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PERSPECTIVES ON
OPPORTUNITY

The Age of Uncertainty—and Opportunity: Work in the Age of AI

Brent Orrell and David Veldran

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The question of how artificial intelligence will affect jobs, skills, and the future of work is open-ended, and answers have been uncertain and contradictory. As AI has advanced, forecasts of labor market impacts have increasingly emphasized AI's potential to automate tasks that require skills—including creativity, writing, and social and emotional learning—previously believed to be beyond the technology's reach. In the face of these advances and the uncertainties they generate, students and incumbent workers should focus on developing balanced skill "portfolios" that support flexibility and adaptation, and policymakers should empower them to do so.

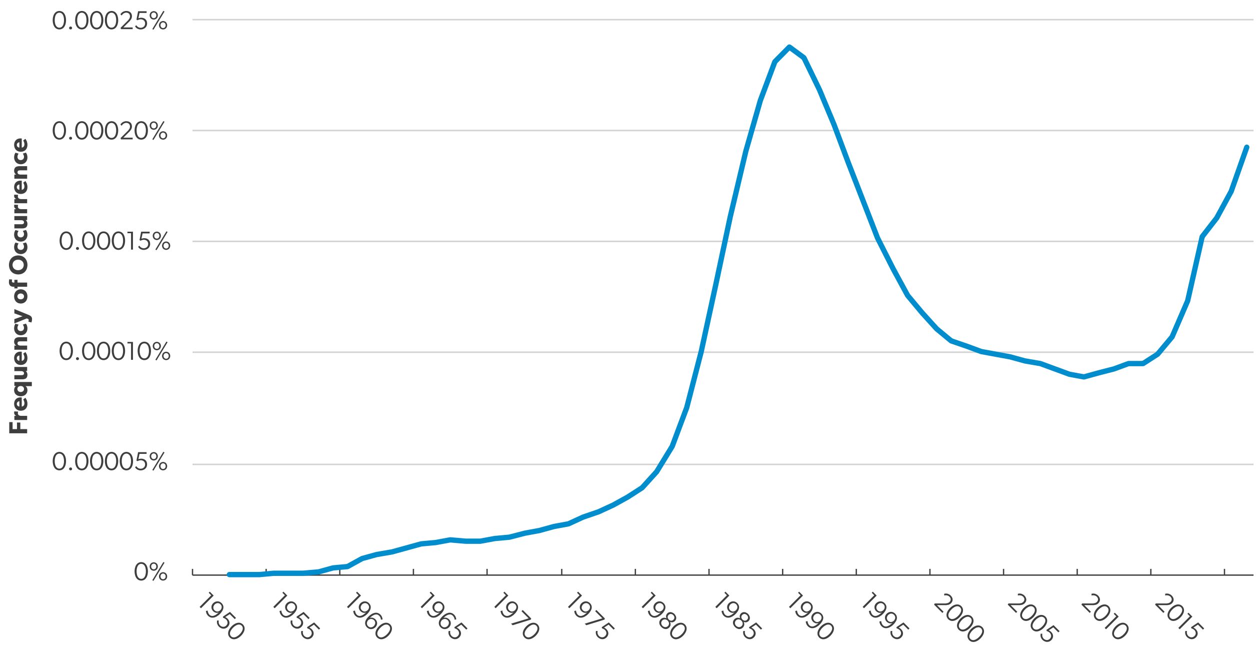
In an era defined by rapid technological advancements, artificial intelligence has emerged as a so-called general-purpose technology, akin to the steam engine, electricity, and the transistor, with the potential to reshape all aspects of our economy and lives. Much of AI's transformative potential is due to recent developments in the field—particularly the rise of generative AI, which can create novel text, images, and audio. According to a recent report published by McKinsey & Company, this new wave of technology could add \$2.6–\$4.4 trillion annually to the global economy, with an outsized impact in industries such as banking, software and tech, and the life sciences (Chui, Hazan, et al. 2023). According to Goldman Sachs (2023), AI could raise the global gross domestic product (GDP) by 7 percent over 10 years.

Changes of this scale in growth and GDP will likely affect businesses and workers profoundly. The question is what those changes will be and how we can prepare for them. In this report, we review over a decade of research on AI's potential and actual impacts on employment trends and demand for skills in the labor market. We then explore this research's implications for skill development and worker training and offer recommendations for workers and policymakers.

As we stand on the threshold of an AI-driven economy, the future of work is at stake. Will work still be an important human activity, or will human labor be rendered surplus to requirements? While machine-based intelligence has loomed over human imagination for centuries,[1] the modern idea of AI emerged in the

1 In 1565, the Spanish-Milanese engineer Juanelo Turriano created a working automaton of a monk, highlighting an early fixation on machine intelligence.

Figure 1. References to "Artificial Intelligence" in Popular Literature

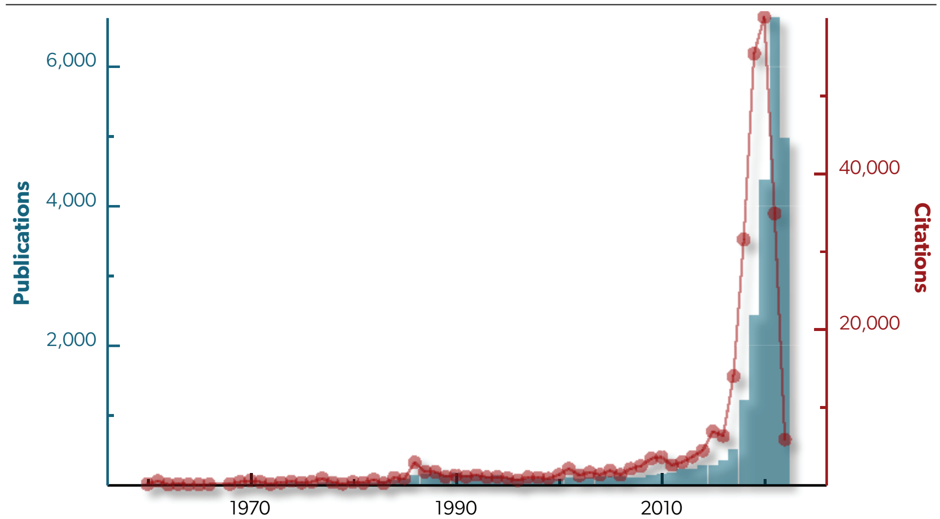


Note: The latest data available are from 2019.
Source: Google Books Ngram Viewer (2024).

mid-20th century with the development of digital computers. As shown in Figures 1 and 2, while references to artificial intelligence in popular literature rose sharply in the late 20th century, peaking between 1985 and 1990, mentions of the term in academic literature remained relatively low until 2010. As the topic gained ground in scientific circles, references to it in popular literature also began to climb.

AI's growing role in the public consciousness coincided with revolutionary change in fields such as image recognition and natural language processing, setting the stage for AI's prominence in public discourse today (Roser 2022).

