Proactively Developing & Assisting the Workforce in the Age of AI

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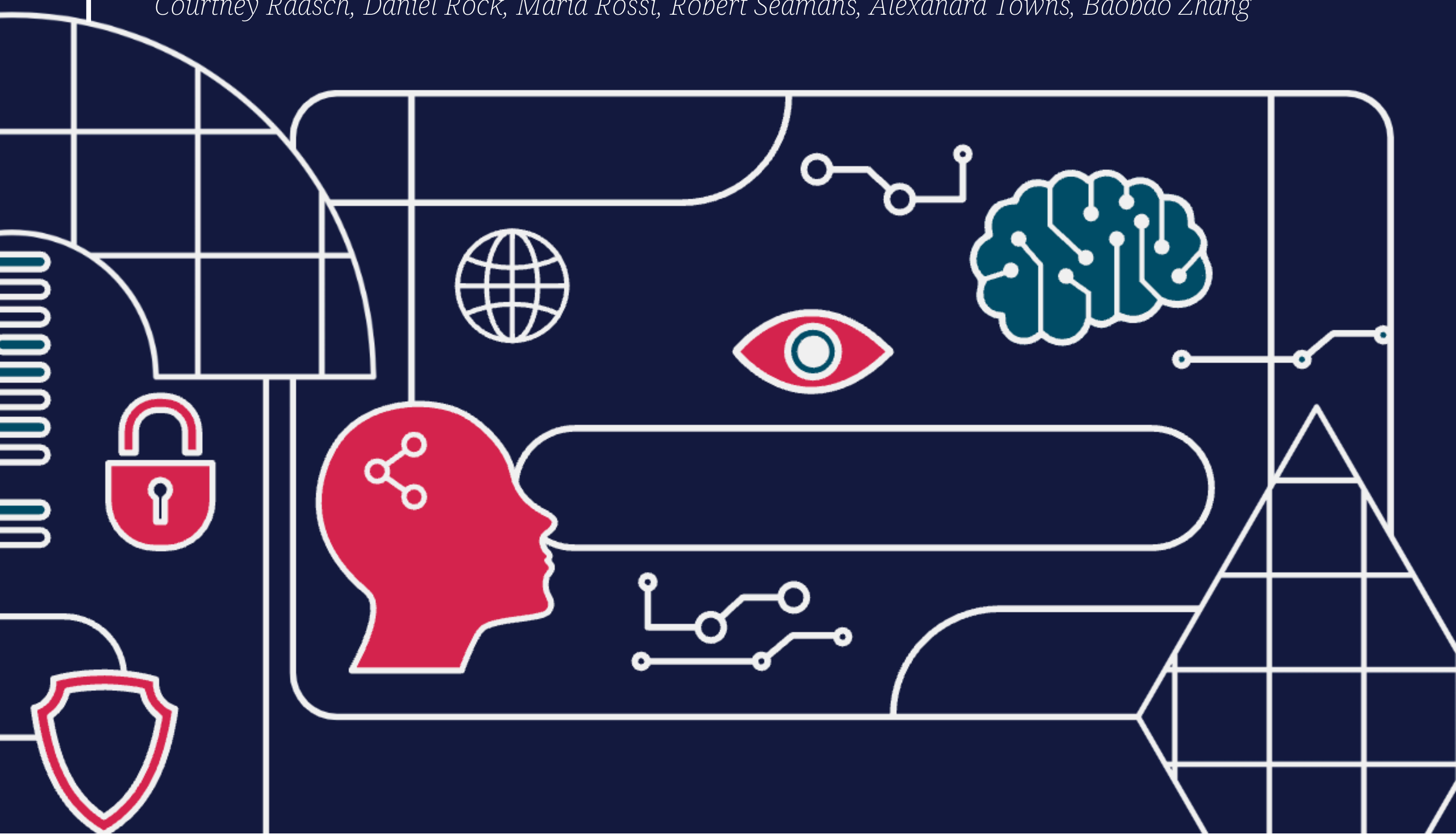

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Proactively Developing & Assisting the Workforce in the Age of AI

Executive Summary

The rapid advancement of artificial intelligence (AI) technologies presents substantial opportunities and risks for the workforce. This white paper examines the impacts of AI on labor markets, identifies critical policy gaps, and proposes policy options to proactively manage labor market disruptions and maximize economic opportunities. It is the outcome of a workshop on AI and labor policy, organized by the Keough School of Global Affairs and the Institute for Ethics and the Common Good at the University of Notre Dame, held in Washington, D.C., on March 11, 2025. The paper is co-branded and distributed in collaboration with Americans for Responsible Innovation.

Basics

AI has been advancing in significant ways in recent years with improved data, compute, and algorithmic innovation. The public release of ChatGPT and the rise of generative AI (GenAI) and large language models (LLMs) was a watershed moment that aroused significant public interest in the technology. They also exposed many tasks to potential automation that were previously seen as immune to automation, such as those in the creative industry. AI technology continued advancing with the introduction of reasoning models and now AI agents, which has further raised concerns about labor market disruption. Further, physical AI (AI-powered robots) is an emerging field that has lagged GenAI, but could cause even further labor market disruption. Finally, artificial general intelligence (AGI) is the most speculative area of AI, but many have become more concerned about the radical impacts it could pose on labor market impacts if it comes to fruition.

The economic literature on AI is emerging, finding both potential benefits and risks that could reshape the economy. While AI has the potential to significantly boost productivity and open new avenues of work and skill development, it also poses considerable displacement risks, notably in industries reliant on creative and analytical work. Empirical research provides mixed evidence of AI's impacts, indicating varying degrees of task substitution and productivity benefits across occupations, sectors, and demographics.

The United States has an established labor policy landscape for educating, training, and retraining workers that will be critical for navigating the changes AI will bring to labor markets. This includes K-12 education, career and technical education, higher education, and other workforce programs and institutions. Further, the government has recently been leveraging AI related work-based learning programs.

Policy Options

The paper focuses on policy options across four areas:

1. Data, research, and measurement
2. Workforce development and education
3. Social safety nets
4. Place-based and industry-level policies

1. Data, Research, and Measurement

Policymakers should have timely and quality data to address the labor market challenges that AI brings. Enhanced data collection can enable policymakers to better monitor and understand AI's labor market impacts, while enabling them to better forecast and respond to rapid change.

Statistical agencies can improve on existing government data collection efforts by making data systems more timely, granular, and flexible. Several databases that this paper suggests improving include the Standard Occupational Classification (SOC) system, O*NET, the Occupational Requirement Survey (ORS), and the Business Trends and Outlook Survey (BTOS). Further private sector data sources can be leveraged to fill critical gaps through public private partnerships that develop mechanisms for secure and ongoing collaboration between government and industry. New government data initiatives, especially ones tracking individual workers long-term to better study the impacts of AI and policy interventions, can also help improve policymaking.

Policymakers should also work on improving institutional capacity at statistical agencies to maximize effectiveness and impact. Improving data system integration, coordinating agencies and standard setting, and appropriately funding cross-agency data collection are several ways to help with this effort. Further, AI can be used for better data collection and management, so agencies should work on ways to best leverage the technology.

2. Workforce Development, and Education

Education and workforce training must significantly adapt to meet the challenges AI brings and empower workers. If they are effective, they can vastly improve work productivity and competitiveness in the AI-driven economy while ensuring that workers share in these benefits.

Policymakers should modernize the educational system to incorporate AI literacy. K-12 education, Career and Technical Education (CTE), and higher education should incorporate AI literacy and skills that complement AI (such as critical thinking, creativity, social interactions and judgment) into their curriculum, which will enable AI to augment their productivity rather than replace them. Further, we should develop and expand outcome-based "talent finance" models for workforce development (such as income-share agreements or outcome-based loans) that can help people access quality programs without fully bearing the costs and risks of doing so.

Additionally, policymakers should modernize workforce training programs to meet the labor market demands of the AI-driven economy. Quality workforce training programs should be supported through the renewal of the Workforce Innovation and Opportunity Act (WIOA) and extending the Federal Pell Grant program (beyond recent legislative changes) to cover more high quality short-term training programs. Further, the human-centered dimensions of AI adoption, like beliefs and emotions, should also be understood and incorporated into training.

Policymakers should finally focus on building lifelong learning infrastructure. In addition to identifying quality programs for delivering this learning, such as apprenticeships, policymakers should also focus on financing mechanisms and developing portable "skill wallets". Finally, these programs should be regularly tested and evaluated for cost effectiveness and impact.

3. Social Safety Nets

Social safety net programs can provide considerable support for displaced workers and will likely be critical in the face of job displacement from AI. However, policymakers have philosophical differences about the size and role of social safety nets as well as concerns about their fiscal costs and potentially negative impacts on employment. Policymakers have multiple options on how to reform the social safety net programs that will in part be based on their political views and beliefs in how severe they expect job disruption from AI to be. Trigger mechanisms that automatically scale up or down safety net programs based on economic data can be a middle ground between more conservative and pro-active approaches, but policymakers should take the best from the different approaches to come up with their ideal political compromise.

Policymakers can lean on various safety net programs to address job displacement and its impacts. Unemployment insurance, wage insurance, tax credits (like the Earned Income Tax Credit and Child Tax Credit), subsidized jobs, and health insurance programs are various tools that can be leveraged to manage the downsides of job disruption, each with their benefits and drawbacks. Further, since many technologists have argued job displacement will be more extreme than many economists have predicted, more dramatic measures (such as basic income programs) should be critically evaluated to understand their benefits and downsides if these extreme scenarios play out.

Finally, policymakers should promote the operational readiness of our major social safety net programs. These programs have faced major stresses in the past, such as during the COVID-19 pandemic, that led to significant inefficiencies and problems. AI job disruption can similarly cause major stress to these programs and would benefit from early efforts to improve their operational efficiency through efforts such as modernizing their technology and fraud detection infrastructure.

4. Place-based and Industry-Level Interventions

The disruptions from AI can impact certain regions or industries especially hard, worsening existing economic disparities or mismatches between the availability of and demand for workers. This is because workers and industries cluster, and AI is expected to have uneven effects. To address these kinds of inefficiencies and inequities, policymakers should consider place-based or industry-level interventions (such as those deployed by the CHIPS Act) in these scenarios.

In regions with strong growth but a shortage of appropriately trained workers, place-based and industry interventions should focus on workforce training and better matching workers with local firms and industries. This can be done through expanding quality sectoral training programs and partnerships between regional employers and skill providers. However, it should be noted that the best programs are difficult to scale and require expensive support services.

In regions that are economically depressed or lagging, economic development should be a higher priority. However, economic development is complicated and difficult in practice, so quality data and research about what could work in a specific region is critical.

Regional "Tech Hub" programs can be studied and evaluated as a potential model for industrial strategies.

Conclusion

To effectively navigate the transformative effects of AI, policymakers must adopt proactive, evidence-based strategies that prioritize agility, equity, and sustainable workforce adaptation. Ultimately, coordinated and informed actions with stakeholders—including governments, educational institutions, businesses, and communities—will determine how successfully society navigates the transformative age of AI, securing both economic prosperity, social stability, and worker dignity.

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1 Introduction

Artificial intelligence (AI) capabilities have been advancing at an unprecedented pace. Broadly defined, AI encompasses systems or machines capable of performing tasks that typically require human intelligence, such as recognizing patterns, making decisions, learning from experience, and generating new content and outputs. In recent years, the focus of AI development has transitioned significantly from traditional machine learning algorithms, which excelled at predictive tasks based on historical data, to more advanced Generative AI technologies capable of producing new content. With the public release of ChatGPT in late 2022, Generative AI, particularly Large Language Models (LLMs), has rapidly permeated various aspects of our daily lives, including our work. The evolution in AI technology has raised critical questions about both potential disruptions and opportunities for labor.

Initially, concerns about AI-driven job displacement primarily involved occupations reliant on predictive tasks where machine learning increasingly outperformed humans (Agrawal et al., 2018). However, the emergence of LLMs shifted attention toward professions involving editing, writing, coding, and content creation, areas once considered resistant to automation. More recently, AI models have demonstrated capabilities in creative domains such as art, design, and even in activities like research and development, further expanding the potential for labor disruption. The latest in AI development, Agentic AI, introduces models capable of autonomously executing tasks such as searching the web, managing schedules, making reservations, and potentially performing the entire spectrum of computer-based worker tasks (Dominski and Lee, 2025).

This white paper aims to suggest policy options to navigate the emerging disruptions and leverage opportunities offered by rapid AI advancement.

1.1 Concerns: Labor Disruptions Risks

The rapid advancement of AI technologies presents significant risks to employment, especially as these systems increasingly automate tasks traditionally performed by human workers. Research examining the impacts of AI on the labor market has produced mixed findings. Some studies find productivity-enhancing outcomes (Babina et al. 2024; Bick, Blandin, and Demming 2024; Brynjolfsson, Li, and Raymond 2023; Noy and Zhang 2023; Peng et al. 2023), while others find evidence of labor displacement (Acemoglu and Restrepo 2021; Gathmann, Grimm, and Winkler 2024; Hampole et al. 2025; Kogan et al. 2023; PMP Strategy Report 2024).

Though evidence of mass job displacement directly attributable to AI remains currently limited, the rapid development and deployment of Generative AI and Agentic AI capabilities has increased concerns about imminent, widespread disruptions (Cutter and Weber 2025; Herrera and Cutter 2025; Herrera 2025; Roose 2025). AI systems now exceed simple automation of routine tasks, demonstrating capabilities in advanced analytical tasks, creative content generation, and autonomous execution of multifaceted digital tasks. With declining computing costs and technological advancements, significant labor market disruptions could become evident in specific sectors or regions, particularly if AI adoption intersects with broader economic shocks or business-cycle fluctuations.

1.2 Opportunities: Productivity, Adaptation, and Skill Development

Despite potential disruptions, AI also offers substantial opportunities to boost labor productivity and relieve workers from repetitive, arduous tasks. Furthermore, it can provide avenues for workers to upgrade their skills and transition into emerging roles, highlighting the importance of robust training systems aligned with employer needs. Whether workers ultimately benefit from AI or experience displacement or wage reductions depends substantially on their ability to adjust and adapt effectively. Successful adaptation may occur through on-the-job learning—enabling workers to complement and leverage AI technologies—or through proactive skill acquisition prior to experiencing displacement or wage decline. Ideally, workers initially at risk of substitution by AI would transition into roles where their skills are augmented by these technologies. The capacity to adapt successfully will vary significantly across occupations, industries, and workforce demographics, especially by age and education level.

Employers will also be pivotal in shaping these adaptation processes; some may actively assist their workers, while others might offer minimal support. The degree of AI-driven task displacement will further influence employer incentives. For example, partial displacement (20-30% of tasks) could encourage active employer engagement in worker adaptation, whereas extensive displacement (70-80%) may substantially weaken such incentives. Employer biases based on education, race, gender, or age may also influence decisions regarding worker assistance. Moreover, the current tax system inherently favors investments in new capital (like AI systems) over supporting existing labor, further complicating this landscape (Acemoglu et al. 2020).

Simultaneously, as AI integration accelerates and reshapes job roles, the U.S. economy will face significant demographic challenges, including a dramatic slowdown in population and employment growth. The latest Congressional Budget Office (CBO, 2025) projections anticipate deaths surpassing births by 2033, coupled with substantially reduced average monthly employment growth over the coming decade . With the U.S. fertility rate persistently at a historic low of 1.6—well below the replacement rate of 2.1— there will be increased economic pressure to enhance worker productivity through automation and AI-enabled solutions (Lee et al. 2025).

1.3 White Paper Goal and Objectives

Recognizing this critical juncture, this white paper offers policy recommendations aimed at helping American workers and organizations navigate both the potential disruptions and opportunities presented by advances in AI. This white paper is the outcome of a workshop on AI and labor policy, organized by the Keough School of Global Affairs and the Institute for Ethics and the Common Good at the University of Notre Dame, held in Washington, D.C., on March 11, 2025. It incorporates subsequent discussions among workshop participants who expressed interest in co-authoring the report, along with contributions from a diverse group of stakeholders, including academics, industry professionals, and members of think tanks. The paper is co-branded and distributed in collaboration with Americans for Responsible Innovation.

