Rethinking Automation Risk:

AI Applicability and Occupational Outcomes, 2019–24

Kristen Broady, Caleb Dunson, and Anthony Barr

July 2, 2026

WP 2026-12

https://doi.org/10.21033/wp-2026-12

FEDERAL RESERVE BANK *of* CHICAGO

Rethinking Automation Risk: AI Applicability and Occupational Outcomes, 2019–24

Kristen Broady[a], Caleb Dunson[b], Anthony Barr[c]

Abstract

Rapid advances in artificial intelligence have renewed concerns that earlier automation forecasts may understate the range of occupations exposed to technological change. This paper provides an ex-post assessment of how U.S. occupational labor-market outcomes evolved during a period of rapid AI advancement. We combine Frey and Osborne's (2017) estimates of occupational computerization risk with Tomlinson et al.'s (2025) AI applicability scores based on Microsoft Copilot usage, matching both measures to O*NET occupational classifications and U.S. Bureau of Labor Statistics employment and wage data for 2019 through 2024. We first assess how recent developments in robotics, large language models, and generative AI have narrowed the engineering bottlenecks that Frey and Osborne identified in perception and manipulation, creative intelligence, and social intelligence. We then compare employment and wage changes across occupations with high and low AI applicability scores and across occupations classified as having high, moderate, or low probabilities of computerization. The results complicate a simple displacement narrative. Occupations with high AI applicability scores experienced overall employment and wage growth between 2019 and 2024, while occupations with high and moderate automation-risk scores experienced weaker employment performance than low-risk occupations. Wages increased across all automation-risk groupings. These patterns suggest that exposure to AI and automation does not map mechanically onto job loss, at least in the short run, and that task-based measures of technological exposure are better understood as indicators of occupational restructuring than as direct forecasts of employment decline.

JEL Classification Codes: J24, J31, O31, O33

Keywords: Labor, Artificial Intelligence, Automation

Acknowledgments: We thank Daniel Sullivan and Han Choi for their helpful comments and suggestions.

Disclosure Statement: Any views expressed do not necessarily reflect those of the Federal Reserve Bank of Chicago or the Federal Reserve System.

[a] (Corresponding) Federal Reserve Bank of Chicago, 230 S. LaSalle St., Chicago IL, 60604 Kristen.broady@chi.frb.org

[b] Federal Reserve Bank of Chicago, 230 S. LaSalle St., Chicago IL, 60604 caleb.dunson@chi.frb.org

[c] National Bankers Association, 1513 P St. NW, Washington, DC 20005, abarr@nationalbankers.org

1. Introduction

This morning when you checked your calendar or alerts, your iPhone or Galaxy may have used facial recognition to unlock your screen. On your way to work, your car's navigation system may have employed artificial intelligence (AI) to suggest stops, share real-time traffic updates, and make routing decisions. At work you may have used AI to transcribe meetings. And in the evening after work, as you decided what movie or show to watch, your streaming app may have used personalized recommendations. If you are an Amazon customer, agentic AI may have helped you shop. In more ways than many of us realize, artificial intelligence has been integrated into our work and personal lives.

If you use AI, you are one of hundreds of millions of users worldwide who now interact with artificial intelligence tools in their daily lives. ChatGPT's consumer product was launched in November 2022, and by July 2025 it had been adopted by 10 percent of the world's population (Chatterji et al., 2025). Anthropic's artificial intelligence assistant, Claude had 12.48 million monthly active users in February 2026, an increase of nearly 50 percent from the number of users just a month prior (Sen, 2026). Microsoft's Copilot has been downloaded 88 million times since its launch in 2023 and has 218 million active users (Curry, 2026).

As AI adoption has expanded among consumers, firms have increasingly integrated these technologies into production processes, workplace operations, logistics systems, and decision-making. Task automation using machines and robots has been used to increase efficiency for decades. More recently artificial intelligence has been leveraged to equip physical machines with the ability to perceive, learn, and make decisions. Automation and artificial intelligence (AI) continue to alter the structure of work and the organization of production at an astonishing rate. Millions of people worldwide leverage generative AI models across billions of visits per month (Liu and Wang, 2026). What began primarily as consumer-facing and programming-oriented tools has rapidly evolved into broader enterprise and industrial applications.

