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Shaping the Future of Work: Generative AI, Inequality, and Opportunity

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The rise of generative Artificial Intelligence (AI) technologies has sparked significant excitement as well as concern, particularly regarding its implications for the future of work and economic inequality. Many policy and tech leaders have made bold proclamations about this future. For instance, Sam Altman of OpenAI has claimed that “In a decade, perhaps everyone on earth will be capable of accomplishing more than the most impactful person can today.”

Fear of a jobless and more unequal future has also become widespread among the general public. A 2023 [McKinsey report](#) estimated that current generative AI tools have the potential to automate work activities that account for 60 to 70 percent of employees’ time today. A 2024 [Pew Research poll](#) of U.S. adults found that only 17% of respondents believed that AI will have a net positive impact on the U.S. over the next 20 years; furthermore, only 23% believe that it will have a positive impact on how people do their jobs. Already, many tech and policy leaders seem to have taken for granted a future of massive job displacement and wealth inequality, arguing in favor of redistribution through a [universal basic income](#). Are these concerns well-placed?

In this report, we aim to provide an overview of the current state of quantitative social sciences research on AI’s implications for economic inequality — including not only its potential for transforming work and displacing jobs, but its potential for advancing economic mobility.¹

1. Note that this report’s analysis is focused on quantitative social sciences evidence of AI’s impacts, from academic institutions and think tanks. These sources primarily use data from administrative sources (such as the Bureau of Labor Statistics), private companies (such as ADP Payroll or AI companies), and lab or field experiments. Non-quantitative assessments and research from outside of economics and public policy were not the focus of literature search. For example, a number of outlets have published commentary on AI’s impacts; additionally, there are large bodies of literature from computer science on algorithmic bias and AI safety, and from neuroscience on the cognitive impacts of AI tools (particularly in learning settings) — these are not the focus of this piece.

AT A GLANCE

This research brief provides an overview of the current state of quantitative social sciences research on AI’s implications for economic inequality.

PILLARS

Work

AI “lifts the floor” for lower-skilled workers but effects are context-dependent.

Education

Efficacy depends on implementation and teacher buy-in, not just tool access.

Career

Early evidence shows AI helps marginalized job seekers get hired, but long-term equilibrium is unknown.

AI's implications for inequality are not necessarily obvious; AI has the potential to create significant job displacement, but also to generate broad-based economic growth, create new forms of work, advance educational attainment, and reduce frictions in the job search process.

We will begin by providing a brief overview of the history of technological development leading up to the creation of generative AI; then, we will describe the research, which falls into three main categories.

- 1. AI in the workplace:** Do AI tools increase worker productivity and firm output? Which tasks does AI complement versus substitute for? In turn, what are the effects on employment?
- 2. AI in education and workforce development:** Can AI improve educational outcomes? How can AI be most effectively deployed to do so? Which individuals benefit most from using AI in K-12 schools, universities, and workforce training programs?
- 3. AI in career navigation, job search, and matching:** How can AI help individuals navigate career pathways, identify job vacancies, and apply for jobs?

We also outline some of the key unanswered questions that are ripe for additional research. Addendum I includes a chart detailing the literature included in this study.

Technological Development of Generative AI

Generative AI technologies entered mainstream public attention with the release of OpenAI's ChatGPT in 2022. These technologies marked a significant departure from previous iterations of machine learning and artificial intelligence technologies, due to their capacity to generate content and operate flexibly across a wide range of contexts, often without requiring retraining or fine tuning on task-specific data.

However, the evolution of artificial intelligence has followed a [long trajectory](#). Since the 1950s, AI has advanced from rule-based systems and specialized data analysis tools to models capable of more creative content generation. Progress was not necessarily always linear, punctuated by several AI winters of reduced funding and interest. However, the introduction of transformer architectures in 2017 brought a major shift. These enabled large-scale models to produce content at a level previously unattainable.

Today, many experts have begun to describe AI as a ["general-purpose technology"](#) — an innovation that has the capacity to drive economy-wide transformations, much like electricity or the steam engine. AI products have been touted as being broadly applicable across industries, ranging from software engineering to drug discovery to robotics.