We believe that proactively developing labor policies related to AI is essential to safeguard workers' dignity and economic prosperity, as well as to prevent potential societal instability. Reactive approaches alone may fall short given the scale, complexity, and rapid pace of AI-driven changes in the labor market. Although AI policy discourse has largely centered on technological innovation, market dynamics, and global competition, concrete strategies for labor market disruption remain underdeveloped. This white paper aims to fill this gap, emphasizing pragmatic policies implementable at federal and state levels and adaptable to international contexts.

The remainder of this paper is structured as follows: (a) Section 2 explores current and emerging AI capabilities; (b) Section 3 provides empirical evidence regarding AI's labor market impacts; (c) Section 4 reviews existing labor policy landscape; and (d) Sections 5 through 8 provide policy options: Section 5 addresses data, research, and measurement; Section 6 covers workforce development and education; Section 7 discusses social safety nets and worker support; and Section 8 examines place-based and industry-level policies. We conclude by emphasizing the importance of coordinated and evidence-based actions across interconnected policy areas.

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2 The State of AI Development and Implications for Labor

In this chapter, we discuss current and future AI capabilities with an eye toward applications and their relation to work. With the release of ChatGPT, discussion and interest around AI capabilities have often focused on generative AI. Prior to the release of ChatGPT, AI capabilities centered around predictive machine learning, and it is worth noting that the development and application of predictive machine learning have continued to expand even after the shift in focus to generative AI. Robotics research also continues to develop, with many applications in industry. The combination of robotics and AI, now often labeled "physical AI," will likely see expanded use in work settings in the near future. We start this section with current model capabilities and recent developments, after which we discuss near-future developments and applications. We conclude with some speculation on the implications of powerful AI systems for labor.

Summary of ChatGPT Model Capabilities

(Dominski and Lee, 2025)

TABLE A

MODEL	RELEASE DATE	KEY FEATURES
GPT-3.5	November 2022	First widely usable ChatGPT; fast, low-cost, text-only
GPT-4	March 2023	Major improvement in reasoning and reliability; text-only
GPT-4o	May 2024	First truly multimodal GPT model with text, image, audio inputs and outputs
GPT-o1	December 2024	First Reasoning model with improved chain-of-thought reasoning
GPT-o3	April 2025	Enhanced reasoning, math, coding, long-context support
GPT-5	August 2025	Current default.

2.1 Current AI Capabilities and Applications

2.1.1 Predictive Machine Learning

AI describes a broad set of computing techniques with the capacity to perform functions that would ordinarily require human intelligence, and in some cases AI capabilities can exceed human performance. Before the introduction of large language models like ChatGPT, machine learning was the most widely developed and used. Especially through neural networks, along with the availability of massive amounts of training data and computing power, machine learning enabled an expansion of applications. In supervised machine learning, with a sufficient amount of input data and some labeled outcomes, a model can be trained to predict the outcome when fed new data (Brynjolfsson and Mitchell, 2017). With continuous improvements in training data, model architecture, and compute power, machine learning algorithms are able to outperform humans in many prediction tasks. These functions include natural language processing (NLP), computer vision (CV), and predictive modeling, with widely used examples such as chatbots, text generation, object and facial recognition, autonomous driving, and recommendation engines. Accordingly, the potential benefits of machine learning include the automation of cognitive tasks such as categorization, perception, and problem-solving, which have widespread applications across various work settings.

As Agrawal et al. (2018) highlight, the key feature of machine learning is prediction that can be directly adopted and accepted by humans, or adopted with minor adjustments. Machine learning algorithms have the unique ability to self-improve their predictive power through repeated training and ultimately perform highly cognitive tasks. For example, pharmaceutical firms have introduced AI techniques to assist in drug discovery during the early stages of R&D by suggesting possible molecular syntheses (Lou & Wu, 2020). Banks have applied AI techniques to better manage risks by predicting fraud and the likelihood of loan defaults (Manser Payne et al., 2021). Consequently, AI could enhance productivity via at least three important mechanisms: (1) automating tasks, (2) reducing human errors and biases, and (3) helping discover new business opportunities (Lee et al., 2022).

Machine learning algorithms are used to analyze data, forecast outcomes, and support decision-making in areas such as healthcare, finance, retail, and manufacturing, among others. Brynjolfsson and McAfee (2017). These applications range from personalized treatment recommendations and fraud detection to predictive maintenance and adaptive learning. Table B presents some use cases, but the applications continue to expand in not only the private sector but also in public service, government administration, and military applications. By automating cognitive tasks and improving accuracy, predictive machine learning contributes to increased efficiency, reduced errors, and enhanced productivity across diverse work environments.

Applications of Predictive Machine Learning

TABLE B

SECTOR	APPLICATION	DESCRIPTION
Healthcare	Predictive diagnostics and treatment optimization	Machine learning models analyze patient data to predict disease progression and recommend personalized treatment plans, enhancing patient outcomes, and resource allocation.
Finance	Credit scoring and fraud detection	Algorithms assess creditworthiness by analyzing financial behaviors and detect fraudulent activities in real-time, improving decision-making, and security.
Retail	Demand forecasting and personalized marketing	Predictive models forecast product demand and tailor marketing strategies to individual customer preferences, increasing sales, and customer satisfaction.
Manufacturing	Predictive maintenance and quality control	Sensors and machine learning predict equipment failures and monitor production quality, reducing downtime, and ensuring consistent product standards.
Transportation	Route optimization and autonomous vehicle navigation	Algorithms optimize delivery routes for efficiency and guide autonomous vehicles by interpreting sensor data, enhancing safety, and reducing operational costs.
Human Resources	Talent acquisition and employee attrition prediction	Machine learning analyzes candidate data to improve hiring decisions and predicts employee turnover, aiding in workforce planning.
Education	Personalized learning and student performance prediction	Adaptive learning platforms use predictive analytics to customize educational content and identify students at risk, facilitating timely interventions.
Energy	Load forecasting and predictive maintenance of infrastructure	Models predict energy demand and anticipate equipment failures in grids and plants, ensuring reliable service and efficient maintenance scheduling.
Government	Public safety prediction and resource allocation	Machine learning models analyze historical crime data, emergency incidents, and demographic patterns to predict public safety risks, optimize emergency responses, and allocate public resources effectively.

2.1.2 Large Language Models and Generative AI

With the public release of ChatGPT in November 2022 and the "Attention is All You Need" paper establishing the transformer architecture (Viswani et al., 2017), large language models (LLMs) have been at the forefront of AI development and adoption. LLMs build on many core features of earlier machine learning algorithms, particularly those involving natural language processing for tasks such as text prediction and translation. However, their key innovation lies in a model architecture known as the *transformer*, which allows models to process vast amounts of text while accounting for the broader context of each word within a sentence or paragraph. This architecture enables LLMs not just to analyze but to generate coherent and contextually relevant content—an unprecedented advancement in natural language understanding.

Large language models represent one of the most significant breakthroughs in AI applications to date. According to the Financial Times, OpenAI recently stated that ChatGPT's users comprise around 10 % of the global population (Financial Times, 2025) and its adoption has outpaced that of previous general purpose technologies (Bick et al. 2024). Trained on massive datasets of text (and increasingly, images and other media), LLMs such as GPT-4, released in 2023, have demonstrated human-level performance on a range of professional and academic tasks. For example, GPT-4 scored in the top 10% of test-takers on a simulated bar exam (OpenAI, 2023). Use of these tools is pervasive in many different domains, with especially high levels of engagement in software-related tasks (Handa et al., 2025).

Generative AI systems, built on LLMs, now produce essays, computer code, marketing reports, and more (Table C) by predicting the most likely next word in a sequence based on learned language patterns as well as information searched online. Pre-Training for these systems involves converting input data into sequences of tokens and building internal representations of concepts represented by token sequences. That is, first the source material is used to build an encoding of content that can subsequently be referenced to create decoded sequences (in response to an input prompt, for example). Importantly, these capabilities extend well beyond text. Tools such as DALL·E 3 and Midjourney generate highly realistic images from text prompts, and recent advancements (e.g., Sora) have made it possible for AI to produce high-quality video content as well (Stanford AI Index, 2025).

As these models acquire multimodal capabilities—handling text, images, audio, and video—they are referred to as generative AI more broadly. They can now perform text-to-image, text-to-video, and even image-to-text and video-to-text tasks, expanding the boundaries of automation to include creative and interpretive tasks.

Applications of Generative AI

TABLE C

SECTOR	APPLICATION	DESCRIPTION
Education	Automated tutoring and content generation	LLMs generate personalized feedback, quizzes, and study materials; adaptive tutors assist students in real-time across subjects.
Healthcare	Clinical documentation and synthetic data creation	Generative AI summarizes patient visits, generates clinical notes, and creates synthetic data for training models while preserving patient privacy.
Finance	Report drafting and scenario modeling	Generate market reports, summarize earnings calls, and assist in financial forecasting with natural language interfaces.
Legal	Contract generation and legal brief writing	LLMs assist in drafting contracts, summarizing case law, and generating first drafts of legal documents.
Marketing	Campaign content creation and customer engagement	Generative AI tools craft emails, social media posts, and ad copy; chatbots powered by LLMs provide real-time customer support with high fluency.
Media & Entertainment	Scriptwriting and virtual character development	Generate movie scripts, plot ideas, and even video clips; game studios use AI to create dynamic characters and dialogue.
Software Engineering	Code generation and debugging	Assist developers by generating code snippets, explaining code, and detecting bugs across multiple programming languages.
Architecture & Design	Concept visualization and prototyping	Generate conceptual images and iterate design options from natural language descriptions.
Human Resources	Job description writing and candidate outreach	Streamline recruiting processes by drafting job postings, screening resumes, and generating personalized messages to candidates.
Scientific Research	Hypothesis generation and literature review	Assist in literature searches, summarization, and even in proposing experimental designs or computational simulations.
Government	Policy drafting and public communication	Generative AI tools draft policy documents, summarize legislative texts, and produce accessible public communications.

One key concern with generative AI models is hallucination, in which these models fabricate information and present them convincingly. Because generative AI models are designed to predict and suggest plausible text continuations, they occasionally produce inaccurate or completely fabricated statements. Moreover, their current design and training often present probabilistic outputs as definitive statements, exacerbating this issue. Such hallucinations have led to real-world problems with serious consequences, including notable examples involving a lawyer referencing fictitious cases (New York Times, 2023) and inaccuracies from Air Canada's chatbot recommendations (Washington Post, 2024). Nevertheless, hallucination rates appear to decline as model size and quality increase (Ul-Islam et. al., 2025)

To address hallucinations and better understand the cognitive processes of these models, AI developers have focused on enhancing reasoning capabilities, resulting in the development of reasoning models. These models incorporate techniques such as chain-of-thought prompting, where inference tasks are systematically decomposed into sequential logical steps, similar to how humans would solve a problem (Wei et al. 2022). Recent advancements in reasoning models have improved reliability, interpretability, and performance, particularly in analytical tasks, for example, mathematics. Consequently, reasoning models have significantly expanded AI's applicability in domains requiring logical reasoning and clear rational explanations, including scientific research, law, and management.

2.2 Emergent Capabilities

2.2.1 Agentic AI

A key emergent AI capability is agentic AI, that is systems capable of autonomously performing multistep tasks by integrating reasoning, planning, and execution. Like some forms of traditional software, AI agents can execute tasks in sequence. Unlike traditional software, agents "independently" determine how to achieve goals using advanced reasoning capabilities provided by large language models. Recently coding agents have been able to perform the full spectrum of coding tasks and develop and launch software applications with minimal human involvement.

AI agents also leverage external tools and resources, enhancing their autonomy. For instance, an agent might autonomously choose to use calculators, databases, or APIs to perform tasks effectively. Early versions showcased promising results, outperforming humans in constrained scenarios like coding competitions (Stanford AI Index, 2025). However, current AI agents still exhibit significant limitations, particularly with complex tasks requiring deep common-sense reasoning. Nevertheless, their ongoing development indicates substantial potential for roles such as executive assistants, project managers, and specialized domain agents (Table D), particularly as multimodal capabilities—processing both visual and textual data—continue to improve (Brynjolfsson & Mitchell, 2025). Notably, the definition of an AI "agent" remains a topic of disagreement. The important component of agentic AI for the time-being appears to be the potential of these new systems to execute tasks on your behalf, or alternatively, the ability of LLM-based systems to call other tools to solve problems (Willison, 2024).

Potential Future Applications of Agentic AI

TABLE D

APPLICATION	DESCRIPTION
Personal Chief of Staff	An agent could manage your calendar, screen and respond to emails, prioritize daily objectives, delegate tasks to other agents, and prepare materials ahead of meetings—all with minimal human oversight.
Autonomous Research Assistant	Given a research question, an agent could search academic databases, summarize findings, run simulations or statistical analyses, and generate first-draft papers or memos.
AI Product Manager	In a tech firm, an agent could gather customer feedback, prioritize product feature requests, coordinate with design and engineering agents, and write specs based on internal and external data.
24/7 Legal and Compliance Monitor	A law firm or regulatory agency could deploy an agent to continuously scan new regulations, flag potential compliance risks, draft initial responses, and propose mitigation strategies.
Self-Updating Knowledge Base Manager	In corporate environments, agents could continuously read new documentation, Slack messages, and meeting notes to keep company wikis and SOPs current without human input.
Field Technician Companion	In industrial settings, multimodal agents could guide field workers by interpreting visual input (e.g., identifying damaged equipment) and suggesting context-aware repairs or ordering replacement parts via API access.

2.2.2. Physical AI / Advanced Robotics

While generative AI has rapidly progressed in recent years, advances in robotics have been more gradual – illustrating the difficulty of automating fine-motor tasks that can easily be performed by humans, such as touch, gripping, and real-time adjustments. AI-powered robots are increasingly being used in manufacturing, warehouses, and retail environments. For example, autonomous warehouse robots manage e-commerce fulfillment, and self-driving vehicles, such as Waymo's autonomous taxis, operate in select cities (Stanford AI Index, 2025). However, general-purpose robots capable of adapting flexibly to unpredictable human environments remain less developed. Tasks requiring complex manual dexterity and real-time environmental adaptation continue to pose significant challenges for robotics. Early assumptions suggested that physical automation would greatly disrupt the workforce first, but language models and cognitive automation have proven more immediately impactful (Brynjolfsson & Mitchell, 2025).

Despite this slower pace, advancements such as robots from Boston Dynamics and Figure illustrate ongoing improvements in mobility and manipulation. Research combining LLMs with robotics to enhance task planning indicates future possibilities, such as household assistant robots or robotic medical aides (Table E) (Stanford AI Index, 2025).

Potential Future Applications of Physical AI / Advanced Robotics

TABLE E

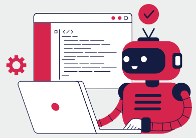
APPLICATION	DESCRIPTION
Household Assistant Robots	Robots capable of performing a wide range of domestic tasks, such as cooking, cleaning, folding laundry, and setting up for events, by interpreting natural language commands and adapting to unstructured environments.
Elder Care and Medical Support Robots	Robots that assist with lifting, mobility, medication reminders, and vital sign monitoring—particularly valuable in aging societies with healthcare labor shortages.
Construction Site Robots	Autonomous robots that can transport materials, lay bricks, perform basic framing, or conduct inspections in real-time, improving efficiency and safety on dynamic job sites.
Hospitality and Service Bots	Multi-functional robots for hotels, restaurants, and airports that manage front-desk tasks, deliver room service, guide travelers, and respond to guest inquiries in natural language.
Agricultural Robotics	Dexterous robots capable of identifying and picking ripe crops, removing weeds, and monitoring soil conditions—enabling precision agriculture and reducing labor demand in rural areas.
Disaster Response and Recovery Units	Rugged, mobile robots that can navigate debris, detect survivors, and deliver supplies in post-earthquake or hazardous environments, reducing risk to human responders.