Beyond their initial use for programming, these models are now being leveraged in a variety of sectors including banking, medicine, and law. As their user base and revenue grow, the firms producing these tools have created ever more sophisticated models. Indeed, recent models from Anthropic and OpenAI have been deemed so powerful that the firms are choosing to delay release to the general public until key sectors have a chance to shore up their security (The Economist, 2026). Simultaneously, technical breakthroughs such as Google's TurboQuant are reducing hardware barriers, allowing models to be faster and less memory-intensive, while not sacrificing accuracy (Coughlin, 2026). These developments, in turn, are allowing open source models to compete with the dominant closed models from firms like OpenAI and Anthropic (Nagle and Yue, 2025). Meanwhile, the converge of AI models and robotics is redefining what machines can accomplish in the physical world, from self-driving cars to autonomous military drones to fully automated warehouses (Deloitte, 2025).

As firms continue increasing investments in AI infrastructure, automation, and digital workflows, questions have emerged about how these changes may affect employment across industries. While not all recent workforce reductions can be directly attributed to AI, many have occurred alongside announcements of expanded AI investment, restructuring, or automation initiatives. In February 2026, H&M Group announced plans to lay off 181 workers from its downtown Chicago customer service call center (Schroyer, 2026). While the H&M announcement did not specifically mention that the workers were being laid off because of AI, a May 18, 2026 release from META shared plans to cut 10 percent of its employees the following day, with additional layoffs later in the year, accompanied by "organizational changes aimed at improving the company's AI workflows" (Paul, 2026). In what some analysts believe could become the largest workforce reduction in Oracle's history, in March 2026 the company began layoffs that could affect between 20,000 and 30,000 of its 162,000 employees worldwide, as it increases its investments in building AI data centers (The Washington Times AI News Desk, 2026). At the same time, AI infrastructure and hyperscale orders increased, with Cisco announcing $5.3 billion in orders between January and mid-May 2026 (Novet, 2026).

According to the May 2026 Challenger Report, U.S.-based employers announced 83,387 job cuts in April, following 60,620 cuts in March 2026, bringing the year-to-date total to 300,749 as technology companies increase spending on AI and innovation (Challenger, Gray, and Christmas, 2026). The report suggested that even if individual jobs in the technology sector are not being replaced by AI, the funding for those is. According to the report, in April 2026 significant job cuts associated with increased investment in AI were also occurring at pharmaceutical companies (-7,440), chemical companies (-4,975 companies), and in the industrial manufacturing sector (-7,799).

While these innovations bring with them important concerns over the displacement of workers, it is important to note that past waves of technological advancement from the automobile to the world wide web have typically generated both harm and opportunity for workers. Moreover, while the exact distribution of benefit or harm from technological innovation has often overlapped with existing societal distributions of power, financial and social capital, innovation has also often led to significant restructuring of existing social dynamics altogether. Recognizing that no one can predict the future, this paper instead seeks to evaluate evidence of early impacts of these nascent technologies on the US labor market between 2019 and 2024.

As context for this paper, Frey and Osborne (2017) reignited the debate about labor markets and automation by applying a machine-learning model to estimate the susceptibility of over 700 U.S. occupations to automation, concluding that nearly half of existing jobs faced a high risk. Their findings underscored a key divide: routine, lower-wage occupations were more vulnerable to automation, while higher-wage, cognitively intensive jobs were more resistant. At the same time, they identified three engineering bottlenecks that constrained automation's reach: perception and manipulation, creative intelligence, and social intelligence. At the time, these limitations represented meaningful barriers to replacing large segments of human labor.

But since that seminal study, the scope and pace of technological innovation have accelerated (Broady et al. 2025). Advances in robotics, large language models (LLMs), and generative AI have reduced many of the technical barriers Frey and Osborne (2017) outlined. Robots now integrate multimodal sensory systems and reinforcement learning, enabling them to navigate unstructured environments, recover from errors, and even reconfigure themselves (Patel and Reynolds, 2025; Tu et al., 2025). Foundation models have transformed creative tasks, with generative AI systems producing coherent text, music, and even humor that rivals human output (Gorenz and Schwarz, 2024); Fišer et al., 2025). Meanwhile, new research demonstrates that advanced AI systems can detect, interpret, and strategically respond to emotional cues in ways that approximate or, in some cases, exceed human performance (Harris, 2025; Fatahi et al., 2025).