The prospect of [artificial general intelligence \(AGI\)](#) — systems matching human cognitive capabilities — raises new economic considerations. While current iterations of AI tools can complete specific tasks, AGI could potentially perform entire job roles. It is difficult to say when or whether we will reach such a level of innovation, but the implications for the labor market could be drastically different from the implications of current AI models. Although many firms have aimed to make projections about this trajectory, for the purposes of this article, we will focus on AI tools in their current form.

AI in the workplace

A significant body of economics research thus far has examined the way in which AI tools are shaping [the workplace](#). In particular, do AI tools increase workers' productivity? Which tasks does AI complement versus substitute for? And, in turn, how will AI tools affect employment and wages?

The earliest body of research on this topic examined AI's impacts on productivity in a broad range of work contexts. For instance, in a lab experiment with college-educated workers

completing [writing tasks](#), access to ChatGPT led to a decrease in time to complete tasks of 40% and an increase in writing quality of 18%. In an observational study with [customer service agents](#), a generative AI conversational assistant tool led to a 14% increase in the number of customer issues that agents resolved per hour. In both of these contexts as well as several others — [software engineering](#), [management consulting](#), [advertising](#), and [legal analysis](#) — productivity impacts were larger for less-experienced or lower-skilled workers, thus helping to equalize workers' output. In other words, AI tools in many settings are able to help "lift the floor" of workers' skills by making domain-specific knowledge more readily accessible.

Conversely, researchers have also found that generative AI tools widen gaps in performance in a number of settings. For example, several researchers studied the effects of a generative AI [business assistance](#) conversational tool, which, in a field experiment with 640 Kenyan entrepreneurs, increased business revenue of the high performers by 15%, but actually decreased revenue of low performers by 8%. Through an analysis of text conversations, the researchers found that this difference in effect was not driven by the types of questions that entrepreneurs asked or the types of advice that they received from AI assistance, but rather their discretion in using the advice. Researchers have found a similar pattern in several additional settings — including in [debate competitions](#) and [investment decisions](#) — where the workers who benefited most from the AI tools were those who started out with the most experience or skills at baseline. In these cases, the generative AI tools actually increased inequality in output and/or performance.

A second body of research has examined the impacts of AI tools on employment. Importantly, AI adoption does not automatically imply massive labor displacement. In particular, productivity improvements can translate to firm growth and new work creation. In one iteration of this

research, papers forecasted AI's labor market impacts by measuring tasks' and [occupations' exposure to AI, using different methodologies](#). Some also combined productivity estimates with [theoretical models](#) of the labor market. For instance, an analysis of conversations with [Microsoft Bing Copilot](#) showed that computer and mathematical, office and administrative support, and communication occupations are the ones with the highest AI applicability. Separately, an analysis of [Claude conversations](#) demonstrated that AI usage was most common in software development and writing tasks. These analyses suggest that certain white collar occupations are observing more significant AI take-up and are more likely to experience transformation due to AI. However, higher occupational exposure to AI does not necessitate greater employment loss. For example, although software engineering is widely considered a highly AI-exposed occupation, many firms have significant capacity to expand their software engineering needs, often through the creation of increasingly technically or socially complex forms of work.

Most recently, a number of papers have directly estimated the employment effects of AI tools, though reaching rather different conclusions. For example, a study using [Danish](#) administrative data finds zero effects of chatbot adoption on earnings or working hours. In contrast, U.S. evidence from [ADP payrolls](#) and [résumé data](#) points to declines in hiring for younger and junior white-collar workers, particularly in AI-exposed occupations. Other work using [Brazilian data](#) finds job losses among office workers but gains for production workers, consistent with task-level complementarity. More research is still needed to reconcile these contrasting results, which may arise from contextual and methodological differences between the papers.

Taken together, the current body of research paints a nuanced picture: while generative AI can serve as a powerful skill equalizer by boosting the productivity of less experienced

workers, its effects are highly context-dependent. Furthermore, some evidence thus far suggests that AI is already having negative employment effects, particularly among junior white-collar workers, but overall the evidence is still mixed and the longer-term impacts are ambiguous.