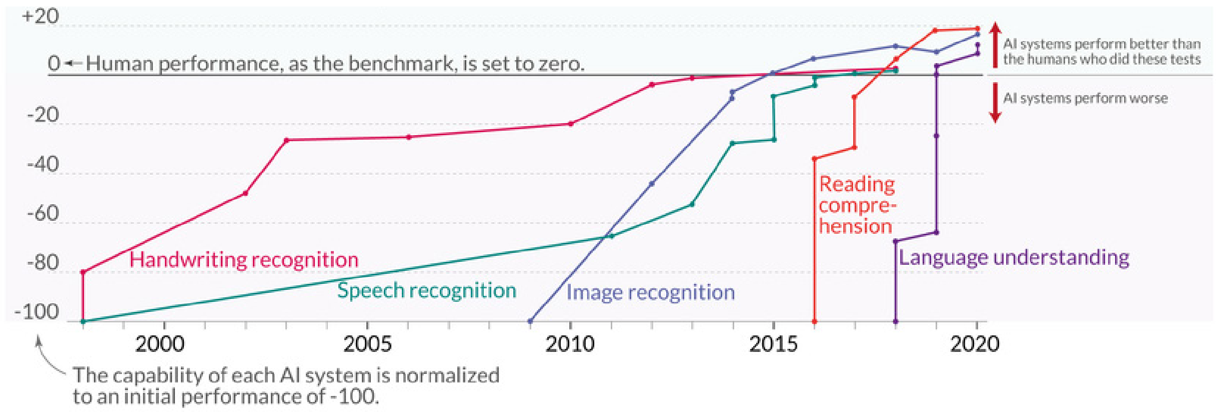
Figure 2. References to "Artificial Intelligence" in Academic Articles, 1950–2022



Note: The red line tracks citations that refer to AI; the blue bars track publications that refer to AI.
Source: Exaly (2024).

Between 2010 and today, AI development can be broken into three major periods. From 2010 to 2016, breakthroughs in neural-network design transformed

Figure 3. AI's Test Scores Relative to Human Performance



Source: Roser (2022).

AI. Powered by these new systems, AI made rapid gains in image recognition and deep learning, especially through models such as AlexNet and AlphaGo, a program that shocked scientists and other observers by defeating a world champion Go player (Albrecht 2023; Google DeepMind n.d.).

AI's advances in 2016–22 built on earlier development with the introduction of highly influential neural-network models including Google's Bidirectional Encoder Representations from Transformers and OpenAI's GPT (Albrecht 2023). These models set new benchmarks in natural language processing, helping rapidly improve AI reading comprehension and language understanding, as noted in Figure 3.

The third era, from around 2022 to the present, has featured the maturation of generative AI and the proliferation of generative AI tools for broad public use. In this brief period, tools such as ChatGPT, Bard, Claude, DALL·E, Midjourney, and a host of other tools have become widely available, spurring debate about the impacts of AI on work (Chui, Hazan, et al. 2023). Below, we examine the key research voices and trends in each of the three major periods of development outlined above.

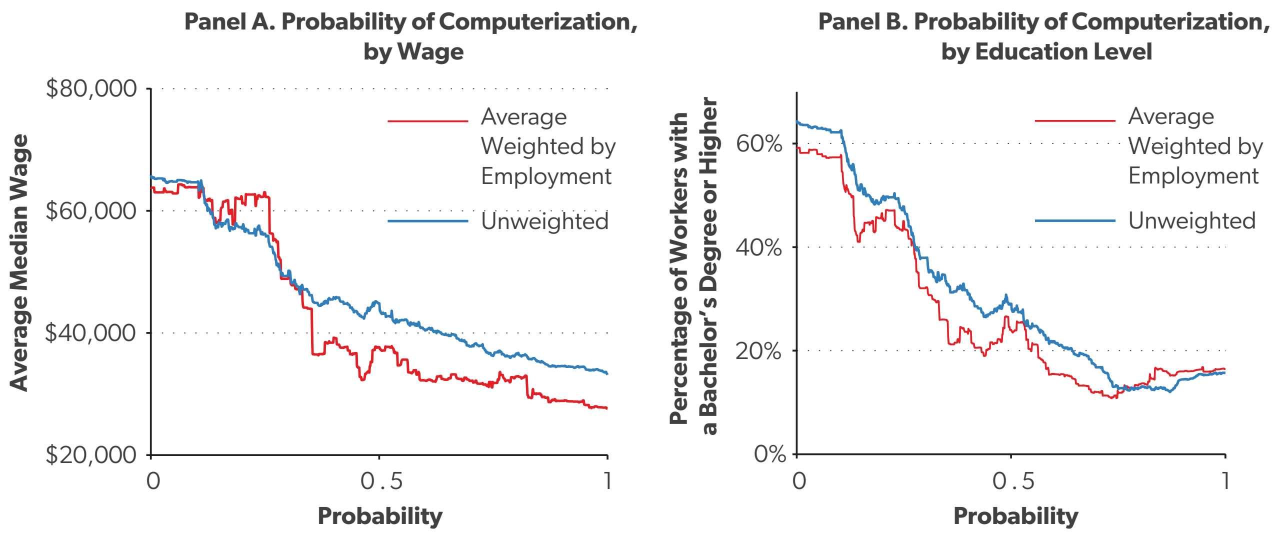
Period I: Circa 2010–16

In this era, advancements in AI fueled debates on how AI would affect employment and demand for skills. These debates featured a wide range of perspectives and predictions. In this section, we discuss some of the most influential voices.

Employment Projections. Coinciding with the acceleration of AI's capabilities was rising anxiety about its potential negative effects on employment. Oxford University researchers Carl Frey and Michael Osborne (2013) estimated that 47 percent of US jobs were at high risk of automation from machine learning and robotics over the next two decades. A similar analysis for the European labor market found that, on average, 54 percent of EU jobs were at risk of computerization (Petropoulos 2018; Bowles 2014). Commentators on these trends warned of a "jobless future," anticipating that AI would eclipse human-level ability across many skill domains (Ford 2009, 2015).

Others researchers reached much less dire conclusions about AI's effects on jobs and skills. David Autor (2015) posited that AI-powered automation would substitute for human labor in some domains but complement it in others, such as in nonroutine tasks that require advanced cognitive skills and creativity. This latter claim was core to a "routinization" theory, which posited that AI and automation would take over repetitive and routinized tasks, leaving humans with highly skilled cognitive tasks and low- to medium-skilled physical labor. Under routinization, some researches argued, AI would further polarize a labor market that already suffered from a shortage of medium-skilled jobs (Albanesi et al. 2023).

Figure 4. Workers' Exposure to Automation Is Anticorrelated with Wages and Education Level



Source: Frey and Osborne (2013), 41.

Skill-Change Estimates. On how AI would affect skill demand, many researchers predicted that AI technology would mainly threaten low- to medium-skilled work, which requires fewer social, cognitive, and creative skills. Daron Acemoglu and Autor (2011), for instance, argued that medium-skilled and highly routinized jobs were often at the greatest risk of automation.

Similarly, Frey and Osborne (2013) predicted that most workers in transportation and logistics, office and administrative support, production, and service occupations were at risk from automation. As shown in Figure 4, they projected that as AI developed, low-skilled workers would be at the greatest risk from automation. These workers, they argued, would need to shift to tasks less susceptible to automation, such as those requiring creative and social intelligence. These predictions are core to the theory of skill-biased technological change, which contends that technological change and automation will increase demand for high-skilled labor (Albanesi et al. 2023).

