SPACE FOR AI-SUPPORTED LEARNING

EXPANDING & ENDANGERED

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Forthcoming in the Handbook of AI and Strategy
(Csaszar & Jia, eds.; Edward Elgar Publishing

Abstract

This article explores a paradox inherent in AI-based training: as AI capabilities expand, offering superior training across diverse tasks, they simultaneously threaten to diminish the need for human involvement in those tasks. To address this, the article identifies seven contexts where AI-supported learning will remain valuable, even in domains where AI outperforms humans: intrinsic human mastery, empathy-driven social interactions, effective human–AI collaboration, the necessity of human oversight, integrated tasks at the "jagged frontier" of AI capabilities, institutional and legal constraints, and the signaling function of human credentials. By synthesizing recent empirical findings, the article illustrates conditions under which human skill development retains enduring relevance and argues that strategic investments in AI-based training can simultaneously leverage AI's strengths and sustain human competencies essential for individual, organizational, and societal success.

Takeaway Box

- AI-supported training faces a paradox: as AI's training capabilities grow, it may simultaneously reduce the relevance of human training by displacing human roles in many tasks.
- Human training will remain crucial in various tasks - including those where AI achieves superior performance.
- Effective human–AI collaboration requires targeted human skill development, including specialized training on how to interpret, critically evaluate, and integrate AI outputs.
- Complex, integrated tasks at the "jagged frontier"—where AI handles certain subtasks but struggles with others—necessitate ongoing human expertise, making them ideal targets for AI-supported training.
- Institutional, legal, and societal constraints significantly limit full AI adoption, ensuring continued demand for human oversight and maintaining the value of human credentials as signals of broader organizational competencies.

Keywords: Artificial intelligence, Human–AI collaboration, Skill development, AI-based training, Learning paradox

1. Introduction

A growing body of research indicates that artificial intelligence (AI) can significantly enhance human learning processes. Empirical studies consistently demonstrate that individuals trained using AI subsequently outperform those receiving conventional instruction across various tasks (e.g., Gaessler & Piezunka, 2023; Choi et al., 2025). Scholars have started to elucidate the mechanisms by which AI augments learning (Bastani et al., 2025; Henkel et al., 2024; Wambsganss et al., 2025), and an increasing volume of research is dedicated to optimizing AI-based training design to maximize learning outcomes (Dell'Acqua et al., 2023; Song et al., 2024; Wiles et al., 2025). Despite this promising trajectory, however, a critical yet underexplored question remains: *For which types of tasks will AI-enabled training maintain relevance and significance in the long term?*

This essay proposes an intriguing paradox inherent in the evolving landscape of AI-supported learning. Specifically, as AI capabilities expand, AI-based training can effectively address an ever-growing range of tasks, thus expanding the space for AI-supported learning and enhancing human capabilities in unprecedented ways. Paradoxically, however, as AI grows more powerful, the necessity for human involvement in these same tasks might diminish, potentially endangering the value and relevance of human training altogether. Thus, determining where AI-supported learning will have enduring relevance requires meeting a clear yet stringent criterion: AI must be sufficiently advanced to effectively train individuals, while there must simultaneously remain compelling individual, organizational, or societal benefits for humans to acquire proficiency in these tasks.

The structure of this essay is as follows. The first section outlines this core paradox in detail, elucidating why the expanding capabilities of AI may expand and endanger the space for AI-supported learning. In the second section, the discussion turns explicitly to identifying and analyzing contexts and domains in which AI-based training will likely maintain significant and sustained relevance, articulating clear criteria and conditions under which this potential will be most pronounced.

2. Expanding and Endangered

I propose that the space for AI-based training is both expanding and endangered simultaneously, driven by two countervailing forces linked to AI's growing power.

