

De-Skilling the Knowledge Economy

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Key Points

- Despite the importance of mid-level workers to sectors like finance, business services, government, and health care, many of these workers are vulnerable to de-skilling, job loss, and forced transitions as AI platforms absorb tasks once handled by humans.
- Workers who pair skills like AI literacy with emotional intelligence, critical thinking, and adaptability will be better positioned to move into new roles helping manage and supervise AI systems, while others may struggle to remain competitive.
- Current workforce programs are underfunded, backward-looking, and poorly aligned to local needs. Improved forecasting, expanded training accounts, stronger early education, and targeted reemployment support are essential to reduce inequality and promote opportunity.

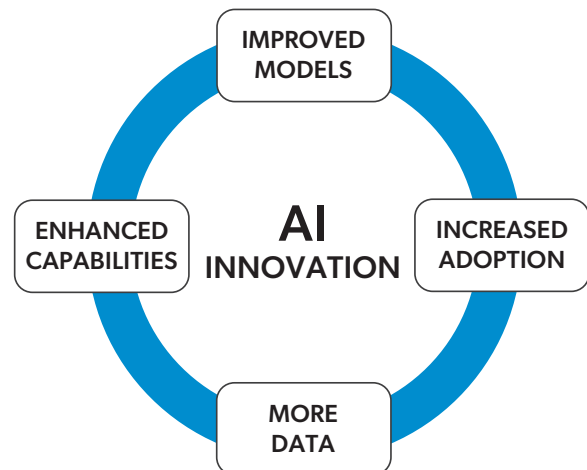
As David Veldran and I examined in our 2024 report, *The Age of Uncertainty—and Opportunity: Work in the Age of AI*, forecasts of how artificial intelligence will affect jobs and skills are remarkably uneven and often contradictory.¹ This is less a matter of poor methodologies or lack of investigation than it is a product of limitations on available data combined with how unpredictably a quickly evolving general-purpose technology like AI is reconfiguring workflows, jobs, and skills. AI is now an innovation flywheel with such rapid, recursive innovation cycles that today's forecasts will be outdated tomorrow. (See Figure 1.)

The purpose of this report, then, is more limited. Since quantitative estimates are, at this point, subject to too much uncertainty to be useful, it is better, from a policy standpoint, to look at broader trends and use them as a template to overlay on current job market activity, thereby gaining a sense of how broad trends will likely affect key employment sectors.

The US, like other developed economies, is dominated by services, with nearly 80 percent of jobs concentrated

in the services sector.² Many of these jobs, particularly the higher-skilled ones, are found in “knowledge activities” (e.g., finance, insurance, business services, government, and health and social assistance), which

Figure 1. AI Innovation: A Self-Reinforcing Cycle



Source: Author.

are information intensive and staffed by workers with college and postgraduate degrees. These are the workers who process and manage information, provide research support, coordinate financial systems, and deliver services and care. Knowledge-worker tasks are often well suited to AI-driven automation because they either are repetitive and can be “coded” and replicated by AI platforms or involve analyzing vast datasets that are cumbersome and inefficient for human workers to manage and use, like those used in biomedical research or investment data.

Aligning these tasks to AI processes means we know big changes in labor demand are on the horizon, but we have insufficient information and insight to say precisely what those changes mean for specific jobs and skills. Friedrich Hayek’s “knowledge problem” has not been repealed.³ In fact, the pace of change may have put further out of reach a detailed understanding of how the economy works and where it might be headed.

With this caveat in mind, it *is* possible to say that some of the future of work’s *contours* are coming into view as generative AI’s capabilities are better defined and more widely deployed. These emerging trends can help us narrow the universe of possible AI futures and help focus policy efforts to assist workers who might find themselves and their jobs affected by the AI transition.

Who’s on First?

To varying degrees, AI is on course to affect virtually all jobs. The novelty we experience today with AI will eventually become commonplace, and AI will become integrated across many human activities. At the moment, however, it is knowledge workers who are facing what economists call decreased labor demand for AI-automatable skills.⁴ Our experience with manufacturing and deindustrialization gives us a picture of how knowledge-economy automation may work: As algorithmic systems replace human workers, many knowledge workers will likely need to re-skill or move into other types of employment, sometimes at a lower wage.⁵ It is reasonable to expect an analogous effect for knowledge workers.

As mentioned previously, these knowledge workers undergird the preponderance of the US economy’s services sector. Workers in the knowledge sector whose jobs are data intensive and repetitive or research

focused—such as medical schedulers, insurance claims investigators and processors, and financial advisers—will likely face a job market that requires skill upgrading, transferring to other sectors and industries that leverage their knowledge and experience for related tasks, or, in the worst case, accepting lower-skilled (and lower-paid) jobs.

This “up or out” feature of the knowledge-workforce future strongly resembles the skills-biased technological change (SBTC) that previously had powerful effects on workers in middle-skill manufacturing jobs.⁶ It’s logical to assume, then, that these workers could face a future like that of the manufacturing workforce over the past few decades, with some highly skilled factory workers moving into jobs that supervise and maintain robotic systems while less skilled workers have moved into other sectors and jobs.

Lest we fall into doom spiraling, it is important to bear in mind that as with other chapters of automation, we can also expect AI productivity increases to generate new wealth and demand for workers.⁷ We cannot say what these jobs will be because they do not yet exist. Further, it is important to understand that AI also holds the promise of *boosting* skills across the spectrum of human talent, giving many low- or marginal-ability workers access to training, knowledge, and skills that may increase their value in the labor market.⁸ Achieving these hoped-for productivity and opportunity outcomes will not be easy and will require a determined, cross-society effort to develop students and workers who are “AI fluent,” have the ethical standards for using AI, and are skilled in applying AI tools in different work contexts.