Period II: Circa 2016–22

Between 2016 and 2022, empirical research on AI's impacts on the labor market challenged early predictions of widespread AI-induced job losses, highlighting a nuanced impact normally associated with the gradual takeoff of new general-purpose technologies. Yet disagreement persisted on whether AI would create more jobs than it displaced and how it would affect the demand for skills.

Employment Projections. As AI technology advanced in this period, new research challenged the earlier, more dire predictions. Melanie Arntz, Terry Gregory, and Ulrich Zierahn (2016), for instance, estimated that only around 9 percent of jobs across developed countries were automatable with current AI technologies. Marguerita Lane and Anne Saint-Martin (2021) observed that while employment in select occupations had declined, predictions of massive technological unemployment had failed to materialize. While AI was capable of performing some nonroutine cognitive tasks, they noted, bottlenecks to adoption remained, especially in tasks that required social interaction and physical labor. For this reason, Lane and Saint-Martin argued humans would still be needed to complete many tasks.

Similarly, Acemoglu et al. (2022) found that, though some AI-exposed industries had reduced hiring, no relationship between AI exposure and employment or wage growth at the occupation or industry level was discernible, implying that AI had affected employment involving a subset of tasks but did not yet detectably affect the labor market as a whole.

Others offered more straightforwardly optimistic views. James Bessen (2018), for instance, argued that AI, though it would likely substitute for human labor in some domains, would create more jobs than it destroyed by increasing productivity in markets with large unmet needs. Acemoglu and Pascual Restrepo (2019) emphasized the "reinstatement effect" of new technology, contending that AI might boost productivity and demand, which would reinstate jobs and result in net job gains.

McKinsey & Company predicted that 75 million to 375 million people—between 3 and 14 percent of the global workforce—might need to switch occupations by 2030 (Manyika et al. 2017). However, it also found that economic growth, rising incomes, aging populations, and energy transitions would create new jobs. These sources of new labor demand, McKinsey's researchers argued, would more than offset the jobs lost to automation, creating up to 890 million new jobs by 2030.

Similarly, the World Economic Forum (WEF) estimated in 2018 that technology would displace 75 million jobs but that 133 million jobs would emerge by 2022, especially in the fields of AI, machine learning, data, information security, and process automations (Leopold, Ratcheva, and Zahidi 2018). Since these roles would require complex skills, however, this new demand might further polarize the workforce, putting a premium on highly skilled workers with AI expertise. Indeed, the WEF predicted that the jobs least in demand would include many medium-skilled roles such as data entry, accounting, bookkeeping, payroll, and office support.

Others offered less optimistic pictures of the future. Oxford University fellow Daniel Susskind argued that in the long term, AI could destroy more jobs than it created, given its rapid advances across a wide variety of domains (Susskind 2020). The WEF lent some support to this more pessimistic view when, in 2020, it noted that job creation had slowed in recent years while job destruction had accelerated (Zahidi et al. 2020). The WEF still predicted that the number of jobs created by 2025 would be greater than the number displaced but that the balance between job destruction and creation would be narrower. By 2025, it said, 85 million workers might be displaced, while 97 million new roles would emerge.

Skill-Change Estimates. Nested in the argument over the number of jobs was a vigorous debate about AI's impacts on skill demands. Lane and Saint-Martin (2021) found AI technologies would change the structure of many occupations and create new tasks in developing, explaining, and sustaining AI systems, requiring workers to become more fluent with technology. These trends would require adaptation, which they believed would be far easier for higher-skilled workers, putting a premium on creativity, technical ability, and advanced cognitive skills.

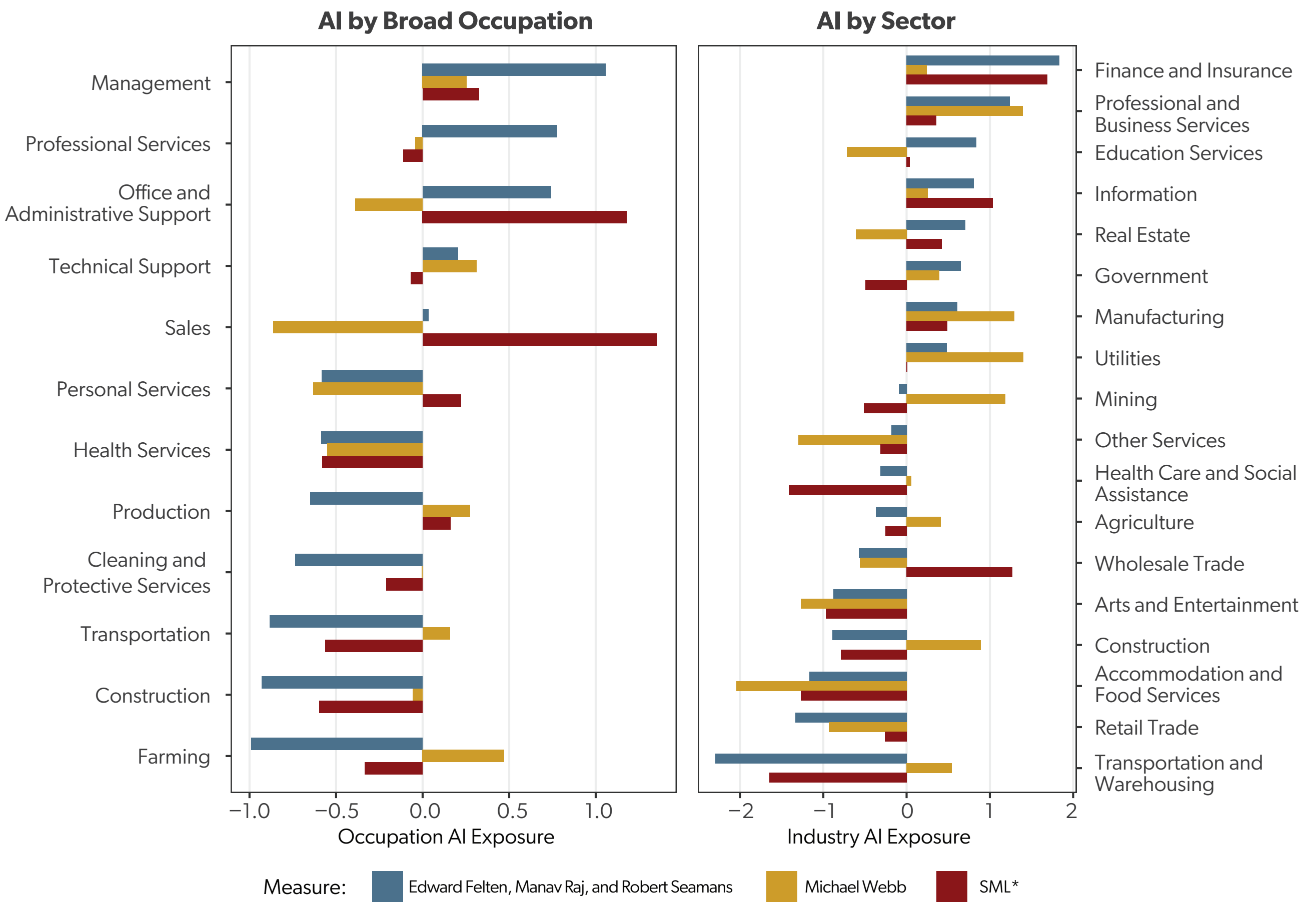
McKinsey found that automation would accelerate the shift in required workforce skills seen in the previous 15 years, putting a premium on basic digital skills and advanced programming (Bughin et al. 2018). It predicted that growth in demand would be concentrated in technological skills. The WEF projected that other complex skills such as analytical thinking, innovation, technology design, and programming would continue to be in high demand (Zahidi et al. 2020).