2.1. The Expanding Potential for AI-based Training

AI can significantly facilitate human learning across diverse tasks, including management consulting, language learning, and creative writing (Dell'Acqua et al., 2023; Doshi & Hauser, 2024; De Simone et al., 2025). Gaessler and Piezunka (2023), for instance, found that chess players significantly improved their strategic abilities when provided with access to chess computers. This outcome is echoed by Choi et al. (2025), who demonstrated similar improvements in the game Go through AI-supported training software. While initial evidence centered on structured games, recent research highlights AI's effectiveness in open-ended, complex professional tasks such as financial security analysis, where analysts aided by AI produce notably better recommendations through enhanced analytical precision and strategic foresight (Kim & Kang, 2024).

A particular appeal of AI-based training lies in enabling the experiential learning of strategic interactions. Unlike routine skill acquisition, strategic interactions involve interdependent sequences of actions and responses, making outcome attribution challenging and necessitating anticipatory skills (Adner et al., 2014; Christensen & Knudsen, 2010; Fang & Levinthal, 2009). Mastery in strategic interaction demands experiential practice with responsive counterparts to foster adaptability and robust anticipation of others' behaviors (Clough & Piezunka, 2020; Giustiziero et al., 2022; Smith et al., 2005; Thatchenkery & Piezunka, 2025). Traditionally, real-life engagement or human-based simulations provided such experiential opportunities, albeit with considerable limitations related to risk, cost, and scalability (Courtney et al., 2013; Gavetti & Levinthal, 2000).

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AI-based experiential learning uniquely mitigates these limitations by combining realistic responsiveness with scalable availability (Gaessler & Piezunka, 2023), effectively bridging the gap between theoretical knowledge and practical experience. Advances in machine learning and computational capacities allow AI systems to replicate human-like interactions more realistically, enabling learners to engage in rich, experiential training without traditional constraints (Agrawal et al., 2018; Wu & Brynjolfsson, 2015).

As artificial intelligence (AI) systems continue to advance, their capacity to train individuals across a broader spectrum of tasks is expanding significantly. Initially, AI applications in training were confined to structured, rule-based activities such as language translation or basic customer service interactions. However, with the development of sophisticated models capable of understanding context, adapting to user inputs, and learning from vast datasets, AI is now being employed in more complex and nuanced training scenarios. For instance, AI-driven platforms are increasingly used to enhance interpersonal skills, leadership development, and strategic decision-making processes. This evolution is facilitated by advancements in machine learning algorithms, natural language processing, and adaptive learning technologies, which allow AI to provide personalized feedback and simulate real-world scenarios effectively. Consequently, as AI continues to improve, its role in training is poised to encompass an even wider array of tasks, offering scalable and customizable learning experiences that were previously unattainable through traditional methods.

2.2. The Endangering of AI-based training

A rapidly expanding body of research underscores AI's superiority in numerous tasks previously reserved for human expertise. For example, AI systems now routinely outperform humans in medical diagnostics, financial forecasting, legal document analysis, and even creative tasks such as content generation and design (Agarwal et al., 2023; Eriksen et al., 2024; Doshi & Hauser, 2024; Jia et al., 2024; Puranam et al., 2025; Meincke et al., 2025; Yilmaz & Peukert, 2025). Particularly transformative is the development of sophisticated AI agents capable of executing complex tasks involving multiple integrated activities, such as generating comprehensive marketing reports or strategic business recommendations—tasks traditionally reliant on extensive human effort and cross-domain expertise.

The emergence and refinement of generative AI systems, exemplified by platforms like OpenAI's GPT-4, further amplify the risk of displacement. Such systems efficiently manage the integration and synthesis of diverse data sources, perform nuanced analyses, and generate coherent interpretative narratives with minimal human intervention. Consequently, AI's ability to assume roles previously performed by humans across integrated tasks may significantly reduce the demand for human participation, potentially undermining the long-term viability and relevance of human-focused training initiatives.

2.3. The Paradox

The increased power of AI creates a fundamental paradox with respect to AI-supported learning. On the one hand, AI significantly broadens training possibilities, offering unparalleled opportunities for scalable, sophisticated experiential learning. On the other hand, the very capabilities making AI valuable as a training tool simultaneously threaten to erode the necessity of human involvement in these tasks. These developments prompt a critical question: *If AI can do a task better than humans, why continue to train humans to do it?* Some technologists have even argued that all kinds of human training in certain fields will soon be unnecessary—for example, Hinton famously suggested "we should stop training radiologists" because deep learning would outperform them within a few years (Agarwal et al., 2023).