To help demonstrate the challenges and opportunities before us, this report focuses on some of the American economy’s key knowledge sectors: finance and insurance, business services, government, and health and social assistance. The report examines the types of credentials currently required for key jobs in these sectors, how AI is being applied, and how AI is reshaping skill needs. The observations included here are a “snapshot” based on current technology, but in broad terms, they give a sense of the direction of AI-driven job market change.

The second part of the report examines the policy questions associated with responding to the de-skilled knowledge economy, whereby previously human-led

Figure 2. US Software Developer Employment Index



Source: Jeff Nezej, “The Rise—and Fall—of the Software Developer,” ADP Research, June 17, 2024, <https://www.adpresearch.com/the-rise-and-fall-of-the-software-developer/>.

Note: January 2018 equals 100 percent.

work is taken over by fully or partially by automation. Such policies include implementing financial and data resources for worker re-skilling and transitions, establishing a life cycle approach to AI literacy, and strengthening noncognitive skills as key building blocks for AI readiness among today’s students and workers.

An Abbreviated History of SBTC

SBTC theory states that technological advancement increases the demand for skilled workers while reducing the demand for less-skilled workers. Until the 1970s, investments in education training—aimed at producing more skill among more workers—did not drive the price of human skill down. Instead, higher levels of education and technical skills, paradoxically, increased productivity and the value of skills and their price expressed as wages.⁹

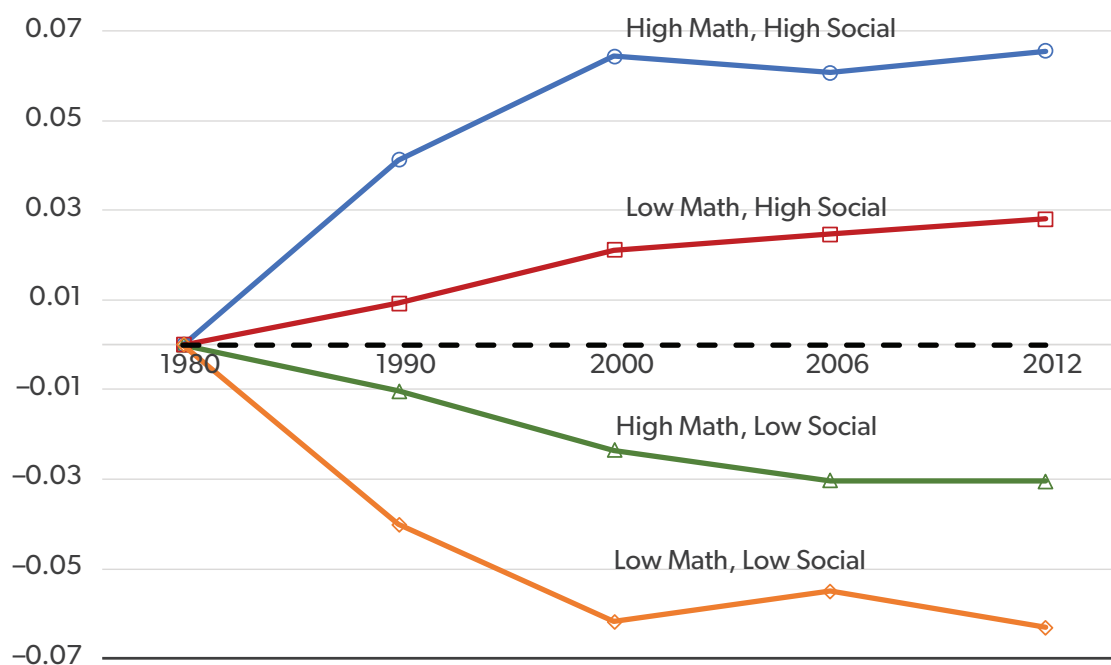
SBTC demonstrates how the rising tide of technology-driven change created both winners and losers. As robotics and information and computer technology (ICT) expanded in the 1980s and 1990s, routinized factory

and industrial labor was significantly “de-skilled,” meaning that automated processes took over job activities previously done by humans. This created a dramatic decrease in factory employment and significant upheaval for workers and their communities, particularly in America’s industrial heartland. Simultaneously, the growing use of ICT boosted demand for workers in the office-centric, knowledge-based, services-dominated economy.¹⁰ Higher wages for these knowledge skills incentivized workers to acquire new credentials, mainly in the form of college degrees, for more plentiful and highly paid knowledge-economy jobs.¹¹

One of the key questions we now face is how SBTC will interact with AI. As noted above, a detailed understanding of precisely which industries, jobs, and skills will be affected is challenging to determine. However, the idea of compression suggests that some of our skilled knowledge-sector workers will require skill upgrading and retraining.

