Issue Brief

AI and the Future of Workforce Training

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Executive Summary

The emergence of artificial intelligence (AI) as a general-purpose technology is poised to transform work across a variety of industries and job roles. Previous waves of technological change mainly led to job displacement and wage pressures for blue-collar workers while enhancing productivity and wages for white-collar workers. In contrast, AI's impact could be more pervasive across all occupational categories, including knowledge workers and those with advanced education. Recent studies indicate that up to 80 percent of U.S. workers might have at least 10 percent of their work activities affected by large language models, with approximately 19 percent of workers potentially seeing half or more of their work activities impacted.

The nature of this transformation depends largely on two factors: the degree to which AI can perform or enhance an occupation's core tasks, and whether AI serves as a substitute for or complement to human workers. Occupations with high AI exposure but low complementarity face the greatest risk of disruption, highlighting the need for comprehensive retraining and upskilling initiatives. This situation is particularly critical given that technical skills now become outdated in less than five years, on average.

Analysis of future workforce demands reveals the following trend: while technical skills remain important, accounting for about 27 percent of in-demand skills, the majority of crucial skills are nontechnical. Foundational skills (such as mathematics and active learning), social skills (including social perceptiveness and negotiation), and thinking skills (such as complex problem-solving and critical thinking) together make up nearly 58 percent of skills needed in growing occupations. This underscores the importance of developing a well-rounded workforce capable of adapting to technological change while maintaining strong interpersonal and analytical capabilities.

The potentially far-reaching impact of AI across occupations, coupled with the likely accelerating pace of skill obsolescence, points to an increasing need for continuous retraining and upskilling opportunities throughout workers' careers. This shifting landscape demands a critical examination of current workforce development infrastructure and its capacity to meet these emerging challenges at scale. Understanding which elements of the existing system can be effectively expanded and which barriers need to be addressed becomes crucial for developing responsive and resilient workforce training solutions.

Community colleges emerge as pivotal institutions in addressing these challenges, particularly when integrated into robust regional ecosystems that include employers and intermediaries. Recent federal initiatives, including $265 million in Strengthening Community Colleges Training Grants since 2021, demonstrate recognition of community colleges' crucial role. Successful workforce development programs often combine traditional education with work-based learning opportunities, such as registered apprenticeships and career technical education (CTE). Several states have already begun implementing AI-specific CTE programs to prepare students for the evolving technical workforce.

However, significant challenges persist in the current workforce development landscape. These include fragmented training systems, insufficient public funding, regulatory disincentives favoring capital investment over labor, and difficulties in scaling successful programs.

While AI may be a source of workplace disruption requiring enhanced workforce training efforts, it also presents opportunities to address some of these systemic challenges in workforce development. The technology's capabilities could help scale effective training solutions and make them more accessible and affordable, potentially bridging gaps in the current system.

Specifically, these capabilities enable personalized learning experiences, rapid content delivery, and increased accessibility. AI tools can provide customized learning paths, instant feedback, and career guidance. However, implementation must be approached cautiously. Concerns include the potential erosion of interpersonal skills, trust and privacy issues, and the risk of exacerbating existing inequalities through algorithmic bias and unequal access. Research indicates that while AI tools can enhance productivity, overreliance on these tools may hinder genuine skill development and learning.

Moving forward, successful workforce development will require a multifaceted approach: strengthening community college programs, expanding alternative career pathways, incorporating AI literacy into training initiatives, and ensuring equitable access to technology-enabled learning opportunities. This should be accompanied by careful consideration of how AI tools are integrated into training programs to maximize benefits while mitigating risks to skill development and learning outcomes. Further research is needed to understand how successful training solutions can be scaled across diverse regions and how AI training tools can be effectively deployed to serve diverse populations while supporting genuine skill development and learning.

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Introduction

Artificial intelligence (AI) has the potential to substantially increase productivity for the U.S. economy, in turn bolstering economic growth and overall living standards. At the same time, it may have the capacity to transform the nature of work across various industries, thereby significantly reshaping employment patterns and job roles. Research suggests that knowledge workers, typically shielded from technological disruption, may be significantly impacted by AI.[1]

As a consequence, the rapid rise and integration of AI has sparked renewed discussions on workforce development, primarily driven by concerns over worker displacement. Moreover, it underscores the pressing need to cultivate a larger pool of skilled but economically resilient talent. In the context of these technological shifts, the United States also faces the challenges of low and declining labor force participation, a decentralized training system, and reduced federal support for training programs.[2]

Against this backdrop, a new era of workforce development is emerging with renewed focus on skills-based learning programs. Both workers and employers are starting to shift away from traditional workforce on-ramps and embracing avenues for re-skilling and upskilling. Government agencies, employers, and educational institutions need to evaluate whether current workforce training and work-based learning programs are designed to maximize the country's ability to reap the economic benefits of AI-driven productivity growth and ensure that these benefits are widely shared across the workforce. Achieving this requires a deep understanding of existing challenges, as well as identifying and scaling the key factors that drive successful workforce training.

As AI is a fast-evolving technology, it is difficult to predict its ultimate impact on the workforce and the economy overall. Acknowledging that, this report aims to highlight some key considerations regarding the impact of AI on the workforce and its implications for workforce training.

Section one provides an overview of the recent empirical evidence on the likely future impact of AI on occupations and skills. It illustrates how AI, as a general-purpose technology, has the potential to transform a wide variety of industries and occupations. While this transformation might make certain skills redundant, it will also create new demand, especially in cognitive and analytical fields. Notably, section one also underscores the increasing importance of social, foundational, and thinking skills. In order to minimize disruption and maximize productivity gains, it is essential to scale up efforts in upskilling and retraining workers, particularly those in jobs with high exposure but low complementarity to AI.

Section two discusses the implications of these impacts for the future of workforce development. As the current literature on this issue is still relatively new, we supplement research results with insights gained from two roundtable discussions we hosted with researchers and practitioners. Our findings indicate that community colleges are playing an important role in successful workforce training. Workforce training programs are particularly successful when leveraging targeted funding and community partnerships. However, challenges to scale effective workforce training programs persist due to fragmented systems, insufficient public funding, and varying engagement from employers.

While AI may disrupt a variety of industries and occupations, it also holds the potential to support training and education. Hence, section three illustrates the role AI could play in addressing existing challenges in workforce training and improving efforts with regard to retraining and upskilling. One of the key advantages is the speed at which personalized training content can be delivered. AI technology enables the rapid creation of tailored learning materials, allowing workers to access relevant information and training modules almost instantaneously. Furthermore, AI tools enhance accessibility by providing personalized learning experiences that cater to diverse needs and learning styles. For instance, individuals can engage with content at their own pace, allowing those with different backgrounds or time constraints to participate more effectively. However, integrating AI tools in workforce training raises concerns about trust, the erosion of interpersonal skills, and the potential to exacerbate existing inequalities within the workforce. As AI tools become more prevalent, careful consideration must be given to their design and implementation to ensure equitable access and positive learning outcomes for all individuals.

1. The Potential Impact of AI in the Workforce

Unlike industry-specific technologies, AI is poised to disrupt a broader range of skills and occupations, with important implications for workforce development and training.[3] This section takes a closer look at what sets AI's impact on the workforce apart from previous waves of technological change.

Similar to the steam engine, electricity, and semiconductors, AI could be considered a general-purpose technology.[4] General-purpose technologies are characterized by the following three key attributes.[5]

- Pervasiveness: the technology can be applied in numerous industries and sectors.
- Technological dynamism: the technology experiences continuous improvements and advancements.
- Capacity to generate complementary innovations: the technology leads to the development of new processes, products, or business models that further enhance its impact.[6]

AI fits this definition well, as demonstrated by its transformative applications across sectors. In health care, physicians are using large language models (LLMs) to draft clinical notes and assist with diagnostic processes. In financial services, AI algorithms help detect fraudulent transactions and automate underwriting decisions. In manufacturing, computer vision systems enhance quality control, while predictive maintenance algorithms optimize equipment performance. In education, adaptive learning platforms personalize student instruction, and AI writing assistants provide targeted feedback. AI technologies are rapidly evolving, showing significant improvements in capabilities such as machine learning and natural language processing. Generative AI, in particular, has the potential to revolutionize areas such as content creation, automated design, and coding, showcasing the continuous technological dynamism of AI.[7] Additionally, AI is a catalyst for complementary innovations, enabling advancements in fields such as data analytics, autonomous systems, and personalized medicine.[8]

With respect to generative AI alone, recent research indicates that the speed of adoption of LLMs such as ChatGPT, Gemini, or Claude exceeds the pace of adoption of the personal computer and the internet.[9] As of summer 2024, 39 percent of working-age adults (18–64) reported using generative AI in their jobs. The potential labor market implications could be significant. Eloundou et al. (2023), for example, find that

80 percent of U.S. workers might have at least 10 percent of their work activities affected by LLMs, and a total of 19 percent of all workers have seen at least 50 percent of their work activities impacted.[10] Similarly, a recent study by the Council of Economic Advisers estimates that around 10 percent of the current workforce is potentially AI vulnerable.[11] Analysis conducted by the Pew Research Center finds that around 19 percent of the U.S. workforce is most exposed to AI.[12] At the global level, Goldman Sachs estimated that AI could automate 300 million of today's jobs.[13]

Even before the introduction of generative AI, advances in general AI and machine learning have impacted labor markets and skill requirements over the past decade. Using information from online job-post data between 2010 and 2018, Acemoglu et al. (2022) find that AI adoption at the firm level substantially changes the demand for skills in occupations exposed to the technology.[14] Importantly, they point out that while AI is going to make certain skills redundant, it also generates demand for new skills.

Previous waves of technological change primarily negatively impacted blue-collar jobs and occupations with lower educational requirements.[15] The advent of AI, however, has shifted this dynamic, now anticipated to affect a broader range of professions, including those requiring higher levels of education and specialized skills.[16] In fact, Felten et al. (2021) find that white-collar occupations appear to have the highest exposure to AI.[17] As a result, AI's potential impact is not confined to tasks and jobs with lower educational requirements and experience but extends to those that include cognitive and analytical activities. [18]

Ultimately, the effect of AI on workers depends on two components. First, how much of an occupation's core tasks and required skills can potentially be performed or enhanced by AI? Second, is AI likely to substitute for or complement workers in specific roles? This helps identify which workers may need retraining and upskilling.

