CAREER OPTIMISM INDEX®

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WHITE PAPER

Learning to Use AI: Challenges and Opportunities

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50% of U.S. workers are learning to use AI independently, as employer support lags. 60% want more guidance in learning AI tools. 73% of U.S. employers say clearer standards for AI skills and pathways are needed. (University of Phoenix, 2026)

Introduction

The University of Phoenix *Career Optimism Index*® was first conducted among workers in 2021; employers were added in 2022. The report includes year-over-year tracking data for both audiences, where applicable. Research objectives included examining American workers' sense of optimism about their careers in the context of workplace, economic, and societal trends and challenges. The study includes additional insights from employers to provide comparison between the workforce and those who hire, train, and retain them. The 20-minute online survey included (University of Phoenix, 2026):

- Workforce: 5,000 United States (U.S.) nationally representative adults, age 18+, who either currently work or wish to be working (MOE ±1.39%),
- Employers: 1,000 United States (U.S.) employers who are influential or play a critical role in hiring and workplace decisions within a range of departments, company sizes, and industries (MOE ±3.1%), and
- Workforce and employer fieldwork was conducted between January 21, 2026 – February 6, 2026.

The 2026 report reflects analysis of the workforce audience of 5,000 US adults and includes year-over-year shifts for tracked questions. There are several demographic and psychographic data callouts to help readers understand the differences between various types of workers among the broader audience. The report also includes data for 1,000 employers. Additional demographic data are available upon request. Selected research highlights included:

- Workers:
  - 50% are learning to use AI independently (University of Phoenix, 2026, slide 8);
  - 60% want more guidance in learning AI tools (University of Phoenix, 2026, slide 8);
  - 84% of workers with AI knowledgeable managers say their employer clearly connects new skills to growth or rewards within the organization (University of Phoenix, 2026, slide 38)
- Employers:
  - 73% say clearer standards for AI skills and pathways are needed (University of Phoenix, 2026, slide 27)

As AI applications proliferate, organizational practices that differentiate high performers include identifying specific AI initiatives and clearly defining a road map for implementation (McKinsey, 2024, p. 20). This white paper describes current practices for learning to use AI, challenges, and strategies to optimize learning to use AI for both workers and employers.

Current Practices: Lack of Role-Specific AI Training

Adoption of Artificial Intelligence (AI) technology continues to transform business and industry. This white paper focuses on current practices for using AI to make accounting more efficient (Zia, 2023; Abdo-Salloum & Chehade, 2026). In accounting, AI technology is used to automate time- and labor-intensive repetitive tasks such as data entry, bookkeeping, and financial analysis. By leveraging AI algorithms, accountants can proactively detect and mitigate risks, protecting businesses from financial losses and reputational damage (Baferani et al., 2026). The technology can be used to analyze large datasets and identify patterns and anomalies that could be overlooked by human accountants (Jones & Free, 2026).

While AI offers remarkable opportunities, its assimilation needs to be approached with care to optimize and reduce risks. Research exploring current practices of accounting managers, accounting staff, and AI technology project leaders in selected organizations in southwestern United States validated challenges experienced by accounting staff learning to use AI (Gojkovic, 2025). Staff noted that existing training was inadequate in preparing employees to use AI tools effectively. Accounting staff characterized current training opportunities as being too generic, too brief, and focused on technical aspects without considering the needs of non-technical users. Participant observations included:

- The main issue was the lack of role specific training. Most of the training provided was general and did not explain how AI could specifically be applied to the accounting processes. I am not sure how to incorporate AI into daily workflow. I would recommend more interactive and role specific training that will include real life examples and use cases. Senior accountants, for example, could benefit from training that explains how AI tools can assist in creating financial forecasts, while junior accountant might need more training on how AI can automate basic bookkeeping tasks.
- Training was patchy and rarely focused on the things that I was most likely to deal with in my job. And I was unable to find sufficient after-training support to properly help me with the learning curve that comes with using new AI tools.
- The training was overwhelming and fast. I would have preferred a more gradual learning curve with practical examples of how AI tools could streamline our workflow.
- The main challenge was that the training was irregular and not integrated into our daily workflows. It would have been much better if the training was continuous and aligned with our real time needs in accounting practices.
- The initial training sessions were generic and didn’t address our specific needs in accounting.
- I recommend ongoing training that includes regular refresher courses to ensure accounting staff stay up to date with new tools and features. Additionally, providing a mentorship could help less-experiences staff learn how to effectively use AI tools in their daily tasks.

Several accounting staff participants reported that after initial training sessions there was little feedback or opportunity to reinforce learning. Accounting staff mentioned the need for post-training resources such as “how to” guides, dedicated support teams, and refreshers at intervals that would reinforce continued learning and competence with using new AI tools.