The evolving job market for computer coders provides an early look at this process (Figure 2). In

Figure 3. Cumulative Changes in Employment Share by Occupational Task Intensity



Source: David J. Deming, "The Growing Importance of Social Skills in the Labor Market," *The Quarterly Journal of Economics* 132, no. 4 (2017): 1593–640, <https://academic.oup.com/qje/article-abstract/132/4/1593/3861633>.

a classic example of de-skilling, many aspects of computer coding—designing and building webpages and customer interfaces, for instance—are being taken over by AI, which often can instantly and effortlessly reproduce much of the work human coders used to do while leaving integration, monitoring, and higher-level analysis to human programmers.¹² As generative AI continues to improve, demand even for this more complex work will probably fall. This represents a huge productivity gain for the IT sector (and, in the future, for the rest of the economy), but it also leaves many skilled coders with fewer job opportunities and a pressing need to adapt their skills to new opportunities.

For the moment, demand remains robust for the most experienced and highly skilled computer coders and engineers—those who focus on full-stack or back-end work (designing, integrating, and maintaining complex computer systems). A good grasp of AI and its capabilities in machine learning and data analytics, coupled with a strong understanding of computer science and noncognitive skills for managing human teams

and multiple types of AI “agents,” is today’s hot ticket to IT workforce success. In other words, this resembles SBTC—the de-skilling of basic technical tasks but rising value for higher-order strategic and analytical skills—with a thumb on the scale for those who also have strong noncognitive skills to complement their technical skills.

The rising demand for noncognitive skills is not new, and it was first noticed by Harvard economist David J. Deming. In his 2017 paper, Deming found that growth in occupational “intensity”—the concentration across the economy of working time devoted to task categories—was highest in jobs that had high levels of social skills and strong math skills.¹³ (See Figure 3.) Those with high social skills but low math skills also saw a significant increase in occupational intensity, suggesting the real driver here was the noncognitive category. And jobs requiring high math skills but low social skills saw occupational intensity fall.

Eight years ago, the future appeared to belong to those “stars” who not only had strong technical abilities but also excelled in critical and strategic thinking and

Table 1. The US Economy’s Top Four Sectors

Sector	Share of Total GDP (Percentage)	Total Employment (Millions)
Finance, insurance, and real estate	21.2	9.2
Professional and business services	13.2	22.8
Government (federal, state, and local)	11.3	22.8
Health care and social assistance	7.6	21.5
Total	53.3	76.3

Source: US Department of Commerce, Bureau of Economic Analysis, “GDP by Industry,” <https://www.bea.gov/data/gdp/gdp-industry>; and US Department of Labor, Bureau of Labor Statistics, “Employment by Major Industry Sector,” <https://www.bls.gov/emp/tables/employment-by-major-industry-sector.htm>.

Note: This table synthesizes estimates of sectoral contributions to US GDP and total employment based on data from the US Bureau of Economic Analysis (BEA) and the US Bureau of Labor Statistics (BLS). GDP contribution percentages are drawn from BEA’s industry-by-industry breakdown of GDP using data as of 2024, while employment figures reflect BLS Current Employment Statistics data as of 2023.

decision-making—along with the noncognitive ability to lead teams toward shared goals. As it takes over ever-more complex technical work, AI will likely continue to drive the US labor market to highly value strong social skills, while demand for math skills will decline due to AI automation.

AI and the “Big Four”

The current employment prospects for computer coders noted above represent the leading edge of a broader trend toward de-skilling all kinds of routine knowledge-economy tasks and the rising value of workers who can blend technical knowledge and legacy technical skills with the “tacit,” subjective, intuitive, and affective aspects of work.¹⁴ It is notable that the Federal Reserve Bank of New York reported in February 2025 that, based on 2023 data, unemployment rates for workers with liberal arts degrees are now about half that of computer scientists and engineers, suggesting we need to revisit the blend of technical and noncognitive skills that the economy demands.¹⁵

Table 1 shows the US economy’s top four sectors, their contributions to gross domestic product (GDP), and the number of workers employed in each.

Table 2 provides an overview of the projected AI skill effects on important skills clusters in the “big four” sectors of the US services economy. The pattern of these

impacts is remarkably consistent. Across sectors, routine knowledge-processing tasks, like coding, are likely to be automated. A 2024 study from the Brookings Institution found that based on existing technology, 30 percent of all US workers could see at least half of their tasks disrupted by generative AI, particularly in roles that include administrative support, data entry, and clerical tasks. A larger sample of the workforce—85 percent of all workers—shows a more modest exposure to AI, with 10 percent of work tasks affected.¹⁶ Emerging skill requirements center on understanding and using AI (e.g., data analytics, machine learning, and natural language processing) combined with increased demand for tacit or noncognitive skills (e.g., critical thinking, decision-making, applied ethics, problem-solving, and empathy).

One of the most pressing challenges AI will exert in the big four sectors—and presumably in the economy’s other knowledge-heavy businesses and industries—is how it will change the demand for skills in clerical, administrative, and research-oriented jobs. In other words, the next turn of the automation ratchet appears to, once again, be tightening the squeeze on middle-skill jobs—only this time in America’s offices rather than its factories.¹⁷ Workers who hold these positions can expect to face upskilling and re-skilling needs to remain relevant in the AI-infused economy.

Life Is Unfair

Consistent with SBTC, the shift to an increasingly automated knowledge sector will not affect all workers equally, and it will favor those who have the combination of a technical background and noncognitive skills referenced above.¹⁸ The most talented, well-rounded, and adaptable will likely prosper; the less talented may have difficulty finding and retaining quality jobs.

Figure 4 provides a visual illustration of how AI could reshape the talent distribution across the workforce. This figure is based on research by McKinsey and the World Economic Forum, relying on skill classifications established by O*NET.¹⁹ The dotted line represents the pre-AI distribution of talent, modeled as a standard bell curve, with the majority of workers concentrated in middle-skill roles, as supported by David H. Autor et al.

