Building an Inclusive AI Economy

A Worker-Centered Blueprint for Policy and Practice

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Executive Summary

Artificial intelligence (AI) holds the potential to reshape the economy in fundamental ways. Some of the most significant economic advances and disruptions from AI are expected to be those that affect labor markets. Public debate is already charged with both optimism and anxiety: some envision a world of abundance, while others warn of widespread job displacement and disempowerment of workers.

Despite vast uncertainty about the impacts of AI on work and the economy, action and evidence are needed now to help ensure that the economic gains it creates translate into inclusive growth for workers, businesses, and communities across the country. The decisions being made, or deferred, now—about the development of the technology, its adoption and use, and the policy context into which it is being deployed—will be critical. This paper provides a blueprint for building the inclusive AI economy that workers deserve, and for building the evidence needed to make it a reality.

The Vision for an Inclusive AI Economy

Our vision for an inclusive AI economy is one where all workers, including those sometimes left behind by past economic transitions, can access meaningful, well-compensated work and navigate change with real support, while businesses thrive and the economy grows. Success means a world where:

1. workers have the skills they need to thrive as AI changes jobs;
2. workers have high-quality jobs in an AI-powered workplace;
3. workers are economically secure during the AI transition and beyond; and
4. innovation in AI empowers workers and drives inclusive economic growth.

The Early and Potential Effects of AI on the Economy

To build the AI economy we want, we first need to understand the one that is currently taking shape. Evidence on the apparent and potential impacts of AI for work and workers, labor markets, and the broader economy is evolving rapidly, but some preliminary themes are emerging:

- **Both workers and firms are rapidly adopting AI and related technologies**, and while early uses of AI at work have been concentrated among specific occupations, workers, and industries—such as tech and finance—available evidence suggests that **many jobs appear to be exposed to AI**: that is, they involve tasks that AI could potentially support or even perform.
- For workers, some evidence finds that **using AI helps workers be more productive, often helping initially less productive workers the most**. For firms, there is some reason to believe that **the benefits for firm performance may emerge more slowly**. In the aggregate, there is some early evidence that **AI may be beginning to contribute to overall productivity growth**.
- Any **broader impacts of AI on employment levels and earnings trends are still too early to fully assess empirically**. There are some indications that AI may be contributing to weaker employment among early career, college-educated workers. Open questions remain as to the path and distribution of these effects, but economic theory suggests likely scenarios.

The Need to Act Now, Even Under Uncertainty

In almost any likely scenario of AI's effects, there will be an affirmative case for intervention—not just as a response to its impacts, but to shape the technological transition toward ends that are broadly beneficial. This is in part because markets on their own can fail to lead to economically efficient outcomes. And in part because the distributional impacts of AI could be economically and socially undesirable. Research and evidence highlight four areas of concern:

- Innovation in AI might be biased toward automation, which might not serve broader economic and societal objectives.
- Labor market transitions due to AI are likely to impose significant costs on workers.
- Longstanding market failures in the labor market might compound with AI adoption and new market failures might emerge.
- The benefits of AI might be unequally shared—across groups of workers, or between workers and owners of capital—in such a way or to such a degree as to have negative social, political, or economic consequences.

What It Will Take to Build an Inclusive AI Economy

Based on this evidence and motivation, we identify and describe the four critical issue areas identified above, where the need for new research, policy innovation, and practice development is most urgent. For each of these issues we highlight key insights from available evidence, sketch the most pressing open questions, and identify promising directions for policy reforms and practice innovation. The four components of this framework are:

1. Workers Have the Skills They Need to Thrive as AI Changes Jobs

The changing demand for skills is one of the most consequential—and least understood—dimensions of AI's impact on workers. Issues include both the near-term challenge of preparing workers for jobs that are changing now and the longer-term question of what education and training systems need to look like going forward.

1a. Identify and Build the Skills Workers Will Need

Workers who cannot access the skills that AI-era jobs demand are at risk of being left behind—not necessarily because the jobs aren't there, but because the pathways to building needed skills can be unclear or unaffordable. At the same time, education and training systems are being asked to prepare workers for a future that is still taking shape. To identify and build the skills workers will need to succeed in an AI-powered economy, education and training institutions, workforce development systems, employers, and other stakeholders will need to develop answers to critical questions, such as: What skills will confer advantage or resilience for workers across different occupations and education levels? And how should K–12, postsecondary, and workforce training systems adapt?

1b. Help Workers Match Their Skills to Goods Jobs and Employers Find their Best-Fit Workers

AI is transforming how workers search for jobs and how employers screen and hire, with the potential to support workers' upward economic mobility and ease transitions between jobs but also the risk it could entrench existing barriers and disparities. To help workers match to good jobs, and firms find their best-fit workers in the age of AI, employers and industry, workforce development practitioners, and technologists and researchers and other stakeholders will need to be engaged to develop answers to critical questions, such as: How effective are AI-enabled tools at matching workers with higher quality jobs? Do these tools have effects for labor markets more widely?

2. Workers Have High Quality Jobs in an AI-Powered Workplace

The quality of work—not just its availability—is at stake in the AI transition and will play a central role in ensuring worker dignity, autonomy, and voice, in addition to economic security. Outcomes will be determined by how employers choose to implement AI, how workers and entities representing workers shape those choices, and how governments set the boundaries within which both can act.

2a. Encourage Employer AI Practices that Serve both Workers and Firms

When employers introduce AI into the workplace, they face a genuine choice—whether to use it to make workers more capable and to improve the work experience, or primarily to reduce headcount, cut labor costs, and automate work already being done. To inform employer practices related to AI adoption that best serve both workers and firms, employers, industry associations, and workers' representatives will need to address questions such as: What AI-related employer practices are associated with positive worker outcomes? Where do worker and employer interests align when it comes to the adoption of AI tools, and where are they in tension?

2b. Incorporate Worker Voice in the AI Transition

Workers are not and cannot be passive recipients of AI-driven change—they have unique knowledge about their day-to-day tasks that should inform how AI tools are used in their workplace. Including workers' voices in decisions about how firms adopt AI tools is critical for a smooth technological transition that maximizes productivity and minimizes workforce disruptions. To realize worker voice in the AI transition, advocates, employers, and policymakers will need to develop answers to questions such as: Which forms of representation are most effective at shaping AI adoption in ways that support both productivity and job quality? What is the role of worker organization, collective bargaining, and voice in seeing that the productivity benefits of AI are shared with workers?

2c. Update Labor Market Policies for the AI Era

Many aspects of the impacts of AI on work will be governed by labor market institutions—workplace and labor market regulations and standards, worker rights and protections—that establish the basic rules for how labor markets operate and what work is like on the job. To update labor market policies for the AI era, policymakers, technology companies, labor law scholars, and researchers will need to tackle matters such as: Where are there gaps in existing labor market institutions that AI might expand, such as wage and hour protections or nondiscrimination protections? What is the appropriate framework for addressing questions related to ownership of data collected on or from workers, including for the purposes of training AI models?

3. Workers Are Economically Secure in the AI Transition and Beyond

Supporting workers dislocated by AI is a social and economic imperative, but current policy is inadequate, as demonstrated by the consequences of past trade- and technology-driven shocks. This will require new approaches not only to meeting the challenges posed by the AI transition, but also to addressing the longer-term distributional question of whether AI's gains are broadly shared.

3a. Support Workers Who Are Displaced

Job loss due to technological advances such as AI—in the absence of adequate worker supports—can leave workers with significant losses in income, both in the near and longer term. If AI-driven job displacement proves larger or more permanent than past disruptions, the scale and duration may surpass what existing worker support systems were designed to provide—requiring policymakers to consider more fundamental reforms to how income and economic security are structured. To do this, policymakers and researchers will need to be engaged to develop answers to questions such as: How similar will AI-driven displacement be to past technological disruptions—and where will it differ? Where can current policy be effectively adapted, and where are new policies needed?

3b. Ensure Broad-Based Prosperity in the AI Economy

A growing economy is not the same as an equitable one. If AI delivers on its productivity promise—as early signs suggest it may—the central question becomes "Who benefits?" If AI drives substantial productivity gains but the benefits flow primarily to business owners and shareholders rather than including workers, without deliberate policy action to both reshape markets and redistribute benefits, the economy can grow while workers' fortunes slump. To ensure broad-based prosperity in the AI economy, policymakers and researchers will need to be engaged to develop answers to questions such as: Where are the gains from AI going, who is being left out, and what levers are available to ensure gains are shared before current patterns become locked in?

4. Innovation in AI Empowers Workers and Drives Inclusive Growth

AI's trajectory is not fixed; innovation responds to incentives that can be structured by policy choices and the priorities set by key actors in the field. Whether AI is designed and deployed primarily to automate and replace workers, or to augment and empower them, depends in part on decisions made by policymakers, funders, and technologists today.

4a. Use Innovation Policy to Incentivize AI that Empowers Workers

The direction of AI innovation will shape its impact on workers, labor markets, and the economy—and right now, most of these decisions are being made by a relatively small number of private actors, optimizing for a relatively narrow set of goals. Private innovation is imperative, but the incentives for technology firms are shaped by innovation policy; sets of rules and institutional features that include research funding, government spending, data and intellectual property rights, and technology and consumer regulations. To shape innovation policy to incentivize development of AI technologies that benefit everyone, policymakers, technology firms, researchers, and funders will need to address critical questions such as: How can we systematically develop a new, integrated science and technology policy orientation toward funding and encouraging pro-worker forms of AI?

4b. Reinvigorate the Role of Universities in AI Development

Some of the most broadly shared economic advances in American history trace back to university labs and publicly-funded research—not because government is better at innovation than the private sector, but because public investment pursues broad social goals that markets won't prioritize on their own. As AI development has shifted toward large private firms with proprietary models, that public engine has weakened at precisely the moment it is most needed. To reinvigorate this model, researchers, funders, and policymakers will need to address critical questions such as: How are US institutions of higher learning utilizing and developing AI? How can universities be better positioned to develop AI tools and train students in ways that translate into broadly beneficial economic outcomes?

A Call for Collaborative Action

The prospect of technology that could either make work vastly more productive, or even do much of the work necessary to meet society's needs while reducing the need for labor, sparks tremendous anxiety. While it could be used to generate widely shared economic prosperity, there are no guarantees that everyone will share in the benefits, and many reasons—including the economic experience of past technological revolutions—to expect that many workers will be left behind.

This time can be different; the harms of the past are also lessons, for policymakers, employers, workers, and other actors. Shared prosperity in the age of AI is genuinely possible, but it will require deliberate action, and soon. The economic transformation expected from AI remains in its early days, and the choices made now by policymakers, researchers, employers, training providers, and workers themselves will shape its trajectory.

Building an Inclusive AI Economy

Artificial intelligence (AI) and related technologies hold the potential to reshape the economy in fundamental ways. Some of the most significant economic advances and disruptions from AI are expected to be those that will affect labor markets.[1] The potential effects of AI include impacts for workers directly, as AI changes how jobs are performed and shifts patterns of employment, as well as through broader economic channels, as AI impacts trends such as productivity growth. High profile claims and anxieties abound about the possibility of a world of abundance on the one hand, but also the potential for widespread dislocation and disempowerment on the other.

Despite vast uncertainty about the eventual impacts of AI on work and the economy, action and evidence are needed now to help ensure the economic gains it might create will translate into inclusive growth for workers, businesses, and communities across the country. This is a pivotal moment, with the nascent technology still rapidly advancing. The decisions being made now, or deferred—about the development of the technology, its adoption and use, and the policy context into which it is being deployed—will be critical. These decisions made by policymakers, employers, technologists, and practitioners will shape whether AI-driven change expands or narrows economic opportunity for all American workers. This paper provides a blueprint for building the inclusive AI economy that workers want and deserve, and for building the evidence decisionmakers need to make it a reality.