This essay suggests that there will be domains in which AI-based training will be relevant. Answering the question in which field AI-based training will be relevant requires conjecture about the technological evolution of AI and the range of tasks it may ultimately handle, the organizational dynamics shaping task automation, and institutional factors—such as norms, regulations, and laws—that influence AI's integration into human roles. Below we discuss why and where AI-based training of humans will continue to matter even in domains where AI achieves superhuman performance.

3. Future Domains for AI-based Training

We discuss in which domains we expect AI-based training. A crucial question as it is part of and contributes to the larger debate around which skills human needs to develop in the presence of AI (Gulati et al., 2025).

3.1. Ongoing Value and Appreciation of Human Performance and Mastery

Even when AI can technically accomplish a task more efficiently or accurately than humans, there remains intrinsic value in human mastery and execution of these tasks. Humans derive deep personal satisfaction, meaning, and identity from the processes involved in skill development and achievement. In both organizational and societal contexts, mastering a craft or profession is frequently viewed as valuable in its own right, extending beyond the immediate output it produces.

Recent advancements have enabled AI to outperform humans in complex tasks, including clinical diagnostics and creative endeavors (Eriksen et al., 2024; Doshi & Hauser, 2024). Yet despite these breakthroughs, humans have continued to pursue excellence and mastery, often redefining their motivations and objectives in the process. For example, in strategy-based games like chess, professional players have continued rigorous training and competition long after AI surpassed world champions. Rather than diminishing interest, the presence of superior AI has provided new insights, enabling human players to refine their techniques by analyzing AI-generated strategies (Choi et al., 2025). The sustained global enthusiasm for chess, evidenced by consistently high viewership and participation rates, underscores how AI can invigorate rather than dampen human interest.

Similarly, competitive events like spelling bees and Rubik's Cube solving competitions illustrate that the intrinsic value of human performance often shifts toward entertainment, personal challenge, and communal engagement, even when AI systems achieve superior performance. Humans remain intrinsically motivated to master such challenges, driven by personal pride, community recognition, and the enjoyment derived from the practice itself.

Moreover, human performance carries intangible cultural and emotional value that AI cannot replicate. Audiences and stakeholders continue to appreciate and reward the unique "human touch" in endeavors such as art, sports, and expert decision-making. The process of acquiring and mastering skills fosters personal growth, resilience, discipline, and creativity—qualities highly esteemed within organizational and societal frameworks (Agarwal et al., 2023; Doshi & Hauser, 2024; Zhou et al., 2024). Thus, the continued pursuit of human excellence and the personal, cultural, and social values associated with human skill provide enduring reasons for ongoing human training, even in scenarios where AI sets a higher performance benchmark.

3.2. Human Connection and Empathy in Social Interaction

While AI demonstrates considerable technical competence, it remains fundamentally limited in delivering genuine empathy and emotional intelligence, which are essential for interpersonal interactions (Kruk et al., 2025; Yin et al., 2024)[1]. In fields such as healthcare, counseling, education, and customer service, nuanced emotional engagement, compassion, and trust-building are pivotal human functions. AI might deliver correct information or advice, yet it still frequently fails to provide comfort to a worried patient or motivate a struggling student in the way a human can. The human capacity for genuine empathy and emotional intelligence forms the foundation of trust, rapport, and satisfaction in interpersonal relationships, making the human element indispensable in domains involving significant social interaction, care, or leadership.

Research consistently documents persistent "algorithm aversion," where individuals discount the perceived authenticity and value of AI-generated empathetic responses once they recognize their artificial origins (Strachan et al., 2024; Tong et al., 2021). Recent social-psychology experiments have illustrated this clearly: GPT-4-generated responses can initially appear more empathetic than those from human counselors, but recipients report feeling significantly less understood upon discovering the responses were

[1] Note that this is currently subject to change (Qin et al., 2023).