Table 2. AI's Impact on Workforce Demands in Key Knowledge Sectors

Sector	Typical Degree or Credential Requirement	Artificial Intelligence Applications	Emerging Skills Requirements	Sample Effects
Finance and insurance	BA in finance, accounting, or economics	Enhancing risk assessment, fraud detection, financial modeling, and customer service	<ul style="list-style-type: none"> • ML • NLP • <i>Critical thinking</i> • <i>Decision-making</i> • <i>Problem-solving</i> • <i>Adaptability</i> • <i>Ethics</i> 	<ul style="list-style-type: none"> • Increased demand for senior, AI-focused change-management leaders and AI-driven financial analysts, risk managers, and algorithmic traders • Increased need for AI engineers and professionals trained in AI supervision, compliance, ethics, and bias prevention and mitigation • Decline in lower-level data analysis roles, manual credit assessment, compliance monitoring, traditional trading roles, and routine financial advisory services
Professional and business services	BA in business administration, marketing, or human resources	Streamlining contract creation and analysis and HR recruitment and marketing analytics; increasing demand for AI-implementation consulting	<ul style="list-style-type: none"> • AI-powered contract analysis • NLP for legal documents • ML for risk assessment • NLP for legal documents • AI business intelligence, predictive modeling, and consulting solutions • <i>Critical thinking</i> • <i>Problem-solving</i> • <i>Collaboration</i> • <i>Emotional intelligence</i> • <i>Creativity</i> • <i>Storytelling</i> • <i>Ethics</i> • <i>Conflict resolution</i> • <i>Empathy</i> • <i>Adaptability</i> 	<ul style="list-style-type: none"> • Increased need for AI-powered consultants, AI-augmented recruiters, and digital marketing strategists • Heavy effects in hybrid tasks that emphasize a combination of technical and noncognitive or "soft" skills • New roles in AI ethics and AI-adoption consulting • Legal services evolving toward AI-assisted contract review and compliance oversight • Decline in traditional support roles in law and consulting

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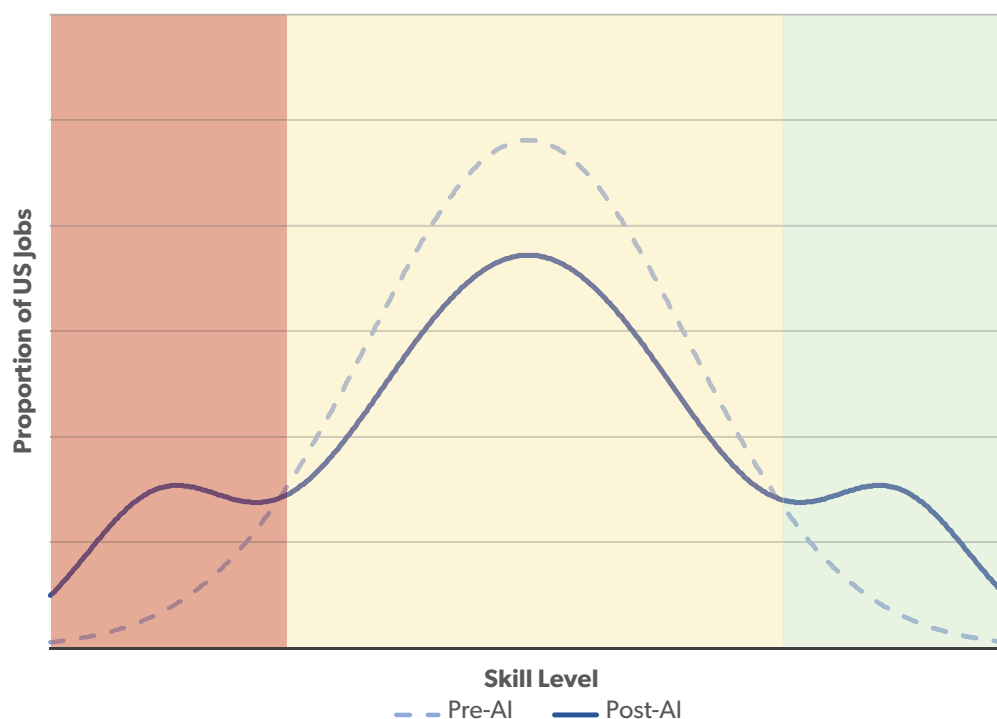
Table 2. AI's Impact on Workforce Demands in Key Knowledge Sectors (continued)