Placing the Focus on Workers

AI is changing the economy at a pace that outstrips existing evidence, policymaking, and institutional capacity, creating both risks and unprecedented opportunities to build a more inclusive economy (for example, Sajadieh et al. 2026). Early evidence on AI's impact on economic outcomes for firms and workers is mixed and quickly evolving. But adoption of the technology has been rapid, as have advances in the capabilities of the technology itself. And while the empirical reality is cloudy, economic theory suggests the possibility that AI might evolve to meaningfully impact economic fundamentals, such as the rate of economic growth, or the distribution of income. Taken together, both the known and potential economic effects of AI make it essential to build a rigorous, adaptive evidence base now, and to set policy and practice on the right course, before outcomes are locked in.

Building an inclusive AI economy will require a focus on work and the labor market (NAS 2025; Autor, Acemoglu, and Johnson 2026). Outcomes of past technological transitions, economic theory, and the available evidence on AI's impacts so far all suggest that many of its most consequential effects will reshape work and, potentially, the role of workers in the economy. Many jobs will change as firms and workers adopt AI tools into workstreams and production processes. Some changes may lead to entirely new roles and forms of work. Other changes are expected to lead to job loss and worker displacement. Moreover, beyond AI's impacts on specific jobs and workers, any effects on economy-wide outcomes, such as productivity growth, will shape the earnings and employment prospects of all workers in less direct but powerful ways.

Available evidence also shows that the potential benefits, and risks, of AI are likely to be unevenly distributed. The impacts of AI are expected to vary not only across groups of workers—by occupations and levels of education, as well as by geography, race, gender, and age—but also between workers and owners of capital (Eloundou et al. 2024; Restrepo 2025). Building an inclusive AI economy will also require attention to which groups gain and lose from the adoption of AI, in both relative and absolute terms. For this reason, in part, it will be essential that those who will be most impacted by the transformative power of AI are part of building the future.

The Vision for an Inclusive AI Economy

Following from this focus on the labor market impacts of AI, and grounded in the research, our vision for an inclusive AI economy is one in which all workers, including those sometimes left behind by past economic transitions, can access meaningful, well-compensated work and navigate change with real support—while businesses thrive, and the economy grows.

Success means a world where:

1. workers have the skills they need to thrive as AI changes jobs;
2. workers have high-quality jobs in an AI-powered workplace;
3. workers are economically secure during the AI transition and beyond; and
4. innovation in AI empowers workers and drives inclusive growth.

These four goals guide the action agenda in the blueprint that follows. Fundamental to achieving each of these goals is high-quality economic data that allows policymakers, businesses, practitioners, and workers to make informed decisions. This report lays out a blueprint for working toward this vision. Throughout, we identify what and who it will take to build an inclusive economy, mapping the decisions, investments, partnerships and necessary evidence for turning these goals into a reality for workers, employers, and communities across the US.

The Evidence and Action Needed to Build an Inclusive AI Economy

In this report, we develop a blueprint for a strategic approach to building the knowledge on AI, work, and the economy that policymakers and practitioners need, and for identifying and defining priority policies and practices to achieve an inclusive AI economy. The remainder of this blueprint report offers the following:

What We Know About the Effects of AI on Work and the Economy

To ground our framework for action and evidence building in the current state of knowledge on AI and its effects on work and the economy, we begin with a brief synthesis of recent empirical and theoretical research into how AI is currently affecting—or might eventually affect—work, labor markets, and the economy. This brief synthesis is not a comprehensive literature review, but describes key evidence and themes organized around questions decisionmakers need answered.

Why We Need to Act, Even with the Effects of AI Being Uncertain

To motivate the need for action even in the face of the current degree of uncertainty about the likely effects of AI for workers and the economy, we provide a brief discussion of ways in which these effects might be expected, in the absence of corresponding policy reforms or practice innovations, to be socially and economically disadvantageous, and so require policy and practice responses.

What, and Who, It Will Take to Build an Inclusive AI Economy

Based on this evidence and motivation, we identify and describe the four critical issue areas identified above, where the need for new research, policy innovation, and practice development is most urgent.

For each of these issues we briefly discuss why the issue is a priority for action, highlight key insights from available evidence, sketch the most pressing evidence gaps and open questions, and identify promising directions for policy reforms and practice innovation. In proposing an action agenda, we note where the field has answers ready to scale, where there is a need for experimentation, and which questions require fresh thinking. Throughout, we also identify what data on AI is needed to inform decisionmaking. Finally, for each issue area, we identify the key actors and institutions that will need to come together to make progress, from among the relevant research, technology, advocacy, employer, practitioner, and policymaking communities.

How AI Is Reshaping Work and the Economy

To build the AI economy we want, we first need to understand the one that is currently taking shape. Evidence on the apparent and potential impacts of AI for work and workers, labor markets, and the broader economy is evolving rapidly, but some preliminary themes are emerging:

- **Both workers and firms are rapidly adopting AI and related technologies**, and while early uses of AI at work have been concentrated among specific occupations, workers, and industries—such as tech and finance—available evidence suggests that **many jobs appear to be exposed to AI**: that is, they involve tasks that AI could potentially support or even perform.
- For workers, there is some evidence that **the use of AI helps workers, often initially less productive workers, to be more productive**. For firms, there is some reason to believe that **the benefits for firm performance may emerge more slowly**. In the aggregate, there is some early evidence that **AI may be beginning to contribute to overall productivity growth**.
- Any **broader impacts of AI on employment levels and earnings trends are still too early to fully assess empirically**. There are some indications that AI may be contributing to weaker employment among early career, college-educated workers. Key open questions remain as to the path and distribution of these effects, but economic theory suggests likely scenarios.

Below, we briefly synthesize some of the recent research on the economic and labor market effects of AI. We organize this discussion around two levels of analysis: (i) direct effects of AI adoption on worker and firm outcomes, and (ii) broader, economy-wide effects for employment and earnings.

Direct Effects on Workers: How AI Is Changing Jobs and Work

Research on the effects of AI on workers and firms has examined: (i) how AI is being used on the job, and how it might be; and (ii) effects on worker and firm outcomes.

AI Adoption and Exposure

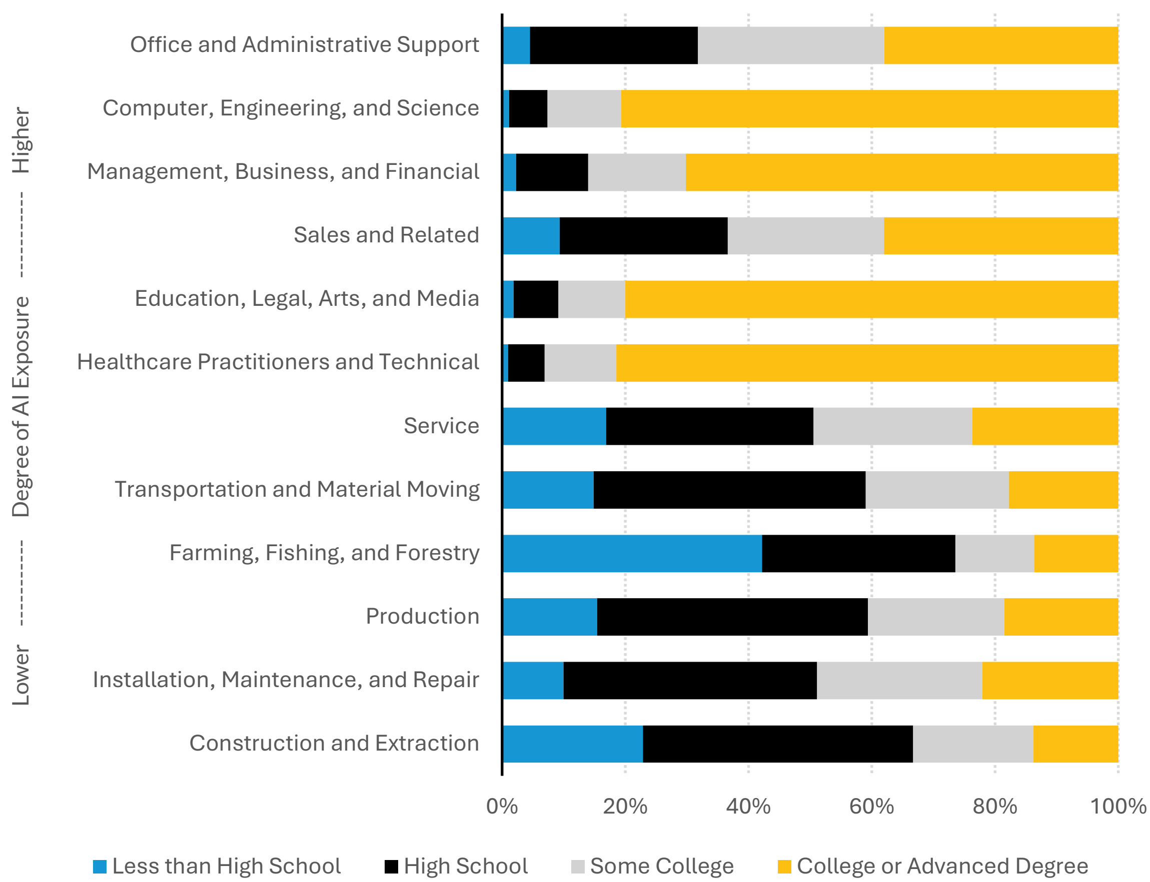
Available measures of AI adoption show a technology still in its early days, but growing rapidly in use, especially among workers in white-collar jobs and firms in the information sector. For workers, a recent survey asking individuals about their use of AI found that roughly one-quarter of all adults report using generative AI at work, comparable to the rate of adoption of personal computers in the 1980s (Bick, Blandin, and Deming 2026).[2, 3] Individuals with college degrees and higher wages are more likely to report using AI, and use is relatively high in computer and mathematical, management, and business and finance occupations, and in the information sector. Other research has investigated usage patterns of generative AI tools, such as interactions with chatbots, to infer how workers are using them, finding consistent evidence that these tools are used mainly for information gathering, computer-related activities, and writing tasks common in white-collar occupations (Handa et al. 2025; Tomlinson et al. 2025).[4] At the firm level, in data from a recent Census survey, 18 percent of all firms reported adopting AI—most often for tasks such as marketing and business development—with the highest rate of use in the information and professional services sectors (Bonney et al. 2026).[5] Adoption is highest among the largest firms, with adopting firms representing nearly one-third of total employment.

While AI adoption measures provide insight into its current use, both economists and technologists expect that AI will, over time, become even more widely integrated into work. To gauge how impacts for workers might unfold, research has also investigated AI exposure—the extent to which jobs involve tasks that AI might be capable of performing, alone or in part, now or in the near future. Examples of tasks found to be exposed to AI in this way include programming, writing, and information or data processing (Eloundou et al. 2024; Felten, Raj, and Seamans 2021; 2023; Webb 2020). Research on AI exposure typically uses standardized descriptions of occupations, and the tasks they comprise, to assess the degree of exposure among different jobs and workers. By one widely cited measure, 80 percent of all workers are in occupations that are to some degree exposed to AI, and roughly 20 percent are substantially exposed—working in jobs where half or more of the tasks are exposed (Eloundou et al. 2024). Notably, this line of research has tended to find a generally positive association between exposure and wages (Eloundou et al. 2024), partly reflecting how many exposed tasks are concentrated in occupations that typically require a college degree, such as analysts and professional service roles (Vasilauskas and Horrigan 2025). Figure 1 provides an illustration of the association between relative AI exposure and the educational composition of occupational categories.