Others analyses complicated this narrative, arguing AI could harm workers as it becomes proficient at nonroutine cognitive tasks in addition to routine ones (Tyson and Zysman 2022; Acemoglu et al. 2022). These advances raise questions about whether creativity, technical ability, and other advanced cognitive skills will remain in high demand.

Several researchers, such as Michael Webb (2020); Edward Felten, Manav Raj, and Robert Seamans (2020); and Brynjolfsson, Tom Mitchell, and Daniel Rock (2018) have attempted to measure occupational exposure to AI. According to these researchers, many of the occupations most exposed to AI are white-collar jobs that require high levels of education and complex cognitive ability. By contrast, occupations less exposed to AI tend to involve social interaction or physical labor and are more likely to be labeled lower skilled. As shown in Figure 5, many occupations and sectors most exposed to AI require high levels of education.

A consensus during this period, however, was that "human" skills (i.e., those related to interpersonal relationships) would remain crucial complements to AI systems for the foreseeable future. McKinsey (Manyika et al. 2017), the WEF (Zahidi et al. 2020), and Pearson (Bakhshi et al. 2017) emphasized the growing demand for interpersonal communication, creativity, adaptability,

Figure 5. Occupations and Industries Have Varying Levels of Exposure to AI-Enabled Automation



Note: * "SML" refers to Erik Brynjolfsson, Tom Mitchell, and Daniel Rock's "suitability for machine learning" index.
Source: Acemoglu et al. (2022), 33.

resilience, emotional intelligence, leadership, and collaboration. These predictions agreed with David Deming's (2017) research showing that as machines took on more tasks, relative demand for social skills increased.

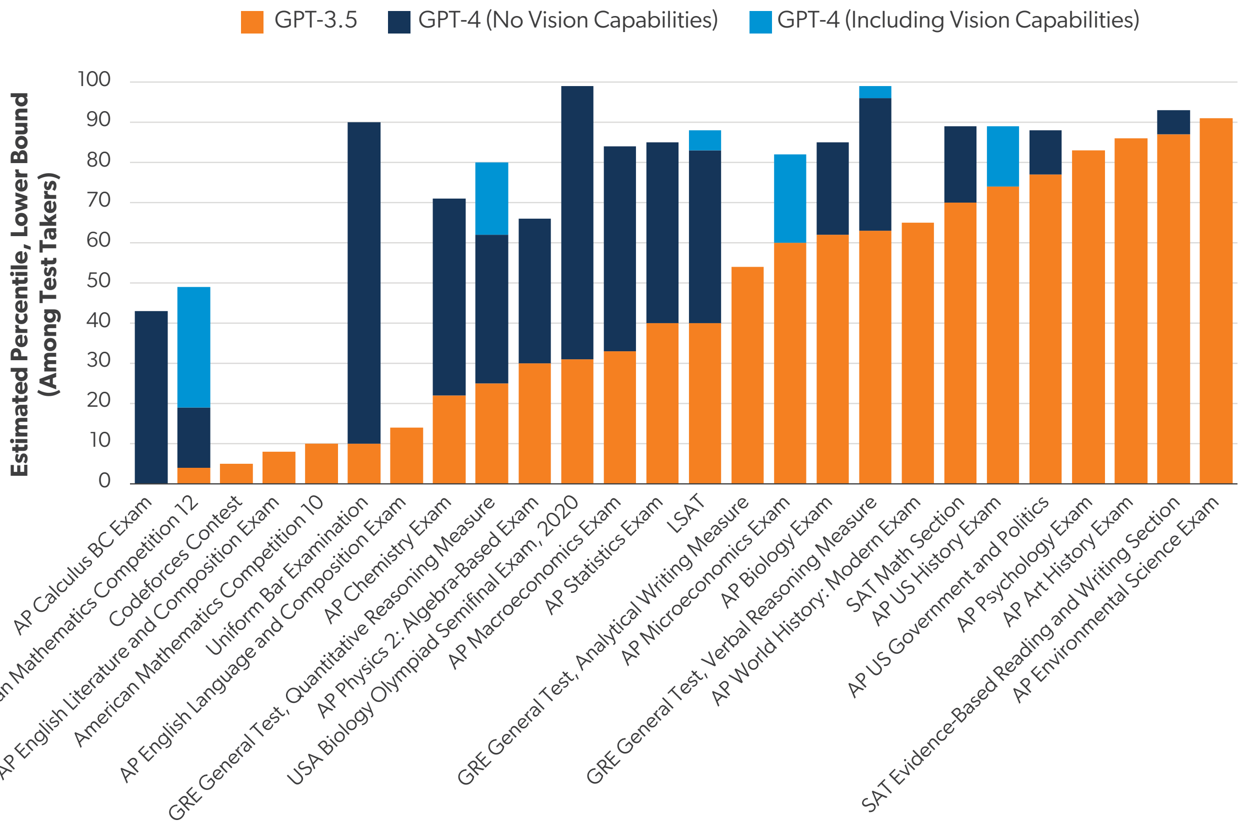
Period III: Circa 2022–Present

Over the past year, the rise of generative AI has prompted a reevaluation of its potential to automate tasks across various jobs, particularly in white-collar professions, with estimates suggesting that AI could automate a significant portion of tasks in the near future. While some researchers have made daunting and far-reaching predictions about AI's impacts, others observe modest and even positive employment effects so far. These perspectives paint a complex picture of AI's impacts on employment dynamics and skill requirements. We outline this picture below.

Employment Projections. Over the past 12 months, many researchers have begun to focus on the rise of generative AI, which can produce novel content, such as text, images, audio, and video. Some researchers fear that, consistent with the pre–generative AI research noted above, generative AI poses a new challenge to the workforce since it could automate a wide range of jobs and tasks, especially in white-collar professions.

Before generative AI, McKinsey estimated that AI had the potential to automate half of workers' tasks on a given day (Manyika et al. 2017). In the past year, McKinsey has revised its 2017 estimates upward, finding that current technology could theoretically

Figure 6. ChatGPT-3.5's and ChatGPT-4's Performance on Various Examinations



Source: Eloundou et al. (2023).