Sector	Typical Degree or Credential Requirement	Artificial Intelligence Applications	Emerging Skills Requirements	Sample Effects
Government (federal, state, and local)	Mid-level public service roles require a BA or BS in political science, public administration, or communications.	Optimizing public services, urban planning, law enforcement, and cybersecurity	<ul style="list-style-type: none"> • Robotic process automation • AI-powered chatbots • Data analytics • NLP • Geographic information systems • Internet of Things integration • ML • Predictive modeling • Network security • <i>Adaptability</i> • <i>Problem-solving</i> • <i>AI ethics</i> • <i>Critical thinking</i> • <i>Communication</i> • <i>Bias awareness</i> 	<ul style="list-style-type: none"> • Expansion of AI-driven policymaking, smart-city initiatives, and automated public services • Growing demand for AI-literate cybersecurity professionals and digital governance experts • Increased emphasis on public-facing communication and translation of AI use and policy • Decline in roles with clerical tasks
Health care and social assistance	No degree is required for nonmedical roles; technical certifications are required for sub-professional roles.	Automating administrative tasks and new technical roles	<ul style="list-style-type: none"> • ML • Predictive modeling • Robotics • Sensor integration • AI scheduling • NLP • Workflow automation • NLP for mental health • Data visualization • <i>Ethics</i> • <i>Empathy</i> • <i>Communication</i> • <i>Collaboration</i> • <i>Critical thinking</i> • <i>Adaptability</i> • <i>Conflict resolution</i> 	<ul style="list-style-type: none"> • Increased need for physicians and technicians using AI-enhanced diagnostics and treatment and robotic surgery • AI-augmented counseling • Human oversight of automated systems • AI-powered scheduling, recordkeeping, and bill coding • Decline in need for traditional administrative support roles (e.g., scheduling, medical records, and billing) across health systems

Source: Organisation for Economic Co-operation and Development, *AI and the Future of Skills, Volume 1: Capabilities and Assessments*, November 18, 2021, https://www.oecd.org/en/publications/ai-and-the-future-of-skills-volume-1_5ee71f34-en/full-report.html; US Department of Labor, Bureau of Labor Statistics, Office of Employment and Unemployment Statistics, *Occupational Outlook Handbook*, <https://www.bls.gov/ooh/>; and David Autor et al., *The Work of the Future: Building Better Jobs in an Age of Intelligent Machines*, Massachusetts Institute of Technology, Task Force on the Work of the Future, 2020, <https://workofthefuture-taskforce.mit.edu/research-post/the-work-of-the-future-building-better-jobs-in-an-age-of-intelligent-machines/>. Also see David J. Deming, "The Growing Importance of Social Skills in the Labor Market," *The Quarterly Journal of Economics* 132, no. 4 (2017): 1593–640, <https://academic.oup.com/qje/article-abstract/132/4/1593/3861633>; Molly Kinder et al., *Generative AI, the American Worker, and the Future of Work*, Brookings Institution, October 10, 2024, <https://www.brookings.edu/articles/generative-ai-the-american-worker-and-the-future-of-work/>; Michael Chui et al., *The Economic Potential of Generative AI: The Next Productivity Frontier*, McKinsey & Company, June 14, 2023, <https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier>; and World Economic Forum, *Future of Jobs Report: 2023*, May 2023, <https://www.weforum.org/publications/the-future-of-jobs-report-2023/>.

Note: Italics indicate tacit or noncognitive skills. "BA" stands for bachelor of arts, "BS" stands for bachelor of science, "ML" stands for machine learning, and "NLP" stands for natural language processing.

Figure 4. Shift in Workforce Talent Distribution: Before and After AI



Source: James Manyika et al., *Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation*, McKinsey & Company, December 2017, <https://www.mckinsey.com/~media/BAB489A30B724BECB5DEDC41E9BB9FAC.ashx>; Michael Chui et al., *The Economic Potential of Generative AI: The Next Productivity Frontier*, McKinsey & Company, June 14, 2023, <https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier>; World Economic Forum, *The Future of Jobs Report 2023*, May 2023, <https://www.weforum.org/publications/the-future-of-jobs-report-2023/>; US Department of Labor, Employment and Training Administration, “All Job Zones,” O*NET OnLine, <https://www.onetonline.org/find/zone?z=0>; David H. Autor et al., “The Skill Content of Recent Technological Change: An Empirical Exploration,” *The Quarterly Journal of Economics* 118, no. 4 (2003): 1279–333, <https://doi.org/10.1162/003355303322552801>; Organisation for Economic Co-operation and Development, “Survey of Adult Skills (PIAAC),” <https://www.oecd.org/en/about/programmes/piaac.html#ESO>; and Erik Brynjolfsson et al., “Generative AI at Work,” Working Paper No. 31161 (National Bureau of Economic Research, April 2023), <https://www.nber.org/papers/w31161>.
Note: Skill levels are color coded, with green representing high-skilled, yellow representing mid-skilled, and red representing low-skilled workers.

and the Organisation for Economic Co-operation and Development’s (OECD) skill-level assessments.²⁰

The solid line reflects a post-AI talent distribution, depicting how various talent levels will respond to the effects of automation exposure. While the middle of the post-AI curve still has the largest group of workers, it flattens as AI automates routine cognitive clerical and analytical tasks—jobs previously dominated by middle-skill knowledge workers. Meanwhile, the lower and upper ends of the distribution see modest growth, as some workers from the middle of the distribution have either upskilled into more complex and higher-level tasks or redistributed into less complex, and presumably lower-paying, jobs. The overall result

is a compressed middle, with a subtle but important expansion of labor market share on both ends. While AI promises broad productivity improvements that will ultimately benefit everyone, these benefits are likely to be unevenly distributed.²¹

Toward a Worker-Focused AI Skills Policy

These outcomes, positive and negative, are not foreordained. Our actual outcomes will depend heavily on the types of re-skilling, retraining, and other transition support policies we adopt (or fail to adopt) in anticipation of AI diffusion.

At the outset of the policy discussion, it is noteworthy that AI diffusion in our economy and lives is both

inevitable and desirable, as it will likely increase economic output, productivity, income, and wealth. These increases will translate into increased demand for new products and services and new work opportunities. This has been the pattern of automation since the dawn of the industrial age.²²

These positive effects, however, have a long time horizon and will accumulate gradually. Or, as John Maynard Keynes observed, “In the long run, we’re all dead.”²³ In the short and medium term, we can expect disruption and anxiety and should prepare for both. What policies should we consider to maximize positive outcomes while mitigating drawbacks?