FIGURE 1

Occupations Vary in Their Relative Exposure to AI

Occupational categories characterized by higher levels of formal education tend to be more exposed to AI



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Source: Author's calculations using 2024 American Community Survey (ACS) (five-year estimates) and data from Eloundou et al. (2024); ACS data are retrieved from IPUMS (Ruggles et al. IPUMS USA: Version 16.0 American Community Survey. Minneapolis, MN: IPUMS, 2025. https://doi.org/10.18128/D010.V16.0); Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock, 2024, "GPTs are GPTs: Labor Market Impact Potential of LLMs," *Science*, 2024, 384 (6702), 1306–8.
Notes: Figure shows the educational composition of occupational categories, ordered by degree of relative AI exposure. The AI exposure values used for ordering are the GPT-4 classified beta exposure measure from Eloundou et al. (2024).

The interpretation of AI exposure is complicated, however, by the question of whether AI is in practice used primarily to automate work in exposed roles—to substitute for workers—or to augment the human-performed work in those roles, complementing workers. Some research has attempted to distinguish between uses of AI that augment versus automate work in this way. By one estimate, the majority, roughly 60 percent, of recent AI use involves augmentation, with some trend toward increasing automation over time (Handa et al. 2025; Massenkoff and McCrory 2026). Which tasks AI is used to perform, and how those tasks complement or substitute for worker skills, will play a key role in determining the effects of AI (Acemoglu and Autor 2011). Some workers may benefit as AI augments tasks that require their specialized skills, potentially seeing their wages rise, while others may be harmed as it automates tasks that currently require their skills (Autor and Thompson 2025).

Evidence suggests that early-career roles and occupations that require less formal education may be more at risk of automation (Pizzinelli et al. 2023). But these effects can be difficult to predict. In one often-cited example, radiologists perform tasks, such as assessing medical imaging, that were predicted a decade ago might be automated entirely.[6] But while radiology has in fact seen widespread adoption of AI tools, in practice the technology has often been adopted in ways that complement worker skills. The challenge in forecasting impacts of AI on particular jobs is in part because the effects of AI adoption are not static: the task composition of occupations can evolve along with changing technology, and workers can adapt to new technology, such as by acquiring new skills, or changing jobs (Atalay et al. 2020; Manning and Aguirre 2026).

It is also important to note that exposure to AI and its consequences likely varies across both demographic groups and geography. This raises concerns of potentially disparate impacts of the technology that could echo past economic and technological disruptions, which left some groups of workers—such as workers with less education, Black workers, and rural workers—relatively disadvantaged. Some research has found, for example, that women may be relatively more exposed to AI (ILO 2026), and that Black workers might be at heightened risk of AI-driven displacement (Cook et al. 2019). Other work has emphasized the particular challenges workers at different ages might face from AI, including both older workers (Briggs et al. 2026) and younger workers (Brynjolfsson, Chandar, and Chen 2025, discussed at greater length below). Early evidence also shows uneven patterns of exposure across counties, with urban areas showing relatively higher degrees of exposure than rural areas (Felton et al. 2021).

Worker and Firm Outcomes

To understand how AI adoption at work is playing out in practice, research has investigated the effects of AI adoption on worker and firm outcomes, with some focus on productivity effects.[7] At the worker level, this research has generally found that generative AI tends to improve worker productivity, with the largest gains often observed among workers with less expertise or lower baseline performance (Cui et al. 2026; Dell'Acqua et al. 2023; Dillon et al. 2025; Noy and Zhang 2023). In one example, the deployment of a generative AI assistant for customer support agents increased issues resolved per hour by 14 percent and improved customer satisfaction, driven largely by productivity gains among newer and less skilled workers (Brynjolfsson, Li, and Raymond 2025).

Adopting AI has not been found to improve worker productivity in all cases. For roles demanding more experience and expertise, effects on productivity are typically smaller and sometimes negative (Becker et al. 2025). For example, in one study, an AI tool provided to radiologists did not improve outcomes, which findings suggest was due in part to difficulties—both among the workers and for the technology—in integrating AI predictions and human expertise (Agarwal et al. 2023). The effects of AI on worker productivity may also be dynamic, as workers adapt to new tools. Some research suggests the possibility that workers' expertise and skills might erode due to AI adoption (Heudel et al. 2026).

At the firm level, the relationship between AI adoption and performance has also been mixed (Babina 2026). While many companies have explored and deployed AI tools, research has not found consistent evidence that these investments have led to significant productivity gains (Babina et al. 2024; Yotzov et al. 2026). One possible explanation is that the benefits to firms from AI may require significant up-front investments, resulting in what has been labeled a "J-curve" relationship, with an initial slowdown and then later acceleration of productivity. Research suggests this phenomenon may occur because of the large, intangible investments and fundamental restructuring of the work needed to incorporate AI technologies, such as developing new business processes, training workers and managers, and implementing software (Brynjolfsson, Rock, and Syverson 2021; McElheran et al. 2025).

Early evidence on the direct effects of AI adoption on outcomes like hiring and employment at the firm level suggests that such impacts may still be modest. Some research finds that, while AI adoption has led firms to adjust both the skill mix of their workforce and the task composition of jobs to complement AI, the effects on their overall employment have been small (Babina et al. 2024; Hampole et al. 2025). This is complemented by evidence from the firm survey data, where most firms report that AI has had no effect on their employment levels (Tierno and Weinstock 2025). But there is also evidence of differences across firms, with research finding that firms with more exposure to AI appear to reduce hiring into and employment in roles where AI might substitute for core tasks (Eisfeldt et al. 2023). Here it is important to note, as well, that employment effects for workers might still emerge in the labor market in the aggregate, which we discuss below.

Consistent with findings that AI adoption and use can raise productivity, some empirical research has found early evidence associating AI exposure or adoption with positive effects on output and, where AI is labor augmenting, wages (Johnston and Makridis 2026). But the effects of AI on wages in particular is the subject of evolving empirical research, with some studies finding negative effects (Azar et al. 2025) and others little effect (Chandar 2025).[8]

AI's Economy-Wide Impacts on Productivity, Employment, and Income

Beyond the effects AI may have for individual workers and specific firms, research also suggests the technology's potential to have broader, economy-wide effects. And if AI alters the trajectory of overall economic growth, or how the benefits of growth are shared, even workers and firms not directly working with the technology could see their fortunes shift. Much of both the doomsaying and the hype around AI comes from research that suggests the possibility that AI might reshape the labor market and economy in such fundamental ways.[9] This more fundamental reshaping of the economy would operate primarily through three interconnected channels: (i) the potential of the technology to significantly raise productivity; (ii) the net effect of its impacts on labor demand and overall employment; and, (iii) the resulting effects on labor's share of national income.[10]

Labor Productivity

Perhaps the central question for understanding how AI might have broader economic effects is the issue of its likely impacts on labor productivity; the amount of output that can be produced per worker.[11] That is, not just whether AI makes specific workers or firms more productive, but if these effects are sufficiently large and diffuse to improve the efficiency of the entire national economy. Faster productivity growth is, fundamentally, desirable—being able to produce and consume more with less time and effort is the basis of rising living standards over time. And rising labor productivity is also beneficial for worker outcomes, specifically—serving as the underlying basis for real wage growth (Lazear et al. 2022; Stansbury and Summers 2017).[12] If AI were to meaningfully alter the trajectory of productivity growth, it could potentially lead to higher wages and rising standards of living.[13]

The likely impacts of AI on productivity are the subject of significant debate in current research. Because the central question is largely prospective—will AI alter the future trajectory of productivity—this research combines early evidence, lessons from past technological innovation, and economic theory, to study both the current and likely trajectory of the effects of AI. One line of reasoning considers AI as likely to evolve as a "normal technology" that, like, past technological innovations, will form the basis for continued productivity growth within historic ranges (Narayanan and Kapoor 2025). Another line of research considers the possibility that AI represents a "general-purpose technology" (GPT), a more foundational technological change, like electrification (Bresnahan and Trajtenberg 1995). Given the broad applicability of machine learning and AI across tasks and sectors, some work makes the case for AI as a GPT in this sense, with correspondingly broader implications for productivity (Brynjolfsson, Rock, and Syverson 2021). Another line of work considers that AI might also represent an "innovation in the method of invention" (IMI) (Griliches 1957), a technology that might itself be used to discover other new technologies, with potential to accelerate productivity growth (Baily et al. 2025; Cockburn et al. 2019). In the case where AI does function as a GPT, or IMI, or both, the potential impacts for productivity—and for workers, who might see both gains but also disruption from these effects—are likely even larger.

The current and likely effects of AI on productivity at this broad economic level, given the nascent state of not just the technology itself but also its adoption and diffusion, remains uncertain. Some researchers interpret the recent, relative rise in productivity growth, corresponding with recent advances in AI, as broadly consistent with evidence of productivity effects.[14, 15] One line of recent research models AI as both a GPT and IMI to estimate that a substantial portion of recent productivity growth in the United States—and a significant factor in its recent acceleration—is attributable to AI and related technologies (Bontadini et al. 2026). But substantial uncertainty remains about the likely impacts of AI on productivity in the intermediate term, and some studies estimate that effects over the next decade may be modest (Acemoglu 2024). One projection drawing on available research estimates a range of potential impacts over the next ten years of between 0.4 and 0.9 percentage points on labor productivity (Filippucci et al. 2024). Effects of this magnitude would be substantial: given recent productivity growth of about 2 percent, this would represent productivity growth rates resembling those of the post-war or information technology-era boom periods.[16]

If productivity effects of AI are in fact more revolutionary than evolutionary, they will produce large economic gains. But whether and how workers—and which workers—will share in in these gains will depend on how these productivity effects translate into employment effects, and their impacts on overall earnings for workers.

Employment

For the impact that AI might have on the overall employment levels, here, too, recent research suggests at least three cases: In the "normal technology" scenario, AI might be expected to mirror the recent historical experience, where new technologies reduce the demand for some forms of work but create demand for others, leaving overall employment levels largely unchanged (Autor 2024; Autor and Thompson 2025).[17] Another scenario arises in the case where AI might produce what have been labeled "so-so technologies" that can be used to automate or replace labor, but which do not spur advances that lead to job creation (Acemoglu and Restrepo 2018, 2019). A third case, sometimes associated with the label “transformative AI,” is the opposite—one in which the productivity gains due to AI are so great that meeting society’s economic needs requires fewer workers, depressing employment overall (Trammell and Korinek 2023). While under any scenario there will be labor displacement in the transition to widespread use of AI, the latter two could lead to persistently lower overall employment levels.