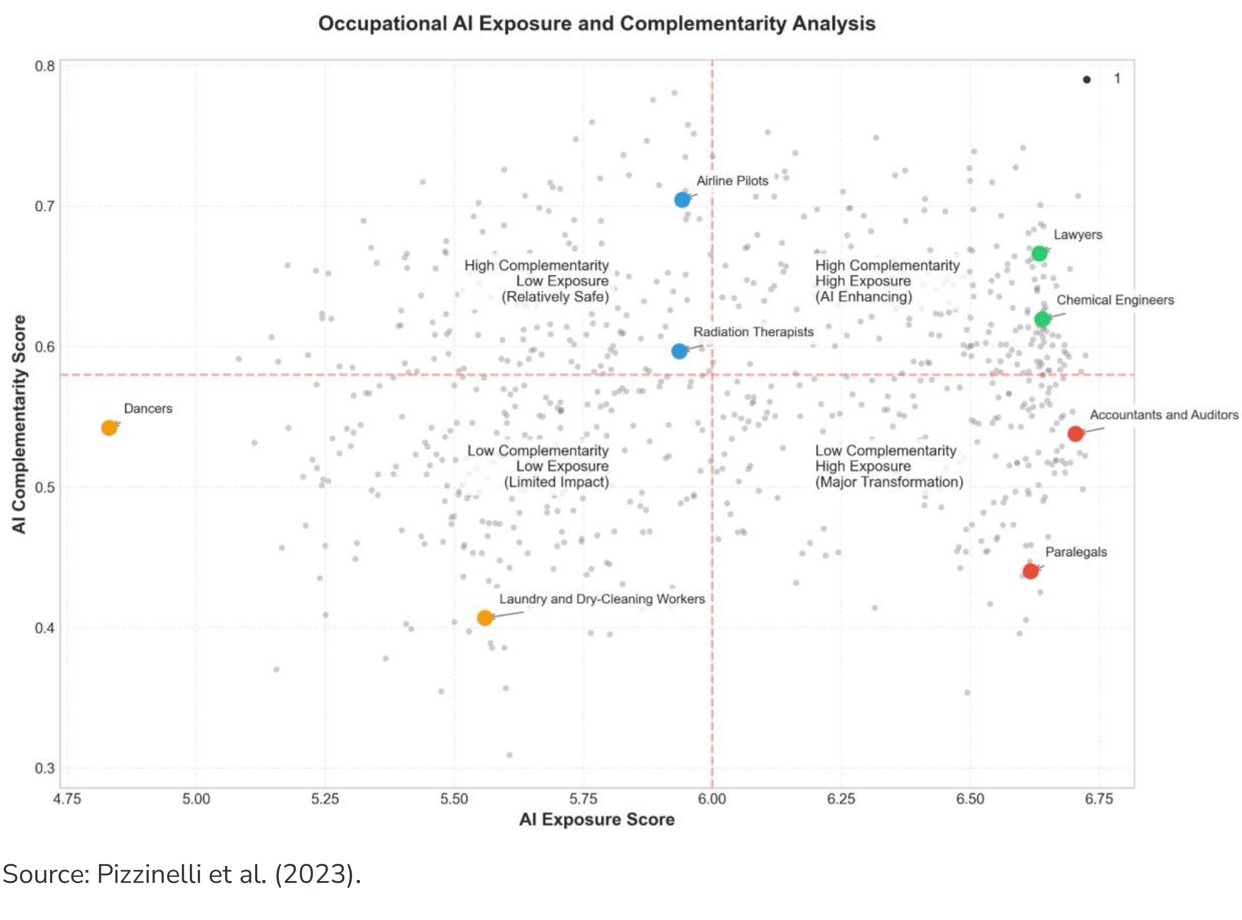
The two dimensions important to assess the impact of AI on the workforce are illustrated in Figure 1 below, reproduced from Pizzinelli et al. (2023).[19] Making use of the O*NET repository, a comprehensive database that provides detailed information about various occupations in the United States, the authors first construct a measure of occupational exposure to AI based on the jobs' respective tasks. The level of occupational exposure is represented on the horizontal axis in Figure 1. Next, for each occupation in O*NET, the authors develop a measure of complementarity to AI, which is depicted on the vertical axis.

Occupations with relatively lower exposure to AI are located in the left two quadrants. These will likely experience very little disruption from AI, as their task composition is less suited for AI solutions.

Occupations located in the upper-right quadrant exhibit a relatively high exposure to AI. At the same time, they also have a high level of complementarity. In other words, these occupations benefit from the technology. As a result, these occupations are likely to experience a boost in productivity as their tasks can be augmented by AI.

Occupations in the lower-right quadrant, in contrast, have high exposure to and low complementarity with AI. In other words, these are occupations that will likely see a negative impact from technological change, including decreased labor demand, job displacement, wage pressure, and potential de-skilling as AI technologies take over core tasks.

Figure 1. AI Exposure and Complementarity



Source: Pizzinelli et al. (2023).

From a policy perspective, it is especially important to know which occupations have a high exposure to and low complementarity with AI, as these are the ones likely to experience the biggest adverse effects. To fully reap the benefits of the productivity-enhancing effects of AI, it would be pertinent to provide these workers with opportunities for retraining and upskilling to increase their employability and earnings potential.

The Impact of AI on Skills and Occupations

Understanding the impact of AI on workforce training necessitates an examination of its effects on skills and occupations. Here, we explore how AI is transforming job roles and the skills required, providing a foundation for assessing its implications on workforce development.

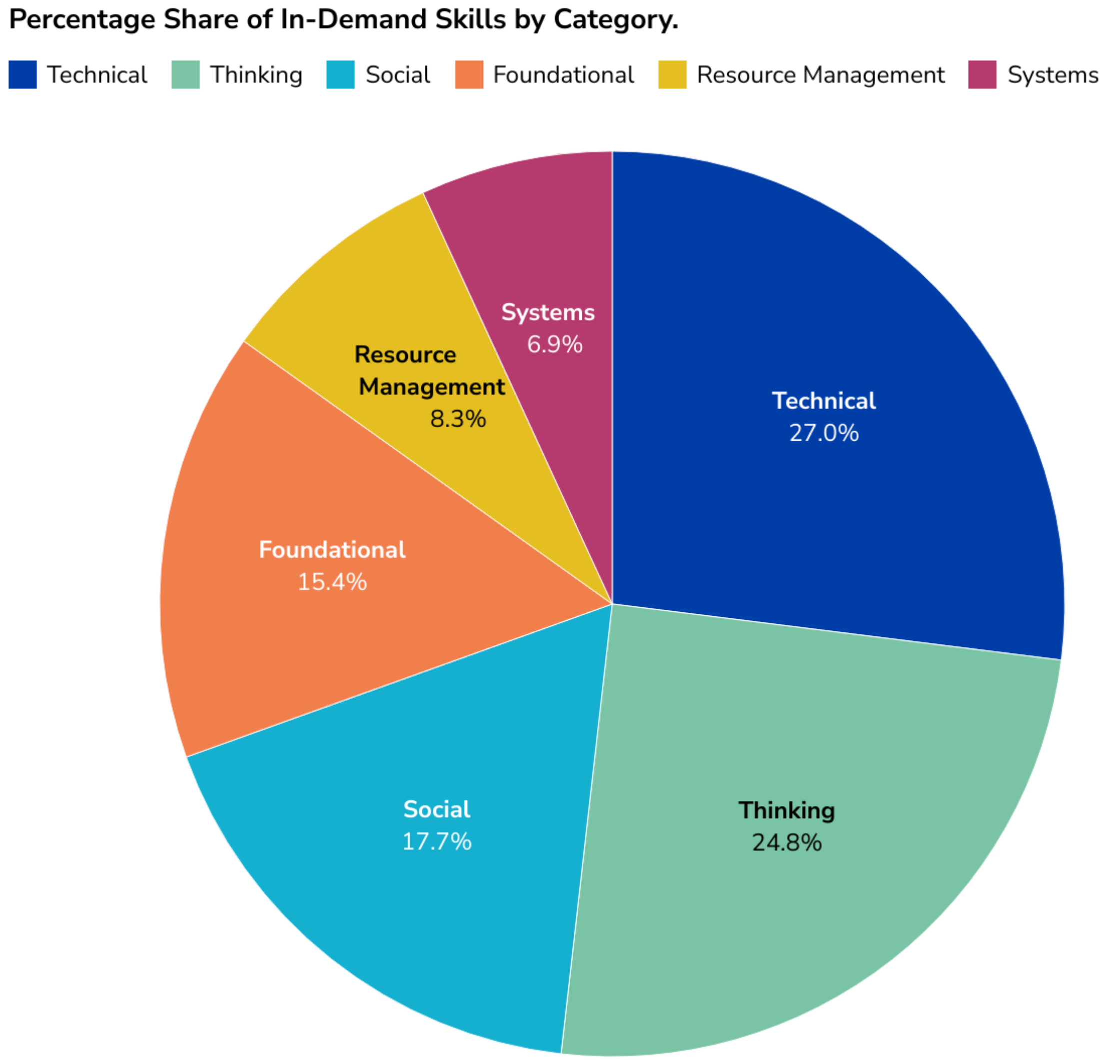
Given current technological developments, some scholars claim that a number of technical skills now tend to become outdated in less than five years on average, with some technology fields seeing this time frame reduced to just two and a half years.[20] This raises the question of which skills will become more important for workers in the foreseeable future. To explore this, we used occupational forecast data provided by the Bureau of Labor Statistics. Focusing only on those occupations for which demand is expected to grow over the next decade, we analyzed which skills are used most intensively in these occupations, applying information from the O*NET repository.[21] We can label these as in-demand skills. Figure 2 depicts the in-demand skills resulting from our analysis.

Figure 2. In-Demand Skills in Growing Occupations

Source: Bureau of Labor Statistics and O*NET; authors' calculations.