More research on the topic is still warranted: for example, when does AI close versus widen productivity gaps between workers? When does AI displace versus complement labor? Finally, given the evolving work landscape, how should our educational and workforce training systems respond? In the next section, we explore the emerging research on AI in education and workforce development, including not only whether AI can improve learning outcomes, but also who stands to benefit the most from these tools.

AI in Education and Workforce Training

One of the most promising avenues for generative AI to advance economic mobility lies in its potential to [reshape education](#) and [workforce development](#). If AI precipitates changes in skill demands, then a transformation in education and workforce training will be essential. Already, many [educational institutions](#), [training providers](#), and [employers](#) are anticipating such shifts. By delivering instructional content in more personalized and engaging ways, and by supporting teachers by automating routine tasks, AI can improve learning outcomes across a range of settings – not only in traditional K–12 and higher education, but also in adult learning and workforce development programs.

Over the past several years, a wide range of AI-powered educational technology (edtech) tools have emerged to serve these different contexts. Some focus on students directly, using AI to assess progress in real time, identify knowledge gaps, deliver tailored tutoring, and provide other forms of virtual training. Others support teachers by automating grading, generating lesson plans, or offering feedback on student work.

Finally, some serve the workforce development space, aiming to personalize content delivery and improve knowledge retention for adult learners and employees seeking to upskill.

Although there has been a proliferation of educational AI tools, research on their impacts is still preliminary. A larger history of research has examined the efficacy of various educational interventions and shaped best practices, emphasizing the importance of active learning and personalized education. For instance, a meta-analysis of 225 studies about [active learning](#) versus lecturing found that student exam performance under the former model was significantly higher than under the latter. Additionally, a meta-analysis of 96 [tutoring](#) studies similarly found a positive and significant standardized test score effect. However, such interventions are costly and logistically difficult to implement. AI educational tools have the capacity to play a similar role to these active education models and these personal tutors, providing more engaging and individualized support, but in a far more cost-effective manner.

More recently, educational technologies have provided more cost-effective ways to scale personalized learning – a [meta-analysis](#) of 19 experiments on non-AI technologies similarly found a positive and significant average effect size. The effectiveness of such technologies, however, depends heavily on implementation. In one large-scale study, researchers evaluated the efficacy of [computer assisted learning \(CAL\)](#) in elementary and middle-school mathematics classrooms. Specifically, the researchers used the Khoaching with Khan Academy program (KWik) to train teachers across two school districts to utilize CAL as part of their curriculum. Importantly, they found significant variation in effect size, depending on teachers' level of buy-in with the technology. In classrooms where teachers indicated commitment to the technologies in survey responses, and thus provided students with at least 25 minutes of CAL-assisted practice each week, improvements in test scores were comparable to those seen with high-dosage

tutoring programs. However, in classrooms with little CAL practice, researchers observed little to no improvement in performance. This study emphasizes an important point in implementation: simply providing students or teachers with access to the educational technology is insufficient; ensuring take-up of the tools is essential to see improvements.

For adult learners, AI tools similarly hold significant promise, particularly given the rising importance of upskilling workers to meet changing employer needs. However, there is little careful research specifically evaluating the efficacy of AI tools for this population. Prior research provides some evidence on best practices more broadly for the design and implementation of [workforce training programs](#), finding that these are very effective when they combine upfront screening, occupational and soft skills training, and wraparound services, providing substantial and persistent earnings increases of 11 to 40 percent. As a result, they are able to not only increase employment rates but also advance workers into better-paying occupations by providing workers with new skills and reducing barriers to employment.

Although AI tools hold significant promise, research about their efficacy in the classroom is only now beginning to emerge. One study of the effects of generative AI tools in [high school math classrooms](#) demonstrated that if AI tools are deployed ineffectively, they can harm learning. Researchers ran an experiment randomizing usage of ChatGPT and a ChatGPT-based tutor with approximately 1,000 students. Students in the treatment group accessing the normal version of ChatGPT performed significantly better on practice problems, but worse on an exam in which they could not use AI. However, students who had access to a modified GPT tutor, which guided them through solutions rather than directly providing them with answers, performed better on the practice problems without negative impacts on exam performance.