As of mid-2026, overall employment levels show few signs of significant AI-related disruptions, but recent signals from some sectors and among some groups of workers merit close attention.[18] Recent research has found negative employment effects associated with AI for some groups of workers—in particular younger, early career workers (Brynjolfsson, Chandar, and Chen 2025; Hosseini and Lichtinger 2025).[19, 20] These employment effects are observed in exposed occupations such as computer and math jobs (data scientists, actuaries), customer service representatives, and finance (Brynjolfsson et al. 2025; Ozzkan and Sullivan 2025). These studies linking employment outcomes with AI exposure are also broadly consistent with recent economic indicators showing an unusually weak labor market for new labor market entrants, including recent college graduates.[21]

Still, it is unclear whether these employment effects might be early signals of shifts in overall labor demand, or simply reflect shifts in relative demand. That is, while AI may reduce the need for some early career roles, this effect could be offset by rising demand for workers in other roles. Research to date has found little evidence of effects of AI on employment and labor demand in the aggregate (Acemoglu et al. 2022; Chandar 2025; Hartley et al. 2024; Massenkoff and McCrory 2026).[22] Some evidence has found that negative effects of AI on labor demand due to automation may be offset by a rise in demand for roles where AI augments workers (Chen, Zakerinia, and Srinivasan 2024). And at least one recent study has found that AI exposure is associated with positive employment effects, which is consistent with uses of AI that primarily augment labor, which can raise both productivity and employment (Johnston and Makridis 2026).[23] Note that even in the case that overall labor demand is not substantially affected by AI, shifts in relative demand—across skills, occupations, and industries—could lead to significant impacts on employment among affected groups of workers, especially in the transition to more widespread AI adoption, a point discussed more below.

Income

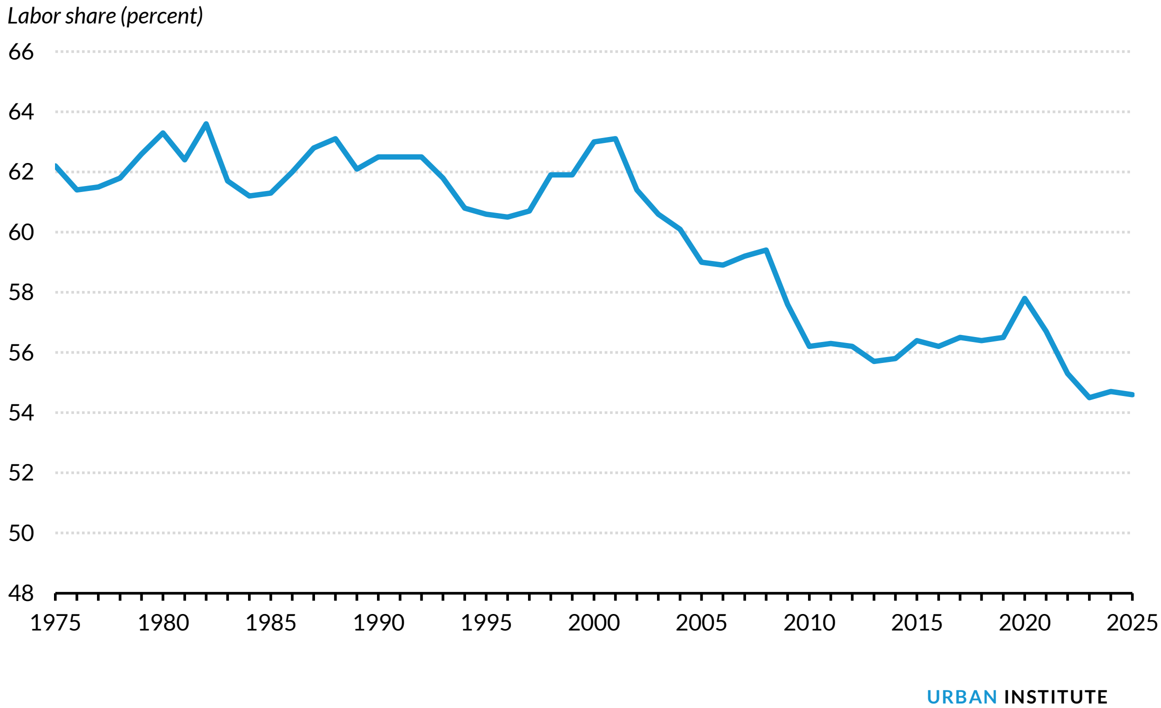
In a more productive economy, national income will be higher. But national income is divided, broadly, into two categories: returns to capital—income that comes from, for example, profits or dividends—and labor income—income in the form of wages and salaries. Changes in production technologies and relationships—changes like those AI could induce—can affect the distribution of income between labor and capital. Already in recent decades, the labor share of income has been falling (see Grossman and

Oberfield 2022): in 2025, it stood at approximately 55 percent, well down from its twentieth century average of about 63 percent.[24] Research has attributed this to a number of factors, including past patterns of technological change (Harrison 2024). The trend over recent decades is shown in figure 2.

FIGURE 2

The Labor Share of National Income Has Been Falling, and AI Could Drive it Lower

Economic theory and emerging evidence suggest AI could shift income from workers to owners of capital



Source: Bureau of Labor Statistics, "Labor Productivity by Major Sectors: Nonfarm Business, Business, Nonfinancial Corporate, and Manufacturing (XLSX)." Data series accessed from: https://www.bls.gov/productivity/tables/home.htm, June 7, 2026.
Notes: Figure shows the labor share of total value-added output in the nonfarm business sector, annually, from 1975 to 2025.

The potential for AI to further reduce the labor share is of particular concern, given the nature of AI as a technology that gives capital (in the form of, e.g., computing power) a larger and more critical role in the production process, and especially where forms of the technology are capable of fully or substantially automating work. In an economy where a significantly larger share of overall production can be accomplished with machines, a larger share of overall income will potentially flow to the owners of the machines—in the form of capital income—and a correspondingly smaller share to labor (Trammell and Korinek 2023). To the extent that aspects of AI reflect a form of capital that incorporates what were previously knowledge or skills possessed by labor, this can be conceptualized as a transfer from labor to capital (Cullen, Li, and Li 2026; Li 2026). At the extreme, in the case of fully transformative AI, the result could be a labor share that tends to zero—the result would be an economy where the role of work and its relationship to economic activity and income would be fundamentally reshaped, and where going to work and getting a paycheck may no longer be a way of earning income for many workers (Korinek and Suh 2024; Restrepo 2025).

Like effects for overall employment, any impacts of AI on a measure as aggregate as the labor share will evolve slowly but will be important for policymakers and researchers to monitor closely. Early empirical research on wage and productivity effects does find some evidence that gains from AI accrue primarily to capital rather than labor, which would tend to further depress the labor share over time (Johnston and Makridis 2026). Even if the most extreme cases are unlikely, intermediate cases—even small impacts on the labor share—merit attention in policy and research, given the magnitudes involved: each 1 percentage point fall in the labor share represents a shift of more than $200 billion in collective earnings from labor to capital.[25] In an economy where, for most individuals, most income comes from work, and where capital ownership is both less common and highly unequal, a fall in the labor share will mean fewer of the benefits of economic growth will reach the typical household.

Uncertainty as a Call to Action

While both the technology and research are evolving rapidly, a consistent theme at both the micro and the macro level is the degree of uncertainty around the likely—even the current—economic and labor market effects of AI. Current AI exposure measures, for example, form the basis for much of the empirical research but have clear limitations (Yin, Vu, and Persico 2026).[26] With AI use across tasks, workers, and firms still in the early stages of adoption, and with only imperfect and lagged data and measures, we simply do not yet know which skills AI will augment versus automate, which jobs will change, and which will be lost.[27] Nor do know whether or how the impacts of AI's transformation of work might have disparate impacts across people or places. And the uncertainty around AI's economy-wide effects on trends like productivity growth and labor share is greater still; discernible impacts on economic aggregates will emerge clearly only over time. But this uncertainty is not a reason for inaction—it is a reason to have a clear vision of the inclusive economy we want to drive towards, test new approaches, build better evidence, and scale what works.

Good Outcomes for Workers Require Action Now

Under almost any likely AI scenario, policymakers will need to intervene—not only to respond to its impacts, but also to steer the technological transition toward broadly beneficial ends. While employers, technology developers, and market forces play important roles, policy and institutional innovation are also necessary for building a future of work that creates equitable, inclusive, and durable opportunity for workers. This is in part because markets on their own can fail to generate economically efficient outcomes. And in part because the distributional impacts of AI—both in the transition and in equilibrium—might be economically or socially undesirable.

There are at least four interconnected reasons why deliberate action will be needed even as the specific effects of the technology continue to evolve: (i) innovation in AI might be biased toward automation, which might not serve broader economic and societal objectives; (ii) labor market transitions due to AI will impose significant costs on workers; (iii) longstanding labor market failures may compound with AI adoption and new market failures may emerge; and (iv) the benefits of AI are likely to be unequally shared—across groups of workers, or between workers and owners of capital—in such a way or to such a degree as to have negative social, political, or economic consequences.

Incentives for AI Innovation Might Favor Automation at the Expense of Workers

From the perspective of society at large, there are potentially better and worse directions that technological innovation might take, and market forces by themselves might not always provide incentives for innovation that are aligned with objectives like broad-based or sustainable economic growth (Acemoglu 2023). In the case of AI, the most commonly cited concern is that current market incentives tend to direct technological innovation toward automation (Brynjolfsson 2022). This is due in part to the use of benchmarks in technology development that incentivize advancement toward automation,[28] and in part to the negative economic effects automation may impose on workers (Acemoglu, Autor, and Johnson 2026), or which may emerge only in the longer term (Acemoglu, Kong, and Ozdaglar 2026). A mix of innovation policy, fiscal and tax policy, and regulatory policies will be needed to shape AI innovation in ways that benefit workers, the economy, and society more widely.

Labor Market Transitions Due to AI Will Have Concentrated Costs for Workers

Even if AI takes its most socially valuable form, and in the long run workers are better off on average, during the transition there are likely to be large social and economic costs that workers will bear. As AI is adopted more widely, many workers will need to develop new skills, others may need to switch jobs, and some will lose work entirely. For the latter group, especially, the costs can be significant: through no fault of their own, many workers who are displaced tend to experience declines in earnings that are large and effectively permanent (Davis and Von Wachter 2011; Fallick et al. 2025). These costs to workers show up in not just earnings impacts but on broader measures of their health and well-being

(Case and Deaton 2022), have spillover effects into the next generation of workers (Ananat et al. 2011), have enduring effects on local economies (Acemoglu and Restrepo 2020), potentially put a drag on overall economic growth, and can contribute to deterioration in democratic resilience (Rau and Stokes 2024). Policies and programs such as unemployment insurance (UI), job search assistance, and job training programs could support workers through such transitions, but are currently inadequate and ill-prepared for the scale and speed of AI-driven change (Dube 2021; Wandner 2023).

Current Labor Market Rules and Regulations Were Not Built for the AI Economy

Ensuring labor markets operate in ways that benefit workers and the wider economy requires a suite of economic and labor market policies and regulations that guarantee and enforce worker rights and protections, promote labor market competition, support workers' power to shape their wages and working conditions, and set workplace and labor market standards to promote job quality (see Congdon (2025) for a general discussion). Research establishes, for example, that employers have relatively more power to set wages, leaving workers at a disadvantage and depressing wages (Manning 2003; Marinescu and Rosenfeld 2022). In response, policies set wage and hour standards, such as minimum wages (Dube and Lindner 2024), seek to promote competition in labor markets (Block and Harris 2021), and establish rights and legal frameworks for collective bargaining (Fortin, Lemieux, and Lloyd 2021). Such labor market regulations and institutions will not only remain necessary as AI is adopted, they are also likely to require modernization as AI impacts the structure and functioning of the labor market and the nature of the employment relationships they are intended to govern.