The confluence of these developments suggests that automation risk is no longer limited to narrowly defined routine or manual occupations. Instead, a growing set of jobs across the wage and skill spectrum may be restructured, augmented, or displaced by AI. To capture these dynamics, Tomlinson et al. (2025) extended Frey and Osborne's framework by analyzing human interactions with Microsoft Copilot, constructing "AI applicability scores" that highlight which occupations are most exposed to AI assistance or substitution. Their results indicate that writing, editing, programming, sales, and customer service occupations, many of which Frey and Osborne originally classified as relatively safe, are now highly susceptible to automation.

We build on these two strands of work. By applying Frey and Osborne's (2017) automation risk scores and Tomlinson et al.'s (2025) AI applicability scores to U.S. labor force data from the Current Population Survey, we analyze shifts in occupational exposure between 2019 and 2024. Our aim is not to speculate about the distant future, but to evaluate whether Frey and Osborne's predictions aligned with what actually happened between 2019 and 2024, and how the acceleration of AI during this period altered those forecasts.

This paper proceeds in four parts. First, we revisit Frey and Osborne's engineering bottlenecks and assess how recent advances in robots, generative AI, foundation models, and emotion-recognition systems have altered the technological constraints that once limited automation. We then review related literature on automation, task-based technological change, AI applicability, and the relationship between technological adoption, employment, and wages. Next, we use Frey and Osborne's automation risk scores and Tomlinson et al.'s AI applicability scores, matched to O*NET and U.S. Bureau of Labor Statistics occupational employment and wage data, to examine how employment and wages changed between 2019 and 2024 across occupations with different levels of exposure to automation and generative AI. Finally, we discuss what these early patterns suggest about the relationship between automation, AI, occupational risk, and labor market outcomes, while identifying directions for future research.

2. The Changing Technological Constraints of Automation and Artificial Intelligence

Frey and Osborne (2017) applied a machine-learning model to estimate the probability that 702 distinct occupations could be automated. Roughly 47 percent of U.S. jobs were deemed high-risk (having an automation risk probability over 70 percent). Their findings indicated that on average lower-wage occupations that required less education had higher automation risk probabilities. Conversely, occupations that required more education and paid higher wages were less susceptible to automation.

Frey and Osborne (2017) identified three engineering bottlenecks that constrained automation's reach: perception and manipulation, creative intelligence, and social intelligence. Since then, advances in robotics, generative AI, and multimodal systems have narrowed or eliminated many of these limitations. The sections below revisit each bottleneck in light of recent technological developments.

2.1. Recent advancements in AI have mitigated previous robot perception challenges

With respect to perception and manipulation, Frey and Osborne found that robots were unable to match the scope of human perception. Tasks that required navigating unstructured work environments or cluttered spaces, and those that involved handling irregularly shaped objects proved challenging for robots. Failure recovery was also found to be an issue as robots were less able to identify and correct mistakes. With recent advancements in AI sensor fusion, combining vision, tactile, and proprioception capabilities, robots can better identify objects, understand their affordances, and anticipate physical interactions, even in cluttered, unpredictable spaces (Patel and Reynolds, 2025). Today, robots can leverage foundation models that bring language and vision together to interpret complex scenes, thereby improving environmental understanding and human-robot interaction in unstructured settings, such as construction sites (Naderi et al., 2024).

Drawing inspiration from the field of biology, researchers are deploying neuromorphic systems and minimalist frameworks that enable tiny, efficient robots to perceive, navigate, and make decisions using minimal sensors that are optimal for micro-robots and resource-constrained environments (Novo et al., 2024; Singh et al., 2024).