2.3 AGI and Implications for Labor Policy

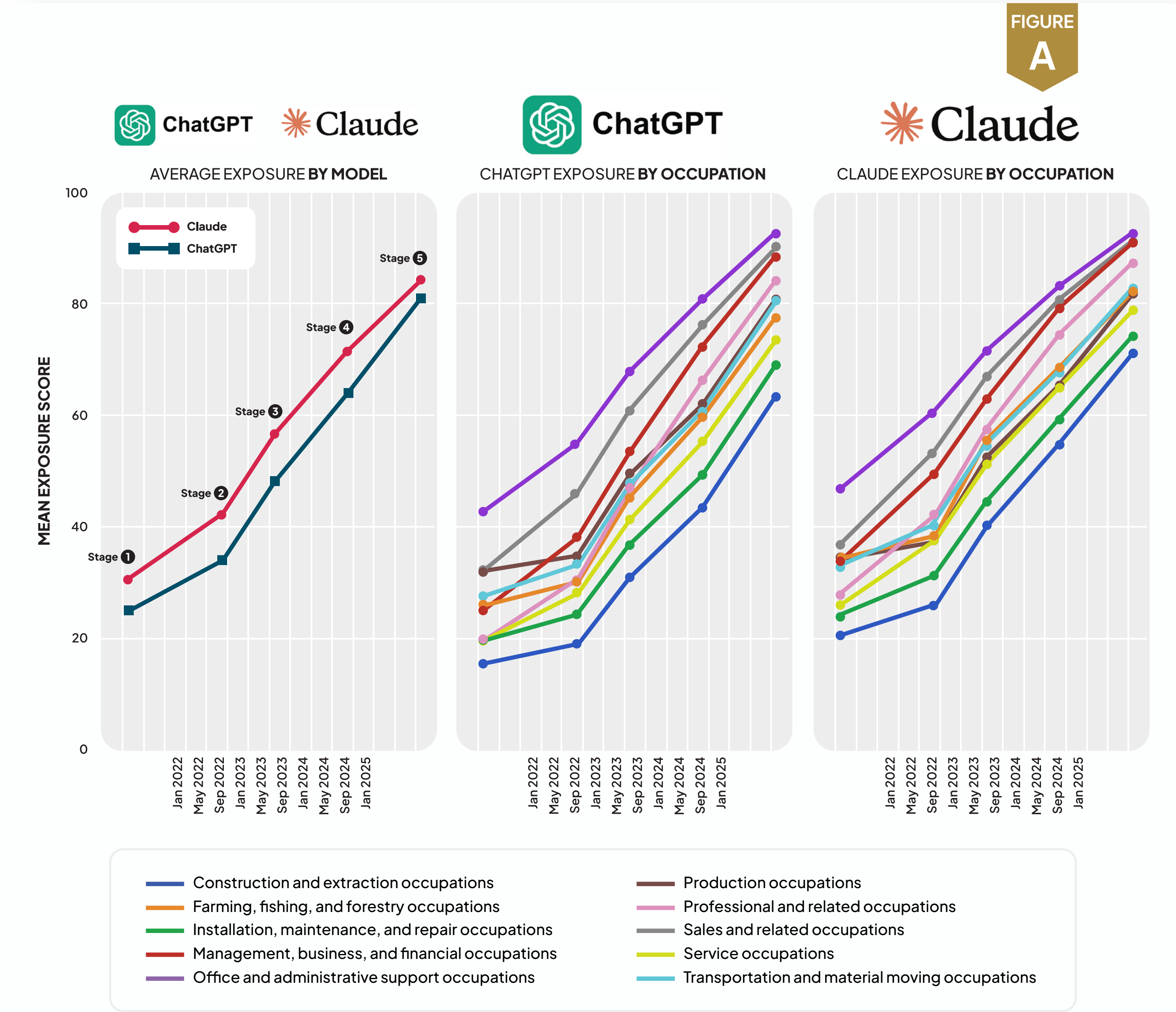
There have been considerable debates and concerns about so-called Artificial General Intelligence (AGI) in recent years. Although the definition of AGI remains unclear and terminology varies among technologists, AGI generally refers to an AI system possessing human-level intelligence and capabilities across a broad range of tasks. On the path towards AGI, AI systems are likely to develop superhuman capabilities in specific tasks that computing systems naturally handle better.

Despite ongoing debates regarding the precise definition or timing of AGI's arrival, for the purpose of this report, we define AGI as an AI system capable of performing nearly all tasks currently performed by human workers at a comparable level. Rather than exclusively analyzing AI's current impacts on the economy and workforce, it is prudent to anticipate future impacts. Indeed, OpenAI's charter explicitly defines AGI as autonomous systems outperforming humans at most economically valuable work. While we will not speculate on implications in a manner similar to more speculative reports (e.g., AI 2027), we remain cognizant of the possibility of large-scale labor disruptions in certain sectors if AI systems continuously advance. Our aim is to ensure that our recommendations are as forward-looking and resilient as possible.

One practical approach to conceptualizing AGI involves assessing the share of occupational tasks an AI system could potentially perform. Dominski and Lee (2025) analyze this share across various stages of AI capabilities to construct an occupational AI exposure measure. As illustrated in Figure 1, AI exposure across occupations rises from approximately 25% at Stage 1 to 82% at Stage 5. This suggests that prior to the release of ChatGPT, when AI primarily involved predictive machine learning (Stage 1), AI systems could potentially perform about 25% of occupational tasks. However, at Stage 5, characterized by AI agents capable of independently performing entire workflows, including prediction, analysis, synthesis, reasoning, and physical actions via robotics, AI could potentially execute about 82% of occupational tasks as outlined by the Bureau of Labor Statistics.



Advanced AI agents could potentially execute about 82% of occupational tasks in the future.



Timeline indicates when model capabilities were introduced. Organizational adoption and mature usage will occur with varying delays.

At the most advanced stage, AI can automate nearly all digitally feasible tasks. The remaining tasks tend to involve executive decision-making, empathy, conflict resolution, and highly complex physical interactions. Nevertheless, superhuman AI systems could theoretically undertake even these tasks, though whether such scenarios materialize will depend on numerous factors beyond economics, including political and ethical considerations. This raises critical questions: What implications arise if AI systems become capable of performing 90%, 95%, or even 99% of human occupational tasks? Of course, this potential outcome may still be many years in the future, but monitoring and documenting what jobs and who are being automated will be critical to understanding the potential impacts of superhuman AI systems on the labor market. Human work is highly improvisational and new task creation will likely reinstate workers into new roles (Acemoglu and Restrepo, 2017). Consideration of AGI in the future as a major workforce disruption catalyst suggests an ongoing need for high fidelity measurement of AI work capabilities now.

As AI systems advance, new businesses, products, and services will emerge and occupations and human tasks will evolve. In addition to the economic and technological forces, politics and ethical considerations will shape the nature of work. Labor policy can serve as a crucial mechanism for navigating these changes, shaping human work trajectories and ensuring human dignity in tandem with AI advancement. It is in this context that we explore and suggest key labor policies in the age of AI.

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3 Empirical Evidence on AI's Labor Market Impacts

Policies designed to assist workers in the age of AI should be grounded in empirical evidence and fundamentally ensure human dignity. In this section, we review the current state of research on AI's impact on labor markets. First, we discuss conceptual frameworks and approaches developed to understand and examine AI's effects on labor and productivity. Next, we review the relevant economic literature. Finally, we present case studies that provide deeper insights and nuanced perspectives on AI's impact on workers. Given that AI's influence on labor will likely continue evolving in the coming years, these conceptual frameworks, empirical findings, and case studies will also evolve. Policymakers should continue to examine and incorporate this evidence into their decisions.

3.1 Conceptual Frameworks

Recent approaches to understanding AI's impact on work have shifted from viewing occupations as a whole to looking at a task-based framework. The framework treats occupations as bundles of individual tasks that differ in their susceptibility to technological change. Using a task-based approach creates a more nuanced understanding of how AI technologies might substitute or complement human labor in different roles. However, the task-based approach is not without critics that think the approach is incomplete or insufficient, since it may not account for the boundaries between tasks well.

According to the new approach, technological change primarily affects employment and wages by reallocating tasks between labor and capital; new technologies automate some tasks, complement human work in others, and sometimes create new tasks over time, which in turn shape both labor demand and wage structures (Acemoglu and Autor 2011). Tasks that are more susceptible to automation are likely to experience slowed wage growth, while tasks complemented by technology may see gains in demand and compensation (Acemoglu and Restrepo 2021). Task-based frameworks can also be used as a tool to analyze the possibility of an occupation being entirely automated. By giving each task in an occupation a "suitability for machine learning" (SML) score, Brynjolfsson, Mitchell, and Rock (2018) find that while many occupations have one or more tasks susceptible to machine learning-driven change, few jobs have all tasks exposed, suggesting that machine learning is more likely to change the job structure on a task-based level instead of replacing entire occupations.

The task-based approach has provided a framework for measuring AI exposure and the potential impact of AI capabilities in numeric terms. By estimating the potential time savings that LLMs can provide for tasks, Eloundou et al. (2024) assess the exposure of U.S. occupations to LLMs. They find that approximately 19% of workers are in occupations where LLMs could significantly affect at least half of their tasks. Other studies have examined the potential impacts of specific AI technologies, such as language modeling and image recognition, by analyzing how closely AI capabilities align with the key abilities required for various jobs (Felten, Raj, and Seamans, 2023). An alternative application of task-based evaluation accounts for not only possible labor replacement by AI but also the possible complement that AI can bring to labor. The approach develops an occupational exposure index and then adjusts the baseline index for factors like job responsibilities, physical work contexts, and education and training requirements. The findings from this alternative approach show that advanced economies face higher exposure to AI overall, but this exposure is more likely to augment tasks rather than substitute for human work, meaning that highly educated workers are both more exposed to AI and more likely to benefit from it (Pizzinelli et al., 2023).

While exposure measures offer valuable insights into which occupations are technologically vulnerable to AI, they do not accurately predict how AI will be adopted in the workplace. Adoption depends not only on technical feasibility but on economic factors, such as the costs and benefits of implementing AI, the relative price of labor, organizational readiness, and regulatory environments (Acemoglu and Restrepo 2018, 2020). Since exposure does not always lead to adoption, adoption patterns, rather than technical exposure alone, ultimately shape labor market outcomes. (Auer, Köpfer, and Švéda 2024).

From a policy perspective, understanding both the potential exposure of occupations to AI and the likelihood of adoption is critical for designing effective interventions. Task-based frameworks, exposure indices, and complementarity adjustments together provide tools to identify which workers are most at risk and which may benefit from technological change. These insights can inform targeted reskilling and upskilling initiatives, support measures for displaced workers, and investments in education systems to better prepare future cohorts for an AI-transformed labor market.

3.2 Job Displacement vs. Job Creation

Since the emergence of generative AI tools and other advanced technologies, concerns about job displacement have re-entered public discourse, frequently framed as the potential for widespread automation-driven unemployment. In practice, AI adoption does not lead uniformly to job loss or gain. Instead, outcomes vary depending on how firms deploy new technologies, how work is reorganized, and whether workers receive support to adjust.

A growing body of research investigates whether AI adoption leads to the destruction of existing jobs or the emergence of new ones. Using U.S. administrative data, Kogan et al. (2023) analyze the effects of labor-saving technologies, such as automotive technologies and labor-augmenting technologies, which are often viewed as complements to labor. They find that labor-saving technologies are associated with lower earnings and a higher risk of job loss for workers, regardless of their level of education or income. Alternatively, labor-augmenting technologies tend to displace older and higher-earning workers whose skills may not align with new technological demands. These findings suggest that both forms of technological change can drive worker displacement, but through different channels, highlighting the need for policy responses that support both broad-based resilience and targeted retraining for experienced workers.

Building on this, Hampole et al. (2025) study how firms' adoption of AI affects employment across different types of jobs. They find that occupations in business, finance, and engineering are more likely to shrink, as many of their tasks, like data analysis, forecasting, or reporting, can be performed by AI systems. By contrast, jobs that combine both automatable and non-automatable tasks often grow as workers shift their focus to areas where human skills remain essential, such as communication, coordination, or problem-solving. Interestingly, even workers in jobs that are not directly exposed to AI may face fewer opportunities if they work in firms that lag behind in adopting the technology. These firms tend to grow more slowly, which can limit job creation across the board, suggesting that AI's labor market effects depend not just on the nature of the job but also on how flexibly firms and workers respond. This highlights the importance of training, task redesign, and broad access to productivity-enhancing technologies.

Looking more specifically at AI Chatbots, a study by Handa et al. (2025) analyzed more than four million conversations on Claude.ai to understand how AI is being used across economic tasks and occupations. They found that AI usage is concentrated in software development and writing tasks, which accounted for nearly half of all usage. Building on the tasks and occupations in the U.S. Department of Labor's O*NET Database, they found that AI is used for a quarter of tasks in 36% of occupations, while only four percent of occupations indicate usage of 75% or more of their tasks. They also analyze how AI is being used for tasks, and document that AI primarily augments human capabilities (57% of usage) rather than fully automating tasks (43% of usage). Additionally, recent empirical research in Denmark, where AI chatbots are widespread, found that AI chatbots have had no significant impact on earnings or recorded hours due to modest productivity gains amounting to time savings of just 3% and weak wage pass-through (Humlum and Vestergaard, 2025).

Complementing this firm-level evidence, a growing line of research examines how AI exposure affects the structure of labor demand, especially through changes in how jobs are defined and staffed. Acemoglu et al. (2022) examine how AI exposure reshapes employer demand by analyzing U.S. online job postings. They find that occupations with high exposure to AI technologies do not disappear entirely; rather, they see a modest reduction in overall job postings and a shift in the types of skills employers seek. Firms exposed to AI often reduce hiring for routine tasks while placing more emphasis on analytical, social, and technical skills. However, there is little evidence that AI adoption leads to higher employment or wages at the occupation or industry level. This suggests that while AI may not be eliminating jobs at scale, it is already transforming the content of work, highlighting the need for policies that help workers adapt to evolving skill demands.

At the worker level, scholars examine how individual workers fare when their employers adopt new technologies, including AI. Using data from Germany, Genz et al. (2021) compare long-term outcomes for workers in firms that adopted advanced digital technologies to those in non-adopting firms. They find that workers in adopting firms, particularly in the service sector, IT roles, and those with vocational training, tend to stay employed longer, earn higher wages, and accumulate higher total earnings. These findings underscore the importance of inclusive technology adoption strategies that support internal mobility and ongoing skill adaptation.

3.3 Productivity and Wage Effects

A central question regarding the emergence of AI is how it will affect productivity. One of the most prevalent ways to understand this is by examining the impact of AI on firm performance. By understanding how AI investments and adoption affect firm employment, revenues, and market performance, researchers aim to understand AI's broader labor market implications. However, recent studies indicate that firms adopting AI experience unchanged or diminishing returns compared to non-AI-adopting firms (Acemoglu et al., 2023; Vu et al., 2024). This is partly because adopters of advanced technologies such as AI and robotics tend to be larger than non-adopters and have faster growth rates before the introduction of these advanced technologies. They suggest that observed performance differences between adopting and non-adopting firms reflect pre-existing trajectories rather than the impact of AI adoption itself and that advanced technologies such as AI may have small negative effects on the employment trajectories of adopting firms. They argue that the automation potential of these technologies creates an ambiguous employment effect for adopters.

Babina et al. (2024) attempt to overcome this firm-level selection concern using resume and job vacancy data and deep learning to classify jobs by their AI-relatedness at the firm level. They find that increased firm-level AI-relatedness measures are associated with increased sales, employment, and market valuation. Conversely, Vu et al. (2024) examine the relationships between AI adoption and productivity growth in Canada. They find mixed evidence for the effects of AI adoption on productivity growth at the firm level and no evidence that AI influences total factor productivity levels or growth.

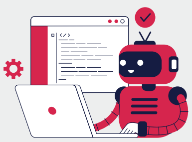
Firm-level studies also examine the effect of AI on market returns and firms' organizational structures. The studies find heterogeneity in the effect of exposure on market returns both across and within industries (Eisfeldt, Schubert, and Zhang 2023) and that adopting firms tend to restructure their workforce composition—bringing in more workers with undergraduate and graduate degrees along with technically skilled workers—-and flatten their hierarchical structures (Babina et al. 2022).