Economic Benefits from AI Will Not Automatically Be Broadly Shared

AI may increase overall economic output while concentrating gains—potentially dramatically—among capital owners, high-income workers, and those in certain industries, occupations, and regions, leaving others behind. Ensuring productivity gains from AI are shared will require deliberate policy choices (Acemoglu and Johnson 2024). The benefits of the technological advances over the past century, for instance, have accrued substantially to workers with higher levels of formal education (Autor, Katz, and Kearney 2006). A wide array of policy responses are designed, at least in part, to ensure the gains from economic dynamism are more broadly shared. The specific effects of AI, however, are likely to create new challenges. One stems from the fact that the distributional effects of AI across workers might differ from those of past technologies, with some evidence suggesting that many more workers with higher levels of education are potentially at risk of exposure to AI (Eloundou et al. 2024). Potentially most challenging is the possibility that the gains from AI might accrue not to any group of workers, but rather to owners of capital, as in the case where AI leads to a fall in the labor share. Supporting workers in this case may require a largely new set of policy tools, ranging from changes to tax policy (Acemoglu, Manera, and Restrepo 2020), to the introduction of new forms of redistribution such as universal basic income, to approaches to more widely shared ownership of capital.

A Framework for Action: Four Goals for an Inclusive AI Economy

Based on early evidence of the role AI is playing, and is likely to play, in the lives of workers, the dynamics of the labor market, and the performance of the economy, we identify four critical outcomes for workers where the need for new research, policy innovation, and practice development is most urgent—and where action is achievable:

1. workers have the skills they need to thrive as AI changes jobs;
2. workers have high-quality jobs in an AI-powered workplace;
3. workers are economically secure in the AI transition and beyond; and
4. innovation in AI empowers workers and drives inclusive growth.

For each focal area, below, we address why the issue matters, highlight key aspects of what current evidence already tells us, sketch the most pressing evidence gaps and open questions, and identify the actors and institutions that need to come together to make progress. Throughout we note where we have answers ready to scale, which need experimentation, and which require fresh thinking, helping to identify where we can act now, and where new evidence is the necessary first step.

1. Workers Have the Skills They Need to Thrive as AI Changes Jobs

The changing demand for skills is one of the most consequential—and least well-understood—dimensions of AI's impact on workers. Issues include both the near-term challenge of preparing workers for jobs that are changing now and the longer-term question of what education and training systems need to look like going forward. This is also related to the question of how the use of AI as a search and matching technology and in the hiring process might be part of the solution to helping workers find jobs that fit their skills sets and help employers identify talent.

1a. Identify and Build the Skills Workers Will Need

Why it matters: Workers who cannot access the skills that AI-era jobs demand are at risk of being left behind—not necessarily because the jobs aren't there, but because the pathways to building needed skills can be unclear or unaffordable. At the same time, education and training systems are being asked to prepare workers for a future that is still taking shape. Getting this right requires near-term responsiveness from education and training systems and collaboration with businesses and employers to help workers adapt to jobs that are changing now. It also requires longer-term systems change in how we define, teach, and credential the skills that will matter most. And in both cases, it requires incorporating the perspectives and expertise of teachers and learners, not only as participants, but as collaborators in innovation.

What we know: Early evidence suggests the tasks and occupations with high exposure and adoption of AI commonly involve processing of information and require a college degree (Bick, Blandin, and Deming 2025; Eloundou et al. 2024). Occupations with greater exposure include those such as analysts, professional service roles, and technical occupations, as illustrated in figure 1, above (Felten, Raj, and Seamans 2023; Vasilauskas and Horrigan 2025). For more highly educated workers in exposed occupations, AI may be more likely to augment tasks rather than automate tasks. Workers in exposed occupations that require less formal education may face a larger share of their tasks being automated and potentially eliminated (Pizzinelli et al. 2023). To the extent that automation reduces entry-level roles, it may also reduce on-the-job training that prepares people for higher-level roles (Heck et al. 2026).

Several skills frameworks have been developed to understand the skills workers need to navigate the use of AI in the workplace. For example, the AI Institute for Europe focuses on the different ways professionals interact with AI, including applying AI in their daily work, integrating AI into systems and processes, building AI, and developing the policies and guardrails related to AI.[29] The authors connect these activities to different kinds of skill development related to AI in the workplace. Dakan and Feller (2025) connect automation, augmentation, and a third category of agency, to the skills and competencies workers need to thrive in an AI-enhanced workplace, including delegation (determining when to use AI), description (effectively communicate with AI systems), assessment of the quality of AI outputs and behaviors, and ethical practice and accountability.[30] These skills apply across occupations and sectors. Thus, using AI effectively may require some of the more general skills developed through formal education—communication, critical thinking, and ethical decisionmaking, among many others.

What we need to know: Key open questions related to skills, training, and education include:

- What skills will confer advantage or resilience for workers across different occupations and education levels? How should K–12, postsecondary, and workforce training systems adapt?
- How does widespread AI adoption in the workplace and educational settings affect incentives for learning and knowledge-building, in the short- and longer-run?
- As systems have been shifting to a stronger focus on technical skills, how can we ensure that students and workers continue to build durable skills (e.g., critical thinking) needed to effectively use AI at work?
- In what ways does automation's impact on entry-level jobs alter traditional pathways for skill development and progression?
- How can education and training systems build and implement technology in ways that benefit learners and workers? What role can AI tools play in teaching and learning?
- How are employers providing opportunities for workers to train and adapt to technological change, in ways that benefit both businesses and workers? Where are the most effective feedback loops between employers and training providers?

Who it will take: Key actors in this space who will need to collaborate to address these issues include:

- *Education and training institutions,* from K–12 through community and technical colleges to workforce programs, who will be responsible for building AI skills as foundational elements of digital literacy, and who will need to integrate use of AI tools as one way of building skills.
- *Workforce development systems*, especially those that support workers with significant barriers to employment, provide incumbent worker training and upskilling, and who will need to communicate with education and training institutions and employers to help ensure that the new pipeline of workers is developing the skills needed for the modern workplace.
- *Instructors and students* are needed to design and guide approaches, and to co-invent how AI can impact learning and jobs through experimentation and reimagining classroom practices.
- *Employers and industry* who can develop skills on the job—including allowing workers to experiment with AI as an approach to skills acquisition, and who can collaborate with educators to identify what AI knowledge is needed for different jobs and pathways.

- *Policymakers* at the federal, state, and local levels, who will need to budget for the investments to provide necessary education and training at scale, and for needed reforms to systems.

The data we'll need: Key data and statistics needed to inform action on these issues include:

- Longitudinal, worker-level data with job-level details—including earnings, employment stability, job quality, hiring, promotion, and training histories, with enough granularity to observe career trajectory disruptions and their downstream effects on skill development;
- Direct skills assessments linked to labor market outcomes—measuring cognitive, technical, and social-emotional skills held by individuals as well as detailed information about credentials;
- Curriculum and instructional data documenting what is being taught in K–12, postsecondary, and workforce training programs, linked to both employer demand and worker outcomes;
- Firm-level training investment data that distinguishes retraining, upskilling, and initial training, and portable from firm-specific training, capturing employer–training provider partnership structures and how (or whether) demand signals translate into curriculum change;
- Representative surveys of workers and learners—with oversampling of low-wage, low-credential, and nontraditional workers—capturing perspectives on AI tools, learning experiences, and adoption, conducted on an ongoing basis rather than as one-off efforts.

1b. Help Workers Match Their Skills to Goods Jobs and Employers Find Their Best-Fit Workers

Why it matters: Finding a job has never been purely a matter of qualifications—it depends on networks, information, and access that are unevenly distributed across workers and employers. AI is transforming how workers search for jobs and how employers screen and hire, with the potential to support workers' upward economic mobility and ease transitions between jobs, but also with the risk of further entrenching existing barriers and disparities. How job search and matching tools are designed and implemented has implications for whether workers find good jobs, and employers find the best-possible workers—or whether it is harder for those already on the margins to get a fair shot.

What we know: For workers, movement between jobs is important for wage growth, especially for lower wage workers (Haltiwanger et al. 2018; Topel and Ward 1992). But structural, informational, and behavioral barriers can hinder workers in finding, pursuing, and taking better jobs (Bartik and Stuart 2022; Jäger et al. 2024); make it costly for firms to hire; and impair the dynamism and competitiveness of labor markets as a whole (Manning 2003). Moreover, much job finding is informal, relying on personal connections and social networks (Lester, Rivers, and Topa 2021). Research on the effects of interventions to improve search and matching outcomes tends to find that programs and policies like job search assistance and employment services improve employment and earnings outcomes for workers (Card, Kluve, and Weber 2018; Manoli and Patel 2019).

Emerging research has begun to study applications of technologies like AI for job search and hiring, However, rigorous evidence on the deployment and impacts of these tools remains thin. Recent experiments have sought to use these and related technologies in job search to improve outcomes, with some evidence of positive impacts on search and hiring outcomes (Horton 2017; Belot, Kircher, and Muller 2019; Wiles, Munyikwa, and Horton 2025). But there are important, outstanding questions about the adoption and effects of AI in these contexts, especially as they are now commonly used by firms in recruitment and hiring (Fuller et al. 2021). For example, the potential for algorithmic bias in recruiting and hiring applications potentially replicates and extends the already pronounced effects of discrimination in labor markets (Kleinberg et al. 2019; Kline, Rose, and Walters 2024; Raghavan et al. 2020).

What we need to know: Key open questions related to job search and matching tools include:

- How effective are AI-enabled search and matching tools at connecting workers with higher quality versus lower quality jobs? What are the impacts of tools firms use for hiring?
- Who benefits from the use of these technologies and which barriers or disparities, such as labor market discrimination, does AI improve or worsen? Can AI-enabled tools expand access to opportunity for workers who have historically faced barriers in job search and hiring?
- What are the effects of AI-enabled job search and matching tools on overall job market outcomes, if any? That is, do these tools impact outcomes only for their users, or do they have effects for labor markets more widely?
- How, if at all, does the use of AI for job search or hiring affect search frictions and their labor market consequences?
- How do job search and matching technologies reshape the role of social capital and social networks in hiring processes?
- What safeguards on job search and matching tools are needed? What does an equitable, AI-enhanced job search and matching system look like?

Who it will take: Key actors in this space who will need to collaborate to address these issues include:

- *employers and industry partners* who provide key information about industry demand and the required skills for success on the job;
- *workforce development agencies and practitioners* who serve job-seekers in the public workforce system to match jobseekers and talent with firm demand;
- *technologists and researchers* designing job search and recruiting platforms and surfacing evidence about labor market frictions and AI applications; and
- *policymakers* at the federal and state level, whose investments will be needed to improve search and matching outcomes, and who may need to regulate applications to mitigate risks.

The data we'll need: Key data and statistics needed to inform action on these issues include:

- firm-level data capturing which AI screening, matching, or assessment tools employers use, date of adoption, and for which roles—with enough variation in timing and tool type to support causal inference about effects of hiring outcomes and workforce composition;
- applicant-level hiring data tracking candidates through hiring funnels—application, screening, interview, offer acceptance—disaggregated by race, gender, education, geography, and other characteristics;
- social network and referral data linked to hiring outcomes—capturing how workers learn about and access jobs, and how AI-mediated matching interacts with or displaces informal networks, with particular attention to whether workers with weaker or less advantaged networks gain or lose relative to pre-AI job searches;
- worker-reported data on job-search experiences, oversampling low-wage, low-credential, and historically-marginalized workers—capturing tool use, perceived fairness, barriers, and job quality outcomes, to center worker perspectives alongside firm-side data; and
- regulatory and compliance data on existing safeguards, audit requirements, and enforcement actions related to AI hiring tools—paired with outcomes data to evaluate what government mechanisms actually reduce discriminatory impacts.

2. Workers Have High-Quality Jobs in an AI-Powered Workplace

The AI transition threatens not only the availability of work but its quality. Job quality is central to worker dignity, autonomy, voice, and economic security. How employers choose to implement AI, how workers and entities representing workers (e.g., unions) shape those choices, and how governments set the boundaries within which both can act, will determine whether AI enhances or erodes job quality along dimensions of pay, autonomy, and the nature of work itself.