Robots can now address the Simultaneous Localization and Mapping (SLAM) problem through the incorporation of visual, tactile, and acoustic sensors (Stachniss et al., (2016). Audio-visual SLAM helps compensate for visual occlusions or low-light conditions (Lahemer and Rad, 2024). Vision-Guided Robots (VGR) are evolving from 2D to 3D, allowing robots to pick up items in dynamic settings, with less set up time, and wider lighting tolerances. While 2D machine vision systems are able to capture and analyze two-dimensional images that provide a flat representation of an object, with the addition of technologies like structured light, laser triangulation, or stereo vision, 3D machine vision systems add depth, creating detailed models of an object's shape and dimensions (Sorall, 2025). In terms of the ability to handle irregular objects and make adjustments, reinforcement learning (RL) allows robots like ANYmal, a fourlegged robot to play badminton, accurately tracking and returning shuttlecocks in real physical environments. The robot is able to adjust to new trajectories and coordinate vision and motion seamlessly (Berdugo, 2025).

Working with Toyota Research Institute, Boston Dynamics's developed Atlas, a dancing humanoid that uses a single large behavior model (LBM) that takes visual, proprioceptive, and even language inputs (Knight, 2025). With capabilities including walking and gasping, it demonstrates natural movement adjustments and can rebalance when reaching. It is also able to recover when an object is dropped. Significantly, it can complete all these tasks without task-by-task training. Further, with respect to self-recovery, self-reconfiguration modular robots can change their physical shape and adapt to constrained spaces, repair damage, and switch locomotion models (Tu et al., 2025). This modularity inherently supports failure recovery and adaptation as these robots have sufficient backup modules to replace faulty modules (Qi et al., 20224).

Universities are also contributing to technological advancements and improvements. Initiatives like the National Science Foundation funded Human AugmentatioN via Dexterity Engineering Research Center (HAND ERC, 2025) are working to revolutionize the ability of robots to successfully complete tasks that involve intuition and dexterity. Researchers at Columbia University created a prototype robot with a type of "robot metabolism," capable of growing or repairing by absorbing parts from the environment or other robots, reshaping themselves to overcome obstacles or damage (Pérez, 2025).

From static, task-specific robots to adaptable, self-correcting, and perceptive machines, today's robotics seem more like humanoids or drones only depicted in movies in 2017. If LLM-style scaling can be applied to robots as it has been for language, it could lead to even more rapid improvements in robotic capabilities and behavior. Robots today are smarter and are able to meet the challenge of being able to rebuild themselves. The gap between human and robot perception, manipulation, and adaptability is narrowing. Technological advancements are moving from static automation to more flexible, autonomous machines that learn, adapt, and in some cases, even improvise. While advances in robotics have narrowed limitations related to perception and physical adaptability, recent developments in generative AI have also challenged earlier assumptions about the limits of machine creativity.

2.2. Technological advancements including generative AI and foundation models have overcome previous concerns about the ability of computers and machines to capture human creative intelligence.

Frey and Osborne (2017) raised doubts about whether automation could truly capture human creative intelligence, especially given the difficulty of coding creativity. But since then, technological advancements like generative AI and foundation models have overcome those challenges. Backed by powerful transformers and large language and image AI models, also known as generative AI or foundation models have transformed content creation. Models like

GPT-3, GPT-4, PaLM, Gemini, and LLaMA can now generate coherent, stylistically rich text, including stories, poetry, and jokes, that often read as authentically as those created by humans (Davenport and Mittal (2022); Gorenz and Schwarz (2024)). Generative AI has come a long way in making us laugh. In a 2024 study conducted by Gorenz and Schwarz, people rated the funniness of human-produced and A.I.-produced jokes, and ChatGPT 3.5-produced jokes were rated as equally funny or funnier than human-produced jokes.

With respect to music, ElevenLabs' Eleven Music is an AI-powered music generation platform, launched on August 5, 2025, that lets users create studio-grade music based solely on text prompts, while also using safeguards to protect rights holders and prevent copyright infringement (MLQ.ai, 2025). Other examples of AI tools that can create music through text prompts include MuseNet, AIVA, and Suno, Udio (Coursiv, 2025). Fišer, Martin-Pascual and Andreu-Sánchez (2025) explored the emotional impact of AI-generated music versus human-composed music. Their results suggested a surprising reverse of Frey and Osborne's finding that creativity was a challenge for computers and machines due to coding challenges. In their study, humans were the ones who had to exert more effort in coding or decoding. Their findings suggested that study participants required greater effort to decode information from AI-generated music than human created music. Additionally, participants found AI-generated music more arousing, while they perceived human created music as more familiar.