AI-generated—a phenomenon known as a "label penalty" (Yin, Jia, & Wakslak, 2024). Complementary work highlights that GPT-4 matches or exceeds human performance on many tasks but consistently struggles with subtler aspects like faux-pas detection, illustrating significant social blind spots in AI systems (Strachan et al., 2024). Large-scale studies indicate that despite GPT-4's superior performance in solving complex diagnostic puzzles compared to human readers (Eriksen et al., 2024), patient acceptance of fully autonomous AI diagnoses remains limited due to trust and empathy considerations.

A key factor limiting AI's effectiveness is that human relationships are often multiplex (Clough & Piezunka, 2020; Ertug et al., 2023; Li & Piezunka, 2025; Ingram & Roberts, 2000; Kuwabara et al., 2010; Rothbard et al., 2022; Thatchenkery & Piezunka, 2025) that is the relationships spawns multiple domains (e.g., two people are colleagues *and* friends). For people to be effective it is crucial to understand and to navigate that multiplexity (Grohsjean et al., 2025; Klapper et al., 2024; Li & Piezunka, 2020;). The AI, is, however constrained in managing such relationships as it tends to have data - and also be focussed on the professional relationship only.

Consequently, human training remains critical to developing communication skills, ethical judgment, and empathetic understanding required in these domains. For example, healthcare professionals must continue to receive training not only in clinical knowledge but also in patient interaction and empathy to preserve essential human dimensions of care. Note that AI may act as a supportive tool; in customer support, a recent field study found that human agents augmented by AI achieved higher customer satisfaction through their understanding of customer needs and emotional states (Brynjolfsson et al., 2025). The presence of empathetic human agents, aided by AI-generated suggestions, created calmer interactions, reducing escalations and enhancing overall customer experience.

3.3. Human–AI Collaboration Requires Human Skill Development

Rather than replacing human labor, many AI applications are increasingly deployed as collaborative tools that complement and augment human workers (Choudhary et al., 2025; Davis, 2024; He et al., 2025;

Krakowski et al., 2019; Puranam, 2025; Marchetti et al., 2025). For example, Jia et al. (2024) show that AI–human collaboration, when structured through a sequential division of labor, significantly enhances employees' creativity and performance in high-stakes sales tasks. These collaborations require human skills, and require humans to learn how to effectively collaborate with AI.

Research consistently indicates that human-AI collaboration frequently outperforms either human or AI performance alone (Dell'Acqua et al., 2023; Agarwal et al., 2023). For example, in medical diagnostics, although AI systems achieve superior accuracy in specific diagnostic tasks compared to human experts, optimal outcomes are often achieved through collaborations that leverage AI's analytical capabilities alongside human judgment and contextual awareness (Agarwal et al., 2023; Brodeur et al., 2024). Similarly, in creative and strategic domains such as business strategy formulation and content creation, studies have demonstrated that human-AI teams generate outputs that are more innovative and practically viable than those produced solely by humans or AI alone (Boussioux et al., 2024; Doshi & Hauser, 2024). Furthermore, research suggests that individuals with stronger foundational skills—such as advanced reading, writing, and critical thinking—derive greater benefits from AI tools (Henkel et al., 2025; Bastani et al., 2025). Consequently, targeted AI-based training that specifically develops these foundational competencies can further enhance human performance and the effectiveness of human-AI collaboration (Gaessler & Piezunka, 2024; Choi et al., 2025).