2a. Encourage Employer AI Practices that Serve both Workers and Firms

Why it matters: When employers introduce AI into the workplace, they face a choice—whether to use it to make workers more capable and to improve the work experience, or to reduce headcount, cut labor costs, and automate work already being done. How employers make choices about workers' pay, benefits, working conditions, job design, and workplace culture plays a key role in determining overall job quality, which directly impacts workers' overall well-being and economic mobility and can also affect employer outcomes like worker retention and productivity (Congdon et al. 2020; Kelly et al. 2023). Employer adoption of AI has the capacity to improve productivity of workers, and along with it, reduce stressors and improve the quality of work, but certain uses of AI technology could also serve to harm or deteriorate the quality of a job.

What we know: Direct evidence is limited regarding how employer AI-use impacts job quality, the factors that drive better outcomes for employers and workers alike, and what would motivate employers to adopt specific practices. To some extent, the job quality impacts of AI adoption will depend on the crucial question of which work tasks the technology automates, and which tasks it augments. AI adoption in the workplace can augment workers' talents, but it can also be used to automate and reduce the value of expertise (Acemoglu, Autor, and Johnson 2026). Additionally, not only does AI exposure impact some groups more than others in terms of displacement, but it may also impact entry and retention as employers adopt AI tools. AI exposure could improve the skills for some less-skilled workers (Brynjolfsson, Li, and Raymond 2025; Noy and Zhang 2023), or free up time to work on other tasks (Dillon et al. 2025).

Available evidence on AI and employer practices finds that the impacts of AI on job quality and worker well-being depend on the context and the specific application of the technology. Some research finds that the use of AI can increase worker productivity and improve job quality. For example, some AI applications have been found to reduce the time spent on work outside of regular hours (Dillon et al. 2025), lower stress, smoothen interactions with customers for customer service workers (Brynjolfsson, Li, and Raymond 2025). and increase the enjoyment of completing certain tasks (Noy and Zhang 2023).

However, AI and related technologies can also erode job quality. For example, algorithmic management and surveillance may introduce reductions of worker autonomy and dignity (Cheon and Erickson 2025; Howard 2022; Nilsson et al. 2025). AI use can also intensify levels of work and contribute to burnout.[31] In some instances, these negative impacts on job quality also harm employers themselves, leading to higher turnover and reduced productivity (Kelly et al. 2023). In other instances, technological advances can improve business efficiency, but also erode job quality for workers. For example, just-in-time scheduling allows businesses to react quickly to fluctuating demand in the service industry, but also creates more unpredictable and irregular schedules for workers thus reducing job quality (Yu 2023).

What we need to know: Key open questions related to employer practices and AI adoption include:

- Where do worker and employer interests align when it comes to the adoption of AI tools, and where are they in tension?
- What AI-related employer practices are associated with positive worker outcomes? How can these employer practices be documented and spread?
- What practices are effective at addressing barriers to using AI on the job?
- How can we mitigate AI's disparate impacts on work by gender, race, and age, to ensure everyone has access to good quality jobs and training to help them advance their careers?
- As AI use becomes a prerequisite for some occupations, how can policymakers, employers, and workers address concerns around surveillance and intellectual property?

Who it will take: Key actors in this space who will need to collaborate to address these issues include:

- *employers* themselves, who will be making the internal decisions about how AI is adopted within their businesses and deployed among their workforces, and weighing impacts on both firm performance (e.g., productivity) and workforce outcomes (e.g., engagement, retention);
- *business communities and industry associations* who will play an essential role in the diffusion of good AI employer practices, and can communicate about their priorities, practices, and AI-use;
- *workers and workers' representatives* such as union and membership groups are also essential for understanding and advocating for how workers want employers to adopt AI, and what employer practices best support workers' wellbeing, economic security, and career paths; and
- *researchers* who can partner with employers to document AI adoption and its impacts on workers and the firm.

The data we'll need: Key quantitative and qualitative data and statistics needed to inform action on these issues include:

- firm-level AI implementation data on not just whether AI tools were adopted, but *how*—e.g. whether workers are consulted, whether complementary investments were made in training;
- nationally-representative worker experience and sentiment data disaggregated by race, gender, age, education, and occupation—capturing perceived fairness of AI tools, comfort and confidence in using them, workload and autonomy effects, and access to training;
- task-level surveillance and monitoring data capturing the scope, form, and intensity of worker monitoring across firms and occupations—linked to worker outcomes and perceptions;
- intellectual property and work-product data tracking how firms govern worker-generated outputs in AI training and workflows—what workers are permitted to share, retain, or build on—linked to firm- and worker-level outcomes on worker wages, and career development; and
- regulatory, litigation, and compliance data on emerging legal and policy responses to AI-related workplace concerns (surveillance, intellectual property, disparate impact) paired with firm- and worker-outcome data.

2b. Incorporate Worker Voice in the AI Transition

Why it matters: Workers are not and cannot be regarded as passive recipients of AI-driven change—they have unique knowledge about their day-to-day tasks that should inform how AI tools are used in their workplace. When workers have meaningful input into how new tools are adopted, the results are often better for everyone: development and implementation of technology that works with workers rather than around them provides an opportunity to surface practical problems early on, build the trust needed to make changes stick, and create feedback loops between workers and managers that accelerate productivity (Kochan et al. 2023). Including workers in decisions about how firms adopt AI tools is critical for a smooth technological transition that maximizes productivity and minimizes workforce disruptions.

What we know: Incorporating worker voice and representation into technological transitions can lead to desirable outcomes for both firms and workers (Kochan et al. 2023; Lowe, Kelmenson, and Myers 2024; Helmer and Johnson 2024).[32] Research has long indicated that worker voice, defined as opportunities for workers to provide input on working conditions, is associated with improved job satisfaction, well-being, burnout, turnover, and other elements of job quality (Díaz-Linhart et al. 2025;

Harju, Jäger, and Schoefer 2025; Kochan and Kimball 2019). Examples from manufacturing—an industry regularly exposed to automation—show that small and medium-sized employers have used worker input during technological change to improve retention, career pathways, and productivity (Lowe, Kelmenson, and Myers 2024). Integrating generative AI into jobs may be particularly well-suited to a bottom-up approach, in which workers are involved in defining the problem, codesigning technology and workflows, participating in education- and retraining, and shaping fair transitions for affected workers (Kochan et al. 2023).

Opportunities to leverage both new and traditional forms of collective voice and bargaining to advocate for worker interests in AI transitions are expanding (Glass 2024; Kochan et al. 2023).[33] Some recent collective bargaining agreements have codified how and when AI can be used in the workplace, including contracts secured by the Writers Guild of America and the United Parcel Service.[34, 35] However, union density remains relatively low in several highly exposed industries, including finance and other professional and business services, with education being a notable exception.[36, 37] This suggests the need for new and nontraditional forms of worker engagement and collective bargaining for addressing the challenges posed by AI, including but going beyond traditional unions, such as forms of sectoral bargaining and coregulation (Naidu 2022; Rosenfeld 2019).

What we need to know: Key open questions related to worker voice, AI, and job quality include:

- Which forms of worker engagement and representation are most effective at shaping AI adoption in ways that support both productivity and job quality?
- What new forms of worker organization and collective voice are appearing in workplaces? Which of these approaches show promise, and what is required for them to scale?
- Where are firm and worker interests aligned and where are they in tension in the transition to AI-enabled changes to work?
- What is the role of worker organization, collective bargaining, and voice in ensuring that the productivity benefits of AI are shared with workers?

Who it will take: Key actors in this space who will need to collaborate to address these issues include:

- *worker organizations and advocates*, who can represent collective worker voice, and have already begun informing and organizing workers around the potential impacts of AI;
- *employers*, who decide how innovations are deployed in the workplace and can incorporate worker perspectives in decisionmaking;

- *policymakers*, particularly those focused on labor relations, who can bring these actors to the table and establish the legal and institutional contexts within which worker voice and power operate, including in collective bargaining and sectoral contexts; and
- *researchers* will be needed to continue examining how worker voice shapes AI transitions as these changes unfold and identify how policy and practice might need to respond.

The data we'll need: Key data and statistics needed to inform action on these issues include:

- Matched employer–employee longitudinal data with firm-level information on worker representation structures linked to AI adoption decisions and worker outcomes measures;
- firm-level AI governance and decisionmaking process data capturing whether and how workers are involved in AI adoption decisions—at what stage, in what form, with what influence over outcomes;
- data on emerging worker voice structures, including documentation of new forms of worker organization (e.g., digital organizing, sectoral bargaining) including membership, tactics, and outcomes, collected consistently enough to enable comparison across models and contexts;
- firm-level productivity and business outcome data linked to worker representation structures and AI adoption practices; and
- worker perception data disaggregated by occupation, wage, race, and gender, capturing whether workers feel they have meaningful influence over AI-related changes at work, what forms of voice they find useful, and how that perception relates to worker and firm outcomes.

2c. Update Labor Market Policies for the AI Era

Why it matters: Many of AI's impacts on work will be governed by the labor market institutions—workplace and labor market regulations and standards, worker rights and protections, and so on—that establish the basic rules for how labor markets operate and what working conditions look like on the job. Labor market institutions, such as equal employment requirements, play an essential role in not just raising the floor and providing direct benefits to workers, but also directing how employers compete for workers, and correcting for other shortcomings in the ways that labor markets might otherwise operate. Without rules updated to reflect the advent of AI, even well-intentioned employers will operate in a system that may reward employers who seek to gain advantages at the expense of workers, and workers will have limited recourse when things go wrong.

What we know: The current landscape of worker rights and protections are already strained by AI-enabled changes to employment relationships, monitoring, and job classification. The framework still in place for most major labor regulations in the United States dates to the New Deal; and this framework has struggled to respond to the evolution of modern labor practices, even before AI (for example, Weil 2014), as evidenced in part by the prevalence of employer violations (Marinescu et al. 2021). The advent of applications of AI in hiring, employment, and management practices is further testing those rules and their enforcement in ways that are already visible: workers are managed by algorithms they can't see or inform (Ajunwa 2018), data is collected on their performance, potentially for use in training models, in ways they may not even know about, employment relationships are structured in ways that avoid labor laws that would otherwise apply, and the use of AI in hiring by firms is increasingly common (Raghavan et al. 2020). Some firms have used AI and related technologies to set wages themselves, a practice sometimes referred to as algorithmic wage discrimination (Dubal 2023).

What we need to know: Key open questions related to labor policy, AI, and job quality include:

- Where might AI widen or create new gaps in the coverage or effectiveness of existing labor market institutions, such as wage and hour protections, collective bargaining rights, and nondiscrimination protections?
- Which existing labor market institutions need updating, and how? What new protections or rights are needed to ensure workers are treated fairly in an AI-enabled economy, both on the job, and in labor markets (e.g., data ownership, algorithmic accountability)?
- What is the appropriate framework for addressing questions related to ownership of data collected on or from workers, including for the purposes of training AI models?
- What is the role of labor market institutions, such as wage and hour policy, or collective bargaining rights, in ensuring that the productivity benefits of AI are shared with workers?

Who it will take: Key actors in this space who will need to collaborate to address these issues include:

- *policymakers, regulators, and enforcers* in relevant labor agencies at the federal, state, and city levels, to develop and implement effective, updated policy and regulatory responses;
- *technology companies* to provide transparency in the development of tools, and to engage with policymakers, workers, and researchers in the design of tools before deployment, as well as to support data access arrangements;

- *employers*, to document and share data on their adoption and implementation of AI tools, to develop and model responsible practices around worker data collection, use, and ownership, and to engage workers meaningfully in AI adoption decisions; and
- *labor law scholars and labor economists* to understand the effects of these practices and the need for and direction of new policies, within the complex set of legal, policy, and economic questions at stake.