Another important form of creative output is computer programming. The AI models discussed above have been particularly powerful in this area of work. Indeed, AI is so useful that firms such as Spotify have announced that most of their developers no longer need to write their own code, but merely to review AI generated code (Perez, 2026). And Anthropic, the firm responsible for the Claude AI model, estimates using its own usage data that nearly 75% of computer programming tasks are automatable (Massenkoff and Peter McCrory, 2026.)

Creative tasks are no longer limited by coding rules. Generative AI can now co-create with humans. But cognitive ability is still required, as human learning, level of technical experience, and adaptability impacts our ability to guide AI models. Licensing issues and industry resistance from artists who want to protect their creations mean there is still room for improvement and ethical evolution in the realm of robotic creative intelligence. Beyond creative production, recent AI systems are also increasingly capable of interpreting, responding to, and simulating elements of human social interaction.

2.3. Technological advancements in large language models and emotion recognition systems have narrowed previous limitations related to social intelligence.

Frey and Osborne (2017) suggested that occupations that involved social intelligence tasks like persuasion and negotiation were difficult to automate because while algorithms could reproduce certain aspects of human social interaction, they were unable to recognize and respond to human emotions in real-time. This is an issue because emotions are a vital part of human social interactions that often influence how we make decisions (Fatahi et al., 2025). This raises the question of whether it is necessary for LLMs to actually be able to replicate, recognize, and/or respond to human emotions to be useful in completing job tasks?

A 2025 study by the University of Geneva found that several LLMs, like ChatGPT-4, Gemini, and Claude 3.5 Haiku scored 82 percent accuracy on emotional intelligence assessments, outperforming humans who averaged around 56 percent (Schlegel, et al., 2025). These models also authored new, valid emotional-intelligence test scenarios with little prompting, previously the domain of human experts. AI is not only passively simulating empathy, but also detecting it, reasoning about it, and generating emotional context at greater speed than humans.

Gorenz and Schwartz (2024) found that ChatGPT did not need to feel human emotions to create jokes that humans deemed funny. And with the respect to recognition of human emotion, research by Finet, Kristoforidis, and Laznika (2025) suggested that AI tools "provided relatively consistent and coherent assessments of the general emotional tone" in texts written by students who participated in an experiment that involved writing a free-form report describing their emotional experience. Further, Fatahi et al. (2025) found that in responses to questions in the domain of medicine human responses were more likely to include concepts related to hope and positivity to offer comfort and reassurance, while responses from ChatGPT were more neutral and were less likely to include words related to optimism. Additionally, Fatahi et al. (2025) found that in response to questions related to finance, human responses contained more definitive and optimistic language, while responses from ChatGPT were more cautious and probabilistic. These studies indicate that some LLMs can recognize and respond to human emotions, but that AI's capacity to interpret and respond properly to human emotions may require further development to increase its integration into various job tasks that rely heavily on human emotional intelligence. These technological developments raise important questions about whether occupations previously considered resistant to automation may now face greater exposure to AI-assisted task substitution or augmentation.

3. Evolution of Employment and Wage Outcomes. 2019 to 2024

With the introduction and expanded application of generative artificial intelligence, even with its current limitations and challenges, some of the occupations for which Frey and Osborne (2017) estimated a lower automation risk score can now be successfully completed by Microsoft Copilot, ChatGPT, and other advanced AI systems built on LLMs. Hence, in addition to automation, we must also consider the impact of AI on occupations and workers. With this goal in mind, Tomlinson et al. (2025) analyzed 200,000 anonymized user-AI conversations sampled representatively from 9 months of Microsoft Copilot usage in the U.S. during 2024 to measure AI's potential impact on occupations. The study used O*NET's occupational work activities database and defined an AI applicability score for each occupation based on how successfully various work activities can be assisted by or performed by Copilot. For each occupation, this score combines the following information: "whether Copilot users are performing its associated work activities successfully and covering a broad share of the work activity." Occupations with higher AI applicability scores are more likely to be impacted by AI than occupations with lower scores. The authors listed the 40 occupations with the highest and lowest AI applicability scores. They found that jobs with high scores involve work activities related to writing, editing, sales, customer service, programming, and clerking, while jobs with lower scores involve tasks that require physically working with people, operating or monitoring machinery, and other manual tasks.