Using a task-based approach, combining previously established measurement tools (Eloundou et al. 2024, Noy and Zhang 2023, Brynjolfsson et al. 2023), Hulten's theorem, and accounting, Acemoglu (2024) estimates that the upper bound for AI-based TFP growth is 0.55% and for AI-based GDP growth is 0.90%. While he cautions that these estimates involve speculative assumptions, he demonstrates that using existing estimates and his theoretical framework, it is challenging to predict substantial macroeconomic gains from AI.

Other studies are far less cautious in their predictions. A Goldman Sachs (2023) report estimates that while AI could at least partially automate two-thirds of occupations, it could also increase global GDP by up to 7% (i.e., around $7 trillion) over a 10-year period. A McKinsey Global Institute (2023) report predicts even larger productivity and GDP gains, identifying 63 AI use cases that they estimate could create $2.6 trillion to $4.4 trillion of economic benefits annually. However, Brynjolfsson, Rock, and Syverson (2021) argue that productivity gains from AI may materialize slowly in national accounts. They claim that general purpose technologies (GPTs) create complementary investments that are hard to measure, leading to productivity growth being underestimated in early years and overestimated in later years.

AI's impact on productivity is also examined using experiments. Experiments in which a treatment group was given access to a form of AI while the control group was not found average time savings of 55.8% (Peng et al. 2023), 40% (Noy and Zhang 2023), and 14% (Brynjolfsson, Li, and Raymond 2023), respectively. Additionally, the greatest productivity gains were seen in older and less experienced individuals, with AI reducing the inequality related to pre-treatment task performance (Brynjolfsson, Li, and Raymond 2023; Noy and Zhang 2023; Peng et al. 2023).

To understand AI adoption and productivity gains at both the firm and individual levels, many researchers use surveys. An OECD (2025) report uses a survey of 840 firms in G7 countries and Brazil. They use this survey to document firm-level AI adoption and its challenges. They find heterogeneous adoption based on firm size, with lower adoption rates for smaller and mid-size firms. They find that 60% of firms rely on new staff to implement AI, while 20% of firms report difficulties hiring qualified candidates. The report also highlights the role of public sector institutions in aiding firm adoption.



Research finds that 60% of firms rely on new staff to implement AI, while 20% of firms report difficulties hiring qualified candidates.

Bick, Blandin, and Deming (2025) construct a nationally representative survey of AI usage, finding that approximately 40% of all adults in the U.S. utilize generative AI. They also find that occupational adoption rates are highly correlated with Eloundou et al.'s (2024) measure of the tasks that can be performed by AI. Based on respondents' reported time savings, they estimate an average time savings of 5.4% among generative AI users, which corresponds to 1.4% time savings among all workers. They use this estimate to compute total TFP gains of 1.1%, similar to that of Acemoglu (2024). In a survey of 100,000 workers in Denmark, Humlum and Vestergaard (2024) find that around 50% of Danish workers have adopted AI, workers predict large productivity gains from using AI, and the restrictions on use and the need for training were the largest barriers to AI adoption. Both surveys document a large discrepancy in gender-based adoption, with men much more likely to use generative AI.

Beyond productivity effects, researchers have also considered the effects of AI on job composition, labor market churn, and wages. Using a patent-based AI exposure measure and survey data on workers' tasks, Gathmann, Grimm, and Winkler (2024) find that AI has decreased the demand for abstract tasks and increased the demand for routine monitoring tasks in Germany. They also find that AI is associated with worker reallocation and a reduction in wages for low-skilled workers in exposed industries, whether they switch jobs or not. Conversely, they find that high-skilled workers in exposed industries see wage gains, potentially reflecting productivity gains or comparative advantage.

3.4 Case Studies by Industry and Occupation

Recent research has studied the effects of AI by examining specific tasks, industries, and occupations. As documented in many of the studies presented in this section, AI adoption is likely to have heterogeneous labor market effects, varying by experience, skill level, education, and occupation. By investigating the effects of AI on specific subgroups, researchers can have a better understanding of the factors driving AI-based labor market changes and the wider macroeconomic consequences of these changes.

Studies highlight how generative AI can enhance productivity in technical and professional writing tasks (Peng et al., 2023; Noy and Zhang, 2023), raising questions about the broader implications of such tools for creative labor. These tensions were visible in the 2023 Hollywood writers' strike, where concerns over the role of AI in scriptwriting became a central point of contention. In a Brookings report, Kinder (2024) argues that this technology has the potential to degrade writing jobs, undermine the career ladder for new writers, and erode recent gains made in the diversity of storytelling. These AI-based concerns were major sticking points in contract negotiations between Hollywood writers and studios, contributing to a 148-day strike. Ultimately, Hollywood writers secured a series of AI protections that regulate AI usage to increase benefits for writers and studios while reducing potential harm. Such labor action has the potential to set a precedent whereby workers gain the power to decide how to utilize generative AI to complement, rather than replace, their jobs. While only 9.9% of American workers are currently union members, according to the BLS, this case study highlights the potential for organized labor to influence the implementation and labor market impacts of AI (2024).

Besides writing, other creative professions may also be differentially exposed to AI. A PMP Strategy Report (2024) uses over 50 interviews with music industry experts to estimate that generative AI music outputs will have a total market value of $16 billion by 2028 and lead to $4 billion of lost revenue for human creators. They warn that, under an unchanged regulatory framework, music creators will likely experience overall welfare losses from the adoption of generative AI. In the healthcare field, Goldfarb, Taska, and Teodoridis (2020) utilize online job posting data to estimate that only 1 in 1,250 healthcare jobs required AI-based skills from 2015 to 2018, compared to 1 in 88 in professional, scientific, and technical services and 1 in 72 in the information industry. They argue that regulatory constraints and misaligned incentives drive the lower AI adoption rates in healthcare. Similarly, through conducting 22 interviews with auditing professionals, Kokina et. al (2025) finds that the main challenges of adoption within the auditing field are transparency, AI bias, data privacy, reliability, and the need for AI guidance. These findings suggest that in more regulated fields, AI adoption is shaped not just by technological applications but also by the profession's accountability obligations, underscoring the importance of guided implementation within these fields.

At the occupational level, Brynjolfsson, Li, and Raymond (2023) find that the use of a generative AI-based assistant increases productivity by 14% on average for customer support agents, highlighting the potential for AI to impact this occupation. Machovec, Rieley, and Rolen (2024) argue that while computer-related occupations often use AI in their day-to-day work, AI is well-suited to augment this work. Despite the potential for AI to complete computer-based tasks, they project that employment growth for software developers and database architects will be faster than the average for all occupations.

Machovec, Rieley, and Rolen (2024) also discuss the potential impacts and employment prospects for legal occupations, business and financial operations occupations, and architecture and engineering occupations. They project that employment growth in the legal services industry will be slower than that of the total economy, due to AI task replacement. However, they project that employment for lawyers will grow at a similar rate to the total economy, partly due to potential productivity gains from AI.

In a report from the OECD report, Lane et al. uses qualitative methods to assess how firms and workers adapt to AI. They examine the impact of AI in the manufacturing and finance industries in the eight OECD countries (2023). Through these industry-specific case studies, they conclude that AI technologies are impacting a wide variety of workers and tasks. Even so, they find that employment levels remain steady despite AI adoption, though adoption may be slowing job growth. They also document that policies play a key role in shaping the impacts of AI. They find that job quality improvements associated with AI, such as reductions in repetitive tasks and improved physical safety, are the strongest benefits of AI from a worker's perspective.

3.5 Conclusion

The section summarized the ongoing research on AI's impact on labor markets. The key insights regarding the conceptual frameworks for empirical analysis, job displacement versus creation, productivity and wage outcomes, and industry-specific differences are summarized as below.

The **task-based framework and AI exposure** literature shows that AI affects work primarily at the task level, given that occupations consist of tasks with different degrees of susceptibility to automation. Exposure scores provide estimates of potential AI impacts, but actual adoption depends significantly on economic and organizational factors. Highly educated workers experience higher exposure yet are also more likely to benefit from AI adoption. Ultimately, labor market outcomes depend on actual AI adoption rather than merely exposure.

Studies on **job displacement versus job creation** indicate that AI adoption can simultaneously cause job losses and spur job creation, largely depending on firms' deployment strategies. Displacement disproportionately impacts older and higher-paid workers, while new opportunities often emerge within hybrid roles that combine tasks requiring both AI and human inputs. Firm flexibility and the degree of access to AI technologies play critical roles in determining employment outcomes. As a result, the labor market effects of AI vary widely across occupations and firms.

Research on **productivity and wage effects** reveals mixed evidence at the firm level, often reflecting underlying firm-specific characteristics rather than solely AI adoption itself. Macro-level estimates indicate modest gains in GDP and total factor productivity (TFP) attributable to AI. Experimental and survey-based evidence consistently demonstrates that AI improves task efficiency, with particularly pronounced benefits for lower-performing workers. However, adoption and usage disparities by gender and firm size continue to exist.

Finally, **case studies by industry and occupation** clearly illustrate that AI's effects differ substantially across sectors. For example, the Hollywood writers' strike demonstrates the capacity of workers to influence AI adoption and integration into their workplaces. Creative industries generally experience revenue losses and significant job restructuring due to AI. In contrast, regulatory and institutional barriers slow AI adoption in healthcare and auditing. Occupations such as software development exhibit notable productivity improvements and significant potential for job growth.

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4 The U.S. Labor Policy Landscape

Labor and education policies build the critical foundations to equip workers and institutions with the skills needed to navigate the changes AI is expected to bring to the labor market. Critical objectives of these public policies and programs include (1) growing the skills of the workforce, both before and after people start working; (2) aligning workers' skills with those demanded by employers; (3) retraining, reskilling, and upskilling workers, including after job dislocations, and (4) improving access to education and training opportunities.

The current labor policy landscape offers some basis for achieving the policy objectives stated above but also faces important shortcomings, including limited funding for programs targeting students in higher education, as well as workers pursuing continued education or reskilling, and work-based learning initiatives. However, as the AI transition proceeds or even accelerates, a better understanding of the merits and gaps in these policies will be essential for helping the workforce adapt to a rapidly changing market.

One way to categorize education and workforce policies and programs is along the following lines:

1. K-12 Public Education
2. Career and Technical Education (Secondary to Postsecondary)
3. Higher Education
4. Other Workforce Programs and Institutions
5. Work-Based Learning

This categorization helps clarify the strengths of existing policies, where gaps persist, and where policy innovations could be made in our following recommendations section.

4.1 K-12 Public Education

K-12 education is where the foundational skills of U.S. workers, which determine their abilities to complement AI over time and adjust to unexpected AI implementation in their workplaces, are traditionally developed. Public K-12 education is primarily funded and regulated at the state and local levels. However, federal funds and regulations also play a role through the Elementary and Secondary Education Acts (ESEA). Last authorized in 2015, the Act distributes funds through Title I to poorer districts and sets standards for student achievement through efforts like No Child Left Behind or The Every Student Succeeds Act (U.S. Department of Education, 2015).

4.2 Career and Technical Education (Secondary to Postsecondary)

Career and Technical Education (CTE) is also primarily regulated at the state and local levels, with modest federal funding and guidance through the Carl D. Perkins Career and Technical Education Act. Perkins provides less than 10 percent of CTE funding at the state and local levels, but it requires each state to define CTE Programs of Study and occupational pathways leading from secondary to post-secondary education. These programs and pathways could be important for determining the ability of students to gain appropriate skills in a world of AI implementation. Certain models of CTE—such as Career Academies[1], technical high schools or P-TECH[2] – have shown notable impacts on student achievement or later labor market success (Kemple, 2008; Rosen et. al., 2023).

4.3 Higher Education

Higher education in the U.S. comes in many forms: public or private (not for profit or for profit), two-year and four-year institutions, and programs offering associate, bachelor, or graduate degrees. The public 2-year institutions are mostly community and technical colleges, which number about 1000; they provide both academic (liberal arts) and workforce training for students in general education and occupational programs that result in certificates as well as associate degrees. The certificates can be for academic credit or not and can take anything from a few months to a few years of classroom time to complete; only students in for-credit programs (at accredited institutions) with a certain minimum length are eligible for federal financial aid, though the not-for-credit programs can provide customized training for regional employers that usually does not require strong academic content.

Federal financial support for students is provided primarily through Title IV of the Higher Education Act (HEA) and comes in three forms: a) Pell grants for low-income students; b) Federal student loans; and c) Federal Work-Study for low-income students. In contrast, states heavily subsidize public institutions to keep tuition levels lower. The Federal Government also provides a temporary tax benefit, allowing employers to contribute up to $5,252 of tax-free assistance to employees continuing their education while working through Tax Code 127. Governance of public institutions and especially community colleges vary greatly across states, as do the rules in most states that tie funding to student performance on a variety of dimensions. "Gainful employment" rules also limit federal funds to institutions with at least minimal performance outcomes among students in occupational programs, in terms of future debt or earnings, to protect students from predatory institutions (especially those that are for profit). The for-profit sector includes institutions ranging from broad providers of degrees and certificates to those that are proprietary and linked to particular occupations or industries.

1 Additional Information on Career Academies: https://www.mdrc.org/work/publications/career-academies-long-term-impacts-work-education-and-transitions-adulthood

2 Additional Information on P-Tech: https://www.mdrc.org/work/publications/p-tech-9-14-pathways-succes

4.4 Other Workforce Programs and Institutions

Outside of higher education, a range of institutions provide job training and workforce services. The most extensive are those funded by the Workforce Innovation and Opportunity Act (WIOA) through the federal and state Departments of Labor. WIOA provides funding streams for training disadvantaged adults, dislocated workers, and out-of-school youth, as well as the Job Corps and other more targeted populations. WIOA also funds American Job Centers, where career services are provided to workers; and adult basic education, various services for the unemployed, and vocational rehabilitation programs (U.S. Department of Labor, n.d.).

State and local workforce boards distribute such funds within their jurisdictions to approved training providers. But WIOA funding has declined greatly over the past 45 years, relative to its level under the Comprehensive Employment and Training Act (CETA) and other iterations of this program; and the Individual Training Accounts (ITAs) which fund training are, on average, worth only a few thousand dollars for each student. Popular models of training that local boards are encouraged to fund include sectoral approaches, where training is provided for occupations in high-demand and high-wage fields; and career pathways, which provide progressions for workers with low skills into better-paying employment. A few other sources of training and support are provided by the U.S. Department of Labor, such as Trade Adjustment Assistance (TAA) for workers who can certify that they lost jobs due to imports (which is phasing out). As the leading causes of worker displacement evolve, support and training programs similar to TAA may develop.

4.5 Recent AI Related Work-Based Learning Programs

Under the Biden Administration, the federal government has started programs to support work-based learning. The programs are specifically related to AI through the National Science Foundation's (NSF) Experiential Learning for Emerging and Novel Technologies (ExLENT) program and The Chips for America's CHIPS AI/AE for Rapid, Industry-informed Sustainable Semiconductor Materials and Processes (CHARISSMA) funding opportunity. The ExLENT program, which is still an active funding opportunity under the Trump administration plans to distribute funding within the year that will support career-enhancing experiential learning for individuals and adult learners with barriers in accessing a formal STEM education and an interest in re-skilling or upskilling (National Science Foundation, 2024). CHARISSMA is a funding opportunity for activities that will use cutting-edge AI and autonomous experimentation technologies to support the long-term viability of semiconductor manufacturing (National Institute for Standards and Technology, 2025). Contracts for CHARISSMA funding have not been cancelled under the Trump administration nor have funds been outlayed (U.S. Department of Treasury n.d.).

Other work-based learning options exist in most states with limited public support and regulation. The National Apprenticeship Act helps define registered apprenticeship programs, which are run by state departments of labor, while unregistered apprenticeships have also grown in recent years. Up to 20 percent of state and local WIOA funds can be used for on-the-job training and several states provide funding as well for on-the-job training; the largest and best-known of the latter is the Employment and Training Panel (ETP) of California (Negoita and Goger, 2023).