It is noteworthy that a majority of the skills depicted in Figure 2 are not actually technical skills. This is illustrated in Figure 3, which breaks down the share of in-demand skills using the O*NET typology. As is shown, technical skills make up around 27 percent of those intensively used in in-demand occupations. These include, among others, operations analysis, quality control analysis, and technology design.
Yet, Figure 3 also shows that foundational skills, social skills, and thinking skills together account for almost 58 percent of in-demand skills. A crucial example of thinking skills is judgment and decision-making, which, in order to be effectively executed, require a certain level of subject-matter expertise. Indeed, recent research corroborates that workers with deep subject-matter expertise are likely to benefit from AI.[22]

Figure 3. Percentage Shares of In-Demand Skills by O*NET Skills Category



Source: Bureau of Labor Statistics and O*NET; authors' calculations.

O*NET defines foundational, or basic, skills as abilities that enhance learning and speed up the acquisition of knowledge. They include mathematics, active listening, active learning, and learning strategies. Social skills alone account for roughly 18 percent of in-demand skills and include social perceptiveness, instructing, and negotiating. Thinking skills include complex problem-solving, critical thinking, and judgment and decision-making, among others.

Our finding that foundational, social, and thinking skills are likely to be of increasing importance in the labor market is corroborated by other recent studies.[23] Deming (2017) shows that the importance of social skills has grown since the early 2000s.[24]

Tripathi (2016) finds that jobs that are difficult to replace typically involve emotional and relational tasks, creativity, problem-solving, synthesis, and intelligent interpretation.[25] The World Economic Forum's "Future of Jobs Report 2023" states that complex problem-solving, analytical thinking, and creative thinking are among the most important cognitive skills. Empathy, active listening, and lifelong learning also rank among the top 10 core skills listed by employers.[26] A recent study on the impact of technological change on vocational training curricula in Germany finds that digital and social skills have become more important over the past two decades.[27]

The potential impact of AI on the demand for skills and the speed at which specific skills might become obsolete necessitates an evaluation of how well current workforce training programs can meet future retraining and upskilling needs. To assess how the current system addresses existing challenges and, where necessary, could be adapted to meet those posed by AI, we engaged in a series of discussions with subject matter experts across various fields. These conversations revealed key insights, which are presented in the following section.

2. Conversations with Subject Matter Experts

While AI is not necessarily a new phenomenon, the rapid development, adoption, and deployment of AI models has sparked renewed concerns for the potential workforce displacement that has historically accompanied technological development. However, the nascent literature on this topic provides limited insight into how AI is or is not fundamentally changing the nature of labor demands and workforce training. If our economy and labor force is to see significant disruption or displacement from AI tools and services, is our workforce training infrastructure prepared to respond? To supplement this study, we organized two virtual roundtable discussions with a total of 15 diverse participants representing industry, academia, nonprofits, and think tanks. Responses are aggregated and anonymized for research purposes. The goal of both roundtable discussions was to gain valuable insights from these practitioners regarding trends in the education system in the wake of AI and how workforce development might be affected.

There were three guiding questions:

(1) What currently works well in workforce training and has the potential to be scaled up?

(2) What are the barriers/problems in workforce training that need to be addressed in the context of AI's impact on the workforce?

(3) What role could AI itself play in improving workforce training? Can you speak about barriers to access, large-scale implementation, and any cybersecurity and ethical concerns?

Based on the general discussion, responses are aggregated into two themes: where to focus workforce development efforts and what challenges remain. Discussion on the first and second guiding questions is captured in this section, while a deeper discussion of the third question is largely the focus of the final section.

Where to Focus?

Community colleges and regional ecosystems. Roundtable participants highlighted that community colleges are the largest provider of workforce development services and programs yet still have enormous untapped potential. Community colleges offer accessible, affordable, and shorter educational programs to a wider variety of learners—in turn, these schools can more nimbly meet local and regional workforce needs and tailor their curriculum so that students gain practical and relevant skills.

This responsiveness enables a feedback loop between the educational system and the employer, creating a more responsive system to employer needs and wants, which participants note is important for success. The federal government has already taken steps to reinforce this feedback loop through the Strengthening Community Colleges Training Grants. Since 2021, this program has granted $265 million to community colleges to improve skill training and meet the demands of local labor markets.[28] Moreover, in April 2024, the Department of Labor announced the award of $65 million to support community colleges in expanding access to training and skill development for in-demand industries. The grants will benefit a total of 41 colleges across the United States.[29]

Roundtable participants also noted that community college programming works best when it's tied to sectoral training programs or regional ecosystems that include employers and intermediaries. Sectoral training programs bring together multiple entities, such as state agencies or local workforce boards, within a single industry to develop needed talent and support local employers.[30] Empirical research suggests that these models are highly beneficial to job seekers and lead to better wage outcomes for workers.[31] Sectoral programs also frequently provide job placement advising, workplace professionalism training, and short-term internships with local firms. These support services and partnerships with local employers can contribute to the programs' long-term successes.[32]

For example, job seekers who participated in sectoral programs such as Per Scholas and Project QUEST have seen their earnings rise by $5,000 or more per year, a trend that continues years after trainees leave the program.[33] Students at Year Up, a program primarily for financial services and information technology careers, have seen an average 30 percent increase in their earnings over six years and were less impacted by the COVID-19 pandemic.[34] Still, sectoral programs have low acceptance rates and often require students to meet certain skill requirements, such as having a high school degree or GED—factors that could contribute to the programs' success rates.

Work-based learning. Roundtable participants, researchers, and policymakers alike were optimistic about the potential for work-based learning and alternative educational pathways to offer learners and workers a viable on-ramp for retraining or upskilling. Work-based learning is a method of instruction that teaches students practical and tangible skills through real work experiences and may be combined with certifications earned following the completion of a program. Two examples of work-based learning, apprenticeship and career technical education (CTE), are highlighted below.

According to the Department of Labor, registered apprenticeship (RA) is a useful mechanism for bringing workers without college degrees into the workforce through structured and hands-on learning.[35] RA programs are approved and validated by the U.S. Department of Labor or a state apprenticeship agency. The value of an RA program sets it apart from other types of work-based learning. Apprentices earn progressive wages as their skills improve, receive worker protections and supervised instruction, and receive a nationally recognized credential following the completion of their program.[36] On the other hand, the employer can mitigate skills gaps in their workforces while reaping the most benefit from their investment.[37]

There was some concern among participants that the apprenticeship model is less attractive to employers and that tension exists between registered and unregistered apprenticeship programs. Existing research on apprenticeship efficacy often touches on ways programs could be improved or how funding streams might be updated. In contrast, there is less research concerning the viability of the apprenticeship model, especially for technical jobs. Essentially, until the apprenticeship model can be scaled to reach and serve more students, it will remain a relatively small on-ramp into the workforce in select areas.

CTE is also gaining traction as training for entry into the skilled workforce. CTE programs are mostly optional courses that prepare students with technical knowledge, skills, and abilities related to specific occupations. Through these programs, students can gain industry-recognized certifications or earn college credit while potentially shortening their time to enter the workforce. CTE programs strengthen the connection between K–12, postsecondary, and workforce development systems, as they are offered at nearly every public school system in the United States.[38]

AI-specific CTE programs are already taking shape. Over the last year, high schools in California, Florida, Georgia, and Maryland have started to design and implement AI-specific CTE programs that prepare students to enter the technical workforce.[39] For example, Florida's statewide AI CTE program focuses on technical skill proficiency and competency-based applied learning of AI, and a Georgia high school's CTE program first introduces students to programming, data science, math, and ethical reasoning skills and then teaches students how to design and test AI-powered solutions.

Updating digital literacy. Additionally, there is a newfound pressure on the education system to quickly update digital skill competencies to include elements of AI and cybersecurity literacy. AI literacy can be tricky to define. Over the last year, a commonly accepted definition has emerged to include the knowledge, skills, and attitudes associated with how AI works and its principles, concepts, uses, limitations, and implications.[40] This also includes elements of data literacy, data management, and cybersecurity or privacy. Roundtable participants suggested that too much trust in or overreliance on AI-powered tools and technologies can be mitigated with such AI literacy skills. For example, a participant posed the idea of how a nurse using an AI-powered note-taking scribe for recording conversations with patients will need to understand the tool's limitations and not rely entirely on its ability to accurately capture the conversation with the patient.

Research suggests that digital literacy holds the potential to enhance lifelong learning. Despite its importance, one-third of American workers lack sufficient digital literacy.[41] Given that more than 92 percent of jobs require digital skills, this significantly reduces economic mobility for these workers and hampers technology adoption and economic competitiveness.[42] National efforts to provide all Americans with digital literacy are also underway. In July, Senators Mark Kelly (D-AZ) and Mike Rounds (R-SD) introduced a bill aimed at developing AI literacy and confidence for consumers and users of AI products, tools, and services.[43] If passed, this bill would direct the secretary of commerce to develop a national consumer literacy strategy and accompanying media campaign to target all consumers, not just those currently enrolled in educational courses.

However, the K–12 education system has been relatively agile in its responsiveness to equipping students with technological competencies. Over time, as new workers transition into the workforce, students who have already been exposed to digital literacy may help to close the divide. At least 32 states have statewide standards for digital learning that include topics like digital citizenship and computational thinking—skills illustrated in Figure 2 that overlap with the emerging topic of AI literacy—which will enable learners to deconstruct problems, recognize patterns, and think critically about solutions.[44] Additionally, at least 60 percent of U.S. high schools offer at least one foundational computer science course, with 11 states requiring completion of computer science for graduation.[45]

What Challenges Remain?

Similar to the decentralized education system, workforce training systems in the United States are fragmented. This has both pros and cons. Decentralization allows for greater experimentation and flexibility but is difficult to assess, compare, or scale due to factors such as significant regional differences, uneven funding, variations in governance structures, and resource allocation.

Lack of public funding. Roundtable participants largely agreed that federal funding for workforce development must increase and pointed to the Workforce Innovation and Opportunity Act, suggesting that more investment is needed but should be targeted toward programs with demonstrable success or proven scalability.[46] The WIOA was signed into law in 2014 and is designed to increase access to employment, education, training, and support services for job seekers. It was the first legislative reform of the public workforce system since 1998.[47]

Others argue that WIOA requires reform. Research shared during the roundtable highlighted that WIOA-funded training programs have a mixed record of connecting students to living-wage jobs.[48] Additionally, there are concerns that community colleges and workforce development ecosystems face an uncertain funding environment, as public funding for workforce development is uneven across sectors and smaller compared to traditional higher education.[49] There is also a broader concern that a lack of good data on these programs—including their efficacy, funding, and outcomes—makes it difficult to properly compare and assess programs.