Despite the proliferation of AI educational tools, more research on their efficacy is still needed. For instance, how does human-only tutoring compare with AI-only tutoring, and what are the most effective ways to combine the two? Which students benefit from — or are left behind by — institutions' adoption of AI tools? What determines take-up of tools, and how can tool design shape this? AI tools have the potential to improve educational outcomes by providing more personalized support and engaging content, which may also be more cost-effective and scalable than other educational solutions. In particular, these could be especially beneficial to less advantaged students in less well-resourced schools or lower-wage workers working with less well-resourced training programs. However, ensuring such efficacy will rely on ensuring that the tools are built and rolled out in a way that allows the less advantaged individuals to utilize them as well.

AI in Career Navigation, Job Search, and Matching

One final way in which AI tools may enhance economic mobility is by improving the [career navigation](#) process. These tools have the potential to reduce informational frictions and lower workers' costs of applying for jobs, ultimately improving the quality and speed of job matches. Furthermore, they have the potential to be particularly effective for disadvantaged workers, who may lack access to information or networks.

As in the education sector, a growing number of companies have emerged to support various stages of the job search journey. Some use AI to deliver personalized career guidance, skill assessments, and digital portfolios, helping individuals chart tailored career paths and better signal their capabilities to employers. Others help individuals prepare applications: resume and cover letter optimization tools suggest formatting and language improvements tailored to job descriptions, while AI-based interview training tools simulate realistic scenarios, offer real-time

feedback, and provide analytics to help job seekers improve their performance. Finally, some job search platforms have begun integrating AI into their tools to recommend relevant openings based on users' profiles and preferences.

A small but growing body of research has begun to assess the impact of these tools. In one experiment, researchers randomized access to an AI [resume writing assistance](#) tool to nearly half a million job seekers on an online labor market platform. The tool improved resume quality, increased the likelihood of being hired, and led to higher wages. Additionally, it did not lead to any detectable decline in subsequent job performance. This addresses a key concern that standardizing resumes might diminish employers' ability to screen for true skills.

In another experiment, researchers studied the efficacy of providing AI-generated [job recommendations](#) on Sweden's largest job board. The job board used job seekers' click history to generate customized recommendations, finding that job seekers who received such recommendations had a higher application rate and a higher employment rate within 6 months, compared with those who did not receive the AI-generated suggestions. The effects were especially pronounced for individuals with lower education, those who were unemployed, and those searching across broader geographies, suggesting the potential of AI tools to especially benefit more disadvantaged jobseekers.

Despite this early promise, many important questions remain unanswered. First, can AI tools meaningfully shift job seekers onto better career pathways, or do they simply help optimize choices within existing trajectories? For example, would users actually pursue recommendations in higher-paying but unfamiliar occupations, or are recommendations only effective when they align with the user's prior behavior or assumptions? Given these potential challenges, how can AI tools be designed to ensure take-up?

Second, do the tools actually reduce persistent unemployment, or do they merely accelerate short-term job matching for those who would have found jobs anyway? Although we observe evidence of shifts in application behavior, these may be driven by individuals who would have found jobs eventually. Additionally, do AI-accelerated matches lead to better job fit and retention, or could they inadvertently increase turnover by focusing on speed rather than quality?

Finally, what are the implications in equilibrium if AI job search tools are widely adopted? While early adopters may gain an edge, mass adoption could eliminate individual advantages and potentially worsen matching overall. For instance, if AI tools make it nearly costless to apply, employers may be inundated with applications, making it harder to identify the best candidates and potentially degrading job match quality.

Early evidence suggests that AI-powered job search tools can increase employment and wages in the short term, especially for those facing greater barriers to employment. But more rigorous, long-term studies are needed to fully understand their role in shaping labor market dynamics and economic opportunity.

Conclusion

Generative AI represents a transformative technological shift with wide-ranging implications for economic inequality and mobility. While the majority of public discourse has fallen into two extreme camps of deep fear or wild optimism, the emerging body of social science research suggests a more complex and contingent reality. Across the domains of work, education, and job search, AI tools show promise not just for increasing productivity, but also for expanding economic opportunity.

