdf
- Wallach, W., & Allen, C. (2009). *Moral machines: Teaching robots right from wrong*. Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780195374049.001.0001>
- Wamsley, E. J. (2019). Memory consolidation during waking rest. *Trends in Cognitive Sciences*, 23(3), 171-173. <https://doi.org/10.1016/j.tics.2018.12.007>
- Wigger, L. (2024). Supply chain economics: A fresh lens for holistic analysis. *Journal of Economic Issues*, 58(2), 440-446. <https://doi.org/10.1080/00213624.2024.2343253>
- Wigger, L. (2025a). Following the light of the sun: Humanity in the new (work) world of AI. *Journal of Economic Issues*, 59(3), 932-939. <https://doi.org/10.1080/00213624.2025.2535932>
- Wigger, L. (2025b). Oregon Trail: Labor and housing as essential links in the critical materials supply chain. *Journal of Economic Issues*, 59(2), 534-541. <https://doi.org/10.1080/00213624.2025.2493561>
- Wilson, H. J., & Daugherty, P. (2018, July). Collaborative Intelligence: Humans and AI are joining forces. *Harvard Business Review*. <https://hbr.org/2018/07/collaborative-intelligence-humans-and-ai-are-joining-forces>, Accessed March 4, 2024.
- Wilson, R. C., Shenhav, A., Straccia, M., & Cohen, J. D. (2019). The eighty-five percent rule for optimal learning. *Nature Communications*, 10(1), 1-10. <https://doi.org/10.1038/s41467-019-12552-4>
- World Economic Forum. (2020, October). *The future of jobs report 2020*. https://www3.weforum.org/docs/WEF_Future_of_Jobs_2020.pdf

Larry Wigger, PhD, is a Teaching Professor of Supply Chain Management and Faculty Director of Assessment and Accreditation at the Henry W. Bloch School of Management at the University of Missouri - Kansas City. His teaching and research interests focus on artificial intelligence, workforce transformation, systems thinking, supply chain economics, and AI-enhanced pedagogy. He teaches across undergraduate, graduate, interdisciplinary, and general education programs, including courses examining supply chains, AI, entrepreneurship, and historical inquiry. His recent scholarly work explores the intersection of AI, institutional adaptation, labor dynamics, and decision making within complex organizational and educational systems.

Citation:

Wigger, L. (2026). Neuroscience-informed theory and strategies for AI-enhanced classrooms. *Journal on Excellence in College Teaching*. Latest articles.