A principal policy failure of the robotics and ICT revolution flowed from a lack of imagination concerning the potential for worker displacement. The US devotes less than every other OECD economy except Mexico to “active labor market programs,” which provide retraining, income replacement, and other supports for workers faced with technological and market transitions.²⁴ During the shift away from manufacturing, our reliance on market mechanisms to reallocate displaced workers to new jobs was a macroeconomic success, driving strong GDP growth and increasing incomes and wealth.²⁵ Much of the so-called hollowing out of the middle class was actually the result of middle-income earners moving up the income scale, not down.²⁶

Nonetheless, millions of workers were left behind in the post-automation and post-globalization economy with limited assistance and support. This lack of preparation for automation impacts has imposed great costs on the US economy in the form of lost human potential, social strife, and socioeconomic dysfunction.²⁷ This should not, and need not, happen again.

Getting Better Data

The most basic challenge we face in designing policy to respond to AI labor market impacts is a lack of data showing how sectors, firms, and workers are reacting—now and in the future—to increased AI adoption. Market economies are infinitely complex because they are driven by individuals and firms as they engage in unguided, opportunity-driven exchanges that maximize individual and firm benefits. This free exchange fosters the efficient use of labor and encourages innovation. It would be shortsighted and probably impossible to manage—or worse, try to control—the effects of market

changes at a detailed level. Yet timely and directionally accurate measurements are important to guide policy solutions and implementation, especially at the local and regional levels, where economies actually operate and decisions are made about investments in education, training, and re-skilling.

Our existing federal-state statistical systems collect a wide variety of data on the economy, such as education and training, work, employment, and earnings. These data are deficient in two key ways regarding the challenge of projecting AI impacts. First, the data mostly provide a national-level scope. Labor market information is like weather reports: National weather maps are good for learning what’s happening broadly but inadequate for anticipating and describing local conditions. For workforce adaptation, we need local and regional data that reflect the changes occurring in specific markets. These data would help workers, businesses, and governments direct investments in education and training policies to maximize their value.

The second problem with our labor market information is that most of the data are “rearview mirror” in nature. They can describe what happened in the past but tell us little or nothing about the changes that are occurring in real time or are around the corner of technological change. A new kind of “headlight” data are vital so that employers, workers, and educational and training institutions can adjust programs and curricula to ensure students are graduating with relevant, in-demand skills.

To address this challenge, AEI is partnering with New York University, Stanford University, and the University of Michigan to design and test data configurations and analytical tools that can anticipate, at least in broad terms, the skill-demand changes arriving in coming years.²⁸ As a recent report from the National Academies of Sciences, Engineering, and Medicine found, AI itself—with its virtually unlimited capacity for interpreting and analyzing large, complex datasets—may be a key ally in identifying linkages and patterns now invisible to us.²⁹

Focusing on Flexibility: It’s About Worker Agency, Not Government Agencies

In a 2022 essay, I argued that one of our workforce system’s biggest needs is to promote agency—at every level—rather than rely on government-driven, centralized approaches to build the AI-competent workforce

of the future.³⁰ Given AI's rapid-cycle advancement, the first line of response is workers themselves. Individuals, empowered and provided with information and financial resources to act in their own self-interest, are usually best positioned to understand local employment opportunities and make decisions about education, training, and employment goals. This means putting workers, rather than bureaucracies, in charge of education and training decisions as much as possible.

One way to do this is to expand and strengthen individual training accounts (ITAs). ITAs were first authorized in 1998 under the Workforce Investment Act and reauthorized in 2014 in the Workforce Innovation and Opportunity Act.³¹ The accounts provide workers with resources to pursue education and training programs that will equip them with in-demand skills.

ITA evaluations suggest that a self-directed approach may be the best way to support training and rapid work reattachment for dislocated workers. No policy is one-size-fits-all, so we will also need to increase funding for our workforce system infrastructure to ensure that those who need support and guidance in managing work transitions are able to access experienced and compassionate help through either human case managers or AI-enabled coaching systems. In the more distant future, it might be possible to transition ITAs to career learning accounts modeled on 401(k) retirement accounts that would allow all workers, as well as employers and government, to set aside money for retraining.

Another promising approach would be to revive and reform the Trade Adjustment Assistance (TAA) program.³² TAA was established under the Kennedy administration to help trade-displaced manufacturing workers find new jobs to replace those lost due to trade agreements. The program provided a range of benefits, including wage insurance for workers who must take lower-paying replacement jobs, generous financial resources for retraining, and, when necessary, relocation assistance to help workers move to better work opportunities.³³ TAA evaluations have demonstrated strong, long-term improvements in employment and wage outcomes for the workers who successfully accessed these benefits.³⁴

Unfortunately, TAA was poorly targeted for populations that lost jobs to automation instead of trade. That was a major problem for manufacturing workers,

since most of the 1980–2010 job losses were caused by productivity-enhancing automation rather than trade.³⁵ TAA has also been criticized as overly bureaucratic and hard to apply for and administer. To address the risks posed by a new wave of automation-driven impacts, TAA should be recast as Automation Adjustment Assistance and reformed to ensure that those certified as experiencing automation-related job displacement can access comprehensive reemployment benefits quickly and efficiently.