This potential is far from guaranteed. In the workplace, AI tools can help "lift the floor" by enhancing the performance of less-experienced workers. However, in settings

that demand greater judgment or discretion, these tools may instead widen performance gaps; additionally, such productivity gains may still eventually induce job displacement. In education and workforce training, AI offers scalable ways to personalize learning and support educators, but the effectiveness of these tools hinges on thoughtful design and high-quality implementation. And in job search, AI can streamline applications and improve matching, but long-term impacts remain uncertain.

Taken together, the research underscores a central insight: AI's effects are shaped as much by human institutions — schools, workplaces, training programs, and platforms — as by the technologies themselves. Whether AI serves to entrench existing inequalities or broaden access to opportunity will depend on how we choose to deploy, govern, and integrate these tools into our economic and social systems. As policymakers, educators, employers, and researchers look ahead, it is important to not simply try to forecast AI's impact but also to actively shape it through careful tool design, investments in equitable access, rigorous evaluation, and building appropriate safety net systems.

A number of outstanding research questions remain to be explored, and could help shed light on the challenges and opportunities posed by AI for learners, workers, and the economy. Key questions for future exploration include:

AI in the workplace

- Which skills and tasks are complemented versus substituted by AI?
- When does AI have equalizing versus inequality-increasing effects on worker performance?

- What are AI's ultimate impacts on employment and wages? How do these impacts differ by occupation or industry?
- How should education and training systems evolve to prepare workers for AI-driven shifts in skill demand?

AI in education and workforce development

- How do AI-based learning tools compare with traditional educational methods — and what are the most effective ways to integrate them?
- Which students or workers benefit most from AI-based educational tools? What barriers limit equitable access to AI-assisted learning, and how might these shape who is able to benefit from their use?
- What enables effective adoption and meaningful usage of AI tools in classrooms or training programs?

AI in job search and matching

- To what extent can AI tools reshape individuals' career trajectories versus optimizing within existing pathways?
- What are the long-term impacts of AI-assisted matching on job quality and retention?
- How does widespread adoption of AI in job search affect labor market dynamics at scale?

Appendix I: Library of Resources

While not a comprehensive list, this chart is intended as a useful resource for practitioners and thought leaders aiming to better understand the evolving impact of generative AI on the labor market through changes to workplace tasks, the design and delivery of education and training, and the job search and matching process for job seekers and employers. The Social Finance Institute will host this dynamic chart on its website, with regular updates to reflect the latest relevant research and insights.

AI in the Workplace

SOURCE & AUTHOR	TITLE & DESCRIPTION
Brookings Babina and Fedyk (2025)	The effects of AI on firms and workers Summarizes research on AI's impact on productivity, firm structure, and worker outcomes.
Noy and Zhang (2023)	Experimental evidence on the productivity effects of generative artificial intelligence Finds that access to ChatGPT speeds writing tasks and improves quality, especially for less-experienced workers.
Brynjolfsson, Li, and Raymond (2023)	Generative AI at Work Shows that AI assistants raise customer service productivity, with largest benefits for lower-skilled agents.
Cui et al. (2025)	The Effects of Generative AI on High-Skilled Work: Evidence from Three Field Experiments with Software Developers Demonstrates that AI coding tools improve speed and quality, especially for junior developers.
Dell'Acqua et al. (2023)	Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality Finds that AI tools increase speed and output among management consultants.

Chen and Chan (2024)	<p>Large Language Model in Creative Work: The Role of Collaboration Modality and User Expertise</p> <p>Shows that AI enhances advertising and creative performance, especially with collaborative use.</p>
Choi and Schwarcz (2023)	<p>AI Assistance in Legal Analysis: An Empirical Study</p> <p>Finds that AI tools improve law students' exam accuracy and efficiency.</p>
Otis et al. (2024)	<p>The Uneven Impact of Generative AI on Entrepreneurial Performance</p> <p>Shows that AI boosts outcomes for top entrepreneurs but can reduce performance for lower performers.</p>
Roldán-Monés (2024)	<p>When GenAI increases inequality: evidence from a university debating competition</p> <p>AI improves students' debate competition performance.</p>
Kim et al. (2024)	<p>From Transcripts to Insights: Uncovering Corporate Risks Using Generative AI</p> <p>Demonstrates how AI improves analysis of financial risks using unstructured text data.</p>
Hampole et al. (2025)	<p>Artificial Intelligence and the Labor Market</p> <p>Links occupational AI exposure to small declines in employment in affected jobs but offsetting gains elsewhere.</p>
Gmyrek, Berg, and Bescond (2023)	<p>Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality</p> <p>Models global labor exposure to AI and projects modest job reallocation rather than widespread losses.</p>
Anthropic (2025)	<p>Anthropic Economic Index</p> <p>Uses AI platform data to map global adoption and task performance trends.</p>