Finally, recent developments for possible federal labor policy expansions focus on extending federal Pell Grants to technical education and expanding labor market data sharing. The Stronger Workforce for America Act (H.R. 6655, 2024), which passed in the 118th House of Representatives but did not advance in the Senate and has not yet been reintroduced, seeks to provide more training and expand labor market data collection and sharing. The bill creates an expansion of labor market data that will help experts and policymakers make informed decisions. The JOBS Act of 2025 (S. 383), introduced in February 2025, seeks to extend Pell Grants to individuals enrolled in short-term or non-credit technical education programs (that meet certain quality standards) at institutions of higher education. The grant recipients must still meet all other requirements for the Pell grant such as exceptional financial need. Extending Pell Grants to Students in short-term or noncredit technical education increases federal funding support to eligible workers looking to reskill and adapt to changes in the labor market from AI.

As AI's unprecedented progress shifts labor markets, education and labor policies must adapt to effectively support workforce development and retraining. The current education and labor policy landscape includes relatively little support for work-based learning and re-skilling, leaving large gaps, especially if the AI transition is rapid and deep in scale or scope. Expanding the landscape by increasing data and measurement tools on AI's impacts, updating education and workforce development programs, and dedicating sufficient support for the scale and scope of worker displacement, can help reorient existing policies and develop new ones to achieve the critical public policy objectives discussed above.

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5 Policy Options for Data, Research, and Measurement

Summary of Policy Options for Data, Research, and Measurement

TABLE F

FOCUS AREA	POLICY OPPORTUNITIES
Improving Current Government Data Collection Efforts	• Redesign Occupational Employment and Wage Statistics (OES) for electronic job title capture and autocoding • Expand The Occupational Requirements Survey (ORS) and O*NET to track AI-related tasks • Add AI modules to the Quarterly Census for Employment Wages (QCEW) and The Census's Management and Occupational Survey (MOPS)
Leveraging Private Data	• Leverage private labor market data for early AI signals • Develop secure public-private data partnerships to inform policy
Starting New Data Initiatives	• Track workers longitudinally to assess AI impact • Augment The Current Population Survey (CPS) to collect task-level job data • Measure downstream and spillover employment from AI infrastructure
Building Integrated Data Systems	• Extend linked Unemployment Insurance and the Statewide Longitudinal Data Systems (SLDS) records to track AI skill impacts • Add job titles and hours worked to Unemployment Insurance records • Auto-code titles into the Standard Occupational Classification (SOC) system for AI workforce monitoring
Building the Institutional Capacity for Integrated Data Systems	• Empower the Office of Information and Regulatory Affairs (OIRA) to lead AI data coordination • Prioritize agency alignment and expand existing surveys and pilots • Expand the Research Data Center (RDS) access and academic-public data partnerships

5.1 Introduction

Recent work by the National Academies (2025) underscores a central challenge facing policymakers: as AI capabilities continue to evolve rapidly, their impacts on jobs and the economy remain difficult to predict. Policymakers are confronted with substantial uncertainty due to the rapid advancements in AI technologies, which could significantly affect labor markets and the wider economy. Policymakers must effectively measure and comprehend these developments to ensure timely responses. Key actions include modernizing the federal statistical system, enhancing real-time data collection, and promoting robust institutional collaboration to accurately track the evolving impacts of AI. Enhanced data collection and analysis will facilitate better forecasting, targeted interventions, and informed policymaking, ensuring agility and responsiveness to AI-driven shifts. The subsequent sections present specific policy recommendations aimed at strengthening data collection, research capabilities, and measurement methods to better understand AI's effects on the labor market.

5.2 Innovations for Data on AI and the Labor Market

5.2.1 Improving Current Government Data Collection Efforts

To respond effectively to AI's evolving impact on the labor market, government data systems must become more timely, granular, and flexible.

We highlight below a set of enhancements to existing federal data programs that would substantially improve our ability to monitor how AI is reshaping work.

- **Developing real-time adaptive mappings:** One immediate need is to develop real-time, adaptive mappings of occupations, tasks, and skills to better reflect the rapidly evolving nature of work due to AI. Existing classification systems, such as the Standard Occupational Classification (SOC) and O*NET, are updated infrequently (usually every 8-10 years) and often lag years behind technological developments. Subsequently, policymakers, researchers, and employers lack timely data on how AI is affecting job content and skill demands and restructuring work, which limits their ability to design responsive education, training, and labor market policies. Agencies like the BLS can be key partners in producing more granular, dynamic data products that track emerging technologies and their impact on work. This could include real-time updates of occupational classifications and integration of employer-reported skill needs. For example, redesigning data collection in the Occupational Employment and Wage Survey (OEWS) to focus on the electronic transmission of job titles would enable the use of machine learning to identify autocoding failures that may reflect emerging occupations not currently represented in the current SOC.

- **Expanding ORS for AI-related job data:** In parallel, the Occupational Requirements Survey (ORS), also conducted by the BLS, could be expanded or adapted to gather more granular information about the cognitive and digital demands of specific jobs. While ORS already collects detailed data on physical, environmental, and cognitive requirements, it offers an underutilized opportunity to track the evolving task and skill composition of AI-exposed roles. Strengthening ORS with targeted indicators, such as the use of generative tools, decision-support systems, machine learning applications, or algorithmic interfaces, would help policymakers monitor the actual content of work more accurately and design appropriate training and transition policies.

- **Enhancing O*NET data collection:** The O*NET survey conducted by the Employment and Training Administration collects data on the relative importance and intensity of the use of AI in occupations. These data are from special sets of questions asked of respondents but are not part of a regular data collection effort. Adding more detailed questions on the use of AI and asking question modules over time would be extremely useful. Additionally, asking O*NET to focus specifically on collecting more detailed data on job tasks related to AI, similar to the recommendation for the ORS, would be beneficial.

- **Improving data on employer AI adoption:** We also need improved data on AI adoption at the employer and establishment levels. Since 2018, the U.S. Census Bureau has included AI questions in the Annual Business Survey, and since late 2023, in the Business Trends and Outlook Survey (BTOS). BTOS provides timely updates, but it collects data at the firm level, which limits our ability to analyze local labor market effects, especially for large firms operating in multiple geographic regions. To better understand how AI is transforming employment outcomes, task structures, and wage dynamics across place and firm type, establishment-level data collection is essential. One approach would be to incorporate AI-related questions into broader establishment-based surveys, such as the BLS's Quarterly Census of Employment and Wages (QCEW), or to expand existing efforts like the Census's Management and Organizational Practices Survey (MOPS) with dedicated modules on AI technologies, deployment contexts, and workforce impacts.

- **Coordinating through OIRA:** The Office of Information and Regulatory Affairs (OIRA) at the Office of Management and Budget (OMB), which oversees the SOC system, is uniquely positioned to coordinate this effort. With its mandate to harmonize federal data standards and promote interagency collaboration, OIRA could convene stakeholders across statistical agencies, industry, and academia to ensure AI-based changes to work are systematically incorporated into future classification updates. This effort would not only improve the granularity of labor market monitoring but also support more forward-looking workforce development strategies.

Among these options, we believe the highest-impact and most feasible actions in the near term are: (1) adapting the OEWS to support electronic job title transmission, enabling more agile occupational classification; (2) expanding the ORS and O*NET to regularly track AI-related tasks; and (3) embedding AI adoption questions into establishment-level surveys such as the QCEW. These steps can be taken using existing infrastructure and would significantly enhance our ability to monitor how AI reshapes work. Longer-term, we recommend that OIRA lead a sustained, cross-agency effort to coordinate AI-relevant data collection standards across statistical agencies. These efforts would create the foundation for a more adaptive, forward-looking labor market data system.

Ultimately, updating classification systems and federal data collection efforts to reflect AI-driven changes is not merely a technical issue. It is essential infrastructure for understanding the future of work, identifying emerging risks, and enabling timely, evidence-based policymaking. Integrating AI-relevant metrics would allow more precise identification of vulnerable jobs, emerging skill gaps, and potential pathways for worker transitions.

5.2.2 Leveraging Private Data Sources

Policymakers can also actively leverage private data sources to fill critical gaps. Firms like Revelio Labs, Lightcast, and others offer high-frequency, granular labor market data that can help identify how AI is reshaping job postings, skill demands, and career trajectories across regions, industries, and occupations. These data sources can provide early signals of labor displacement or augmentation, especially when combined with public data infrastructure. Developing mechanisms for secure, ongoing collaboration between government and private-sector data providers can help ensure these insights are translated into scalable, policy-relevant tools.

5.2.3 Starting New Data Initiatives

In addition to improving existing data sources and utilizing private data sources, we believe that new high-quality data collection efforts are needed, particularly at the individual worker level.

We highlight four high-impact opportunities for collecting more detailed, longitudinal, and task-level information at the worker level.

- **Tracking workers longitudinally:** To inform a robust policy response to AI's labor market effects, we need evidence on which workers and occupations are more likely to experience AI as labor-augmenting versus labor-displacing. Longitudinal tracking of workers over time would allow for better measurement of AI's impact on occupations, tasks, and worker outcomes over time, especially across different types of workers (for example, the effects of AI on a given occupation may be different for older versus younger workers or more versus less educated workers). This would help policymakers understand who is being affected by AI and how this effect is changing over time.

- **Observing tasks and worker characteristics:** To understand why some workers are more exposed to AI than others, even within the same occupation, we need data that jointly capture job tasks and labor market outcomes. For example, two workers in the same job may face very different exposures to AI depending on their task mix, digital tool use, or workplace setting. This kind of detail is largely absent in existing surveys but could be introduced by augmenting tools like the Current Population Survey (CPS); the CPS could add a supplement asking respondents about the tasks they perform in their jobs, such as tasks as measured in the O*NET survey. Richer details of this kind would expand understanding of AI's effect on jobs and how AI augments or displaces labor for a given job and worker. This would deepen understanding of the mechanisms and occupational task content driving AI displacement and augmentation.

- **Exploring downstream employment:** The rapid buildout of AI infrastructure, including data centers, fiber networks, and next-generation power sources (such as small modular nuclear reactors), creates demand for construction workers, electricians, maintenance technicians, and clean energy specialists. These investments could create a sizable economic impact, yet we lack systematic data on these spillover effects and how they are affecting jobs across regions and supply chains. Tracking the indirect labor market consequences of AI, through both infrastructure and complementary industries will help us understand the full employment footprint of AI investment. Federal agencies, in coordination with regional planning bodies, could create reporting standards and data collection efforts to measure these second-order effects.

- **Requiring access to confidential data:** Statistical agencies could develop estimates that require access to confidential data on establishments that are part of the broader AI infrastructure build-out, allowing for the measurement of their direct employment effects. This analysis could be supplemented by studies that use multipliers for indirect employment effects by industry and occupation, such as those provided by Regional Economic Models Inc. (REMI) or Impact Analysis for Planning (IMPLAN) models.

Augmenting the CPS to collect task-level data stands out as both feasible and impactful among these proposals. As a long-standing and widely used survey, the CPS offers an efficient platform for piloting new question modules that capture AI-relevant task information. Adding a short supplement on workplace technologies and task content would significantly improve our understanding of how AI exposure varies across workers without the cost or delay of launching a wholly new survey.

5.2.4 Building Integrated Data Systems

While improving individual data sources is essential, realizing the full value of these efforts requires building integrated data systems that leverage these sources effectively. Linked administrative records, such as wage, occupation, education, and demographic data, can provide a more comprehensive view of how AI is transforming work. These integrated systems would enable policymakers to identify emerging labor market disruptions, track regional disparities, and tailor interventions.

Below, we outline several opportunities to modernize U.S. data infrastructure by expanding access to linked datasets, enhancing reporting elements, and learning from successful models at home and abroad.

- **Leveraging integrated earnings and education data:** One promising approach to measuring AI impacts in the workplace is to link quarterly earnings records from the Unemployment Insurance (UI) system with public education data from State Longitudinal Data Systems (SLDS). Virtually all states have linked these two bodies of microdata to assess how various kinds of education are rewarded in the workplace. SLDS systems capture detailed information on coursework and field of study, which can be linked to post-school earnings trajectories. This infrastructure could be extended to track employer demand for AI-related skills and assess how hiring AI-proficient workers affects incumbent employees. For example, the *Industries of Ideas* project (Lane, 2023) follows grant-funded university researchers into the workplace to study their broader organizational impacts using linked UI and SLDS records. A similar effort could incorporate measures of AI or computer science coursework in secondary and postsecondary settings and examine its effects on worker outcomes, as well as the outcomes of other workers at the same firms. Over time, these linked data could provide valuable insights into how workers with AI-related skills interact with those without, revealing patterns of substitution, complementarity, and displacement.

- **Adding occupational codes to wage records:** A critical step toward understanding AI's labor market effects is expanding the use of "enhanced" UI wage records by incorporating SOC codes. Currently, only a handful of states collect occupational classifications alongside wage data. The ability to track the impact of AI on occupational employment and staffing patterns, especially within North American Industry Classification System (NAICS) industries, would provide critical insight into the penetration of AI across occupations and industries. To improve feasibility, states could ask firms to report job titles directly rather than SOC codes. These titles could then be autocoded using machine learning. The difficulty is in its implementation. While technically feasible, progress has been slow because adoption is voluntary. To accelerate this effort, the Department of Labor's Employment and Training Administration (ETA) should require all states to add occupational data elements to their UI wage records.

- **Incorporating worker hours into wage records:** Adding hours worked to UI wage records would provide critical insight into how AI is affecting job structure, such as shifts between full-time and part-time work or changes in work intensity. Washington State has already implemented this enhancement, offering a valuable case study. Researchers and statistical agencies should examine whether hours vary systematically across occupations or industries in ways that signal AI-driven changes. Filling these data gaps is critical for workforce planning. Without detailed information on job structure and intensity, policymakers cannot accurately identify where AI is being deployed, which workers are most affected, or which communities may be vulnerable to disruption. Understanding these shifts is especially important given AI's uneven geographic impact and potential to exacerbate regional inequalities.

Of these proposals, expanding the use of enhanced wage records by incorporating job titles autocoded into SOC codes offers the most feasible near-term opportunity with high analytical return. This approach builds on existing infrastructure, requires minimal additional burden for employers, and would unlock powerful insights into how AI is reshaping employment structures across occupations and industries.

5.3 Building the Institutional Capacity for Integrated Data Systems

As emphasized in a recent American Economic Association Committee on Economic Statistics white paper (Brynjolfsson and Mitchell, 2025), addressing these data needs and filling these research gaps requires targeted data collection, sustained institutional support, and clearly defined interagency roles. This includes leveraging emerging data sources, such as BTOS described above, while addressing their limitations and expanding research capacity through academic and institutional partnerships. No single agency can meet the analytical and policy challenges posed by AI-driven labor market change. A coordinated institutional strategy is essential.

These investments are also critical for identifying and addressing regional disparities in AI adoption and impact. Just as with these other technologies, AI may have a more significant impact on certain geographies than others. Research by Muro and Liu (2021) suggests that AI activity is highly concentrated in a few "superstar" cities, primarily located on the East and West Coasts. The same appears to be true more recently for generative AI as well (Muro, Jacobs, and Liu, 2023). Globally, a recent IMF report noted that international differences in AI adoption might exacerbate existing economic inequalities (Alonso et al., 2022). If the adoption and implementation of AI is uneven across regions, this might magnify the positive and negative effects and exacerbate existing economic differences across regions. Integrated data systems are crucial for identifying such disparities early.

Below, we list the policy recommendations we believe are key to building the institutional capacity for a coordinated, sustained AI-centered labor market data collection system.

- Coordinating agencies and standard setting: To implement a coherent national strategy on AI and the labor market, the federal government must ensure sustained coordination across statistical and administrative agencies. Building on its existing role, OIRA should not only oversee updates to occupational classification systems but also formalize its leadership in aligning AI-related data efforts across agencies like BLS, Census, ETA, and NSF. This includes supporting cross-agency working groups and establishing shared standards for measuring AI exposure, task content, and workforce outcomes. Establishing this leadership function is essential for a coherent national strategy.