Research also suggests that to effectively harness AI, humans must develop new skills, competencies, and understanding specifically tailored to operating AI effectively. Learning to work with AI, therefore, constitutes a critical form of training essential for maximizing collaborative potential and ensuring successful outcomes in the AI era (Dell'Acqua et al., 2023; Doshi & Moore, 2025 (as in this volume)). For instance, in an experiment combining AI with human expertise in radiology, researchers discovered that providing AI diagnostic assistance did not, on average, improve radiologists' accuracy (Agarwal et al., 2023). This occurred despite the AI's high accuracy, exceeding roughly 75% of the radiologists in the study (Agarwal et al., 2023). This shortfall arose because many radiologists either ignored useful AI insights or overly relied on incorrect AI recommendations, exhibiting biases like "automation neglect." Such errors prevented optimal synergy, highlighting that effective human-AI collaboration requires explicit training in skills such as interpreting, critically evaluating, and integrating AI recommendations into professional judgment. Agarwal and colleagues argue that specialized training on how and when to incorporate AI outputs could significantly enhance human performance.

Similar insights emerge from educational studies. Bastani et al. (2025) conducted field experiments with nearly a thousand high school students using an AI-based math tutor, revealing that unrestricted access to generative AI led students to rely excessively on it, improving immediate homework scores but hindering deeper learning and subsequent independent performance. Conversely, when AI tools provided guided prompts and step-by-step interactions, students achieved better long-term learning outcomes. Thus, effective AI integration is contingent upon training users in appropriate methods of interaction, ensuring that AI tools enhance rather than impede human skill development.

Field experiments and case studies from diverse professional settings further illustrate the critical role of specialized training. Management consultants experienced significant productivity and quality improvements using GPT-4, but only after receiving targeted training in effective AI interaction techniques, such as prompt engineering and interpretation of AI-generated insights (Dell'Acqua et al., 2023). Csaszar et al. (2024) similarly found that managers could approximate expert venture-capital judgments by aggregating multiple AI-generated opinions, but this outcome required precise training in prompt engineering and role-setting techniques. Doshi and Moore's (2025) Human–AI Task Tensor framework further codifies the specific competencies needed for effective human-AI collaboration, emphasizing the complexity and specificity of these emerging collaborative skills.

3.4. Incomplete Automation and the Need for Human Oversight

Despite their advanced technical capabilities, AI systems continue to exhibit critical errors, particularly in unsupervised or inadequately monitored environments, underscoring the persistent necessity of human oversight (Agarwal et al., 2023; Eriksen et al., 2024). Historical analyses highlight that automating complex, interconnected tasks can be protracted and challenging, even when technologically feasible. For instance, AT&T's gradual transition from manual to automatic call switching illustrates how tasks deeply interwoven with organizational functions can delay full automation by decades (Feigenbaum & Gross, 2024). This historical insight emphasizes that human operators remain essential in scenarios involving high task interdependencies and significant error costs.

In many contemporary domains, AI tools do not completely automate tasks but instead manage certain portions under human supervision. This arrangement ensures that human oversight acts as a critical safeguard against AI errors, biases, and unforeseen situations. AI systems, even those demonstrating "superhuman" performance, can produce erroneous, biased, or internally inconsistent outcomes, especially outside their training scope or in edge cases (Agarwal et al., 2023; Eriksen et al., 2024; Doshi & Hauser, 2024). For instance, Agarwal et al. (2023) observed that GPT-4 delivered incorrect or internally inconsistent answers in 43% of radiology cases when not monitored by experts, demonstrating the indispensable nature of human oversight.

Formal models further illustrate potential pitfalls when human experts fail to verify algorithmic advice effectively. When experts only verify AI outputs after acting on them, a "verification bias" can arise, leading to chronic mistrust or excessive overrides of potentially superior AI recommendations (de Véricourt & Gurkan, 2023). Explicit oversight training, combined with periodic exploratory tests of AI accuracy, is proposed as a remedy to these biases, emphasizing the need for comprehensive human oversight mechanisms.

A vivid illustration of oversight importance comes from critical domains like aviation and medicine. Bastani et al. (2025) use the analogy of aviation autopilot systems, noting that overreliance on automation may cause pilots to lose manual flying skills, leading to inadequate responses during emergencies when autopilot systems fail or disengage. This highlights a significant trade-off: while AI often enhances average performance, reliance without proper oversight training can introduce new vulnerabilities.