In April 2024, the U.S. House of Representatives introduced a bill to amend and reauthorize WIOA, which is the main source of federal funding for states and local communities to provide workforce development services and job training.[50] Updates to the WIOA include a requirement that at least half of the direct funding must be used for skills training and work-based learning opportunities, and some funding may be used for administrative purposes such as wraparound services. However, it is important to note that training funding is not necessarily equal to training quality.[51]

Sectoral programs, on the other hand, are considered effective but are difficult to scale up. Year Up, for example, is a one-year, full-time program that trains young adults (age 18 to 24) from low-income backgrounds for jobs in high-demand professions, usually financial services and information technology. Year Up has educated over 45,000 students in 24 years and now has about 30 campuses across the United States. However, the cost of educating a Year Up participant in 2021 was about $28,000.[52]

Another long-standing program, Per Scholas, has trained over 25,000 low-income adults for high-demand tech careers in 20 locations across the country. In 2019, Per Scholas' cost per participant per course was $7,500, and currently the program offers up to $15,000 of free training per learner.[53] Tuition for Per Scholas and Year Up participants is free. Funding largely comes from employers that work with the programs to hire graduates, grants from foundations, and private donations.[54] In contrast, the average cost of training a participant through WIOA was just $1,854 in 2019, and WIOA training vouchers generally have upper limits ranging from $5,000 to

$10,000.[55] To mitigate these scaling challenges, Year Up has begun to provide virtual training and is partnering with community colleges to reach more participants.

Regulatory disincentives and insufficient employer engagement. Insufficient employer engagement can prevent the creation of a successful workforce training ecosystem.[56] Training programs work best when the ecosystem parts—the academic institutions and the companies—are working in harmony. However, participants noted that this is not always the case. For example, ongoing CSET research indicates that employers are less interested in apprenticeship programs. One reason is that employers might be reluctant to invest in retraining existing employees out of concern that competing companies will hire this talent. Another is that companies are disincentivized by the administrative burden of committing to an apprenticeship program.[57]

Additionally, U.S. tax policy favors capital investment over labor, meaning businesses often find it more cost-effective to invest in machines rather than human workers. This is primarily because equipment and software investments benefit from lower tax rates (sometimes as low as 5 percent) due to generous depreciation allowances. In contrast, labor incurs much higher tax burdens, with payroll and income taxes exceeding 25 percent.[58]

Challenges of age diversity, varied backgrounds, and large cohorts. As a few roundtable participants pointed out, learner diversity with respect to age, abilities, and proficiencies can be an additional challenge for those looking to re-skill or upskill their employees. Employees differing significantly in age might bring varying levels of technological proficiency and learning styles. This can make it difficult to implement a one-size-fits-all approach, potentially increasing the cost of training. These challenges can be compounded in cases where a large cohort of employees requires retraining or upskilling.

In the academic context, accurate and comprehensive data collection for noncredit students remains a challenge. This makes it difficult for colleges to determine the effectiveness of the workforce training programs and for students to transfer the credit should they decide to pursue a degree later or more advanced certification later.[59] Additionally, noncredit programs are often ineligible for state and federal funding, potentially decreasing the accessibility of these programs.[60]

Some evidence also suggests that community colleges must significantly reform certification and associate's degree programs to meet labor market demands. In 2024, Georgetown University's Center on Education and the Workforce (CEW) reported that education and training in communities are often misaligned with local labor demands. This trend is particularly prevalent in middle-skills certifications (above a high school degree but below a bachelor's), which community colleges play a large role in providing. CEW's research found that at least 50 percent of middle-skill credentials would need to be granted in different fields of study to meet projected labor demands through 2031.[61]

One potential way to address this problem would be to increase short-term re-skilling programs. These programs could offer flexibility for adults with full-time jobs, children, and years of workforce experience. Virginia's FastForward program was designed for such adult learners, offering six-to-12-week re-skilling and upskilling courses at community colleges. By 2026, Virginia is expected to have a middle-skills gap of 2.6 million, which this program aims to close.[62] Since 2016, FastForward has granted over 52,000 credentials, and students have seen an average increase of over $11,000 in wages, according to FastForward's data.[63] Another analysis of this same program argues that the increase in average earnings is only $4,000.[64]

3. The Role of AI in Workforce Training and Development

In addition to the existing workforce development infrastructure discussed above, AI has the potential to support improvements in workforce training and work-based learning. With recent developments in generative AI, an expansive array of use cases is possible. That said, any implementation must be executed with caution and careful consideration.

Already, several industries have adopted AI tools to train new workers and provide existing employees with upskilling and re-skilling opportunities. For instance, manufacturing industries rely on virtual reality simulations (a technology sometimes built with AI) to train employees for the floor, ensuring their safety from dangerous machinery until they are ready to operate it in real time.[65] Other platforms allow aspiring programmers to practice their coding skills with automated feedback.[66] Research efforts have developed a suite of tools that work in tandem to augment online learning.[67] And AI career and job-searching tools have exploded in their accessibility and performance. These initiatives, and many more, are already changing the nature of workforce development and will only continue to accelerate in their impact. However, the widespread adoption of many AI tools could lead to an erosion of interpersonal skills, trust and privacy concerns, and an amplification of existing inequalities fueled by algorithmic bias and inequitable access. Below, we explore the key dimensions through which AI alters workforce development.

Personalization

AI tools personalize workforce training by improving two key dimensions: knowledge tracing and career development. Tools can help instructors trace a student's existing knowledge base, attuning them to the student's strengths and weaknesses. Then, once tools gain an understanding of the student's baseline, the AI can generate and recommend content, coursework, and career road maps that best align with the user's interests. In this section, we explore how personalization can potentially improve these aspects of workforce training.

First, AI tools can automate knowledge tracing for instructors. In a traditional classroom setting, instructors often struggle to modulate their lesson plans to fit the various backgrounds and knowledge bases of their students. With time and planning constraints, instructors do not often have the bandwidth to personalize their lessons for the needs of every student. They may rely on feedback from short quizzes at the end of a lesson or other diagnostic mechanisms to assess students' learning. Still, it is impossible to ask an instructor to adapt their lessons for each student, and the rise of large, virtual classrooms renders this task even more difficult. The diversity of student backgrounds and preparation is also a major challenge in community colleges.

AI tools can support and simplify this process by highlighting differences in the knowledge base among participants. Akin to a teacher in a classroom who must be attentive to the varying knowledge base of each student, AI tools can personalize the process for the online learning world, where students often enroll in a one-size-fits-all course that does not modulate content for each student and has limited or no interaction with an instructor. One example of this is the National AI Institute for Adult Learning and Online Education (AI-ALOE)'s SMART tool, which models students' understanding by generating a concept map of a textbook reading and compares it with a student's summary of the same section. The tool then uses the differences between the student's summary and an expert concept map to identify knowledge gaps and generate personalized feedback for the student. This lightens an instructor's workload by modulating the learning content to fit each student's needs and automatically scaffolding the lesson for the student.

Furthermore, knowledge tracing can greatly benefit on-the-job training, which often needs to occur quickly to accommodate the rapid nature of frontline, customer-facing work. Managers in charge of training many new workers across different shifts and time periods may not always have the bandwidth to modulate their instructions to each worker. AI tools can support the customization of course modules to meet employees' existing skill levels and fill skill gaps based on the previous shift's answers, delivering quick, personalized content. AI can use this data to predict potential problems employees might face and provide help based on the company's culture and requirements. It can take into account a business's procedures, the worker's behavior, and potential issues the worker might face to provide individualized knowledge in real time.[68] By tracing the existing knowledge of learners and recommending relevant content that addresses practice areas, this wide array of upcoming AI tools personalizes the workforce training experience.

In addition to knowledge tracing, AI tools can generate personalized learning content calibrated to a learner's career interests and aspirations. Some tools employ natural language to chat with users about their career goals and desired skills, using the insights gleaned from the conversation to recommend personalized coursework, skill assessments, and hands-on labs.[69] Individuals seeking new employment can use AI tools to generate career and job recommendations based on their interests and existing skill sets. Some tools can match job seekers to local employers and use predictive models to forecast which skills will be most in demand in local labor markets.[70] As such, AI can help users gain greater clarity about their careers, turning passion into attainable pathways and resources, and recommend and generate personalized content to help users achieve those goals. These tools could potentially connect users with existing workforce development opportunities while inspiring students to plan their next steps.

Speed

The ability to deliver personalized content is only possible due to the near instant content-generating capabilities of AI.[71] This saves instructors time previously spent creating instructional materials, and the content itself is tailored and rapidly adjustable to each student's needs. As students' learning diverges across lessons into varying patterns of understanding, AI tools can quickly provide the training necessary at each step of the way.

The speed at which AI can generate customized materials allows for just-in-time learning that accommodates busy schedules. Current tools can atomize learning by generating short daily lessons. For example, Axonify's AI generates under-10-minute lessons for frontline workers to complete at the beginning of a shift. The micro-learning model is made possible by AI's ability to quickly adapt to the worker's past performance and create a personalized daily lesson.