- Funding and aligning cross-agency data collection strategically: In an environment of constrained federal budgets, it is essential to prioritize and coordinate investments in data systems that are foundational for understanding the labor market effects of AI. Rather than calling for wholesale new spending, agencies should identify high-impact, scalable opportunities, such as enhancing existing wage record pilots or updating current surveys like OEWS and ORS, to align data collection efforts around shared goals. Cross-agency coordination can reduce duplication, maximize efficiency, and ensure that limited resources support the most critical infrastructure. The strategic use of existing authorities and data systems, combined with deliberate prioritization of AI-relevant improvements, can help statistical agencies modernize effectively, even amid fiscal pressure.

- Managing workforce and budget constraints strategically: To remain effective, agencies such as the BLS, BEA, and Census must prioritize core survey programs, assess how budget reductions impact AI-related data efforts, and make informed decisions about where to allocate limited resources. To mitigate the loss of senior technical staff and early-career talent, agencies should expand partnerships with academia, the private sector, and industry groups. Public-private partnerships can enhance internal capacity, bring fresh methodological expertise, and shorten response times from data collection to policy implementation. Agencies should also streamline researcher access to secure administrative microdata, such as through Census Research Data Centers (RDCs) and by facilitating direct applications to BLS, BEA, and other agencies. This would accelerate research processes and maximize the value of existing data assets. Strategic investment in these institutional roles, paired with smart collaboration, will help ensure that labor market policy remains evidence-based and forward-looking in the face of the rapid advancement of AI. It would also support research transparency and reproducibility, boosting public trust in research findings and enabling more confident, evidence-based policymaking. These efforts will require sustained interagency cooperation and engagement with the research community.

Strong models already exist. The SLDS, for example, links education records with workforce and earnings data to support state policy and academic research. This infrastructure has enabled evidence-based decisions on workforce training, curriculum design, and funding allocation, especially when combined with labor market outcomes. Census Bureau Research Data Centers (RDCs) similarly provide researchers with a wealth of linked confidential survey and administrative data. Internationally, New Zealand's Integrated Data Infrastructure (IDI) is a leading example of an integrated data infrastructure enabling evidence-based policymaking. The IDI links anonymized microdata from across government agencies, including education, employment, health, and justice, into a secure, longitudinal research environment.

The OECD has repeatedly highlighted the IDI as a benchmark for using administrative data to inform public policy (OECD, 2018; OECD, 2020). These endorsements underscore how sustained investment in interoperable data systems, designed with both research access and policy responsiveness in mind, can enhance the agility and effectiveness of public decision-making. Similar models could inform U.S. efforts to build better infrastructure for tracking the labor market impacts of AI.

The Foundations for Evidence-Based Policymaking Act of 2018 ("Evidence Act") is based on the principles that government decisions should be based on rigorous evidence and that policymakers should seek high-quality evidence. Fulfilling these data needs will require sustained interagency collaboration, academic partnerships, and greater openness to private-sector data integration.

5.4 Using AI for Better Data Collection and Management

Across the federal government, including the statistical agencies, there has been substantial recent innovation in the application of AI to improve data collection, management, and dissemination. These innovations include the automation of coding processes, enhanced predictive analytics, image and text analysis, and advanced query tools to streamline operations and reduce reporting burdens. However, further opportunities exist to expand AI use in areas such as real-time data processing, integration of disparate data sources, and improving data accuracy through automated error detection and correction. Agencies should invest in building AI capabilities and cross-agency collaboration to share best practices and models effectively. Notable examples of AI use by federal data collection agencies include[3]:

- **Office of Management and Budget (OMB)**: OMB now reports annually on AI usage by federal agencies, highlighting diverse applications such as software coding automation, LLMs for text autocode classification, predictive analytics, image processing, query tools, and research documentation summarization.

- **Census Bureau**: The Census Bureau employs AI extensively, including text analysis and predictive analytics for coding business activities, race/ethnicity, industry classifications, and structural classifications. Other uses involve logistic regression modeling, detecting changes in geographic features, group quarters listings, and verifying survey text responses. AI-driven query tools improve data accessibility and customer interaction. A significant partnership with Intel has developed an LLM to standardize unstructured firm data across Census surveys, significantly reducing reporting burdens (e.g., Amazon's reporting time reduced from 200 hours to 30 minutes quarterly).

- **Bureau of Economic Analysis (BEA)**: BEA uses AI to modernize coding platforms, strengthen cybersecurity measures, and enhance research capabilities through advanced large language models.

[3] Below examples are based on discussion by one of the authors of the report and the agencies on AI use for data collection.

- **Bureau of Labor Statistics (BLS)**: BLS leverages machine learning models, particularly neural networks, to automate text coding in surveys such as the Occupational Employment and Wage Survey (OEWS), Census of Fatal Occupational Injuries (CFOI), and Survey of Occupational Injuries and Illnesses. Recently, BLS integrated heavily parameterized machine learning with Bayesian models to provide uncertainty distributions, facilitating research-based creation of synthetic data. Notable projects include developing detailed geographic CPI estimates, forecasting consumer expenditure weights, and state-level estimates for the Job Openings and Labor Turnover Survey. Additionally, BLS employs sentence similarity models in the Occupational Requirements Survey (ORS) to align job characteristics data with O*NET's job task hierarchy, enhancing task classification information available to researchers.

5.5 Conclusion

To effectively address the rapid and unpredictable impacts of AI on labor markets, it is imperative for policymakers to prioritize comprehensive data collection, robust research, and strategic measurement methods. Innovations such as real-time adaptive occupation mapping, enhanced data products from the BLS, detailed worker-level data, and leveraging private-sector insights will significantly strengthen understanding of AI's effects. Furthermore, investing in integrated and interoperable data systems, enhancing longitudinal research, and expanding institutional capacities will improve evidence-based policymaking. Strategic use of AI itself within data collection processes can improve operational efficiency, accuracy, and responsiveness. Together, the recommendations in this section can equip policymakers and researchers with the necessary tools to anticipate workforce shifts, effectively target interventions, and manage economic transitions with agility and precision in the face of AI-driven labor market disruptions.

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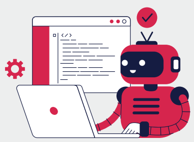
6 Policy Options for Workforce Development and Education

TABLE G

FOCUS AREA	POLICY OPPORTUNITIES
Modernizing Education for the AI Era	• Build AI literacy and skill development to complement AI into K-12 Curriculum • Embed AI usage into Career and Technical programs (CTE) • Strengthen employer-college partnerships, allowing colleges to build curriculum that is relevant for AI-induced changes in labor market demand • Develop "talent finance" models like income-sharing agreements and outcome-based loans to fund retraining needed by workers when AI shifts skill demands
Innovating the Workforce Innovation and Opportunities Act (WIOA) and other Federal Efforts to Help Workers Gain New Skills in Response to AI	• Support the renewal of The Workforce Innovation and Opportunity Act, a federal worker support program which improves access to employment, education, training, and support services for workers facing changing skill demands • Expand the Federal Pell Grant and Student Loan Programs (Title IV of the Higher Education Act) to cover not only short-term certificate programs for high quality worker retraining but also some non-credit programs that meet quality guidelines • Use Trade Adjustment Assistance (TAA) and the Re-employment Services and Eligibility Act (RESEA) programs as models for building programs specifically for workers displaced by AI or other automation • Rigorously evaluate existing and proposed programs to ensure effectiveness and fiscal responsibility
Expanding to New Models: Work-based Learning, Public-Private Partnerships, and Adult Learning in the AI Era	• Incorporate human-centred dimensions of AI-adoption like beliefs and emotions into AI training programs • Utilize already successful and accessible cross-sector AI training programs • Rigorously and regularly evaluate programs to promote quality and impact
Building a Lifelong Learning Infrastructure for the AI Era	• Promote lifelong learning by experimenting with, evaluating, adopting, and expanding mechanisms for financing and delivering lifelong learning • Create national digital credentials to uniformly verify AI-relevant skills • Introduce portable "skill wallets" which hold digital credentials, certifications, on-the-job training, and informal learning • Develop subsidized life-long learning accounts modeled on retirement savings plans to support financial costs from up-skilling and reskilling education • Increase universal access to short-term learning using various approaches, such as bootcamps, micro-credentials, and modular programs, that have been evaluated for quality and designed for working adults • Regularly test and evaluate programs to shift funding towards most impactful programs and away from poor performing ones

6.1 Introduction

The rapid pace of AI advancement is outstripping how quickly organizations are preparing their people to keep up. According to the *2024 State of AI at Work* report by Asana and Anthropic (2024), knowledge workers estimate that generative AI could take over 31% of their job responsibilities. Yet despite the magnitude of that shift, 82% say their organization hasn't provided any training on how to use generative AI tools. That gap isn't just a missed opportunity—it's a growing source of anxiety. As documented in Asana's *State of Work Innovation* report (2024), nearly two-thirds of workers (64%) are worried about falling behind if they don't learn how to use AI effectively.



Knowledge workers estimate that generative AI could take over 31% of their job responsibilities.

Technical training alone is not enough. Preparing the workforce for the AI era demands a broader, more human-centered approach—one that prioritizes critical thinking, empathy, adaptability, and collaboration. It also means reimagining career pathways, redesigning education systems, and promoting a culture of lifelong learning.

6.2 Modernizing Education for the AI Era

6.2.1 K-12 Education

A comprehensive education reform is essential to ensure that all young people are equipped to adapt to AI-induced labor market dynamism in their postsecondary education and careers. This begins with expanding high-quality early education to ensure all students start school with a strong base of cognitive and non-cognitive skills. In these formative K-12 years, students should have opportunities to build their AI literacy—allowing them to understand and successfully work alongside emerging technologies. Additionally, the skills of the future will be difficult to predict, but schools should try to constantly identify and teach skills that will likely complement (or augment) their use of AI such as critical thinking, social, and communication-based skills, while regularly reevaluating them based on new evidence. Building these skills into K-12 curricula help create smoother pathways for students to develop AI literacy.

6.2.2 Career and Tech Education: Secondary and Postsecondary Education

Career and Technical Education (CTE) training is closely tied to industry standards, certifications, and licenses. Traditionally, partnerships between community colleges, CTE centers, workforce development agencies, and businesses are often used to identify what skills, curricula, and training courses are needed. Most CTE programs are offered at the secondary and post-secondary levels and include educational and technical training, hands-on training, and work-based learning. The advent of AI adoption by industries may increase the need for institutional partnerships within CTE programs to identify, share, and integrate industry use of AI into the learning environment. There is an ongoing need to develop and revise curricula that teach students how industries are using AI and the skills that are needed for those applications.

The use of AI in the CTE educational environment can leverage the variety of ways in which AI can translate learning materials into audio files as alternatives to text formats, create adaptive learning modules versions of course materials, and develop engaging interactive and personalized learning experiences.[4] AI based virtual reality platforms are increasingly being used in CTE skill development such as forklift operation, HVAC, electrical work, and plumbing. One example is Interplay learning which offers over five-hundred virtual reality based CTE courses.

6.2.3 Higher Education

Students who pursue higher education–whether in bachelor's programs or shorter-term pathways, and whether they enroll directly after high school or later in life–must be informed about labor market changes in real time and have appropriate opportunities for reskilling and upskilling, with financial assistance for those who need it and less risk. Enabling students to do so begins with expanding career guidance based on high-quality labor market information and expanding both for-credit and especially not-for-credit workforce programs, where the latter effectively respond rapidly to dynamic labor markets and allow some integration into for-credit programs through stacking of certificates. The expansions create accessible opportunities for reskilling and upskilling.

Taking a curriculum-centered approach will also be effective in expanding these opportunities. By expanding employer-college partnerships, colleges can build curricula and programs relevant for a market with high and rapidly changing labor demands. Additionally, developing higher- quality virtual college education with AI-driven content and intelligent tutoring systems could make educational opportunities more accessible for those who need training throughout their career. Further expanding accessibility to vital educational opportunities, expanding Title IV programs to include short certificates and non-credit programs with appropriate quality guardrails could allow for quicker retraining.

The increasing demand for reskilling and upskilling due to AI's impact on the labor market has made access to financial assistance more critical than ever for students. Developing "talent finance" models like income-sharing agreements and outcome-based loans will lower student risk and help finance for-credit and especially non-credit programs which are important for supporting reskilling and upskilling.

[4] AI is also being used to support individuals in their job search by career matching and resume and cover letter writing (Hseih and Fu, 2024). The impact of AI assistance in these use cases should be further evaluated to better understand their benefits and downsides.

6.3 Innovating the Workforce Innovation and Opportunity Act (WIOA) and Other Federal Efforts

The Workforce Innovation and Opportunity Act (WIOA), passed in 2014 and currently up for renewal, aims to support both job seekers and employers by improving worker access to employment, education, training, and support services. It emphasizes demand-driven strategies, encouraging partnerships between businesses, community colleges, and workforce agencies to align training with in-demand occupations. WIOA supports state-level occupational projections and establishes performance metrics for its core programs, including service counts and outcome indicators like employment status, earnings, and credential attainment. While rigorous impact evaluations are encouraged, they are not mandated. WIOA also targets underserved populations, including youth, individuals with disabilities, and low-income adults.

Core WIOA programs include the Adult, Dislocated Workers, and Youth Programs, as well as Wagner-Peyser Employment Services, Adult Education and Literacy programs, and Vocational Rehabilitation. These are delivered through nationwide One-Stop or American Job Centers, which may also offer access to unemployment benefits and social services, depending on the state. Local Workforce Boards, composed of business and workforce leaders, help tailor services to regional needs.

Additional federal efforts (besides Pell grants and Title IV higher education programs) which can be expanded to support workers displaced by AI include the Trade Adjustment Assistance (TAA) program for trade-displaced workers and the Reemployment and Eligibility Assessment (RESEA) program, which offers individualized reemployment planning to unemployment insurance recipients. The TAA and RESEA programs can be used as models to build supports for workers specifically displaced by AI.

While the use of AI in delivering these programs and services is still emerging, it holds significant promise. In theory, AI can enhance career services through resume-job matching, predictive career guidance, and personalized training pathways. It can support real-time labor market analysis by processing vast job posting data, and improve training through adaptive learning platforms. AI tools also offer opportunities to streamline case management, automate service delivery via chatbots, and identify potential fraud. For special populations, AI can provide assistive technologies such as translation, speech-to-text, and personalized service navigation. Finally, AI can strengthen performance tracking and evaluation by using predictive models to assess program outcomes. Creatively integrating AI into workforce programs can expand existing worker development. However, these potential benefits need to be rigorously evaluated and considered against the potential downsides, such as costs, bias, and hallucination risks.

6.4 Expanding to New Models: Work-Based Learning and Public-Private Partnerships and Adult Learning

One-size-fits-all training programs often miss the mark. When reskilling efforts don't align with the realities of workers' day-to-day responsibilities—or fail to resonate with their values, motivations, or sense of professional identity—resistance is inevitable. To succeed, workplace development must be designed around how people see themselves and what they care about.

First, training should be tailored to workers based on their needs. For instance, increasing role- specific training, such as training a marketer to apply AI to coordinate a product launch, can help tailor AI training.

Second, training must also go beyond the technical "how-to's" of learning how to prompt an AI tool or set up an AI-powered workflow. Effective training must also address the human-centered dimensions of AI adoption—in particular, the beliefs, assumptions, and emotions people bring to the table. This includes helping workers understand their technology frames—"the underlying assumptions, expectations, and knowledge that people have about technology."(Orlikowski and Gash 1994) Do they see it as a threat to their job or a partner that enhances their work? Framing AI as "amplified intelligence" or "augmented intelligence," as organizations like H&M and Evernote have, could dramatically increase openness and trust. When people view AI as something that complements their strengths rather than competes with them, they're more willing to experiment, adapt, and find creative ways to integrate it into their workflows. However, training must meaningfully engage the skeptics—not just the early adopters. Some skeptics are wary of the real risks: misinformation, bias, privacy breaches, or just plain job loss. Brushing aside these concerns or offering unfettered optimism backfires. Instead using transparency—acknowledging AI's limitations, naming the tradeoffs, and making space for dialogue builds trust.