Similar findings are reported in healthcare, where integrating AI diagnostic assistants necessitates robust oversight frameworks to ensure safety, reliability, and accountability. Brodeur et al. (2024) found that even when AI demonstrates "superhuman" clinical reasoning performance, extensive preparation, training, and human oversight remain crucial. Healthcare regulations often mandate such oversight, reinforcing human roles for managing liability, accountability, and ethical considerations.

The necessity for human oversight is also underscored in judiciary contexts, where a machine-learning model might significantly reduce crime rates or pre-trial incarcerations, yet judges remain critical to maintaining legitimacy, fairness, and accountability (de Véricourt & Gurkan, 2023). This demonstrates that oversight requirements frequently govern AI deployment rather than raw accuracy alone.

It is also plausible that the AI can only handle a particular kind of task with only a subset of instances. For example, while AI is very able to drive a car in certain kinds of weather conditions, it may not be able to drive the car in snow or heavy rain. Dahlander et al (Dahlander et al., 2023) show that AI can help organizations to select a subset of ideas. This is crucial as the selection of ideas is essential when crowdsourcing ideas from customers (Park et al., 2024; Piezunka & Dahlander, 2015; Piezunka & Dahlander, 2019). However, what Dahlander et al. (2023) illustrate isa that the AI is only useful in filtering unhelpful in the initial set, but that for the later section stages humans are needed and in fact deployed.

3.5. Integrated Tasks and the “Jagged Frontier”

Despite the impressive scope of tasks AI can now perform, its performance remains uneven across various domains, leading researchers to characterize this phenomenon as a "jagged frontier," where human expertise continues to be essential (Dell’Acqua et al., 2023; Mollick, 2024). This uneven boundary refers to contexts and subtasks where AI capabilities diminish and human skills retain a comparative advantage, particularly in creativity, adaptability, holistic understanding, and nuanced judgment (Felten et al., 2021; 2023). Occupational exposure data illustrate this pattern clearly, revealing that AI's impact disproportionately affects certain high-skilled cognitive roles while sparing others, highlighting the selective and uneven nature of automation's advancement across knowledge-intensive work (Eloundou et al., 2024; Felten et al., 2021; 2023).

Consider integrated tasks composed of multiple interdependent subtasks, such as medical treatment, strategic decision-making, or creative project management. In such settings, the task can often not be cleanly separated into discrete units performed independently. For instance, diagnosing a patient (subtask A) and subsequently discussing treatment options empathetically (subtask B) form an integrated task in healthcare. AI may outperform humans in diagnostic accuracy (subtask A), yet remain incapable of delivering empathetic, context-sensitive communication (subtask B). Consequently, a human must manage the complete integrated task. In these scenarios, human workers significantly benefit from AI-based training tailored explicitly to improve their performance in the subtask where AI is superior.

3.6. External Constraints: Institutional, Legal, and Data Limitations

Beyond technological capabilities, the pace and extent of AI adoption are significantly constrained by external factors, including institutional inertia, legal regulations, and data availability (Feigenbaum & Gross, 2024; Furman & Seamans, 2019). These factors collectively necessitate ongoing human involvement and expertise to navigate the practical realities of AI integration effectively.

Data constraints represent a crucial limitation in AI deployment. High-quality, extensive datasets are essential for developing effective AI algorithms. However, data availability is frequently scarce, proprietary, or ethically restricted across numerous domains. A study of AI startups by Bessen et al. (2022) highlights that access to proprietary data significantly determines startup growth and investment attractiveness. Their research indicates that 83% of surveyed AI startups depend heavily on customers' proprietary data, with limited access acting as a critical barrier to growth, driving many companies towards alternative solutions such as AI-as-a-Service partnerships or synthetic-data strategies (Bessen et al., 2022). Consequently, humans remain indispensable for tasks where data limitations hinder AI capabilities, particularly in niche or emerging areas where sufficient historical data is unavailable.

Institutional and organizational structures further influence AI adoption. Studies reveal that successful automation integration often depends more substantially on organizational preparedness, labor relations, and regulatory compliance than on technological innovation alone (Raj & Seamans, 2018; Yiu et al., 2025). Historical analyses, such as Feigenbaum and Gross's (2024) investigation into telephone-operator mechanization, illustrate that legal and organizational inertia can significantly delay complete automation, creating an ongoing demand for human involvement and retraining.