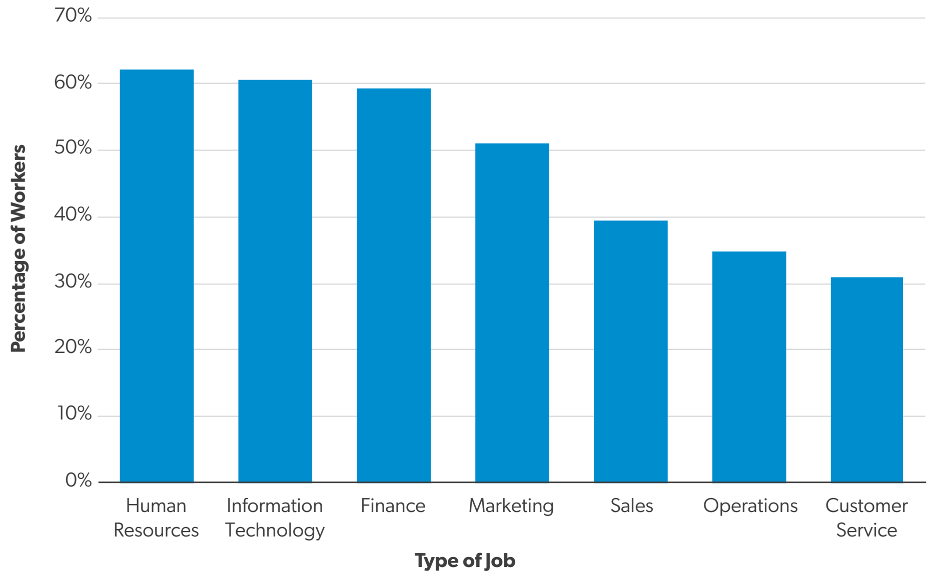
automate 60 to 70 percent of the hours worked today (Chui, Hazan, et al. 2023). The company also predicts that AI will automate half of today's work between 2030 and 2060, roughly a decade earlier than its pre–generative AI estimates.

Others have made similarly dramatic forecasts. Tyna Eloundou et al. (2023) found that generative AI could affect at least some tasks in 80 percent of jobs and, in around 20 percent of jobs, affect at least half of required tasks. These authors also found, as seen in Figure 6, that generative AI has quickly progressed on standardized tests such as the Uniform Bar Examination, AP Chemistry Exam, and the GRE's quantitative section, providing insight into how quickly AI is approaching human-level performance in many domains of knowledge. According to Valoir (2023), AI could automate about 40 percent of the average workday and, as shown in Figure 7, could replace workers across industries. According to Goldman Sachs (2023), AI could partially automate two-thirds of jobs.

Others point out that AI has not demonstrated significant employment effects and may have even boosted labor shares among the workers who have been labelled as highly exposed to AI. For instance, looking at data from 2011 to 2019, Albanesi et al. (2023) found that, for low- and medium-skilled workers, greater exposure to AI did not affect employment shares, defined as the percentage of total employment that a group accounts for in the overall workforce. For high-skilled workers, the authors found, greater exposure to AI increased employment shares. These data suggest that AI may not harm employment and in some cases may boost it.

In agreement with the latter conclusion, Andrew Green (2023) found little evidence that AI significantly

Figure 7. Employees Across Industries Say AI Could Replace a Large Portion of Their Coworkers



Source: Valoir (2023).

expose highly skilled workers to automation. It also aligns with Xiang Hui, Oren Reshef, and Luofeng Zhou's (2023) finding that ChatGPT has disproportionately affected top freelance writers on a large online platform.

On the opposite end of the skill distribution, by contrast, early evidence shows that, for lower-skilled workers, AI could be a boon. Brynjolfsson, Danielle Li, and Lindsey Raymond (2023) found that chat technology dramatically raised job performance among lower-skilled customer service representatives, largely by improving social interactions with customers. Similarly, a March working paper by Massachusetts Institute of Technology researchers documented that ChatGPT disproportionately benefited lower-skilled workers in writing tasks. This may lessen the value of above-average writing skills but broaden access to jobs for those less skilled in written communication (Noy and Zhang 2023). Most recently, Ajay K. Agrawal, Joshua S. Gans, and Avi Goldfarb (2023) argued that this leveling effect will reduce barriers to entering jobs involving various skilled tasks (e.g., transportation, language translation, writing, and medical diagnosis) and could reduce inequality by broadly boosting human capital and reducing the wage premiums of highly educated and highly skilled workers.

As AI's capacity to take on more complex and "human" tasks grows, some have suggested that many technical skills, such as coding, will lose value as AI can increasingly perform tasks that require them (Korducki 2023). Others, however, such as Julie Lassébie (2023), continue to stress the value of scientific and technical skills, including basic "AI literacy." According to this view, workers who can effectively wield AI tools will see their economic value grow. A recent survey by Retool bears this out, finding that hiring managers are more likely to hire candidates with AI skills—for instance, coders who

harms employment. Despite their higher exposure to AI, Green argued, high-skilled workers have seen employment gains relative to lower-skilled workers over the past 10 years, perhaps because AI has created new tasks. In other words, AI *may* present serious challenges to work availability for some of the workforce, but, as yet, the only identified effects have been mildly positive.

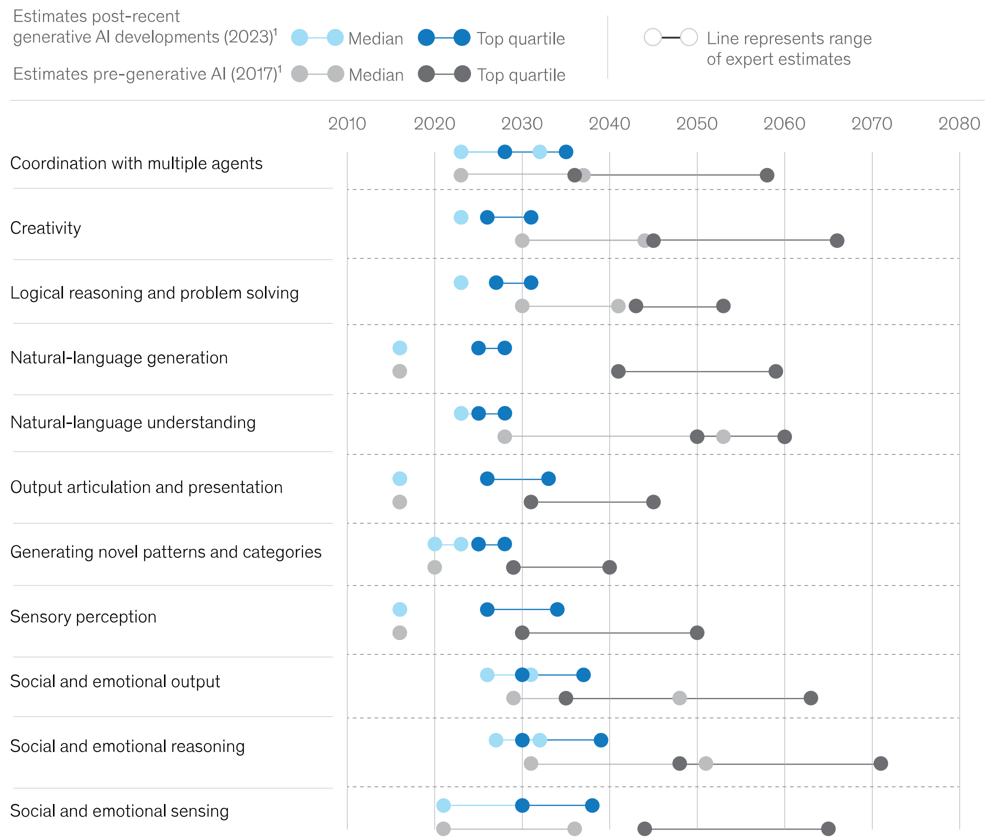
Skill-Change Estimates. As AI has advanced in this period, some have argued (Figure 8) that it is beginning to advance beyond analytical thinking and creativity to perform noncognitive or "human" skills and behaviors such as social and emotional reasoning and sensing, creativity, and curiosity (Chui, Hazan, et al. 2023; Di Battista et al. 2023).