Real-time feedback can enhance and improve workplace training.[72] In light of these possibilities, the Defense Advanced Research Projects Agency (DARPA), the Department of Defense's research and development (R&D) arm, has funded a competition to create AI tools for adult learning in high-demand technical fields.[73] The competition responds to concerns set forth by the 2023 National Defense Science and Technology Strategy, which calls for updating workforce training to maintain U.S. strategic advantage in science and technology innovation.[74] DARPA's contest, called Building an Adaptive and Competitive Workforce, supports products that leverage AI to deliver self-paced, personalized learning, aiming to reach a wide audience at a low cost. Most of the programs focus on tech skills such as cybersecurity, AI, and data science, but some products branch into other high-need fields, including manufacturing and HVAC workforce training.[75]

Trust

Part of what makes generative AI unique is that it is not only a tool for learning but a source of knowledge itself.[76] Concerns remain about the trust and accuracy of the generated information, and researchers have demonstrated that these tools can fabricate information.[77] As developers build AI tools for workforce training, it is important to ensure that they are safeguarded with additional checking procedures.[78] One possible framework is retrieval-augmented generation, which enhances model-generated output with information from a searchable database, like the internet or a proprietary dataset, so results do not rely solely on the training data. This prevents hallucinations and incorporates updated information into results.[79] In addition, developers can build trust by disclosing where their data is from and by demonstrating compliance with the ethical standards laid out in the Institute of Internal Auditors' AI Auditing Framework. They can also increase the interpretability of generated content by showing how models arrived at a solution. Additionally, our roundtable participants emphasized the importance of deploying AI tools with proper AI literacy training.

Accessibility

AI provides access to one crucial resource: time. The speed and flexibility of AI-powered training allow workers to have more time to focus on other aspects of their lives. Here, the converse is also true. Instructors who delegate some tasks to AI tutors have more time to foster relationships with their students, increasing students' access to the instructor and the instructor's knowledge.[80]

Perhaps the greatest impact that AI tools could have on workforce training is by increasing access to social capital and knowledge. AI's ability to quickly generate massive amounts of learning content at a large scale tailored to an individual's needs lowers costs and lightens instructors' loads. In tandem with the increase of accessible, high-quality learning, career-navigating tools empower learners with visions of a different future and guidance for how to achieve it. Previously, mentorship, role models, and a professional network provided individuals with the social capital to envision and navigate their future, creating a resource gap between different populations.[81] AI's ability to pave a personalized career path may offer disenfranchised individuals the opportunity to see beyond their circumstances and explore new possibilities.

While AI has the potential to provide greater access, it's important to critically examine whether these benefits are truly enjoyed by everyone. If people do not have fair and equal access to the tools, then AI could potentially exacerbate existing inequalities by only optimizing the workforce training and development experience for certain groups while excluding marginalized populations.

In principle, AI's ability to provide job and career navigation has the potential to aid many people who may not otherwise have the resources to know how to proceed. For instance, an AI-powered tool by Jobs for the Future and McKinsey & Company is tailored for job seekers who may have in-demand skills and experience but lack a four-year degree and earn less than $42,000 a year. This job transition tool provides career pathways based on workers' résumés and existing roles, identifying target occupations that could transition them into higher-paying work.[82] In this case, AI is employed to help workers envision a way to greater prosperity, providing them with the information that they may not have.

However, it is important to note that these career-building tools have significant limitations. Marginalized populations, for example, could become edge cases for these models, which are not robust enough to handle cases with low-quality (or little) training data. Upwardly Global, a nonprofit organization that helps refugees and immigrants restart their careers in the United States, found that 35 percent of education credentials and 20 percent of work experience credentials on refugee and immigrant résumés were misidentified by an AI-powered career navigation tool. For example, when given the résumé of an Italian PhD with eight years of experience in education technology, the tool listed "folding bed linens" and "vacuum cleaning" as top skills, and an Afghan refugee with 12 years of experience as a military pilot and a civil engineering degree received zero relevant recommendations. This echoes a Stanford University study that found that AI tools misidentified 98 percent of essays written by non-native English speakers as generated by Chat GPT while only misidentifying 10 percent of native speakers' essays as machine authored. Given these current limitations, AI career-building tools could exacerbate existing inequalities in hiring and job access. As these tools are more frequently deployed and used, they need to be developed with an inclusive approach in mind. This will ensure that they also serve the most vulnerable and underrepresented groups.

Engagement

Previous research finds that online learning leads to lower retention rates and worse student performance.[83] Lack of face-to-face instruction and in-class time results in lower test scores and knowledge acquisition.[84] As learning environments become more digitized with the rapid adoption of AI tools, learner engagement is both impeded and improved in several important ways. In some instances, AI tools have the potential to facilitate more interactive learning. In others, they may lead to a decrease in knowledge acquisition. The following discussion outlines how AI tools affect engagement in two key ways: the interactive and the social. Additionally, we examine how AI tools have affected learning outcomes.

It is challenging to make broad claims about AI's ability to increase engagement when there are many different tools. However, some studies suggest that AI's personalized feedback increases learning engagement.[85] This is especially true for distance learning, where AI chatbots can make learning more interactive.[86] Additionally, because AI can adapt as learners become more skilled, some studies suggest that AI has the potential to encourage lifelong learning.[87] AI tools can leverage engagement tactics such as prompting students to answer questions as they read a text or making the learning into a game. Whether gamifying learning increases engagement can depend on the student's disposition, as studies in the young adult education field have shown. Students who are more introverted and less open sometimes benefit more from gamification.[88] On the other hand, one experiment in gamification at the accounting firm KPMG found greater performance improvements among workers who were already more engaged with their jobs to begin with.[89]

Digital learning is often an isolating experience with little social interaction. Yet, just as AI tools have the potential to further exacerbate loneliness, they may also provide an antidote. For instance, the AI-ALOE project created SAMI (Social Agent-Mediated Interaction), a tool that uses natural language processing and AI to connect virtual classmates. Using introduction posts on the class forum, SAMI parses out students' interests, identities, and learning styles to offer each student recommendations for whom to reach out to. With AI tools, online workforce training can become an opportunity for potential connection, offsetting the isolation of the virtual, asynchronous online environment. We cannot yet measure the success of SAMI and similar tools, as these technologies have not been deployed at a large scale.

Human Capital Development and Learning Outcomes

The aim of personalizing learning is to boost student engagement, which, in turn, is intended to enhance the acquisition of skills and knowledge. As organizations incorporate AI tools into their training protocols, we can begin to evaluate how well these tools promote learning. While research in this area is still nascent and many of the tools presented in this paper have not been deployed at a wide scale, emerging research does exist on the outcomes of AI-assisted learning.

Early studies have shown that incorporating AI tools into tasks spurs on-the-job learning. In a study by Brynjolfsson, Li, and Raymond (2023), researchers paired 5,000 customer service agents at a large software company with an AI tool that provided response recommendations to customer chats. While the tool did little to increase the performance of seasoned and highly skilled workers, it increased the productivity of novice and low-skilled workers by 34 percent.[90] Though Brynjolfsson, Li, and Raymond's result is widely cited as evidence that AI tools can not only aid but also teach the workforce, we must be cautious about generalizing their conclusions. Their study did not account for key confounding factors, such as the worker's experience level, which may have influenced the results. It is possible that the improved performance observed was not the result of AI, as attributed, but of the natural rapid improvement of new workers at the beginning of their tenure. Experienced agents who do not need to learn the ropes of the job and already have a steady modus operandi would not necessarily see a large leap in their performance. As a result, we cannot attribute the improved performance to AI when it could be due to the natural learning curve of employees.[91]

Competing studies have shown that AI tools benefit more experienced and skilled workers, suggesting that the technology does not *teach* workers with skills gaps but *augments* the performance of workers with expert knowledge. A 2024 study at a telemarketing company by Jia et al. concluded that the technology enhanced the creativity of higher-skilled workers but made limited improvements in the performance of lower-skilled workers.[92] Another recent study comes to similar conclusions, finding that the output of top scientists in the R&D lab of a material sciences firm nearly doubled with the assistance of AI-powered materials-discovery technology, while the bottom third of scientists saw little benefit.[93] The inability of lower-skilled workers to improve their performance implies that AI cannot train these workers with new skills. This skills bias of AI tools could potentially lead to greater performance gaps between low- and high-skilled workers if organizations do not invest in training their low-skilled employees.

Furthermore, as we evaluate the effectiveness of AI tools, we must be wary of equating productivity with learning. Even if workers may appear to perform better, as they did in the Brynjolfsson study, this does not imply that they have learned the skills of the job properly and can operate without the assistance of AI. While AI tools might support on-the-job training, they can also contribute to cognitive automation and the erosion of crucial skills.[94] As Rinta-Kahila et al. found in a case study at an accounting firm, workers became reliant on software that automated most of their tasks. This led to them having a weaker understanding of their work and an inability to perform tasks without the assistance of automation. Analogously, a 2024 study by Bastani et al. demonstrates how the overreliance on automation among students leads to poorer learning outcomes. In that experiment, researchers asked one group of high school math students to use ChatGPT to help with their homework questions and another to use a GPT-based tutoring system. While students using ChatGPT answered questions more correctly on their practice problems, their performance was 17 percent worse on the final exam than students who never had access to the tool.[95]

This process of automation could additionally lead to skill erosion. In the above-mentioned study where an AI-powered materials-discovery tool was introduced to material scientists, adopting the tool led to lower job satisfaction. Scientists complained that their skills were underutilized and that their work became less creative and more repetitive.[96] Hence, as AI becomes more widespread, it could lead to workers regressing in their expertise. However, more specialized tools that guide rather than generate thinking can potentially be an effective training mechanism. The Rinta-Kahila study also observed that students using the GPT-based tutoring system performed just as well as traditional students on the exam, implying that they were able to grasp the material with an AI-based tutor. All of this reveals that the type of interaction users have with AI can greatly affect learning outcomes. While an overreliance on generative AI tools can inhibit learning and erode existing knowledge, a more moderate, tutor-based approach could increase learning outcomes.

An overreliance on AI not only risks eroding technical skills but also puts soft skills in jeopardy. As one of our roundtable participants described, students are often reluctant to ask questions in class for fear of being perceived as unintelligent. AI allows students to ask their questions to the tool and circumvent any social anxiety. Our participant framed this as a learning improvement, but such a phenomenon could erode or inhibit important skills such as taking risks, articulating ideas, navigating a mentor-mentee relationship, and communicating with other people. Learning to ask questions, being comfortable with the unknown, and facing classroom anxieties are all important aspects of a student's confidence building and development that may be underexercised with an overreliance on AI.[97] Though there is an argument that interacting positively with AI tutors will translate to improved relationships with instructors and peers, we do not have any concrete evidence for how AI will build these soft skills. As we discussed in section one of this paper, while the demand for soft skills is expected to grow, there is concern that AI training tools could potentially undermine the development of these crucial abilities.