Some of the most promising innovations in workforce development are coming from cross-sector partnerships—companies that are stepping up to fill the training gap with programs designed to reskill mid-career workers for AI-era jobs. These programs are designed to be completed in under six months, and don't require a college degree.[5] Additionally, other organizations like Per Scholas and Year Up have demonstrated the power of higher-touch sectoral training, built in collaboration with employees to align with specific local/regional job demand, including with direct placement partnerships. Per Scholas partners directly with employers to deliver free, full-time training programs in fields that include AI. Year Up also offers AI-focused training under an umbrella program that also includes mentorship, stipends, and coaching.

Programs like these appear to be expanding access and reimagining the learning process, but they need to be rigorously studied after incorporating AI to evaluate effectiveness and quality. To expand the impact of high-quality programs across more organizations and industries, we need stronger public-private partnerships. This includes pooling funding, sharing curricula, and offering real in-

[5] Google's Program Serves as a case study with high rates of positive career outcomes within the first 6 months of graduation. https://grow.google/certificates/

centives—such as tax credits or technical assistance—for employers to invest in high-quality training when a government subsidy is justified. We also need a shift in mindset: from one-time training events to continuous learning ecosystems that support adult learners throughout their careers. Apprenticeships and work-based learning are key examples, providing workers with real-world experience as skill demands evolve.

6.5 Building a Lifelong Learning Infrastructure

Since AI demands constant reinvention, a single round of AI training will be woefully insufficient to meet worker needs. As AI evolves, the half-life of specific occupational skills will likely shrink—meaning that workers trained today will likely need to reskill multiple times throughout their careers. We need a durable, flexible infrastructure that supports learning for life—regardless of age, background, or job title.

To build a future of education compatible with lifelong learning and constant reinvention, a four-pronged plan is proposed. The plan starts with creating national digital credentials that verify AI-relevant skills and are recognized across employers, states, and platforms. Credentials must be interoperable, stackable, and aligned with labor market demand—not trapped in proprietary systems or locked within a single employer or learning management system (LMS). Next, to support national digital credentials along with other AI related achievements, we propose creating portable "skill wallets"—digital records of verified achievements that follow workers across jobs and industries. These should include certifications, micro-credentials, on-the-job training, and informal learning, offering a holistic view of a person's capabilities beyond a degree or resume. Additionally, subsidized lifelong learning accounts, modeled on retirement savings plans can support the financial demands that education brings. These would be supported by federal and state contributions, employer matches, and optional payroll deductions—giving every worker access to a personal upskilling fund. Finally, creating universal access to high-quality, short-form learning through micro-credentials, bootcamps, and modular programs designed for working adults will make lifelong learning more accessible. These programs should be affordable, flexible, and laser-focused on market-relevant skills—especially for underserved populations, who face systemic barriers to traditional education–but also rigorously and regularly evaluated to ensure quality and cost effectiveness for taxpayers.

Lifelong learning should also go beyond AI literacy and focus on skills that will complement AI or be resistant to automation. While these skills will be hard to predict and regularly change, we should put in place both the right financing and training mechanisms that can regularly adapt given the unpredictable changes AI brings. This can include leveraging, experimenting with, evaluating, and scaling mechanisms like apprenticeship programs and lifelong learning tax credits.

How AI transforms the workforce—and society—depends on whether we give people the tools to adapt. Building the infrastructure right takes lifelong learning from a buzzword to a core part of the social contract: a system that enables everyone, not just the privileged few, to keep up with change and shape their own future.

6.6 Conclusion

Our proposals above are promising ways to adapt to an era of AI-driven volatility in the labor market; but most have not yet been rigorously evaluated for cost-effectiveness. Accordingly, we should experiment with different versions of the above approaches and rigorously evaluate them. Programs or practices that appear cost-effective at small scale should be replicated and scaled for further evaluation. Over time, we can learn what works and what doesn't and focus our national resources on proven policies and practices.

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7 Policy Options for Social Safety Nets and Worker Support

TABLE H

POLICY APPROACHES FOR STRENGTHENING SOCIAL SAFETY NETS	
“Wait and See” Approach (Option #1)	Wait until there are clearer signs of major job disruption from AI before considering expanding any safety net programs
“Preemptive” Approach (Option #2)	Preemptively expand social safety net programs in anticipation of major AI job disruption
“Trigger Mechanism” Approach (Option #3)	Consider a range of scenarios like massive job losses and implement conditional trigger mechanisms that expand existing or create new programs only if these conditions are met and can automatically reverse themselves if new conditions are met
Combining the Best of All Approaches	Apply each Approach on a case-by-case basis instead of taking a blanket approach to social safety net mechanisms

POLICY OPTIONS TO SUPPORT WORKERS IN AN AI-TRANSFORMED LABOR MARKET	
Unemployment Insurance	• Require all states to provide 26 weeks of benefits • Federally provide longer periods of benefit receipt for permanent layoffs • Allocate more funding for The Reemployment Services Eligibility Assessment • Raise the minimum taxable wage base or require employers generating more permanent layoffs to pay higher Federal Unemployment Tax (FUTA) and State Unemployment Tax (SUTA)
Adjustment Support and Wage Insurance	• Build adjustment support programs for automation modeled around what worked in TAA
Tax Credits	• Expand the Child Tax Credit and Earned Income Tax Credit Programs • Implement Operational reforms at the IRA to prevent improper payments
Subsidized Jobs Program	• Expand the Subsidized jobs programs like transitional jobs
Health Insurance Programs	• Place triggers on expanding government healthcare programs to improve healthcare in the face of massive job displacement
Evaluating More Drastic Measures like Basic Income Programs	• Study and evaluate more drastic measures, like Universal Basic Income, to inform policymakers about their potential costs, benefits, and unintended consequences in more extreme scenarios

7.1 Introduction

As AI transforms the workforce, social safety nets will become increasingly important in mitigating economic disruption, supporting displaced workers, and enabling smoother labor market transition. While some interventions aim to prevent displacement or promote retraining, affected workers may still face income loss, reduced benefits or difficulty re-entering the labor market. In this context, social safety net programs - whether universal, targeted, or conditional - can help stabilize households, preserve consumer demand, and support displaced workers and their families.

With this context, this section is mindful of different political views around the size and role of social safety net programs by providing several approaches to consider based on a policymaker's political philosophy. These different approaches can help readers navigate the rest of this section.

7.2 Policy Approaches for Strengthening Social Safety Nets

Projections about AI's impact are subject to high levels of uncertainty regarding labor markets with a wide range of plausible scenarios. This uncertainty makes it difficult to decide how the size and scope of safety net programs should change to meet the challenges of AI job disruption in a fiscally prudent manner. If many technologists are correct, we will likely need major expansions in social safety net programs to meet the challenges of massive job disruption. However, if skeptics are right, major increases in social safety net programs could prove overly costly and imprudent.

Social safety net programs have also been the subject of considerable debate among policymakers from across the political spectrum with differing views about the appropriate size and role of these programs. This white paper looks to provide three broad approaches for responding to potential massive disruption that is mindful of both uncertainty and political differences.

7.2.1 "Wait and See" Approach (Option #1)

Some policymakers are skeptical of expanding social safety programs and either think existing programs are adequate for the disruption AI brings or stronger signals are needed of massive disruption to warrant changes. This group may be hesitant to expand any programs and generally even prefer shrinking them instead. They may prefer a "wait and see" approach that only expands social safety net programs based on clearer signals of job disruption. Further, some may only accept this through discretionary programs that Congress must regularly approve and are offset by spending cuts. Those interested in this approach can consider the recommendations in section 7.4 based on if, when, and under what conditions it may be prudent to expand safety net programs in response to AI disruption.

7.2.2 "Preemptive" Approach (Option #2)

Other policymakers may prefer a more generous social safety net or are concerned enough about AI job disruption to believe that immediate social safety net expansion is necessary. This group may view existing social safety net programs as inadequate for the workforce disruptions that AI will bring, and leaves too many workers vulnerable. Further, some policymakers in this group may advocate for the expanding mandatory programs which do not require regular Congressional authorization, and are primarily funded through revenue raising mechanisms targeting wealthier individuals. Policymakers interested in this approach could preemptively pursue the recommendations outlined in Section 7.4.

7.2.3 "Trigger Mechanism" Approach (Option #3)

Policymakers may find trigger mechanisms appealing as a means to scale social safety net programs automatically according to prevailing economic conditions, especially when there is a high level of uncertainty. Trigger mechanisms can reduce policy uncertainty and allow adjustments that are fiscally prudent, yet proactive when necessary based on the changing economic conditions. Trigger mechanisms are currently used for some existing social safety net programs. For example, the Extended Benefits (EB) program in Unemployment Insurance is currently triggered by higher unemployment at the state level.

For this approach, policymakers could pre-plan for a range of scenarios and implement conditional trigger mechanisms to expand existing or initiate new programs if massive job losses occur or other conditions are met. Trigger mechanisms can be based on variables such as total unemployment rates, changes in unemployment, job openings, and fiscal constraints. For example, policymakers could consider establishing a trigger mechanism that expands unemployment insurance benefits if new job creation is less than a certain percentage of job losses over a year, and GDP has risen by at least a specified percentage, making such an expansion fiscally reasonable. Trigger mechanisms can also be designed to scale back these programs if disruptions diminish or fiscal conditions render them unaffordable. Trigger mechanisms can balance the need for fiscal prudence with strong support for displaced workers in cases of significant job disruption.

7.2.4 Combining the Best of All Approaches

The three approaches outlined above are not mutually exclusive, and policymakers could combine their most appealing elements. For example, a policymaker might adopt a "preemptive approach" when establishing programs similar to Trade Adjustment Assistance but prefer a "wait and see" approach when deciding on subsidized job programs. Trigger mechanisms serve as a political compromise or help address uncertainty when necessary.

7.3 Policy Options to Support Workers in an AI-Transformed Labor Market

The following section reviews a range of worker support policies that may be appropriate to address AI-driven job disruption and displacement. From an implementation standpoint, expanding or reforming existing programs (e.g. EITC) is more feasible than creating entirely new systems, and politically and fiscally more realistic. Bolder proposals may become more necessary in the long term depending on how circumstances change. In general, by sequencing interventions and investing in rigorous evaluation along the way, public policy can promote a more adaptable and resilient labor market that protects individuals and communities while also supporting growth and innovation.

7.3.1 Unemployment Insurance

AI is expected to displace many workers as the economy adjusts. Unemployment insurance (UI) can provide support to many displaced workers during this period by offering beneficiaries a financial cushion while they reskill or search for new employment.

A variety of reforms to UI (Wandner, 2023) could expand worker eligibility or duration while strengthening work incentives and its financial system. For instance, federal law could require all states to provide 26 weeks of benefits (as some states are now reducing benefit durations). The federal government or states could also provide longer periods of benefit receipt for permanent layoffs than for temporary ones, since the permanent layoffs create much greater hardship for workers. The federal government could also strengthen the Extended Benefits section of the law, which automatically provides extra weeks of unemployment insurance when state unemployment rates rise. At the same time, the work incentives and services portion of the Unemployment Insurance could be strengthened by providing more funding for Reemployment Services and Eligibility Assessment (RESEA), which appears cost effective at reducing unemployment and returning workers more quickly to jobs (Michaelides et al., 2021).

Finally, the financing of the program could become stronger by raising the minimum taxable wage base (i.e., the amounts of worker earnings that are subject to state or federal unemployment taxes), which is currently quite low (just $7,000 of earnings) or by strengthening the "experience rating" of those taxes, in which employers with a history of generating more layoffs pay somewhat higher FUTA (federal-level) and SUTA (state-level) unemployment taxes. Given the greater hardships associated with permanent than temporary layoffs, the government could impose higher FUTA taxes on employers generating permanent rather than temporary layoffs, which would limit their incentives to displace workers due to AI or other forms of automation and trade.

Pre-arranged trigger mechanisms building on the existing Extended Benefits program can improve UI programs by adjusting them based on how the economy evolves. Two hypothetical scenarios can help illustrate this point:

- In the first scenario, the economy sees a rapid increase in the ratio of job loss to job openings, because new jobs are not emerging fast enough or at all. A trigger mechanism can be built for this scenario to expand worker eligibility and increase the duration of unemployment benefits to account for the shortage of job openings in the face of significant job loss.

- In the second scenario, job loss and job openings are both high, because new jobs are rapidly being created that replace old jobs. A trigger mechanism can be built for this scenario that still makes benefits more generous (given the high amount of job loss due to displacement and need for macroeconomic support), but strengthens work incentives and does not change benefit duration to encourage people to find new jobs

7.3.2 Adjustment Support and Wage Insurance

As AI reshapes labor demand in unpredictable ways, many workers are likely to experience transitions where future roles are not yet clear or viable. Providing support beyond unemployment insurance to workers displaced by AI could help lessen the disruptive impacts to workers and their families. Policymakers should account for how unpredictable AI advancement makes it difficult to know what the best combination of monetary support, training, relocation assistance, and other benefits would be for such workers.

A program modeled after the bipartisan Trade Adjustment Assistance program (TAA) could provide income support, health care benefits, training subsidies, and relocation assistance for displaced workers during the transition to an AI-centric economy. The fiscal costs of such an expansion would have to be considered before such legislation is enacted.

Several studies have identified some of the benefits of TAA. One study (Hyman et al. 2024) shows that wage insurance in TAA for older workers displaced by imports has led to higher employment among them and higher earnings over time, suggesting wage insurance incentivizes displaced workers to accept lower-wage jobs, rather than remaining unemployed. A separate study (Hyman, 2018) shows that TAA trained workers see a wage premium for roughly a decade relative to comparable workers. However, these benefits should be considered in the context of the costs and scalability of the program.

If new labor demand and employment prove insufficient in the short term to absorb workers displaced by AI or those struggling to find new jobs, policymakers could consider a version of TAA focused primarily on wage replacement and monetary compensation rather than retraining. However, if labor demand remains strong and job vacancy rates continue to be high (as has been the case in recent years), an emphasis solely on income replacement may become counterproductive, potentially reducing employment and participation in job training programs. An appropriate balance must therefore be found between these options.

7.3.3 Tax Credits

Expansions of the Child Tax Credit and the Earned Income Tax Credit can bolster the incomes and work incentives of low-income families, and provide stronger income floors for families with children. The EITC raises employment levels and earnings for its recipients, and improves child outcomes over time (Schanzenbach & Strain, 2021), while expansions in the CTC (as in the 2021 ARPA) strongly reduced child poverty rates (Waldfogel, 2025). While these are federal programs, many states have implemented additional EITC and several are exploring CTC. These programs can support workers and families in the face of job disruption and economic change.

Concerns about improper payments with these tax credit programs should be tackled through operational reforms, such as expanding certain authorities at the IRS to prevent improper payments (Wielk, 2024). It should be noted that dramatic expansions of the CTC, along the lines of the 2021 expansion that had no earnings requirements, raise concerns about labor supply reductions that would need to be revisited.

7.3.4 Subsidized Jobs Program

An expansion of subsidized jobs programs could help preserve employment (Grant and Cooper, 2023). These programs involve government funding to partially or fully cover wages for workers, usually for a defined period, to incentivize employers to hire individuals who face barriers to employment or have recently experienced displacement. Subsidized jobs can be deployed during economic downturns or in structurally affected labor markets to maintain workforce attachment and reduce long-term unemployment. A particular model within this category – transitional jobs – targets individuals with limited recent work experience and places them into time-limited, wage-paying positions that are often paired with support services. These programs have generated popular interest, particularly after the Great Recession, and research indicates that they lead to significant short-term employment gains for participants. However, those gains often diminish once the subsidies end unless they are coupled with strong pathways to unsubsidized employment (Cummings and Bloom, 2020). Policymakers can create ad hoc subsidized jobs programs if unemployment unexpectedly spikes, but this can lead to operational challenges, so it might be wiser to put in place the infrastructure for such programs in advance that can trigger a pre-planned program if a sudden spike in unemployment is realized. Fiscal costs should be considered in deciding whether to implement such a program.