According to McKinsey, as AI improves on these skills, its disruption will be unevenly distributed across the economy—and disproportionately felt by highly skilled workers (Chui, Hazan, et al. 2023). Generative AI's impact on a given profession, McKinsey argues, increases with the amount of education the profession requires. That is, it will affect jobs that require a PhD or master's degree most and jobs that don't require a high school diploma least. This conclusion accords with projections we discussed above that AI would disproportionately

Figure 8. Predictions on When AI Could Reach and Surpass Human-Level Performance in Various Skills

As a result of generative AI, experts assess that technology could achieve human-level performance in some technical capabilities sooner than previously thought.

Technical capabilities, level of human performance achievable by technology



[1]Comparison made on the business-related tasks required from human workers. Please refer to technical appendix for detailed view of performance rating methodology.

Source: Chui, Hazan, et al. (2023), 35.

are comfortable using the AI assistants GitHub Copilot and ChatGPT—and that tech professionals are increasingly adopting AI (Retool n.d.).

The Certainty of Uncertainty

Overall, research on AI's future impact has featured significant uncertainty and disagreement (Martens and Tolan 2019; Georgieff and Hyee 2022; Tyson and Zysman 2022). While some researchers have made alarming forecasts about mass worker displacement, empirical studies have generally found, to date, minimal aggregate employment effects across skill and education levels. Some studies seem to confirm a reinstatement effect, others point to AI-driven gains among the lower skilled, and others suggest the age-old pattern of automation-led increases in wealth, income, and aggregate demand, lifting all boats over time. A summary of these conflicting assessments can be found in Table 1.

Several factors underpin the widely variant estimates of AI's employment effects. Most significant, of course, is the speed of AI's evolution as it takes on new capabilities and moves into unforeseen market applications. Additional factors include adoption lags (the time between when a technology launches and when it is in

Table 1. Summary of AI's Projected Impacts on Employment and Skills

Researchers' Names	Year	Prediction
Acemoglu and Autor	2011	Many jobs are at risk of automation, especially medium-skilled and highly routinized ones.
Frey and Osborne	2013	Forty-seven percent of US jobs, especially lower skilled, are at high risk from automation by machine learning and robotics over the next two decades.
Autor	2015	AI will substitute for human labor in some domains but complement it in others, such as in nonroutine tasks that require advanced cognitive skills and creativity.
Martin Ford	2015	As AI advances, it raises the possibility of a "jobless future."
Arntz, Gregory, and Zierahn	2016	Around 9 percent of jobs across developed countries are automatable with current AI technologies.
Manyika et al.	2017	Between 75 million and 375 million people, up to 14 percent of the global workforce, might need to switch occupations by 2030; AI may create up to 890 million new jobs by 2030.
Till Alexander Leopold, Vesselina Ratcheva, and Saadia Zahidi	2018	Technology will displace 75 million jobs, but 133 million new jobs will emerge by 2022.
Bessen	2018	AI will likely substitute for human labor in some domains, but it will create more jobs than it destroys by increasing productivity in key markets.
Jacques Bughin et al.	2018	AI automation will put a premium on basic digital and advanced programming skills.
Brynjolfsson, Mitchell, and Rock; Webb; Felten, Raj, and Seamans; and Acemoglu et al.	2018–22	Many occupations most exposed to AI are white-collar and require high education levels and complex cognitive ability.
Acemoglu and Restrepo	2019	AI may boost productivity and demand for labor, which could result in job gains.
Susskind	2020	In the long term, AI could destroy more jobs than it creates.
Zahidi et al.	2020	By 2025, AI may displace 85 million workers but create 97 million jobs.
Lane and Saint-Martin	2021	AI can perform some nonroutine cognitive tasks, but many jobs, especially those requiring social interaction and physical labor, cannot yet be automated.

(continued on the next page)

Table 1. Summary of AI's Projected Impacts on Employment and Skills (*continued*)

Researchers' Names	Year	Prediction
Michael Chui, Eric Hazan, et al. and Chui, Lareina Yee, et al.	2023	Generative AI and other technologies could automate work activities that absorb 60 to 70 percent of employees' time, AI technology could automate half of today's work between 2030 and 2060, and AI can increasingly perform high-skilled tasks involving management, application of expertise, and decision-making.
Eloundou et al.	2023	Generative AI could affect some tasks in 80 percent of jobs and half or more of component tasks in 20 percent of jobs.
Valoir	2023	AI could automate 40 percent of activities in the average workday.
Goldman Sachs	2023	AI will expose two-thirds of US occupations to automation, but AI will more likely complement than substitute for most jobs.
Brynjolfsson, Li, and Raymond; Shakked Noy and Whitney Zhang; and Ajay K. Agrawal, Joshua S. Gans, and Avi Goldfarb	2023	AI may help level the playing field for lower-skilled workers by boosting their skills' value.

Source: Authors.

widespread use), the availability of semiconductor chips and other hardware, and the effects of government regulation. People crave certainty about AI and the future of work, but that craving is unlikely to be satisfied.

Implications for Workers: Skills and Workforce Development

This unpredictability poses a dilemma for workers, educators, and training institutions: How should they prepare when they do not know what to prepare for? While generative AI will certainly strongly influence skill requirements, the precise effects and timelines are, at best, vague and largely unknowable. As AI advances and reaches human-level performance in more skill areas, decisions about investment in skills development will probably become more difficult, not less.