Legal regulations also play a pivotal role in mandating continued human oversight across various industries. For instance, healthcare regulations often require licensed practitioners to approve AI-generated diagnoses and treatment recommendations, ensuring accountability and ethical standards (Brynjolfsson et al., 2023). Similarly, the development and deployment of self-driving cars remain heavily regulated, with jurisdictions requiring human supervision despite the technological feasibility of autonomous driving systems. Such legal frameworks reflect societal preferences for accountability and transparency, reinforcing the need for human intermediaries to manage responsibilities tied to AI-driven decisions.

Moreover, ethical and societal acceptance constraints further limit AI's complete automation capabilities. Public apprehension and resistance toward fully automated roles—such as AI judges or executives—highlight the importance of maintaining human involvement to uphold fairness, ethical judgment, and trust. In summary, external constraints—ranging from data access issues to regulatory compliance, institutional inertia, and societal acceptance—significantly shape AI's practical integration. Continued human expertise remains critical for navigating these constraints, bridging the gap between technological potential and real-world applications, and ensuring ethical, accountable, and socially acceptable automation deployment.

3.7. Signaling, Status, and the Value of Human Credentials

There are tasks in which AI now consistently outperforms humans, such as playing chess or conducting complex diagnostic reasoning (Agarwal et al., 2023; Choi et al., 2025; Eriksen et al., 2024). From a purely economic standpoint, investing in human training for these tasks may seem inefficient given AI's demonstrated superiority. Nevertheless, human excellence in these areas continues to hold significant value as it reliably signals broader competencies—including strategic insight, adaptability, creativity, and disciplined thinking—that are otherwise challenging to measure directly (Csaszar & Steinberger, 2022; Horton, 2017).

Precisely because AI excels in structured and measurable tasks, these activities represent ideal domains for AI-based training. Leveraging AI's analytical precision, personalized feedback, and scalable, adaptive training capabilities (Bastani et al., 2024; Dell'Acqua et al., 2023; Gaessler & Piezunka, 2024), AI-supported instruction can efficiently foster human mastery in these signaling activities. Thus, AI-supported training not only helps individuals achieve excellence in these specific domains but also indirectly cultivates broader organizationally relevant capabilities, enhancing their value and effectiveness across varied contexts (Dell'Acqua et al., 2023; Doshi & Moore, 2025; Wiles, Munyikwa, & Horton, 2025).