Nevertheless, AI could offer one solution to its own problem by providing tools to train soft skills. Some platforms offer soft-skill training courses by simulating social interactions with instant natural language responses. In mixed and virtual reality simulations of situations such as job interviews, sales pitches, talks, and one-on-one interactions, users interact with avatars who react and converse in real time, training their ability to hold difficult conversations and navigate group discussions.[98] Other programs focus on networking, body language, and leadership communication. In these early stages of research, whether an AI-powered tool that teaches soft skills is a sufficient proxy for authentic human interaction remains unknown. Still, perhaps these tools are only necessary in an environment where soft skills are heavily eroded by technological isolation, a stop-gap measure to a self-inflicted problem whose only solution is real social interaction.[99] As AI tools become more prevalent in workforce training, they must guide workers in their learning, not generate outcomes for them. Only with this approach can skills be taught instead of eroded.

Conclusion

AI, as a general-purpose technology, may have the capacity to transform a wide range of industries and occupations. This potentially broad impact underscores the need for comprehensive and adaptive workforce development strategies. While AI is a fast-evolving technology and its ultimate impact on the workforce is still rather speculative, it is prudent to evaluate the implications for workforce training and lifelong learning. This is especially critical given the accelerated pace at which AI is likely to render certain skills obsolete.

As this report highlights, community colleges play a crucial role in workforce development, and best outcomes are achieved when they are embedded in a strong regional ecosystem that includes employers, intermediaries, and sufficient wraparound services. Efforts around workforce training should include alternative career pathways, such as apprenticeships and CTE programs, as well as a stronger move toward skills-based hiring. Moreover, bridging the digital divide in the workforce is imperative. This requires a concerted effort to enhance digital skills education and incorporate AI literacy into training initiatives.

The latter is specifically important as AI tools might become more prevalent in training and education. AI technologies enable personalization of learning experiences, rapid delivery of tailored content, increased accessibility of training resources, and enhanced engagement through interactive learning tools. These capabilities have the potential to make training more effective, efficient, and accessible to a wider range of learners. However, the implementation of AI in workforce training also raises important concerns. These include issues of trust and safety related to AI-generated content, the potential exacerbation of existing inequalities due to unequal access to AI tools, the risk of eroding interpersonal and soft skills, and the possibility that overreliance on AI could hinder genuine learning and skill development. These concerns underscore the need for careful and ethical implementation of AI in training contexts.

Finally, our report highlights a few knowledge gaps that warrant further research to support viable policy solutions. First, exploring how successful training solutions and ecosystems can be scaled and replicated across diverse regions is essential. This involves identifying the key factors that facilitate such expansion, including infrastructure, stakeholder engagement, and contextual adaptability. Second, it is important to further our understanding of how AI training tools should be developed and deployed to maximize their effectiveness for diverse target audiences. This involves exploring the specific needs and contexts of these audiences to ensure that the tools are both accessible and impactful. Finally, assessing the ultimate impact of AI on the workforce necessitates comprehensive research into its long-term effects on job roles, skills, and industry dynamics. By addressing these themes, future research can better inform strategies that harness AI's potential while mitigating its challenges, ultimately leading to more effective and equitable workforce training outcomes.

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Appendix 1. Determining In-Demand Skills

The following describes our approach to determining in-demand skills as depicted in Figures 2 and 3. Our analysis focuses on skills prevalent in growing occupations rather than economy-wide skill trends because this approach better captures forward-looking workforce needs. While analyzing skill-demand changes across all occupations can reveal broad technological and organizational shifts, the data may include skills that are increasingly required in declining occupations—a potentially misleading signal for workforce planning. By focusing on growing occupations, we better align our skills analysis with future labor market opportunities and can more effectively guide workforce development investments.

In a first step, we use occupational projection data from 2022 to 2032 provided by the Bureau of Labor Statistics, keeping only those occupations that display a positive growth rate over this decade.

Next, we extract the skill composition for each of these occupations from O*NET. O*NET assigns both an importance measure and a level measure for each skill by occupation. More specifically, skills are assigned importance ratings on a scale from 1 to 5, with 1 indicating that the skill is not essential for the occupation and 5 signifying that it is crucial. If a skill receives a rating of 2 or higher, a corresponding level rating, ranging from 1 to 7, is assigned. This level rating assesses the complexity required for executing the skill within the occupation.

For each skill by occupation we then calculate the average value of importance and level. Next, following Alabdulkareem et al. (2018), we calculate the location quotient for each skill by occupation.[100] Applied in a variety of cases in economics, the LQ is a measure to evaluate the concentration of a particular subject of analysis in a specific area compared to a larger reference area, such as the national level. This can include an industry, an employment category, or a specific skill. An LQ greater than 1 suggests a higher concentration, which can imply that the area may be a hub for that subject, while an LQ less than 1 indicates a lower concentration.

Applying this concept to skills by occupation using the information from O*NET, we calculate the LQ as follows:

$$LQ_{O,s} = \frac{\left(\frac{S_{O,s}}{\sum S_O}\right)}{\left(\frac{\sum S_s}{\sum S}\right)}$$

Where:

- $LQ_{O,S}$ = Location quotient for skill *s* in occupation *O*
- $S_{O,s}$ = Skill *s* in occupation *O*
- $\sum S_O$ = Sum of all skills for occupation *O*
- $\sum S_s$ = Sum of skills *s* across all occupations
- $\sum S$ = Sum of all skills across all occupations

An LQ > 1 indicates that skill *s* is more concentrated in occupation *O* than in the overall workforce.

An LQ < 1 indicates that skill *s* is less concentrated in occupation *O* than in the overall workforce.

An LQ = 1 indicates that skill *s* is equally concentrated in occupation *O* as in the overall workforce.

Having calculated the LQs for each skill in the growth occupations, we then filter for those with an LQ>1. These are the skills depicted in Figures 2 and 3.

Appendix 2. Skills Required for In-Demand Occupations

Projected In-Demand Skills.

Skill Name	Number of In-Demand Occupations Requiring Skill
Systems Analysis	361
Systems Evaluation	353
Reading Comprehension	346
Writing	345
Active Learning	345
Complex Problem-Solving	343
Judgment and Decision-Making	332
Speaking	329
Critical Thinking	324
Active Listening	324
Management of Personnel Resources	320
Instructing	316
Operations Analysis	315
Social Perceptiveness	314
Persuasion	313

Source: Authors' calculations.

Endnotes

[1] Jorge Tamayo et al., "Reskilling in the Age of AI," *Harvard Business Review*, September–October 2023, https://hbr.org/2023/09/reskilling-in-the-age-of-ai.

[2] Harry J. Holzer, "Should the Federal Government Spend More on Workforce Development?," Brookings, May 23, 2023, www.brookings.edu/articles/should-the-federal-government-spend-more-on-workforce-development/#FN2.

[3] Manuel Trajtenberg, "AI as the Next GPT: A Political-Economy Perspective" (National Bureau of Economic Research, January 2018), https://www.nber.org/system/files/working_papers/w24245/w24245.pdf.

[4] Ajay K. Agrawal, Joshua S. Gans, and Avi Goldfarb, "Similarities and Differences in the Adoption of General Purpose Technologies" (National Bureau of Economic Research, February 2023), www.nber.org/papers/w30976.

[5] Timothy F. Bresnahan and M. Trajtenberg, "General Purpose Technologies 'Engines of Growth'?," *Journal of Econometrics* 65, no. 1 (January 1995): 83–108.

[6] Boyan Jovanovic and Peter L. Rousseau, "General Purpose Technologies," in *Handbook of Economic Growth*, vol. 1, part B, eds. Philippe Aghion and Steven N. Durlauf (Amsterdam: Elsevier, 2006), 1181–1224.

[7] Zarif Bin Akhtar, "Unveiling the Evolution of Generative AI (GAI): A Comprehensive and Investigative Analysis toward LLM Models (2021–2024) and Beyond," *Journal of Electrical Systems and Information Technology* 11, no. 1 (2024): 22; Stefan Feuerriegel et al., "Generative AI," *Business & Information Systems Engineering* 66, no. 1 (2024): 111–126.

[8] Francesco D'Alessandro, Enrico Santarelli, and Marco Vivarelli, "The Knowledge Spillover Theory of Entrepreneurship and Innovation (KSTE+ I): Approach and the Advent of AI Technologies: Evidence from the European Regions" (Institute of Labor Economics, August 2024); Robert M. Wachter and Erik Brynjolfsson, "Will Generative Artificial Intelligence Deliver on Its Promise in Health Care?," *JAMA* 331, no. 1 (2024): 65–69.

[9] Alexander Bick, Adam Blandin, and David J. Deming, "The Rapid Adoption of Generative AI" (National Bureau of Economic Research, September 2024).

[10] Tyna Eloundou et al., "GPTs Are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models," arXiv preprint arXiv:2303.10130 (2023).

[11] CEA, "Potential Labor Market Impacts of Artificial Intelligence: An Empirical Analysis," White House, July 10, 2024, www.whitehouse.gov/cea/written-materials/2024/07/10/potential-labor-market-impacts-of-artificial-intelligence-an-empirical-analysis/.

[12] Rakesh Kochhar, "Which U.S. Workers Are More Exposed to AI on Their Jobs?," Pew Research Center, July 26, 2024, www.pewresearch.org/social-trends/2023/07/26/which-u-s-workers-are-more-exposed-to-ai-on-their-jobs/.

[13] Joseph Briggs and Devesh Kodnani, "The Potentially Large Effects of Artificial Intelligence on Economic Growth," Goldman Sachs, March 26, 2023, www.gspublishing.com/content/research/en/reports/2023/03/27/d64e052b-0f6e-45d7-967b-d7be35fabd16.html#.

[14] Daron Acemoglu et al., "Artificial Intelligence and Jobs: Evidence from Online Vacancies," *Journal of Labor Economics* 40 no. S1 (April 2022): S293–S340.

[15] David H. Autor, Frank Levy, and Richard J. Murnane, "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics* 118 no. 4 (November 2003): 1279–1333.; C. Goldin and L. F. Katz, "The Race between Education and Technology," in *Inequality in the 21st Century* (London: Routledge), 49–54; Daron Acemoglu and Pascual Restrepo, "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy* 128, no. 6 (June 2020): 2188–2244.