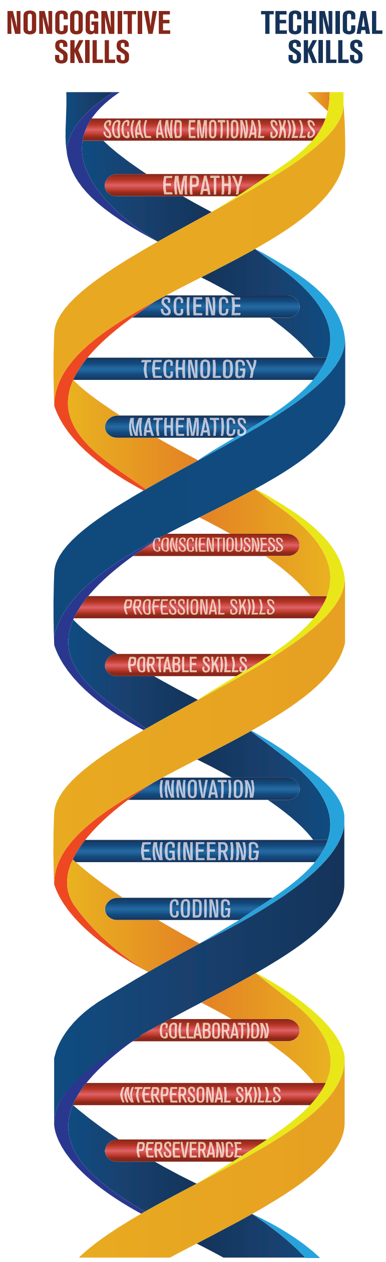
In the face of radical uncertainty, the most important skills for the future will likely be those that enhance flexibility in adjusting to change. Close attention should be paid to how skills develop and how they are applied. We describe these factors using two models, the skills double helix and the skills pyramid.

The skills double helix (Figure 9) can be thought of as the "human operating system." It helps us visualize how the two types of skills—noncognitive and technical—together prepare the student or worker for education, training, ongoing skill acquisition, and task execution.

On one side of the double helix are technical skills: industry- and task-specific abilities that lend themselves to formal classroom, laboratory, or on-the-job training. Technical skills, in a word, are formally *taught*. On the other half of the helix are noncognitive skills (also known as soft or durable skills) that make up the interpersonal dimension of learning and work. These skills are *caught* as we move through the social world, gradually improving our ability to read and respond to social cues and cooperate on complex tasks. Noncognitive skills are crucial for learning, task execution, and ongoing skill progression.

The skills pyramid (Figure 10) shows how the double helix applies to employment. Because of noncognitive

Figure 9. The Skills Double Helix



Source: Authors.

skills' role in learning, they form the pyramid's foundation, on which basic skills (e.g., reading, math, science, and problem-solving) and industry-specific skills (e.g., coding and welding) are built. In workforce development and training, teaching technical skills is more difficult if the learner's noncognitive skills are weak.

Even if technical training succeeds, weak noncognitive skills tend to impair job performance. In workforce development parlance, technical skills get you *hired*; noncognitive skills get you *fired*. This dilemma suggests that if educators and workers want good employment outcomes at the top of the pyramid, they should focus time, energy, and resources on the noncognitive and basic levels.

AI's recent advancement in some noncognitive skills, which we discussed above, seems to undermine the argument that workers should continue to invest in these skills. If AI can communicate or empathize more effectively than humans can, these skills seem ripe for replacement. Yet there are several reasons to believe that this conclusion is unjustified—and that workers should continue to invest in noncognitive skills.

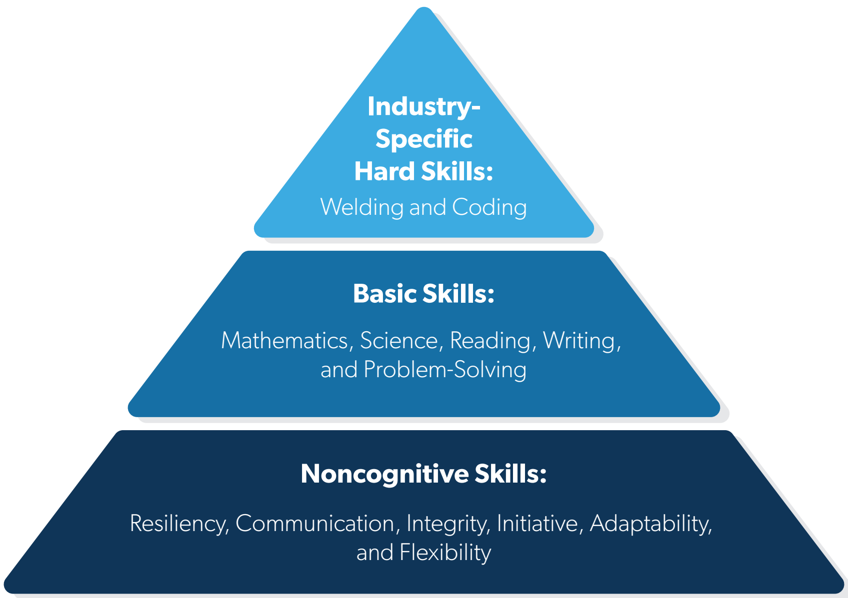
First, despite AI's improvements on some skills, these skills have so far proved resilient. Noncognitive skills' impressive economic value and the fact that they still top the list of the most in-demand skills reflect their continued importance (Deming 2017; Edin et al. 2022; Jayaram and Engmann 2014; Hart Research Associates 2013; LinkedIn 2023; Masterson 2023; Goldstein et al. 2023). As shown in Figure 11, a recent IBM survey of over 25,000 C-suite executives and workers worldwide shows how over the past few years, these skills have replaced those gained through STEM-related training as the most crucial skills required of the workforce.

Second, noncognitive skills will likely remain evergreen because, as the pyramid model illustrates, they form the foundation of all other skills. Thus, as long as any skill is valuable, the noncognitive skills that undergird it—and facilitate learning and adaptation—will likely remain valuable as well.

Finally, beyond their economic value, noncognitive skills serve people throughout their lives, enabling them to move fluidly in society and form the attachments to spouses, family members, and friends that make for happier, more fulfilled lives.

In light of the uncertainty about employment and skills, economist Nouriel Roubini argues that students and workers should treat investment in skills much as they treat financial investments: Diversify to spread risk. Don't concentrate too much "capital" (time and energy) in a single "stock" (skill). Diversification of educational investment protects against sudden shifts in skill demand and helps workers adjust to evolving economic circumstances and skill demands (Roubini, Chui, and Bush 2023).