Accounting staff also indicated that training was not organizationally supported by policy. The lack of mandates or standardized expectations led to inconsistent participation and a perception that AI literacy was optional rather than a strategic priority. Comments include:

- The policy should include clear guidelines on when and how to use AI tools, along with comprehensive training sessions on the specific applications of AI in accounting field. It should also outline how to address errors or challenges with AI outputs and provide a process for escalating issues to a technical support team.
- The training policy should emphasize the importance of how to use AI tools but also the importance of ethics and data privacy considerations involved using AI technologies. It is important to make accounting staff aware of their responsibilities in ensuring the accuracy and confidentiality of the financial data being processed by AI technology.

Study findings validated the lack of role-specific training adversely affected implementation and adoption of AI technologies in accounting practices. Structured training programs, clear policy guidelines, and consistent data governance practices are foundational to strengthening user confidence and competence.

Unanticipated Outcomes

Organizations’ reactive integration of AI technologies can lead to problematic outcomes that fail to deliver expected results. Consider Stanford researchers’ identification of AI’s “mirage reasoning,” where AI can provide X-ray diagnoses without access to any images (Asadi et al., 2026), and the misadventures of Amazon, IBM Watson for Oncology, Zillow, Uber, Tesla, Facebook, and X, as chronicled by Harvard research team Saviano et al. (2024) as unequivocal evidence supporting the need for AI governance and regulation. Equally problematic are potential risk exposures generated by employee experimentation with AI tools. The tendency for organizations to view AI as a specific tool, rather than strategic asset, represents misalignment linked to lack of evidence-based strategic approaches to effective AI integration (Balasooriya & Sedera, 2026).

While AI is intended to reduce time- and labor-intensive labor, results of an 8-month study of generative AI and employee work habits at a U.S. technology company suggested that AI intensified, rather than reduced, the pace of work (Ranganathan & Ye, 2026). Although the employer did not mandate AI use, workers were offered enterprise subscriptions to commercially available AI tools. Researchers concluded that changes caused by enthusiastic AI adoption can be difficult to maintain. “Once the excitement of experimenting fades, workers can find that their workload has quietly grown and feel stretched from juggling everything that’s suddenly on their plate” (Ranganathan & Ye, 2026, p. 3).

In a study of 195 municipal government and nonprofit communicators, 81.5% reported using generative AI tools to brainstorm, draft content, and edit narrative without basic training and discussion about responsible and ethical use (Maben et al., 2026). Workers may learn to use AI tools to expedite workflows, task completion, and improve performance. Employees use these tools to enhance productivity, automate tasks, generate creative content, and solve complex problems sometimes before official organizational frameworks have been established. Self-directed AI exploration may occur outside of existing organizational channels and generate unanticipated risk exposures.

Bottom-up approaches to learning AI (Alshowab & Sposato, 2026) can lead to Shadow AI, defined as "the unauthorized use of AI tools within organizations." (Catherine et al., 2025, p. 1). Challenges of Shadow AI include unanticipated exposure of corporate data by uploading to public AI platforms and triggering privacy breaches or intellectual property disclosure. Use of unreliable or inaccurate AI tools may impugn organizational credibility. Employees experimenting with AI may not be aware of the repercussions, such as decisions based on incorrect information (Alshoweb & Sposato, 2026).

Setting boundaries for acceptable and responsible AI use is useful and can be integrated into employee training and security measures. Sahoo et al. (2026) synthesized academic and practitioner conceptual frameworks in a five-stage AI training model, complete with feedback loops to ensure continuous refinement. The model's five stages include contextual readiness, training design, governance, mechanisms, and organizational outcomes and provide a roadmap to optimize learning about AI and simultaneously promote productivity, retention, and. psychological safety. Alshowab and Sposato (2026) favor legitimizing grassroots AI, envisioning that managers can clarify organizational constraints to employees and convey operational realities to leadership. In this approach, managers transform "scattered individual experiments into coordinated team capabilities" (Alshowab & Sposato, 2026, p. 2). Chien, Co-Director of the Berkeley Center for Law & Technology, mused:

> We underestimate how much . . . seeing our peers do things has a big impact. It is not going to be because [some tech CEOs] tell you to use a tool that you'll use it. You'll use it because your friend said, 'Oh my gawd, I just saved all this time by . . . . (Barry, 2026, para. 2)

While research confirms that AI offers remarkable opportunities when complemented by cautious assimilation, lasting technological change transcends technical upgrades and represents an organizational shift that necessitates changes in people, processes, culture, and technology (Gojkovic, 2025). Although use of AI tools continues to increase, most organizations have not redesigned workflows or implemented controls to scale AI at enterprise level. To optimize learning about AI may require transitioning to a new paradigm.

From Misalignment to a New Paradigm?