The data we'll need: Key data and statistics needed to inform action on these issues include:

- matched employer–employee longitudinal panel data with fine-grained job quality measures such as wages, benefits, autonomy, scheduling, workload intensity, and so on;
- high-frequency, firm-level, AI deployment data capturing how AI tools are changing the content, pace, and conditions of work—including workload intensification, deskilling, and new task creation—linked to worker well-being, compensation, and turnover outcomes;
- regulatory and enforcement data documenting which workers are covered by existing wage and hour, collective bargaining, and nondiscrimination protections—disaggregated by employment relationships type, industry, and worker;
- classification and nonstandard work arrangement data capturing the prevalence and growth of employment relationships that fall outside of traditional labor law coverage (gig, contract, and other work arrangements), linked to AI-enabled monitoring and management practices;
- firm-level data on AI-enabled monitoring and management practices (e.g., productivity metrics, biometrics, behavioral data, communication records; hiring, scheduling, performance evaluation, and termination), worker consent practices, and firm and worker outcomes; and
- litigation, administrative, and enforcement data tracking how existing labor protections are being invoked (or failing to be invoked) in response to AI-related workplace harms (e.g., wage theft, discrimination, surveillance, unsafe working conditions).

3. Workers Are Economically Secure in the AI Transition and Beyond

Supporting workers dislocated by AI is a social and economic imperative, but the set of policies in place is inadequate, as demonstrated by the consequences of past trade- and technology-driven shocks. This will require new approaches to meeting both the challenges posed by the AI transition as well as the longer-term distributional question of how AI's gains are shared—if the gains from AI accrue largely to capital, for instance, it might require policy to ensure workers share in the benefits.

3a. Support Workers Who Are Displaced

Why it matters: Economic security for workers is the foundation of a healthy economy, and job loss due to technological advances such as AI—in the absence of adequate worker supports—can leave workers with significant losses in income, both in the near and longer term. Workers who are worried about making rent between jobs cannot take on the necessary work of retraining and job search that successful transitions require. Workers whose skills lose their market value can face enduring economic hardships, even with retraining and reemployment. If AI-driven displacement proves larger or more permanent than past technological disruptions, the scale and duration of support required may surpass what existing worker support systems were designed to provide—requiring policymakers to consider more fundamental reforms to how income and economic security are structured.

What we know: Past shifts in the economy—driven by factors such as globalization and technological advancement—have formed the basis of overall economic prosperity that has benefited many workers, especially those with college degrees. But these same shifts have left many workers and communities behind (Autor, Dorn, and Hanson 2013; Hershbein and Stuart 2024; Stuart 2022). For displaced workers who have difficulty finding quick reemployment, these negative effects can be especially impactful and persistent (Davis and Von Wachter 2011; Fallick et al. 2025). Social insurance programs, like unemployment insurance (UI), and active labor market policies like job training, can help workers through transitions (Farooq, Kugler, and Muratori 2020; Rothstein 2011). Programs like wage-loss insurance have shown promise in helping displaced workers (Hyman, Kovak, and Leive 2024).

While we know these programs are important, we also know that—as currently or recently implemented—they have not operated at the scale and efficiency necessary to fully protect workers through past economic transitions. For example, Trade Adjustment Assistance (TAA), though focused on disruptions due to international trade rather than due to technology, was designed on precisely this logic and model (Baicker and Rehavi 2004).[38, 39] In practice, however, TAA was not sufficient to effectively insulate workers from the magnitude of the economic shocks they faced (Acemoglu, Akcigit, and Kerr 2016; Autor, Dorn, and Hanson 2013).[40] In broadly similar ways, while UI provides the larger scale and longer standing form of social insurance for workers against the effects of job loss, without emergency adjustments or significant reform, it no longer provides protection to many workers against the risk of severe and enduring income loss (Congdon and Vroman 2022; Kling 2006).

Early indicators suggest that AI is expected, like past waves of technology, to lead to some degree of job displacement. At the same time, at the time of writing, large scale displacement associated with AI is not evident in the data. Evidence of AI exposure by occupation (Eloundou et al. 2024), and impacts across the age distribution (Brynjolfsson, Chandar, and Chen 2025) provide suggestive but not dispositive evidence of the potential scale and distribution of potential displacement.

What we need to know: Key open questions related to AI and economic supports include:

- How similar will AI-driven displacement be to past technological disruptions—and where will it differ? Will AI disproportionately affect workers at different skill levels than past waves?
- What place-based dimensions of displacement and job loss require targeted responses?
- What role should existing worker supports play? Where are new supports needed?
- Where could current policy be scaled or adapted, and where are new policies needed?

Who it will take: Key actors in this space who will need to collaborate to address these issues include:

- *policymakers and program officials* focusing on economic security programs including unemployment insurance in particular, to develop policy at the state and federal level to reform or build new forms of policy responses that will match the moment; and
- *researchers* focused on monitoring and evaluating labor market impacts of AI to build evidence on the job loss and displacement impacts of AI as they emerge.

The data we'll need: Key data and statistics needed to inform action on these issues include:

- worker transition data tracking workers and their employment and reemployment longitudinally, including earnings, occupation, job quality, and geographic mobility;
- place-based labor market data at a granular geographic resolution, including local industry composition, employer concentration, labor demand, and community-level economic resilience, linked to AI adoption rates and worker displacement outcomes;
- administrative data from unemployment insurance, publicly funded workforce development programs and other public supports, linked to AI diffusion and long-run outcomes;
- firm-level displacement and transition practice data capturing how employers are managing workforce reductions and role changes driven by AI adoption (e.g., what notice, support, and retraining do firms provided voluntarily versus under legal obligation).

3b. Ensure Broad-Based Prosperity in the AI Economy

Why it matters: A growing economy is not the same as an equitable one. If AI delivers on its productivity promise—as early signs suggest it may—the central question becomes "Who benefits?" History offers a cautionary note: the gains from past technological transformations were real, but they were unevenly distributed by income, education level, race, and place. If AI drives substantial productivity gains but the benefits flow primarily to business owners and shareholders rather than including workers, without deliberate policy action to both reshape markets and redistribute benefits, the economy can grow while workers' fortunes slump.

What we know: The early evidence suggests that effects of AI on productivity are beginning to be evident, though the magnitude is uncertain, as is the most likely future path (Filippucci et al. 2024). Theoretically it is clear that under plausible assumptions about AI, substantial increases in productivity could come at the expense of workers in general (Trammell and Korinek 2023). Early evidence provides some support to suggest that current AI adoption might be disproportionately benefiting capital rather than labor (Johnston and Makridis 2026). There is also emerging evidence that some elements of current policy might be, even if inadvertently, nudging the economy along a path that may direct the benefits of AI toward capital owners relative to workers, due to the relatively favorable tax treatment of capital (Acemoglu et al. 2020).

What we need to know: Key open questions related to AI and economic prosperity include:

- Where are the gains going, who is being left out, and what levers are available to ensure shared gains before current patterns are locked in?
- What are the current impacts of AI on productivity and its distributional effects, including the distribution of benefits between capital and labor?
- How will AI's effects unfold across the income distribution?
- Are there features of the current policy environment, like tax policy, that are pushing economic outcomes along particular paths? Are there policy actions that can be taken now to shift or move between likely future paths?
- What policy levers—tax, labor, investment—are best suited to ensuring gains are shared equitably in market outcomes? What levers might be best suited to redistributing gains, if necessary, such as a universal basic income (see, for example, Hoynes and Rothstein 2019)?

Who it will take: Key actors in this space who will need to collaborate to address these issues include:

- *policymakers* focusing on labor market policy, tax and transfer policy, and potentially other areas, such as innovation and science and technology policy, to develop policy options; and
- *researchers* from fields such as labor economics and macroeconomics, focusing on how AI is affecting productivity, labor share, and the distribution of income, to better understand the current and potential impacts of AI on broader economic outcomes.

The data we'll need: Key data and statistics needed to inform action on these issues include:

- national accounts and productivity data disaggregated by industry, capturing whether AI-driven productivity gains are materializing, at what pace, and whether they are concentrated in a small number of industries or diffusing broadly across the economy;
- income distribution data with enough granularity to track how AI shifts the functional distribution of income over time, including capital returns, labor compensation, and profit shares at the firm and industry level, and linked to firm-level AI investment and adoption;
- firm-level financial and workforce data linking AI investment, productivity outcomes, profit distribution, shareholder returns, executive compensation, and worker wages;
- high-frequency, household-level income and wealth data disaggregated by income, capturing income sources, asset holdings, and consumption across the full income distribution; and
- tax and policy administrative data linking firm-level tax treatment to AI investment (e.g., depreciation schedules, research and development credits, equipment expensing) to investment behavior, productivity, employment, and wage outcomes.

4. Innovation in AI Empowers Workers and Drives Inclusive Growth

The trajectory of AI development itself is not fixed—innovation responds to incentives that can be structured by policy choices and the priorities set by key actors in the field. Whether AI is designed and deployed primarily to automate and replace workers, or to augment and empower them, depends in part on decisions made by policymakers, funders, and technologists today.

4a. Use Innovation Policy to Incentivize AI that Empowers Workers

Why it matters: The direction of AI innovation will shape its impact on workers, labor markets, and the economy, and right now, most of these decisions are being made by a small number of private actors, optimizing for a relatively narrow set of goals. Private innovation is imperative, and often transformative. But the incentives for technology firms and developers are shaped by innovation policy—the collective set of rules and institutional features, including research funding, government spending, data and intellectual property rights, and technology and consumer regulations.

What we know: Historically, some of the most consequential and broadly beneficial technological advances—from the internet to GPS to the basic research underlying most of modern medicine—were shaped by public innovation policy in varying forms and to varying degrees (Gross and Sampat 2020; Kantor and Whalley 2023). This has come in the form of direct federal research and development spending, grant funding and incentives to private sector research and technology development, and from mechanisms intended to stimulate and focus private efforts. For example, efforts around the development of autonomous vehicles, the subject of significant private sector investment in recent decades, were kickstarted several decades ago by the DARPA Grand Challenge, a prize competition funded by the Department of Defense. Direct federal spending and investment, including forms of industrial policy, sometimes directed specifically to induce innovation and investment in a particular direction, has also shaped innovation (Juhász, Lane, and Rodrik 2024). Beyond spending to spur or direct innovation, policies such as intellectual property rights, industrial regulation, and consumer protections have also been used to shape the direction of innovation in ways that align with broader, longer term social and economic goals, and to protect workers and consumers.

What we need to know: Key open questions related to innovation policy and AI include:

- How do current, legacy policies and regulatory environments shape incentives for innovation, and are these incentives biased toward developing forms of AI that are more likely to harm workers? For example, do tax incentives for firms induce demand for forms of AI that automate work relative to forms that augment workers (Acemoglu et al. 2020)?
- How do incentive structures in private AI development interact with public interest goals?
- How can we systematically consider and develop a new, integrated science and technology policy orientation toward funding and encouraging pro-worker forms of AI (Acemoglu, Autor, and Johnson 2026)?
- What innovation policy levers are most consequential for the direction of AI development? What regulatory approaches effectively balance innovation and worker protection? How can public spending shape AI innovation?