AI Literacy

The rise of AI and its nearly universal impact on life and work means we have a new “basic” skill that all students and workers need. In addition to reading, writing, and arithmetic—the traditional building blocks of learning and literacy—we also need to foster incumbent workers’ ability to use AI. Unfortunately, US rates of AI literacy remain low: A 2024 Vention report found that 25 percent of US workers are deploying AI on the job, compared with 60 percent of workers in China and India.³⁶ This skills gap is compounded by a trust gap. According to the 2025 Edelman Trust Barometer, 77 percent of Chinese and 75 percent of Indian respondents trust AI, while only 47 percent of Americans do.³⁷ These figures suggest that AI fluency will not be a matter of technical training only but also technological trust building, especially among worker groups most vulnerable to AI-driven change.

This is not just a matter of mandatory AI classes and graduation requirements for our primary and secondary education systems or simply providing AI literacy programs for incumbent workers, though those are good ideas that need to take priority. AI, as a learning tool and thought companion, should be integrated into studying topics across the curricula—from social studies to science—and in every workplace to build technological proficiency. The “digital natives” who have no memory of a world without the internet and social media are going to find themselves competing with “AI natives,” who cannot conceive of a time without an “external brain” and digital adviser. The time to start teaching AI skills to the K–12 population and incumbent workers as they adapt to change was yesterday.

Fortunately, some schools and businesses are already taking steps to begin this process, with education and training that extends from K–12 AI literacy and

Table 3. Early AI-Adoption Examples

Program Name	Target Audience	Delivery Model	Features
Montour, Pennsylvania, School District AI curriculum	K–12 students and teachers	In-class curriculum with teacher training	<ul style="list-style-type: none"> • Partnership with Carnegie Mellon University and International Society for Technology in Education • Integrated AI learning across subject matter areas • Training for ethical AI use • Teacher professional development • Business partnerships to educate students about AI use in jobs
Massachusetts Institute of Technology Media Lab and i2 Learning	Middle school students	Weeklong “How to Train Your Robot” program	<ul style="list-style-type: none"> • Supervised machine-learning projects • Algorithmic bias education • Using ethical frameworks for designing AI tools
IBM Open P-TECH and IBM SkillsBuild	High school and early college students	Self-paced online courses	<ul style="list-style-type: none"> • Self-paced online learning • Industry-relevant content • IBM-branded credentials and badges in AI, cyber-security, data science, and design thinking
PwC Digital Fitness app	Corporate employees (all levels)	Mobile first, self-assessment, and gamified learning	<ul style="list-style-type: none"> • Digital fitness assessment • Personalized learning pathways • Game-based learning • AI instruction content library • Optimization for smartphone
Microsoft AI Business School	Executives and business leaders	Modular online course	<ul style="list-style-type: none"> • AI strategy • AI-ready culture and cross-functional collaboration • Ethics training to ensure responsible use and development of AI technologies
Google Machine Learning Crash Course	Corporate developers and technical staff	Hands-on technical training	<ul style="list-style-type: none"> • Foundation in machine learning • Data handling • Model development • Responsible AI use and development • Hands-on use of TensorFlow Agents
Accenture Responsible AI Toolkit	Corporate teams and clients	Role-based ethical training	<ul style="list-style-type: none"> • AI governance • Risk assessment and mitigation • Tools for AI fairness, explainability, and privacy • Regulatory compliance • Ethics training to ensure responsible use and development of AI technologies

Source: Randi Williams et al., “AI + Ethics Curricula for Middle School Youth: Lessons Learned from Three Project-Based Curricula,” *International Journal of Artificial Intelligence in Education* 33 (August 2022): 325–83, <https://link.springer.com/article/10.1007/s40593-022-00298-y>; IBM, SkillsBuild, “IBM SkillsBuild: Power Your Future in Tech with Job Skills, Courses, and Credentials—for Free,” <https://skillsbuild.org/>; PwC, “Enabling Our People to Develop a Digital Mind-Set,” <https://www.pwc.com/gx/en/about/stories-from-across-the-world/enabling-our-people-to-develop-a-digital-mind-set.html>; Microsoft, “Transform Your Business with Microsoft AI,” <https://learn.microsoft.com/en-us/training/paths/transform-your-business-with-microsoft-ai/>; Google, “Machine Learning Crash Course,” <https://developers.google.com/machine-learning/crash-course>; and Accenture, “Accenture’s Blueprint for Responsible AI,” <https://www.accenture.com/us-en/case-studies/data-ai/blueprint-responsible-ai>. For the collaboration between Montour School District and Carnegie Mellon University, see Miriam Bogler, “Teardown: How This School District Successfully Integrated AI into Their Project-Based Curriculum,” ProjectPals, August 1, 2024, <https://projectpals.com/post/teardown-how-this-school-district-successfully-integrated-ai-into-their-project-based-curriculum/>; and Kristen Loschert, “‘Student Centered, Future Focused’: Montour School District Designs Schools That Are Future Ready,” All4Ed, <https://all4ed.org/blog/student-centered-future-focused-montour-school-district-designs-schools-that-are-future-ready/>.

Note: This chart summarizes selected AI education and literacy programs aimed at various learner segments, including K–12 students, post-secondary learners, and corporate professionals. It draws on publicly available program descriptions and third-party evaluations to highlight delivery models and each initiative’s core features.

integration to strategy and culture programs for senior executives. These efforts can help create templates for infusing AI into education, the workplace, and society more broadly to promote learning and adoption at the individual and organizational levels (Table 3).