[16] Carlo Pizzinelli et al., "Labor Market Exposure to AI: Cross-Country Differences and Distributional Implications (International Monetary Fund, October 4, 2023).

[17] Edward Felten, Manav Raj, and Robert Seamans, "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses," *Strategic Management Journal* 42, no. 12 (December 2021): 2195–2217.

[18] Erik Brynjolfsson and Andrew McAfee, *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies* (New York: W. W. Norton, 2014); Manuel Trajtenberg, "Artificial Intelligence as the Next GPT," in *The Economics of Artificial Intelligence: An Agenda*, eds. Ajay Agrawal, Joshua Gans, and Avi Goldfarb (Chicago: University of Chicago Press, 2019), 175.

[19] Pizzinelli et al., "Labor Market Exposure to AI."

[20] Tamayo et al., "Reskilling in the Age of AI."

[21] A detailed description of the methodology and data sources used can be found in Appendix 1.

[22] David Autor, "Applying AI to Rebuild Middle Class Jobs" (National Bureau of Economic Research, February 2024); Pizzinelli et al., "Labor Market Exposure to AI."

[23] See, for example: Andrew Green and Lucas Lamby, "The Supply, Demand and Characteristics of the AI Workforce Across OECD Countries" (OECD, February 16, 2023); Anna Milanez, "The Impact of AI on the Workplace: Evidence from OECD Case Studies of AI Implementation" (OECD, December 1, 2023); Marguerita Lane, Morgan Williams, and Stijn Broecke, "The Impact of AI on the Workplace: Main Findings from the OECD AI Surveys of Employers and Workers" (OECD, March 22, 2023); Julie Lassébie

and Glenda Quintini, "What Skills and Abilities Can Automation Technologies Replicate and What Does It Mean for Workers?: New Evidence" (OECD, December 13, 2022).

[24] David J. Deming, "The Growing Importance of Social Skills in the Labor Market," *Quarterly Journal of Economics* 132, no. 4 (November 2017): 1593–1640.

[25] A. K. Tripathi, "The Future of Technology and Jobs: An Interview with Dr. RA Mashelkar," *Ubiquity*, April 2016, 1–12.

[26] "The Future of Jobs Report 2023" (World Economic Forum, 2023).

[27] Cäcilia Lipowski, Anna Salomons, and Ulrich Zierahn-Weilage, "Expertise at Work: New Technologies, New Skills, and Worker Impacts" (ZEW-Centre for European Economic Research, 2024).

[28] Employee Training Administration, "Strengthening Community Colleges Training Grants Program," U.S. Department of Labor, accessed August 2024, www.dol.gov/agencies/eta/skills-training-grants/scc.

[29] U.S. Department of Labor, "US Department of Labor Awards $65M in Strengthening Community Colleges Grants to Expand Access to Training, Skill Development for In-Demand Industries," news release, April 10, 2024, www.dol.gov/newsroom/releases/eta/eta20240410-0.

[30] Iris Palmer and Shalin Jyotishi, "Using Funding to Support High-Quality, Non-Degree Community College Workforce Programs," New America, December 8, 2022, www.newamerica.org/education-policy/briefs/new-models-of-career-prep-policy-brief/.

[31] Palmer and Jyotishi, "Using Funding to Support High-Quality, Non-Degree Community College Workforce Programs"; Brent Orrell et al., "What Works in Workforce Development—and How Can It Be Better?," Brookings, March 8, 2023, www.brookings.edu/articles/what-works-in-workforce-development-and-how-can-it-work-better/.

[32] Angela Hanks and David Madland, "Better Training and Better Jobs: A New Partnership for Sectoral Training," Center for American Progress, February 22, 2018, www.americanprogress.org/article/better-training-better-jobs/.

[33] Harry J. Holzer, Testimony to the Subcommittee on Higher Education and Workforce Development, House Committee on Education and Labor, 118th Congress, May 11 2023, https://edworkforce.house.gov/uploadedfiles/5.11.23_holzer_testimony_hewd_hearing_on_workforce_skills_development.pdf.

[34] David Fein and Samuel Dastru, "Benefits that Last: Long-Term Impact and Cost-Benefit Findings for Year Up" (Pathways for Advancing Careers and Education, 2022), https://www.acf.hhs.gov/sites/default/files/documents/opre/year%20up%20long-term%20impact%20report_apr2022.pdf.

[35] "Explore Registered Apprenticeship," U.S. Department of Labor, April 2024, www.apprenticeship.gov/sites/default/files/DOLIndFSApprent101-043024-508.pdf.

[36] U.S. Department of Labor, "Explore Registered Apprenticeship."

[37] Mary Alice McCarthy, Iris Palmer, and Michael Prebil, "Connecting Apprenticeship and Higher Education" (New America, December 2017), https://d1y8sb8igg2f8e.cloudfront.net/documents/Connecting-Apprenticeship-HigherEd.pdf.

[38] Ali Crawford and Cherry Wu, "Riding the AI Wave: What's Happening in K-12 Education?" (CSET, April 2, 2024), https://cset.georgetown.edu/article/riding-the-ai-wave-whats-happening-in-k-12-education/.

[39] Crawford and Wu, "Riding the AI Wave."

[40] "AI Guidance for Schools Toolkit," TeachAI, accessed 10 September 2024, www.teachai.org/toolkit.

[41] Amanda Bergson-Shilcock, "The New Landscape of Digital Literacy" (National Skills Coalition, May 2020), www.nationalskillscoalition.org/wp-content/uploads/2020/12/05-20-2020-NSC-New-Landscape-of-Digital-Literacy.pdf.

[42] Amanda Bergson-Shilcock and Roderick Taylor, "Closing the Digital Skill Divide: The Payoff for Workers, Business, and the Economy" (National Skills Coalition, February 6, 2023).

[43] Office of Senator Mark Kelly, "Kelly, Rounds Introduce Bipartisan Bill to Enhance Consumer Literacy and Confidence in AI," news release, July 31, 2024, www.kelly.senate.gov/newsroom/press-releases/kelly-rounds-introduce-bipartisan-bill-to-enhance-consumer-literacy-and-confidence-in-ai/.

[44] Crawford and Wu, "Riding the AI Wave."

[45] Hannah Weissman et al., "The State of Computer Science Education" (Code.org Advocacy Coalition, 2024), https://code.org/assets/advocacy/stateofcs/2024_state_of_cs.pdf.

[46] Orrell et al., "What Works in Workforce Development."

[47] Employment and Training Administration, "Workforce and Innovation Opportunity Act," U.S Department of Labor, accessed October 1, 2024, www.dol.gov/agencies/eta/wioa.

[48] Palmer and Jyotishi, "Using Funding to Support High-Quality, Non-Degree Community College Workforce Programs."

[49] David Deming et al., "Navigating Public Job Training" (Harvard Project on Workforce, March 2023), https://889099f7-c025-4d8a-9e78-9d2a22e8040f.usrfiles.com/ugd/889099_06ca8851a90f43c98534daeffdb80479.pdf.

[50] A Stronger Workforce for America Act, H.R. 6655, 118th Congress (2024), www.congress.gov/bill/118th-congress/house-bill/6655/text.

[51] Deming et al., "Navigating Public Job Training."

[52] "5 Ways to Move the Needle on Major U.S. Social Problem," Arnold Ventures, January 8, 2021, www.arnoldventures.org/stories/5-ways-to-move-the-needle-on-major-u-s-social-problems.

[53] "Fact Sheet," Per Scholas, 2019, https://perscholas.org/assets/courses/Per-Scholas_Fact-Sheet_2019.pdf; "What Is Per Scholas?," Per Scholas, accessed September 13, 2024, https://perscholas.org/about-per-scholas/launch-your-tech-career/.

[54] Fein and Dastru, "Benefits that Last"; "2023 Annual Report" (Per Scholas, 2023), https://perscholas.org/2023-annual-report/.

[55] Deming et al., "Navigating Public Job Training."

[56] Shayne Spaulding and David C. Blount, "Employer Engagement by Community-Based Organizations" (Urban Institute, May 22, 2018).

[57] Antonios Panagiotakopoulos, "Staff 'Poaching' in the Small Business Context: Overcoming This Key Barrier to Training," *Industrial and Commercial Training* 44, no. 6 (August 31, 2012): 326–333.

[58] Daron Acemoglu, Andrea Manera, and Pascual Restrepo, "Does the US Tax Code Favor Automation?" (National Bureau of Economic Research, April 2020); Daron Acemoglu, "Remaking the Post-COVID World," *Finance and Development* 58, no. 1 (March 2021).

[59] "Strengthening Community College Workforce Training" (Community College Research Center, April 2021), https://ccrc.tc.columbia.edu/media/k2/attachments/workforce-federal-policy-brief.pdf

[60] Iris Palmer, "An Explainer: Non-degree vs Non-credit Programs," New America, March 24, 2021, www.newamerica.org/education-policy/edcentral/an-explainer-non-degree-vs-non-credit-programs/.

[61] Jeff Strohl, Zachary Mabel, and Kathryn Peltier Campbell, "The Great Misalignment: Addressing the Mismatch between the Supply of Certificates and Associate's Degrees and the Future Demand for Workers in 565 US Labor Markets" (Georgetown University Center on Education and the Workforce, 2024), cew.georgetown.edu/GreatMisalignment.

[62] "FastForward," Virginia's Community Colleges, January 2024, https://fastforwardva.org/wp-content/uploads/2023/01/2024-FastForward-Fact-Sheet.pdf.

[63] Virginia's Community Colleges, "FastForward."

[64] Betsy Tessler, Kelsey Brown, and Di Xu, "Noncredit Career and Technical Education Programs in Virginia" (MDRC, June 2024), www.mdrc.org/sites/default/files/VCCFastForward_Brief_FINAL.pdf.

[65] Weichao Wang et al., “Towards AI-Assisted Smart Training Platform for Future Manufacturing Workforce,” National Science Foundation Public Access Repository, March 23, 2020, https://par.nsf.gov/biblio/10184361.