Not so long ago, healthcare theorists recognized that foundational conceptual flaws skewed results and led to incorrect conclusions (Institute of Medicine (U.S.) Committee on Quality of Health Care in America, 2001). In Appendix B of the 2001 Institute of Medicine (U.S.) Committee on Quality

of Health Care in America (IOM) report, *Crossing the Quality Chasm*, Plesk posited viewing hospitals and clinics as living ecosystems instead of rigid machines. In this perspective, redesigning health care with insights from the science of complex adaptive systems (CAS) provides a new paradigm to guide system design:

> Because the parts of a CAS are adaptable and embedded within a unique context, every change within a CAS can stimulate other changes that we could not expect. This approach to system design can never provide the assurance that is possible in a mechanical system. This is the nature of CAS. Therefore, rather than agonizing over plans, the goal is to generate a "good enough plan" and begin to observe what happens. Then, modifications can occur in an evolutionary fashion. (Plesk, 2001, final para.)

Research suggests viewing "AI as a system" because its "effects come from the interaction of many interdependent parts, not from any one part alone" (McKinsey, 2026, system section). Data correlate increases in AI use with increases in risk: About 51% of respondents reported negative consequences associated with inaccuracy and explainability, with mitigation measures lagging behind (McKinsey, 2025). While 88% of respondents report using AI in at least one business function, the majority are in experimental or pilot phases; sustained, enterprise-level implementation (AI scaling) is elusive (McKinsey, 2025; Tinkoff et al., 2026).

Critics of consulting surveys such as McKinsey's research suggest AI initiatives fail to scale because outcomes are misinterpreted. The significance of challenges associated with emergent behavior, such as learning lags, Shadow AI, and informal workarounds, is overlooked because studies focus on formal structure (Driver, 2026). Analysis of independent research, analyst research, consulting surveys, and regulatory and standards frameworks correlated failure to scale AI to theoretical mismatch (Driver, 2026).

Applying models designed for deterministic systems to technology that learns, adapts, and changes with use generates inaccurate and/or incomplete results.

> Unlike prior digital systems, AI-enabled applications are probabilistic rather than deterministic, adaptive rather than static, and embedded rather than peripheral. Their influence accumulates through repeated, often small decisions rather than through discrete, auditable events. So, in contrast to prior digital systems, AI applications learn and adapt through use, complicating traditional governance assumptions (National Institute of Standards and Technology, 2023). And as a result, the relationship between decision, impact, and review is reordered. (Driver, 2026, p. 6)

> Seen in this light, the recurring disappointment surrounding AI outcomes is less a story of overreach than of misalignment. Organizations are attempting to stabilize systems that require staged learning, and to govern adaptation using mechanisms designed for predictability. Until this misalignment is addressed, the same failure patterns will repeat regardless of technological progress. (Driver, 2026, p. 8)

Recommendations from other thought leaders range from conceptual frameworks to process management principles. Some envision AI as an ecosystem (Yurdunkulu et al., 2025), while others

suggest philosophical shifts moving AI design from task automation through AI tools to augmenting human engagement through AI systems that offer probing questions to catalyze users' critical thinking (Nwashili, 2026). University leaders reaffirm that "Higher education has a responsibility to help students understand how to use AI and where the boundaries are. The goal should not be blind adoption, but informed adoption" (Veloria, 2026, August 11, para. 7-8).

A systematic review of orga/nizational AI integration validated the importance of proactive leadership support, cross-functional collaboration, knowledge sharing through personnel training, and clear compliance and ethical guidelines to offset resistance to change, lack of skills, and compromised data (Romeo & Lacko, 2026). Professional development consultants propose an "AI gallery" concept to "share AI tips and techniques throughout your firm" (Barry, 2026, para. 1). Other researchers focus on organizational opportunities for improvement in collaborative e-learning, presenting targeted service-oriented architecture and AI-driven adaptive assessment solutions that synthesize modularity and interoperability (Hadyaoui & Cheniti-Belcadhi, 2026).

Research suggests that successful AI adoption encompasses structured integration planning, aligned with long-term financial goals, organizational infrastructure, and risk mitigation strategies. AI should not be considered a technical process update, but a strategic decision-making process that affects forecasting, budgeting, and overall financial growth. Incremental implementation aligned with clear business goals is pivotal to success. Many organizations fail because they rush to integrate AI without aligning it with existing financial and operational strategies (Gojkovic, 2025).

Conclusion

Major challenges facing the adoption of AI include development of effective strategic policy for AI, mobilizing skilled manpower, and lack of motivation and commitment to AI from leadership. As University of Phoenix President Chris Lynne observed, "AI should enhance human expertise, not replace it" (C. Lynne, personal communication, July 14, 2026). This white paper contributes to existing literature on strategies to optimize learning to use AI for both workers and employers.

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