Anthropic: Handa et al. (2025)

[Which Economic Tasks are Performed with AI? Evidence from Millions of Claude Conversations](#)

Analyzes user interactions to identify which professional tasks are most frequently completed with AI.

Tomlinson et al. (2025)

[Working with AI: Measuring the Occupational Implications of Generative AI](#)

Uses occupational task data to measure how AI changes the nature and frequency of work activities.

OpenAI

Eloundou et al. (2024)

[GPTs are GPTs: Labor market impact potential of LLMs](#)

Estimates AI exposure across occupations and finds routine cognitive jobs most affected.

Felten, Raj, and Seamans (2018)

[A Method to Link Advances in Artificial Intelligence to Occupational Abilities](#)

Develops a framework linking AI progress to specific job skills and automation risk.

Felten et al. (2021)

[Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses](#)

Provides datasets estimating AI exposure across sectors and regions.

Bryjolfsson, Mitchell, and Rock (2018)

[What Can Machines Learn, and What Does It Mean for Occupations and the Economy?](#)

Analyzes the limits of AI capabilities and their implications for job substitution and complementarity.

Webb (2020)

[The Impact of Artificial Intelligence on the Labor Market](#)

Examines how AI technologies shift demand from routine to non-routine occupations.

Brookings

Kinder et al (2024)

[Generative AI, the American worker, and the future of work](#)

Assesses which U.S. occupations are most affected by generative AI based on task-level analysis.

Brynjolfsson et al. (2025)

[Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence](#)

Finds that early AI adoption reduced employment among young white-collar workers but left total jobs unchanged.

Acemoglu (2024)

[The Simple Macroeconomics of AI](#)

Models macroeconomic outcomes and predicts output gains with transitional job losses.

Acemoglu et al. (2022)

[Artificial Intelligence and Jobs: Evidence from Online Vacancies](#)

Finds reduced postings for routine jobs but increased demand for analytical and managerial roles after AI adoption.

Wang and Wong (2025)

[Artificial Intelligence and Technological Unemployment](#)

Projects limited long-run job losses from AI-driven automation using a macroeconomic model.

Humlum and Vestergaard (2025)

[Large Language Models, Small Labor Market Effects](#)

Finds no measurable impact of chatbot adoption on earnings or hours using Danish administrative data.

Hosseini and Lichtinger (2025)

[Generative AI as Seniority-Biased Technological Change: Evidence from U.S. Résumé and Job Posting Data](#)

Use resume data to demonstrate decline in junior employment, without change in senior employment.

de Souza (2025)

[**Artificial Intelligence in the Office and the Factory: Evidence from Administrative Software Registry Data**](#)

Finds AI lowers office employment but raises production jobs, implying task complementarity.

Appel et al. (2026)

[**Anthropic Economic Index Report: Economic Primitives**](#)

Analyzes Claude usage across tasks using new “economic primitives.”

Aguirre and Manning (2026)

[**How Adaptable Are American Workers to AI-Induced Job Displacement?**](#)

NBER working paper finding heterogeneity in workers’ capacity to adapt (with clerical roles more vulnerable).

Brookings

Aguirre et al. (2026)

[**Measuring US workers’ Capacity to Adapt to AI-Driven Job Displacement**](#)

Companion/related Brookings analysis combining exposure and adaptation indicators.

Brookings

Kinder (2026)

[**To save entry-level jobs from AI, look to the medical residency model**](#)

Proposes structured, supervised entry-level roles to help workers gain skills alongside AI rather than be displaced by it.