Who it will take: Key actors in this space who will need to collaborate to address these issues include:

- *policymakers*, including from science and technology policy, tax and fiscal policy, infrastructure spending and industrial policy, and industry and consumer regulatory agencies, to develop a more modern and integrated approach to federal innovation policy;
- *technology firms*, to share and inform perspectives from building the technology; perspectives from firms adopting the technology will also be needed;
- *researchers*, including academics and private sector technology developers and adopters, who conduct the research leading the direction of the technology; and
- *funders*—both policymakers and research program officials at the federal and potentially state levels, as well as potentially private sector funders, who shape incentives for innovation.

The data we'll need: Key data and statistics needed to inform action on these issues include:

- firm-level AI investment and tax treatment data linking specific tax incentives to the types of AI being adopted (automation-oriented vs. augmentation-oriented), employment and wage outcomes, and task composition changes;
- AI research and development pipeline data capturing what kinds of AI capabilities are being developed, by whom, and with what funding sources—disaggregated by whether applications are oriented toward automation, augmentation, or new task creation;
- public research funding data tracking federal and state research and development investment by agency, program, and project data, linked to downstream commercialization outcomes, firm adoption, and labor market effects;
- private AI development incentive structure data capturing how profit motive, investor expectations, competition dynamics, and liability environments shape firm decisions about which AI capabilities to develop and deploy; and
- regulatory environment and compliance data across jurisdictions, documenting existing rules governing AI development, deployment, and workplace use and linked to innovation activity, firm behavior, and worker outcomes.

4b. Reinvigorate the Role of Universities in AI Development

Why it matters: Some of the most broadly shared economic advances in American history trace back to university labs and publicly-funded research—not because government is better at innovation than the private sector, but because public investment pursues broad social goals that markets won't prioritize on their own. As AI development has shifted toward large private firms with proprietary models, that public engine has weakened at precisely the moment it is most needed. The stakes go beyond who builds the technology: universities shape the next generation of workers and innovators, and how they engage with AI now will determine how prepared the next generation is for the future.

What we know: Through prior technological revolutions, the US greatly benefitted from symbiotic relationships between research universities and government spending. Much of the basic research in fields including computer science has been conducted in and published by university-based research labs, often with public funding support. In the case of AI, some early evidence shows the location of research has shifted, with industry playing a relatively larger role in research and development related to the underlying technology (Ahmed, Wahed, and Thompson 2023). Further, there is evidence that the location of such research at institutions of higher learning also generates social benefits that operate through the teaching function of research universities. Historically, university-based research has shaped the adoption and application of technology by students as learners and, as they move into the workforce, as users, workers, and innovators (Goldfarb 2006; Zamir et al. 2025).

What we need to know: Key open questions related to AI research and the role of universities include:

- How are US institutions of higher learning utilizing and developing AI, how is this related in practice to the skills developed by students, and how does this translate into preparation to leverage new tools and make new ones as workers and innovators themselves?
- What public investment strategies in AI research and development would best serve worker interests?
- How can universities be better positioned to develop AI tools and train students in ways that translate into broadly beneficial economic outcomes?

Who it will take: Key actors in this space who will need to collaborate to address these issues include:

- *researchers* working in AI tech development and innovation, in both university-based settings and in the tech sector and at research universities;

- *funders* both from government research funding agencies and programs, along with philanthropy and major private sector funders, who shape research and practice; and
- *educators and education policymakers*, to develop and implement innovations in curriculum and pedagogy and to institutionalize practices that are demonstrated to be effective.

The data we'll need: Key data and statistics needed to inform action on these issues include:

- data on AI adoption and implementation in universities and community colleges, capturing how higher education institutions are integrating AI into instruction and research functions—disaggregated by institution type (e.g., research university, community college, HBCU), linked to student learning outcomes and post-graduation labor market outcomes;
- student skill development and assessment data—measuring not only credentials but actual skills and capabilities developed, including the ability to critically evaluate and direct AI tools;
- university research portfolio and funding data capturing the composition of AI research and activity across institutions (e.g., problems being worked on, industry partnerships), linked to downstream commercialization, licensing, and outcomes for graduates;
- data on public research and development investment, tracking federal and state funding flows to university AI research by agency, program, mission, orientation, and educational institution type—linked to research outputs and students' educational and economic outcomes; and
- higher education and industry partnership data on the structure, terms, and outcomes of collaborations between universities and private AI firms, including intellectual property arrangements, data sharing agreements, and influence over research agendas.

A Call for Collaborative Action

The prospect of technology that could make work vastly more productive—or even do much of the work necessary to meet society's needs while reducing the need for labor—sparks tremendous anxiety. While it could be used to generate widely shared economic prosperity, there are also no guarantees that everyone will share in the benefits, and good reasons—including the economic experience of past technological revolutions—to worry that many workers could be left behind.

This time can be different; the harms of the past are also lessons, for policymakers, employers, workers, and other actors. Shared prosperity in the age of AI is genuinely possible, but it will require deliberate action, and soon. The economic transformation expected from AI remains in its early stages, and the choices made now by policymakers, researchers, employers, training providers, and workers themselves will shape its trajectory.

From our review of recent research on AI and its economic effects, historical lessons and theoretical possibilities, and current labor market trends and conditions, we extract four essential, achievable goals for an inclusive AI economy:

- workers have the skills they need to thrive as AI changes jobs;
- workers have high-quality jobs in an AI-powered workplace;
- workers are economically secure during the AI transition and beyond; and
- innovation in AI empowers workers and drives inclusive growth.

Each of these goals is based in evidence that can inform early action, but all will require additional research, experimentation, and collaboration to generate the knowledge-building the moment demands in order to build the future we know is possible.

Notes

[1] Artificial intelligence (AI) lacks a precise technical definition, but in contemporary discussions related to technology and the economy it is often used to refer to a general class of technologies “that can perform complex tasks that are typically associated with human intelligence” (from Briggs et al. 2026). For the purposes of this report, this nontechnical classification of the technology as defined by its functions is both practical and appropriate, as its economic impacts will follow from how it can be used by workers and firms, and not its specific technical features. In this report, when we refer to AI we mean it in this general sense, inclusive of not just large language models (LLMs), generative AI, and agentic AI, but also economic and workplace applications of other forms of machine learning (ML), automation, and similar technologies.

[2] AI adoption statistics in Bick, Blandin, and Deming (2026) are based on data from the 2024 Real-Time Population Survey (RPS), available at https://sites.google.com/view/covid-rps/home.

[3] Another recent, survey-based approach to learning about AI adoption is offered by Malihe Alikhani, Ben Harris, and Sanjay Patnaik in the research “How Are Americans Using AI? Evidence from a Nationwide Survey.” See https://www.brookings.edu/articles/how-are-americans-using-ai-evidence-from-a-nationwide-survey.

[4] Handa et al. (2025) analyze anonymized Claude.ai conversations to map patterns of AI use to job tasks and occupations; Tomlinson et al. (2025) perform a conceptually similar analysis for Microsoft Bing Copilot.

[5] Firm-level statistics from Bonney et al. (2026) are based on the Census Bureau’s Business Trends and Outlook Survey (BTOS) from 2025 and 2026: “Business Trends and Outlook Survey (BTOS) Data,” United States Census Bureau, August 28, 2024, https://www.census.gov/programs-surveys/btos.html; prior BTOS statistics on AI adoption from 2023 and 2024 were also reported in Bonney et al. (2024); on earlier AI adoption, McElheran et al. (2024) present statistics based on the 2018 Annual Business Survey.

[6] See, for example: https://fortune.com/2026/05/04/godfather-of-ai-geoffrey-hinton-radiologists-future-of-work-tech-ai-job-anxiety.

[7] While we focus in this brief on discussing the use of AI in production and its impacts on productivity, given the central role these effects will play in determining the economic impacts of AI, this is of course neither the only application of AI relevant for workers and firms, nor the only relevant set of outcomes. Important strands of research have studied, for example, the use of AI in job search and hiring (Fuller et al. 2021; Wiles, Munyikwa, and Horton 2025), as well as the use of AI by firms for purposes such as employee monitoring and management. Research has also investigated a wider range of worker outcomes, such as mental fatigue (Bedard et al. 2026). We incorporate discussion of some of these aspects of AI in relevant portions of our action agenda, below.

[8] Scott Davis, “AI Is Simultaneously Aiding and Replacing Workers, Wage Data Suggest,” Federal Reserve Bank of Dallas, February 24, 2026, https://www.dallasfed.org/research/economics/2026/0224.

[9] Discussion of the potentially transformative economic impacts of AI is widespread—and increasingly common—in popular discussions of AI and its potential effects. For one recent example, among many, see, for instance: https://www.nytimes.com/2026/02/04/opinion/ai-jobs-employment-industry.html.

[10] While these are the primary real channels by which AI as a technology would be expected to affect the wider economy, they are not the only ways in which factors related to current investments in the technology could have broad economic consequences. One such additional channel is financial, and relates to debates around the question of whether AI represents a “bubble”—a level of investment and valuation that has become untethered from fundamentals—that is likely to eventually burst, leading to negative real economic impacts. See, e.g.: https://www.nytimes.com/2025/10/14/opinion/ai-bubble-stock-market-tech-stocks.html.

[11] More technically, labor productivity is a measure of the level of economic output per unit of labor input, measured in hours worked. On the basics of productivity and its definition and measurement, see, for example,

the official statistical series on productivity produced by the Bureau of Labor Statistics: https://www.bls.gov/productivity.

[12] Note that the importance of productivity growth for wage growth has remained true even as other factors have reduced the degree to which the benefits of rising productivity have passed through to the typical worker, an issue we return to below in the case of AI. See, Economic Policy Institute. n.d. "The Productivity–Pay Gap." accessed May 23, 2026. https://www.epi.org/productivity-pay-gap/

[13] See, for example, the alternative trajectories illustrated in: Martin Neil Baily, Erik Brynjolfsson, and Anton Korinek, "Machines of Mind: The Case for an AI-Powered Productivity Boom," *Brookings*, May 10, 2023, https://www.brookings.edu/articles/machines-of-mind-the-case-for-an-ai-powered-productivity-boom.

[14] On productivity trends and data, see: https://www.bls.gov/productivity.

[15] See, for example: https://bsky.app/profile/jasonfurman.bsky.social/post/3mnhqforycq25

[16] See, e.g.: "Productivity Change in the Nonfarm Business Sector, 1947 Q1—2026 Q1," US Bureau of Labor Statistics, May 7, 2026, https://www.bls.gov/productivity.

[17] See an articulation of this view in David Autor's essay "AI Could Actually Help Rebuild the Middle Class," *Noema*, February 12, 2024, https://www.noemamag.com/how-ai-could-help-rebuild-the-middle-class.

[18] On recent job growth, unemployment, and other indicators of the overall employment trends, see the most recent Employment Situation report at: "The Employment Situation," Bureau of Labor Statistics, May 6, 2026, https://www.bls.gov/news.release/pdf/empsit.pdf.

[19] Tyler Atkinson, and Shane Yamco, "Young Workers' Employment Drops in Occupations with High AI Exposure," Dallas Fed Economics, January 6, 2026, https://www.dallasfed.org/research/economics/2026/0106.

[20] Note that the widely discussed Brynjolfsson et al. (2025) results have been the subject of some debate, in particular with respect to whether the timing of their reported employment effects are due to AI or AI alone. See, for example: https://agglomerations.eig.org/p/looking-for-the-ladder. For an update and response by Brynjolfsson and colleagues, see: https://digitaleconomy.stanford.edu/news/canaries-interest-rates-and-timinga-more-on-recent-drivers-of-employment-changes-for-young-workers.

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