[66] For example, see: Leetcode, https://leetcode.com/; HackerRank, www.hackerrank.com/; CodeSignal, https://codesignal.com/learn.

[67] See “About AI-ALOE,” AI-ALOE, Georgia Institute of Technology, accessed September 15, 2024, https://aialoe.org/.

[68] Zhisheng Chen, “Artificial Intelligence-Virtual Trainer: Innovative Didactics Aimed at Personalized Training Needs,” *Journal of the Knowledge Economy* 14 (February 24, 2022), https://link.springer.com/article/10.1007/s13132-022-00985-0.

[69] For instance, see Pluralsight’s Iris: “Meet Iris, Pluralsight’s AI Assistant,” Pluralsight, accessed September 15, 2024, www.pluralsight.com/product/iris.

[70] For instance, see Lilian Roth, “JobsFirstNYC’s Skill Mapping Academy: Unlocking Opportunities for Jobseekers with the Help of Generative AI,” JobsFirstNYC, December 4, 2023, https://jobsfirstnyc.org/latest/jobsfirstnycs-skills-mapping-academy-unlocking-opportunities-for-jobseekers-with-the-help-of-generative-ai/. For specific tools, see FutureFit AI and SkyHive.

[71] Bharati B. Belwalkar and Bruce Maki, "Role of Artificial Intelligence in Workforce Development," *American Institutes for Research*, November 2023, https://www.air.org/sites/default/files/2023-11/Role-of-Artificial-Intelligence-Workforce-Development-Nov-2023-508.pdf.

[72] Maarten de Laat, Srecko Joksimovic, and Dirk Ifenthaler, “Artificial Intelligence, Real-Time Feedback and Workplace Learning Analytics to Support In Situ Complex Problem-Solving: A Commentary,” *International Journal of Information and Learning Technology* 37, no. 5 (November 2020): 267–277.

[73] DARPA, “AI-Enabled Tools Show Promise in Upskilling National Security Workforce,” news release, July 25, 2024, www.darpa.mil/news-events/2024-07-25.

[74] U.S. Department of Defense, *2023 National Defense Science and Technology Strategy* (Washington, D.C.: U.S. Department of Defense, 2023), 9, www.cto.mil/wp-content/uploads/2024/05/2023-NDSTS.pdf.

[75] DARPA, “DARPA Reboots AI Tools for Adult Learning Competition,” news release, January 22, 2024, www.darpa.mil/news-events/2024-01-22; DARPA, “AI-Powered Education Tools Chosen for Further Development,” news release, September 7, 2023, www.darpa.mil/news-events/2023-09-07.

[76] Hamsa Bastani et al., “Generative AI Can Harm Learning” (Wharton School, July 18, 2024), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4895486.

[77] Yijun Xiao and William Yang Wang, "On Hallucination and Predictive Uncertainty in Conditional Language Generation," in *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, eds. Paola Merlo, Jorg Tiedemann, and Reut Tsarfaty (Kerrville, TX: Association for Computational Linguistics, 2021), 2734–2744.
[78] Natalia Díaz-Rodríguez et al., "Connecting the Dots in Trustworthy Artificial Intelligence: From AI Principles, Ethics, and Key Requirements to Responsible AI Systems and Regulation," *Information Fusion* 99 (November 2023): 101896.

[79] Patrick Lewis et al., "Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks," in *NIPS '20: Proceedings of the 34th International Conference on Neural Information Processing Systems*, eds. H. Larochelle et al. (Red Hook, NY: Curran Associates, 2020), https://dl.acm.org/doi/abs/10.5555/3495724.3496517.

[80] Julia Freeland Fisher, "AI Can Make Schools More Human, but Only if Schools Prioritize Relationship Metrics," Harvard Advanced Leadership Institute Social Impact Review, September 12, 2023, www.sir.advancedleadership.harvard.edu/articles/ai-can-make-schools-more-human-if-schools-prioritize-relationship-metrics.

[81] Sean Breslin, "Enhancing Social Capital: Policy Recommendations for First-Generation, Low-Income, and Students of Color in Higher Education" (Center for Research on College-Workforce Transitions, November 2020), https://ccwt.wisc.edu/wp-content/uploads/2022/04/ccwt_report_Enhancing-Social-Capital.pdf.

[82] Rework America Alliance, "Job Progression Tool," McKinsey & Company, accessed September 15, 2024, https://jobprogressions.mckinsey.digital/.

[83] See Katy Seery et al., "Retention Strategies for Online Students: A Systematic Literature Review," *Journal of Global Education and Research* 5, no. 1 (June 2021): 72–84, www.doi.org/10.5038/2577-509X.5.1.1105; Chris Sorensen and Judy Donovan, "An Examination of Factors that Impact the Retention of Online Students at a For-Profit University," *Online Learning* 21, no. 3 (2017): 206–221, www.doi.org/10.24059/olj.v21i3.935; Stephanie Riegg Cellini, "How Does Virtual Learning Impact Students in Higher Education?," Brookings, August 13, 2021, www.brookings.edu/articles/how-does-virtual-learning-impact-students-in-higher-education/; Cassandra M. D. Hart, Elizabeth Friedmann, and Michael Hill, "Online Course-Taking and Student Outcomes in California Community Colleges," *Education Finance and Policy* 13, no. 1 (2018): 42–71, https://doi.org/10.1162/edfp_a_00218; Ted Joyce et al., "Does Classroom Time Matter?," *Economics of Education Review* 46 (June 2015): 64–77, https://doi.org/10.1016/j.econedurev.2015.02.007; William T. Alpert, Kenneth A. Couch, and Oskar R. Harmon, "A Randomized Assessment of Online Learning," *American Economic Review* 106, no. 5 (May 2016): 378–382, www.aeaweb.org/articles?id=10.1257/aer.p20161057; David Figlio, Mark Rush, and Lu Yin, "Is It Live or Is It Internet? Experimental Estimates of the Effects of Online Instruction on Student Learning," *Journal of Labor Economics* 31, no. 4 (October 2013), https://doi.org/10.1086/669930.

[84] Joyce et al., "Does Classroom Time Matter?"

[85] Rose Luckin et al., "Intelligence Unleashed: An Argument for AI in Education" (Open Ideas at Pearson, 2016), https://edu.google.com/pdfs/Intelligence-Unleashed-Publication.pdf; Ebere Pearl Ezeoguine and Stella Eteng-Uket, "Artificial Intelligence Tools and Higher Education Student's Engagement," *Edukasiana* 3, no. 3 (2024), https://ejournal.papanda.org/index.php/edukasiana/article/view/733.

[86] Michael Olumide Edwards-Fapohunda and Modinot Adebisi Adediji, "Sustainable Development of Distance Learning in Continuing Adult Education: The Impact of Artificial Intelligence," *Iconic Research and Engineering Journals* 8, no. 1 (July 2024), www.irejournals.com/formatedpaper/1706017.pdf.

[87] Tobias Oberdieck and Enrico Moch, "Lifelong Learning with Artificial Intelligence: Potentials, Challenges and Future Perspectives," *International Journal of Advanced Research* (June 2024), http://dx.doi.org/10.21474/IJAR01/18915; Luckin et al., "Intelligence Unleashed"; María Pérez-Ortiz et al., "An AI-Based Learning Companion Promoting Lifelong Learning Opportunities for All" (UNESCO, November 2020), https://ircai.org/project/ai-based-learning-companion-promoting-lifelong-learning/.

[88] Rodrigo Smiderle et al., "The Impact of Gamification on Students' Learning, Engagement and Behavior Based on Their Personality Traits," *Smart Learning Environments* 7, no. 3 (2020), https://slejournal.springeropen.com/articles/10.1186/s40561-019-0098-x.

[89] "Does Gamified Training Get Results?," *Harvard Business Review*, March–April 2023, https://hbr.org/2023/03/does-gamified-training-get-results.

[90] Erik Brynjolfsson, Danielle Li, and Lindsey R. Raymond, "Generative AI at Work" (National Bureau of Economic Research, 2023), www.nber.org/system/files/working_papers/w31161/w31161.pdf.

[91] In the study, the researchers measured the performance of workers when the AI assistant tool was offline. During an offline outage one month after adopting an AI assistant, workers did not have quicker processing times than prior to AI adoption. However, for an outage three months after adoption, workers did improve their processing times relative to prior to adoption. Workers who did not use AI regularly did not have improved processing times even three months after adoption. Brynjolfsson, Li, and Raymond use this experimental result to justify their claim that AI adoption led to worker learning without taking into account confounding variables such as worker experience levels and quality of work.

[92] Nan Jia et al., "When and How Artificial Intelligence Augments Employee Creativity," *Academy of Management Journal* 67, no. 1 (February 2024), https://doi.org/10.5465/amj.2022.0426.

[93] Aidan Toner-Rodgers, "Artificial Intelligence, Scientific Discovery, and Product Innovation," November 6, 2024, https://aidantr.github.io/files/AI_innovation.pdf.

[94] Tapani Rinta-Kahila et al., "The Vicious Circles of Skill Erosion: A Case Study of Cognitive Automation," *Journal of the Association for Information Systems* 24, no. 5 (2023), https://aisel.aisnet.org/jais/vol24/iss5/2/.

[95] Bastani et al., "Generative AI Can Harm Learning."

[96] Toner-Rodgers, "Artificial Intelligence."

[97] Robert Hooijberg and Michael D. Watkins, "When Do We Really Need Face-to-Face Interactions?," *Harvard Business Review*, January 4, 2021, https://hbr.org/2021/01/when-do-we-really-need-face-to-face-interactions.

[98] VirtualSpeech, https://virtualspeech.com; "Paths," CodeSignal, accessed September 15, 2024, https://learn.codesignal.com/course-paths/browse?collectionId=clzxd7bz70003134n69a521ep.

[99] Arianna Prothero, "Artificial Intelligence and Social-Emotional Learning Are on a Collision Course," *Education Week*, November 13, 2023, www.edweek.org/technology/artificial-intelligence-and-social-emotional-learning-are-on-a-collision-course/2023/11.

[100] Ahmad Alabdulkareem et al., "Unpacking the Polarization of Workplace Skills," *Science Advances* 4, no. 7 (July 18, 2018), https://doi.org/10.1126/sciadv.aao6030.