Brookings

Kinder et al. (2025)

[**New data show no AI jobs apocalypse—for now**](#)

Finds that AI adoption has not yet caused widespread job loss, though risks remain for certain occupations and regions.

Brookings

Levy Yeyati (2025)

[**Hybrid jobs: How AI is rewriting work in finance**](#)

Shows how AI is reshaping finance jobs by combining human judgment with automated analysis rather than replacing workers outright.

Brookings
West (2025)

[**Ways to help workers suffering from AI-related job losses**](#)

Outlines policy approaches to support displaced workers through retraining, income support, and targeted workforce programs.

Brookings
Muro et al. (2025)

[**The geography of generative AI's workforce impacts will likely differ from those of previous technologies**](#)

Finds that generative AI may affect a broader range of regions than past technologies, including higher-skill labor markets.

Massenkoff and McCrory
(2026)

[**Labor market impacts of AI: A new measure and early evidence**](#)

Introduces "observed exposure," a new AI displacement risk metric that blends LLM capability with real-world usage, emphasizing automated and job-related tasks.

AI in Education and Workforce Training

Center for American Progress (2025)

[Enhancing the Use of Technology in K-12 Schools](#)

Outlines policy strategies to integrate AI tools effectively in schools.

Brookings

Winthrop (2025)

[Generative AI is coming for our students, and now is the moment to shape it](#)

Discusses how education systems can prepare for widespread AI adoption in learning.

AIR

Belwaker and Maki (2023)

[Role of Artificial Intelligence in Workforce Development](#)

Reviews how AI can support workforce training and skill alignment with employer needs.

Lohr (2025)

[How Do You Teach Computer Science in the A.I. Era?](#)

Universities struggling to shift computer science curriculum in response to AI.

Abel et al. (2024)

[AI and the Labor Market: Will Firms Hire, Fire, or Retrain?](#)

Survey of service and manufacturing firms, finding that AI adopting firms plan to retrain rather than reduce head-counts.

Amin and Cade (2023)

[Boosting Readiness for Tech Careers with Intelligent Tutoring: A Learning Partnership with Per Scholas](#)

Program integrating AI-driven intelligent tutoring systems into tech training.

Lee et al. (2025)

[Proactively Developing & Assisting the Workforce in the Age of AI](#)

Describes policy strategies to help workers adapt and thrive amid AI-driven labor market change.

Freeman et al (2014)

[Active learning increases student performance in science, engineering, and mathematics](#)

Meta-analysis finds large positive effects of active learning over lecturing on student learning outcomes.

Nickow, Oreopoulos, and Quan (2023)

[The Promise of Tutoring for PreK–12 Learning: A Systematic Review and Meta-Analysis of the Experimental Evidence](#)

Meta-analysis finds large positive effects of tutoring on student learning outcomes.

Escueta et al. (2023)

[Upgrading Education with Technology: Insights from Experimental Research](#)

Synthesizes evidence showing that educational technologies improve learning when well-implemented.

Oreopoulos et al. (2024)

[Teaching Teachers to Use Computer Assisted Learning Effectively: Experimental and Quasi-Experimental Evidence](#)

Finds teacher training in computer-assisted learning improves student math performance when engagement is high.

Katz et al. (2022)

[Why Do Sectoral Employment Programs Work? Lessons from WorkAdvance](#)

Shows workforce programs combining training and wraparound services raise long-term earnings.

Bastani et al. (2024)

[Generative AI Can Harm Learning](#)

Finds that unguided AI use lowers test performance while guided AI use supports learning.

AI in Job Search and Matching

Fuller et al (2023)

[Unlocking economic prosperity: Career navigation in a time of rapid change](#)

Reviews how AI-powered tools can improve career guidance and job matching.

Wiles, Munyikwa, and Horton (2023)

[Algorithmic Writing Assistance on Jobseekers' Resumes Increases Hires](#)

Shows that AI résumé assistance improves hiring rates and wages without harming performance.

Le Barbanchon, Hensvik, and Rathelot (2023)

[How Can AI Improve Search and Matching? Evidence From 59 Million Personalized Job Recommendations](#)

Finds that AI-generated job suggestions increase applications and employment, especially for disadvantaged jobseekers.