7.3.5 Health Insurance Programs

More than 60 percent of Americans under age 65 get healthcare through their employer (Claxton et al, 2024), meaning that job displacement and technological disruptions will also lead to termination of benefits with repercussions for workers and their dependents. Government safety net programs for healthcare can function as an economic stabilizer and improve worker resilience, providing workers with needed health insurance while pursuing retraining and new job opportunities. Improving healthcare access and quality, lowering costs, and promoting insurance portability are challenging, especially given fiscal constraints, incentive structures, and the complexity of healthcare that are beyond the scope of this paper.

Policymakers should continue to look for solutions and debate the appropriate role of government in healthcare programs, but they should at least place automatic triggers that expand these programs based on factors like unemployment rates and budget constraints that can help counter and improve healthcare coverage in the face of massive job displacement. For instance, the Federal Medical Assistance Percentage (FMAP) formula for Medicaid could become more generous in areas with high job displacement or higher unemployment.

7.3.6 Evaluating More Drastic Measures like Basic Income Programs

Many technologists believe the impacts of AI will be far more dramatic than many economists think and more drastic measures are necessary. A variety of drastic measures have been proposed (job guarantee programs, basic income programs, etc.), but universal basic income (UBI) has received the most attention. Whether extreme job disruption scenarios occur or not is difficult to project, but we think studying basic income programs and exploring other policy options is appropriate given the high level of interest in the topic.

As mentioned, some commentators fear that AI will lead to large employment losses, and therefore advocate for Universal Basic Income (e.g., Lowrey, 2018). Depending on how generous such a UBI plan would be, it could provide a floor under Americans' incomes that would limit poverty and income inequality, to some extent. A number of cities and states - notably, Los Angeles and Stockton in California, plus Denver and New Mexico - have begun pilot testing of basic income programs, with limited results to date (Vivalt et al. 2025). The findings of a recent pilot in Germany reinforce similar patterns observed in trials from Finland and the U.S. While unconditional income improves psychological well-being and has minimal effects on labor supply in the studies to date, it stops short of providing compelling evidence that basic income leads to large shifts in employment, risk-taking, or economic mobility (Niemeyer, 2025).

There are concerns that UBI may limit worker interest in training or other adjustment programs like wage insurance, given decades of research on the potential negative labor supply effects of unconditional income support in the U.S. (McClelland & Mok, 2012). However, if implemented, UBI would likely replace all existing safety net programs to enhance administrative efficiency and fiscal feasibility.

The fiscal costs of a basic income program could be daunting, as providing meaningful levels of support would require substantial new revenue sources or significant reallocation of existing public spending. Given that the federal government currently faces substantial future budget deficits due to retirement and healthcare programs (Congressional Budget Office, 2025), and considering political paralysis limiting efforts to raise revenue or reduce spending, introducing another potentially large entitlement program without replacing existing ones would be inadvisable.

7.4 Ensuring Operational Readiness for Social Safety Nets

Regardless of one's political views, promoting operational efficiency can help increase the value we get from our social safety net programs and improve their cost effectiveness. If the job displacement from AI is widespread, many existing social safety programs will rapidly expand, even under current law. For example, government spending on unemployment insurance programs will increase as more people are displaced. Expected expansions to social safety net programs from AI job disruption make it critical to consider not only the goals of the program but also the process of their operationalization.

Existing social safety net infrastructure on both the national and state levels has faced operational challenges and vulnerabilities at many points in the past during periods of stress. A notable recent example can be found in the unemployment insurance system during the recent COVID-19 pandemic, in which criminal actors were able to take advantage of existing system deficiencies on a rapidly increased scale, leading to the estimated loss of 11%-15% of distributed money in payouts to fraudulent actors (United States Government Accountability Office, 2023).

A March 2025 report by the Bipartisan Policy Center identified these deficiencies in the UI system as including reliance on outdated technology, staffing challenges, and inadequate fraud prevention infrastructure. The same report offers a number of recommendations to address these vulnerabilities and strengthen the system, including increased allocation of funding to UI administration, and boosting federal support to states and central oversight (Malde & Antonioli, 2025). Such enhancements would increase operational expediency and security, ensuring fiscal prudence and optimal cost-effectiveness in delivering these services.

Faced with the potential prospect of large-scale expansion of social safety net programs to address AI-driven workforce displacement, strengthening the operational capacity and security of existing social safety net systems is a key preemptive measure. Any expansion of social safety net policies should include a robust plan for ensuring their operational efficacy and resistance to exploitation.

7.5 Conclusion

Although this section primarily addresses general considerations about social safety nets, its relevance to AI-related labor market disruptions lies in the necessity of preparing existing systems for potentially rapid increases in demand. AI-driven displacement could create acute stress on safety net programs, as illustrated by previous economic shocks like the COVID-19 pandemic. Ensuring the operational readiness, scalability, and security of programs such as unemployment insurance and worker adjustment assistance becomes crucial to effectively manage transitions and mitigate economic hardship. This preparation includes strengthening administrative infrastructure, enhancing fraud prevention, and establishing responsive trigger mechanisms to adapt quickly to changes in employment dynamics driven by AI.

Additionally, the outlined policy approaches—ranging from cautious "wait and see" strategies to more preemptive expansions—highlight the complexity of managing uncertainty around AI's labor market impacts. Policymakers should consider flexible strategies such as trigger mechanisms to balance responsiveness with fiscal responsibility, providing timely support without prematurely committing extensive resources.

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8 Policy Options for Place-Based and Industry-Level Interventions

TABLE I

FOCUS AREA	POLICY OPPORTUNITIES
Sectoral Training: Matching Skills to Regional Labor Markets	• Expand and increase accessibility to high-quality sectoral training programs, which are training partnerships between regional employers and experts with highly specific skills
Place-based Policies for Local Economic Development	• Research the geography of potential AI displacement or augmentation to create effective and efficient place based policies. • Increase survey data on AI adoption to help understand which sectors will be most impacted by AI
Industrial Strategies for Economic Development	• Use the CHIPS "Tech Hubs" program as a model if policymakers decide to apply a regional focus to industrial strategies

8.1 Introduction

Turning to place-based policies or industrial strategies can be an important approach for addressing the expected disruptions that AI will have in the labor market. The AI transition is expected to change the demand for and supply of labor, and concerns about its exacerbating effects on inequality are emerging (Sholler and MacInnes 2024). Moreover, because industries and occupations are regionally concentrated, and because workers are geographically sorted along skill and occupation, it is also an emerging concern that AI's impacts will be localized, worsening trends in regional economic inequality and further widening the gaps between rich and poor places (Gaubert et al. 2021). Broadly, there are two categories of "place-based" labor policies:

1. Those that aim to **raise the skill levels of workers** in a region and **better match them to local firms and industries** through workforce development

2. Those that **encourage more and better labor demand** in these locations, typically through economic development (which often requires a workforce focus as well).

The first category is more relevant in regions with strong economic growth but where shortages of appropriately trained workers often can occur, at least in the short run (National Academies of Science, 2017). These shortages can arise when externalities or information asymmetries lead to regional coordination failures and underinvestment in places so addressing them can, in principle, increase economic efficiency (Fajgelbaum and Gaubert 2020, 2025; Neumark and Simpson 2015; Kline and Moretti 2014).

The second category is more appropriate for depressed regions that have experienced deindustrialization or lagging economic growth for other reasons (Austin et al. 2018). In this case, people-based targeting may be less feasible or the externalities may be spatially concentrated. Further, when workers cannot easily move to another part of the country, there is also a role for the second category of policies to address lagging labor demand to boost growth in the region.

In contrast to place-based labor policies, industrial strategy aims to achieve a policy objective or set of objectives by making strategic investments in particular industries. Sometimes, the incentives offered to firms receiving strategic public investments require them to invest in the local workforce, such as through training, wages, or job quality.

8.2 Sectoral training: Matching Skills to Regional Labor Markets

One approach to improving regional skills and better matching them to firms with high skill needs and well-paying jobs is sectoral training. In this approach, intermediaries with knowledge about specific high-demand sectors of the economy with unmet skill needs – such as health care, advanced manufacturing, IT or transportation and logistics – bring together regional employers in these sectors and skill providers. The employers communicate their skill needs to the providers, who then train appropriately-skilled workers for these jobs (along with needed supports to help improve their successful completion) who are then hired by the employers (Conway and Giloth 2014).

At their best, sectoral programs generate large and lasting earnings improvements for disadvantaged workers (Katz et al. 2020). Well-known programs such as Per Scholas (or WorkAdvance), Project Quest, Year Up, Jewish Vocational Services and the Wisconsin Regional Training Partnership have been among the most successful such efforts (see also Maguire et al. 2010). On the other hand, there is no guarantee of such success; for instance, many efforts at community colleges to engage in such efforts with regional employers have mixed success, and fail to adopt best practices in such efforts (Fuller and Raman 2023). The best programs are hard to scale (Holzer 2025) and require costly support services.

Improving sectoral efforts could enhance the abilities of workers to obtain well-compensated skills in a dynamic regional market, where AI may be rapidly changing employer skill needs. Improving the abilities of regional training providers to engage in high-quality sectoral training could thus have important economic payoffs for workers and firms in many scenarios resulting from AI disruptions. Helping the best programs replicate and scale themselves, likely in partnerships with other training providers or community-based groups, could be important as well.

8.3 Place-Based Policies for Local Economic Development

Generally speaking, deploying place-based policies to support local economic development leads to three important practical challenges for policymakers. First, unlike with sectoral training or, more broadly education or workforce policies, there are few off-the-shelf place-based or programs that could be expeditiously implemented, adapted, or scaled. Even prominent state-level Enterprise Zone programs are typically geared toward real estate development and small business attraction, rather than job creation or training. Moreover, federal place-based programs for local economic development like Empowerment Zones or the "Recompete Pilot" in the CHIPS and Science Act would need to be reauthorized and funded. Even so, these federal programs could offer a model for strengthening local labor demand in distressed regions.

Second, as with sectoral training efforts, the evidence on place-based policies is both mixed and insufficient, leaving policymakers with few concrete guideposts for designing new programs. Some policies are well-designed and effective at achieving job creation, strengthening worker training, or alleviating economic distress, such as policies featuring block grants that can be targeted toward solving specific problems. However, others are not, such as policies that subsidize businesses solely based on their location, making them difficult to justify based on findings from the available research.

Third, current data and measurement of AI adoption are insufficient to support robust policy design and implementation. Policymakers looking to pursue place-based policies will need to better understand the geography of potential AI displacement or augmentation, as well as which industries and occupations are most exposed to AI. As discussed in an earlier section, expanded data collection efforts are necessary to help target grants to vulnerable communities, help ascertain the magnitude of redistribution, and determine what form that redistribution would take (e.g. cash assistance versus training versus relocation grants). More survey and administrative data related to businesses would also inform how different industries are adopting or being shaped by AI.

8.4 Industrial Strategies and Workforce Development

In the context of labor policy, industrial strategies seek to achieve economic security or resilience by making strategic investments in particular industries and nudging private-sector investments in workforce training, job quality, and other markers of "good jobs." For example, the semiconductor industry revitalization efforts in the CHIPS and Science Act feature incentives for workforce training and education. These nudges are meant to help businesses find the workers they need and help the communities where semiconductor fabs are being built benefit from the growth of a skilled workforce.

Like with place-based policies for local economic development, policymakers will likely face practical hurdles in designing and implementing industrial strategies. The U.S. has a limited track record with industrial strategy, leaving few fully-developed approaches to adopt and implement. And among the available approaches, most are from other countries, like Taiwan and South Korea, that were still developing economies and not in a situation where they were confronting concerns about the labor market in the face of seismic technological change. Evidence on recent U.S. industrial strategies, such as the CHIPS and Science Act or the tax incentives for climate policy in the Inflation Reduction Act, is still nascent and it may be some time before more concrete lessons for policymakers can be drawn.

Should policymakers decide to invest in regional innovation, the "Tech Hubs" program from the CHIPS and Science Act offers a model for applying an industrial strategy focused on catalyzing select technological clusters. This program funded regions to invest in critical and emerging technologies that would have local economic spillovers, so as to geographically spread the benefits of technological innovation through job creation and local economic growth. The basic contours of the "Tech Hubs" program could be adapted to scale the regional economic benefits of AI technological development, adoption, and application.

8.5 Case Study from Michigan

As one of the most recent AI related updates to state level-workforce plans, the state of Michigan has recently released an AI addendum to its 2024 Statewide Workforce Plan that focuses on three areas: Investing in skill development for the AI economy; providing business and workers with information on how AI is affecting the economy and the availability of new AI-related training opportunities; and providing explicit technical support to small and medium businesses in the adoption of AI and using AI to improve workforce services. Michigan's workforce plan is an example of the first category of labor policies discussed above, which seek to increase workers' skills and better match them to employers.

The first area, investing in skill development, calls for embedding AI in career training and K-12 curriculum, building new AI certification and degree programs; increasing the number of registered apprenticeships in fields with increasing use of AI technologies; and expanding the focus on AI training in the state's Going Pro program, in which firms identify their training needs and compete for state sponsored resources to fund them.[6]

The second area is focused on providing information to both businesses and workers on the changing landscape of how AI is affecting the nature of work. These include recommendations to provide real-time data and ongoing analysis on how AI is affecting the economy and occupations; expanding the resources available for competitive grants to regions for investments in AI capacity building efforts.[7]

The third area focuses on supporting small and medium sized businesses (SMBs) to enable them to compete effectively with larger businesses in the use of AI in production processes and to provide job seekers with better career information using AI related tools. The goal in supporting SMBs is to direct state resources into priority industries including transportation (especially SMBs in the electric vehicle supply chain), healthcare, financial services, and advanced manufacturing. The state is also

6 This pillar is modelled after the Colorado ElevateAI program that is focused on aligning K-12, community and 4-year college programs with business needs in AI education, particularly in mathematics and computer science.

7 This pillar is modelled after a similar program in New Jersey through its New Jersey Future of Work Task Force. The task force commissioned six academic studies on the impacts of AI, technology, and automation on the future of work in key industries in New Jersey.

investing heavily in developing predictive analytic models using machine language tools to provide career advice to job seekers, as are workforce agencies in other states.

With federal support, states should pilot, evaluate, and consider adopting similar plans for how AI will be used in training and workforce development, in ways that fit their own industries and local economy.

8.6 Conclusion

To address AI-driven labor market disruptions effectively, policymakers should consider robust sectoral training programs, carefully targeted place-based economic development initiatives, and industrial strategies designed to encourage workforce investments and regional innovation. While challenges exist, particularly regarding scalability, data availability, and clear program effectiveness, the outlined approaches provide a framework for developing resilient regional labor markets and mitigating economic inequality exacerbated by AI.

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9 Conclusion

As artificial intelligence continues to reshape the labor landscape, policymakers face the dual challenge of mitigating workforce disruptions and leveraging opportunities to enhance productivity and economic growth.

To navigate these challenges effectively, this white paper considers a comprehensive and proactive approach across several interconnected areas:

- **Enhancing Data and Research Infrastructure:** Modernize government data collection, integrate private-sector insights, and support longitudinal studies to track AI's evolving impacts on jobs.
- **Innovating in Education and Workforce Development:** Align education and training systems with real-time industry needs, and implement scalable, lifelong learning solutions that equip workers to adapt continuously to technological advancements.
- **Modernizing Social Safety Nets:** Enhance operational readiness, scalability, and flexibility of safety net programs to provide timely support for displaced workers, ensuring economic stability and worker resilience.
- **Considering Targeted Place-Based and Industrial Policies:** Support localized workforce training, encourage strategic investments in industries critical to economic resilience, and address regional inequalities exacerbated by AI adoption.

When policymakers proactively develop labor policy strategies, stakeholders—including governments, educational institutions, businesses, and communities—can ensure a more resilient and adaptive labor market that generates abundant opportunity for all. Ultimately, coordinated and informed actions will determine how successfully society navigates the transformative age of AI, securing both economic prosperity, social stability, and worker dignity.