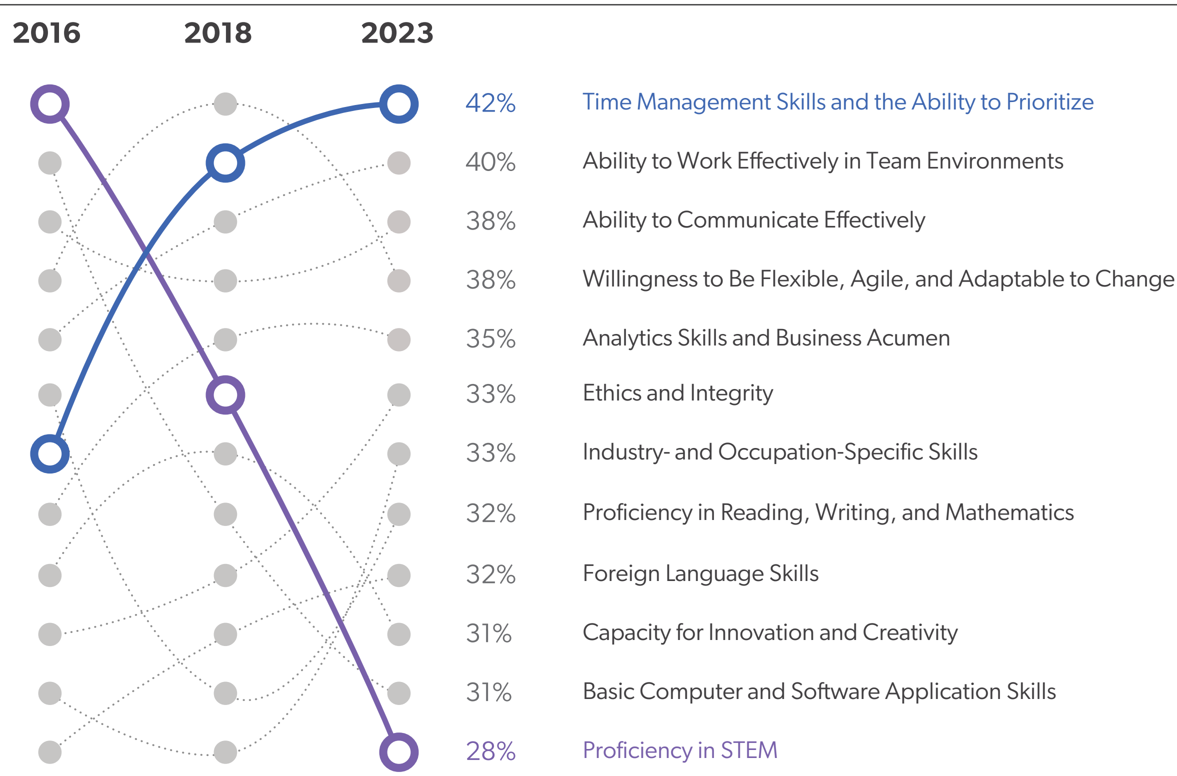
Figure 10. The Skills Pyramid



Source: Orrell (2023).

Students and workers with strong quantitative and technical skills should seek to improve in nontechnical domains, while those with strong nontechnical skills should bolster their knowledge of and abilities in math, science, and technology to create a balanced education and training "portfolio." The knowledge and skills acquired through nontechnical education and training can support the noncognitive side of the double helix, adding to tactical on-the-job learning and flexibility. Roubini's insights are borne out by the evidence. A balanced skill set has been shown to have great economic value and be crucial to success among workers in technical fields, such as IT and engineering (Huber et al. 2020; Gallagher et al. 2010; Male, Bush, and Chapman 2011).

Figure 11. The Most Crucial Skills Required of the Workforce, 2016–23



Note: The percentages represent the portion of survey respondents who identified a particular skill as the most crucial.
Source: Goldstein et al. (2023), 7.

Implications for Policymakers

How can public policy support current and future workers as they navigate an uncertain employment and skills environment and seek to develop the flexible skill portfolio we recommend? The answer lies in promoting education, training, and reskilling that recognize the structural challenges workers will face while empowering them to find their own way in a fast-changing labor market.

Integrate Technical and Noncognitive Skill Development. The Workforce Futures Initiative—a bipartisan collaboration of scholars from AEI, the Brookings Institution, and the Harvard Kennedy School's Project on the Workforce that seeks to investigate what works in workforce development—has identified sector-based training programs as an important worker-centered approach to skills training and employment advancement with demonstrated results in increasing work and income (Hendra et al. 2023). The training and services that sector-based programs provide to students and workers, while robust and generous, ultimately depend on workers' commitment to their own success. The habits of learning and action developed through such training programs may strengthen the double helix that undergirds self-development.

Emphasize Flexibility in Retraining. Previous experience teaches that when AI-driven automation displaces workers, policymakers should increase the range and flexibility of transition supports for the workers. One way of achieving this objective could be modeled on the Trade Adjustment Assistance (TAA) program.[2] TAA, first established in the early 1960s to aid workers who lost their jobs due to foreign competition, provided benefits such as job counseling and training, financial support during retraining, and job-search and relocation allowances. (The program lapsed in 2022.) One comprehensive study found that TAA participants reaped significant rewards from the program, earning on average about $50,000 more over their working lives than did similar workers who did not participate (Hyman 2018). As AI rapidly advances, an "automation adjustment assistance" program could be a safety net for AI-affected workers.

Congress might also consider creating worker-owned personal employment training accounts (PETAs), similar to existing individual training accounts, for financing displaced workers' education and retraining. PETAs would allow workers to accumulate pretax savings for ongoing education and training, with contributions from themselves, their employers, and the government. PETAs could finance needed retraining and would avoid the challenge of beggar-thy-neighbor policies, employer-financed retraining wherein employers invest in training only to see competitors hire away their workers. At retirement, unused balances could be moved to individual retirement accounts or be designated for educating and training family members.

Improve Training Guidance. A third intervention would be to increase public investment in career guidance and counseling in high schools, community colleges, and four-year colleges. These services have proved effective at helping students make informed decisions about their careers and lives (Sanders, Welfare, and Culver 2017). Yet they are often underfunded, especially in regions with a high concentration of low-income and first-generation students (Murphy 2016). Given the plethora of education and training options available to students and workers, increased investment in education and career guidance can help compensate for noncognitive weaknesses in areas such as executive function[3] and would help maximize the effectiveness of public spending on education, training, and retraining programs.

Empower Workers. These interventions, while substantial, share a common goal: to give individual workers greater control over their careers while buffering them against macroeconomic changes over which they have little, if any, control. Far from a one-size-fits-all solution, these interventions are flexible and can be tailored to the needs of individual workers, who may benefit from temporary financial assistance, relevant and up-to-date labor market information, career advice and counseling, reskilling opportunities, and other transitional support.

2 In 2018, Sens. Gary Peters (D-MI), Joe Donnelly (D-IN), and Kirsten Gillibrand (D-NY) introduced legislation to extend the Trade Adjustment Assistance program to workers who lose their jobs due to automation—particularly robotics and AI.

3 "Executive function" refers to skills such as memory, cognitive flexibility, and organization that help people solve daily problems.

Conclusion

Since the early 2010s, a rich debate has unfolded regarding how AI will transform the labor market, skill demands, and the nature of work. Over time, the discourse has shifted notably. Early on, predictions of mass technological unemployment vied with more sanguine visions of AI that emphasized its potential to boost productivity and complement human skills. The emergence in the past few years of generative AI, with its ability to produce novel content, has spurred reassessments of AI's potential to automate a wide array of jobs and tasks.

Uncertainty is our only certainty when it comes to AI and the future of work. This does not mean workers, businesses, and the government have no options to prepare for that future. The most important step they can take is to promote and strengthen workers' noncognitive skills to enhance their ability to adapt and persevere amid rapid change. While we cannot predict all the ways AI will alter the landscape of work in the coming years, we can cultivate and support the capacities that improve the likelihood of successful work transitions.

About the Authors

Brent Orrell is a senior fellow at the American Enterprise Institute, where he works on job training, workforce development, and criminal justice reform. His research focuses on expanding opportunity for all Americans through improved work readiness and job training and improving the performance of the criminal justice system through rehabilitation and prisoner reentry programs.

David Veldran is a research assistant at the American Enterprise Institute.

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Robert Doar, president; Scott Winship, director of the AEI Center on Opportunity and Social Mobility; Kevin Corinth, editor, Perspectives on Opportunity

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