Brookings

Yeyati and Seyal (2025)

[Digital footprints and job matching: The new frontier of AI-driven hiring](#)

Explains how AI uses digital data to improve job matching while raising concerns about privacy and bias.

Brookings

Yeyati and Seyal (2025)

[The future of hiring: Advantages of a skill-based, AI-powered, hybrid approach](#)

Argues that combining AI tools with human judgment can improve hiring fairness and better match workers to jobs based on skills.



General

McKinsey Global Institute

Chui et al (2023)

[**The Economic Potential of Generative AI: The Next Productivity Frontier**](#)

Estimates productivity and growth potential from generative AI across industries.

McKinsey Global Institute

Ellingrud et al (2023)

[**Generative AI and the future of work in America**](#)

Projects workforce shifts by combining task-level AI exposure data with employment forecasts.

Burning Glass Institute

Lebanon (2025)

[**Generative Artificial Intelligence and the Workforce**](#)

Analyzes job postings and worker skills to track early signs of AI adoption and workforce change.

Pew Research Center

McClain et al (2025)

[**How the U.S. Public and AI Experts View Artificial Intelligence**](#)

Surveys public and expert attitudes toward AI's risks, benefits, and regulation.

National Academies of Sciences, Engineering and Medicine

Brynjolfsson et al (2025)

[**Artificial Intelligence and the Future of Work**](#)

Synthesizes evidence and expert perspectives on AI's long-term effects on work and productivity.

Business Insider

Nolan (2025)

[**The tech industry wants to create an AI utopia. Its leaders think Universal Basic Income is the answer**](#)

Profiles tech leaders' visions for AI-driven economic change and universal basic income.



Cao et al (2023)

[A Comprehensive Survey of AI-Generated Content \(AIGC\): A History of Generative AI from GAN to ChatGPT](#)

Reviews the evolution of generative AI technologies from early models to modern LLMs.

McAfee (2024)

[Generally Faster: The Economic Impact of Generative AI](#)

Generative AI as a general-purpose technology.

Deming, Ong, and Summers (2025)

[Technological Disruption in the Labor Market](#)

Examines how emerging technologies, including AI, are reshaping skill demand and inequality.

Roser (2023)

[AI timelines: What do experts in artificial intelligence expect for the future?](#)

Analyzes expert surveys to forecast the expected pace of AI development.

Jones (2023)

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Explores how increasingly capable AI could reshape long-run economic growth, labor markets, inequality, and potential risks.

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Brookings

Alikhani, Harris, and Patnaik (2025)

[How are Americans using AI? Evidence from a nationwide survey](#)

Analyzes national survey data to show how Americans are adopting AI tools, highlighting differences by age, education, and income.

Brookings

Muro, Methkuppally (2025)

[AI seems everywhere, but regional readiness is uneven](#)

Shows that while AI adoption is widespread, regions vary significantly in workforce preparedness, infrastructure, and economic capacity to benefit.

Brookings

Baily et al. (2025)

[Generative AI at the crossroads: Light bulb, dynamo, or microscope?](#)

Argues that generative AI could transform productivity in multiple ways, depending on whether it augments creativity, efficiency, or analysis.

Brookings

Alikhani (2025)

[Breaking the AI mirror](#)

Explores how AI systems can reinforce existing social and economic biases unless intentionally designed and governed otherwise

Brookings

Baily and Kane (2025)

[Harnessing AI for economic growth](#)

Examines how strategic AI investment and policy choices can drive productivity growth while minimizing inequality.

Athey et al. (2026)

[The Heterogeneous Earnings Impact of Job Loss Across Workers, Establishments, and Markets](#)

Applies causal machine learning methods to study how earnings losses after job displacement vary with observable characteristics that may be relevant for targeting policy interventions for workers..

□ ABOUT THE AUTHOR



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Fiona is an Economics Ph.D. candidate at Harvard University, affiliated with Opportunity Insights and the Stone Program in Wealth Distribution, Inequality, and Social Policy. Her research examines the economic impacts of new technologies. She holds a B.S. in Mathematics and Economics from MIT.



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