Bio

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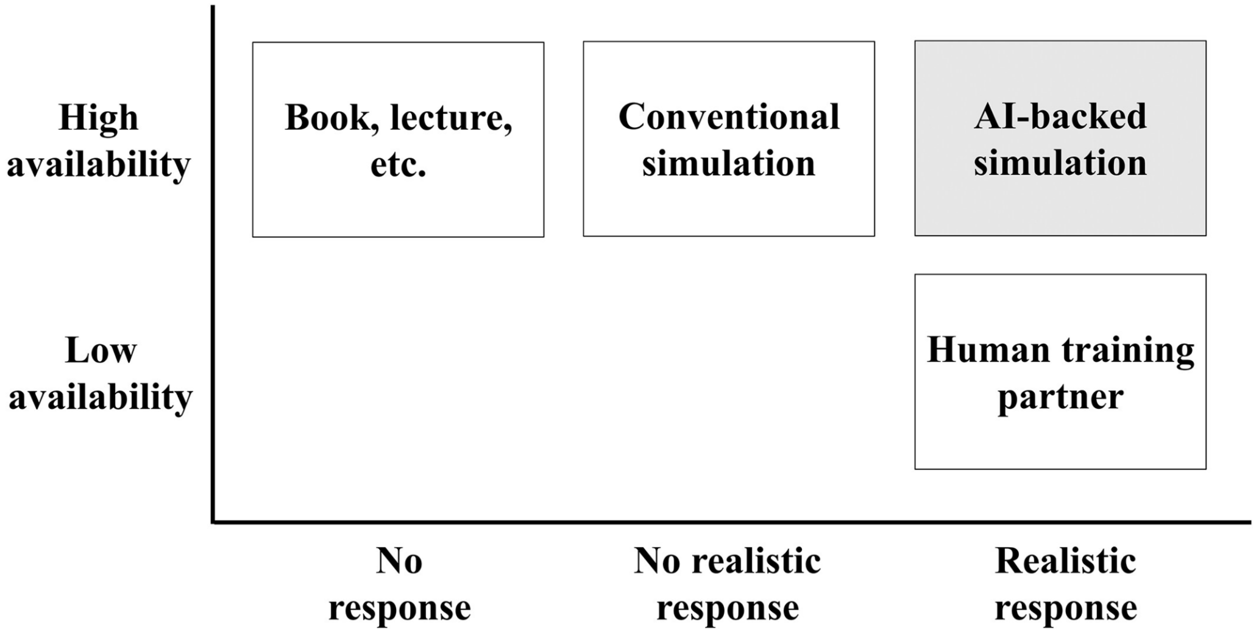
Reason AI Training Matters	Underlying Logic	Representative Task Domains
Intrinsic Value of Human Performance	Human achievement and mastery are valued for their own sake, even if AI outperforms. People derive meaning, enjoyment, and cultural value from excelling at tasks themselves.	Competitive sports (chess, esports, Rubik's cube solving); artistic and creative hobbies.
Human Connection and Empathy	Many activities require emotional intelligence, trust, or social presence that AI cannot fully replicate. Human-to-human interaction is often preferred for comfort, authenticity, or ethical reasons.	Psychotherapy and counseling; medical consultations; teaching and caregiving roles; personal services.
Human–AI Collaboration Skills	Effectively using AI often demands skilled human operators. Humans must be trained in fundamental skills and new competencies to work alongside AI or to interpret and manage AI outputs.	Coding with AI assistants (e.g. GitHub Copilot); data analysis with AI tools; basic literacy and numeracy (to verify AI results); AI-assisted design and planning.
Incomplete Automation & Oversight	AI typically can handle only parts of a task or standard conditions, so humans are trained to handle the rest. For safety-critical systems, a human operator remains as a fallback or supervisor to intervene when the AI fails or faces novel situations.	Semi-autonomous driving (human takeover in bad weather); airplane autopilot with pilot backup; industrial automation with human supervisors for anomalies.
Integrated Tasks (Jagged Frontier)	Certain tasks are too complex, context-dependent, or poorly defined for full automation. AI's capabilities across subtasks are uneven ("jagged"), so humans train to handle integrated tasks requiring adaptability, creativity, or open-ended decision-making. AI can be used as a tool for training simulations, but human judgment remains central.	Frontline service roles (requiring multitasking and improvisation); strategic planning in dynamic environments (e.g. airline route strategy); high-level creative problem solving; negotiations and people management.
External Constraints (Institutional, Legal, Data)	In some domains, AI cannot replace humans due to external constraints. Laws or liability concerns may forbid full automation; sometimes AIs lack access to the necessary proprietary or tacit data; in other cases, success criteria are ambiguous or socially constructed, making purely algorithmic decisions untrustworthy.	Autonomous vehicles (legal/safety regulations require a human driver); academic tenure or hiring decisions (reliance on peer judgment and confidential information); group decision-making and governance (no clear objective metric for AI to optimize).
Signaling and Credentialing	Achieving difficult skills through training serves as a credible signal of ability, effort, or merit. Even if an AI can do a task easily, a human's proficiency in that task (or obtaining a credential) signals their talent and perseverance. This preserves incentives for human training as a means of social and professional differentiation.	Academic degrees and certifications; competitive accomplishments (e.g. high test scores, chess titles); any skill used to demonstrate expertise or intelligence to employers and peers.

Old Notes

Figure 1



Replicated from Gaessler and Piezunka (2023)