Strengthen Noncognitive “Master” Skills

A through-line of this report is the paradoxical importance of noncognitive skills—the personal attributes, social abilities, and emotional capacities that underlie effective human interaction—in an AI-infused society and economy. A 2023 study by Zety analyzed 50,000 resumes to uncover how the skills listed on them show priorities have changed. In response to employer demands, job seekers are increasingly listing problem-solving, teamwork, and communication at the top of their resumes, replacing an earlier emphasis on technical skills like coding or software proficiency.³⁸ As routine knowledge work is automated, workers will increasingly focus on higher-order tasks that engage the strategic and creative thought that places a premium on leadership, decision-making, and team-based work.

A recent Harvard Business School study of AI’s impact on work at Proctor and Gamble helps illustrate what this might look like in the future. The study found that using AI significantly improved individuals’ and teams’ work outcomes. Teams working with AI produced higher-quality results and were far more likely to achieve breakthrough-level insights that added value to Proctor and Gamble processes.³⁹ This performance boost was achieved by encouraging inclusive and democratized teamwork, helping teams tap the strengths of all members rather than over-relying on the specialized expertise of just a few.⁴⁰

As I noted in *STEM Without Fruit: How Noncognitive Skills Improve Workforce Outcomes*, our noncognitive abilities are heavily influenced by early life experiences and can be disrupted by family and community instability. Children whose noncognitive development is disrupted by chronic, “unbuffered” adverse experiences (i.e., trauma that occurs without the support of a caring adult) often fall victim to a wide range of negative long-term social outcomes, including educational failure, substance abuse, juvenile justice involvement, and unmarried births.⁴¹ Remediating these deficits is difficult, expensive, and uncertain work. Prevention is far more likely to result in positive outcomes.

This framing of the critical importance of noncognitive development means that our investments in protecting and nurturing family and child development are among the most important policies we can enact to prevent noncognitive deficits and give future generations the tacit skills they will need to navigate change. Nurses making home visits for new mothers, intensive childhood mentoring for the disadvantaged, and early childhood education programs like Head Start have been shown to significantly improve noncognitive skills among adults who had access to program services as children.⁴² Healthy marriage and responsible fatherhood programs may also help improve the parenting skills that are decisive for noncognitive development. Increased spending on quality early childhood and family-support programs is not just an investment in the lives and well-being of children; it is critical to building the flexible and adaptable human beings who can respond to the shifting demands of the AI future.

Finally, we must remember that AI itself may be an important ally in addressing noncognitive problems. These technologies are trained on human thought, writing, and experiences. When well-designed and properly used, they provide access to the best of who we are as human beings. We have tantalizing early evidence that AI chatbots can aid workers in reshaping noncognitive behaviors through digital coaching—helping those who, for reasons that are organic (e.g., autism spectrum disorders) or developmental (e.g., chronic trauma), have difficulty understanding social behaviors and responding in an appropriate and productive manner.⁴³ Government and the private sector should invest in developing these AI tools as a remedial technology for addressing noncognitive deficits.

Conclusion

The evidence I present in this report points to a transformative AI-driven shift in the knowledge economy. Much like the ITC and robotics revolution that reshaped manufacturing, AI is now reshaping the knowledge economy—but with important characteristics that require thoughtful planning and program implementation to prepare and re-skill the workforce.

The patterns across the finance, business services, government, and health and social assistance sectors reveal a consistent trajectory: Routine knowledge work

is being automated, and the pace and scope of that automation will increase in the future, raising demand for workers who can combine technical AI fluency with strong interpersonal, learning, and leadership skills. For the upper end of the talent distribution, AI is likely to be a significant benefit, but the technology raises significant questions for the rest of the workforce.

Unlike during previous technological transformations, we have the benefit of reviewing recent experience in considering how to approach these changes. The de-skilling of the knowledge economy is in its early stages, giving us a critical window to implement policies that can mitigate negative impacts while maximizing positive outcomes. This requires a three-pronged approach.

First, we must develop better data systems that provide headlight capabilities for monitoring changes as they occur while helping anticipate future demand. AI itself may prove invaluable in analyzing patterns and identifying emerging skill needs at local and regional levels, where such information is most actionable.

Second, policy solutions should prioritize worker agency rather than centralized control. Expanded ITAs and a reformed Automation Adjustment Assistance program (based on the former TAA) can enhance flexibility and empower workers to make decisions about education and career transitions with appropriate financial and advisory support.

Third, we must develop a comprehensive AI literacy strategy across all stages of education and career development. From K–12 integration to executive leadership training, AI competency is becoming a basic skill alongside traditional literacies. Early-adoption programs already underway in schools and corporations provide promising templates for broader implementation.

Perhaps most critically, we must recognize the paradoxical importance of noncognitive skills in an AI-powered economy. As routine cognitive work is automated, the premium on human capabilities like critical thinking, empathy, communication, and collaboration is increasing. This makes investments in early childhood development, family stability, and targeted interventions for disadvantaged youth not merely social priorities but economic imperatives for developing the agile and adaptive workforce of tomorrow.

With thoughtful policies that emphasize flexibility, individual agency, and lifelong learning, we can shape an AI-enabled workforce that expands opportunities rather than simply sorting winners and losers. The choices we make today about education, worker support, and social investment will help ensure AI's benefits are broadly shared and minimize its risks to the well-being of workers, families, and communities.

About the Author

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