While neither Frey and Osborne's automation risk scores, nor Tomlinson et al.'s AI applicability scores can positively predict the future of what jobs will be impacted by automation or AI, the metrics they developed can help us better understand which occupations and workers are more likely to have their job tasks altered by automation and AI. We can also apply their metrics to historical occupation data to see if employment shifts align with trends in technological advancement.

Beyond predictions of which occupations might be automated, a large body of work in labor economics has analyzed how technology alters the demand for skilled labor by changing the task content of work. Autor, Katz, and Krueger (1998) showed that the diffusion of computer technology contributed to skill-biased technical change and widening educational wage differentials. Later, Autor (2015) emphasized that tasks rather than entire occupations are automated, and that technological change often displaces some tasks while creating demand for others. Acemoglu and Restrepo (2019) formalized this as a framework of "displacement" and "reinstatement" effects, with net outcomes depending on whether new, complementary tasks are created at scale. Autor and Salomons (2018) found that while productivity growth can reduce employment within industries, new tasks and industries offset some of these losses at the aggregate level. More recently, Autor (2022) argued that digital technologies may no longer create new tasks at the same pace, raising concern about broader exposure across occupations once thought insulated from automation.

This body of work underscores why ex post evaluation is important. Whether forecasts align with actual shifts depends on technical feasibility and on the balance between displaced and newly created tasks. Our analysis draws on this task-based perspective by evaluating whether occupations classified as high- or low-risk of being impacted by automation experienced changes in employment and annual wages between 2019 and 2024.

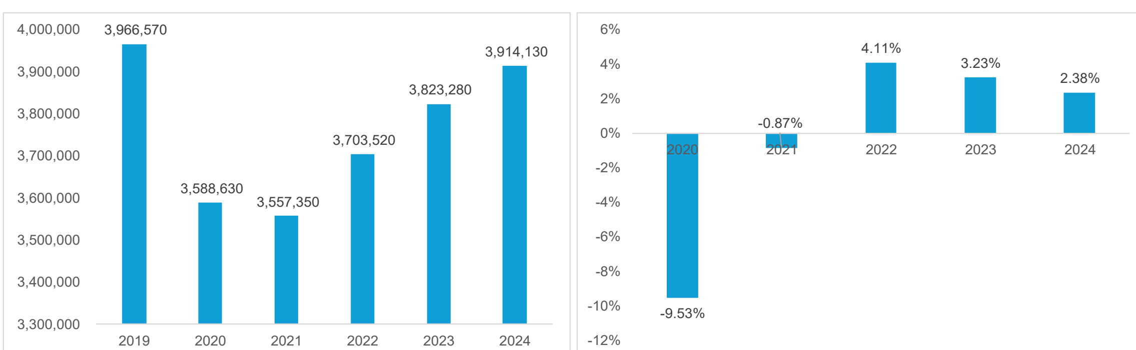
The O*NET Program's O*NET-SOC taxonomy provides data for 1,016 occupational titles (O*NET, 2026). As some occupation titles changed between 2019 and 2024, we used the O*NET SOC codes to match occupations from Frey and Osborne (2017) with occupations from Tomlinson et al. (2025) and occupational employment and wage statistics (OEWS) from the U.S. Bureau of Labor Statistics (U.S. Bureau of Labor Statistics, 2025). While Frey and Osborne conducted their study in 2017, our analysis begins in 2019, as the BLS and related agencies transitioned from the 2010 SOC system after 2018. Beginning our analysis with 2019 allowed us to match data for a greater number of occupations.

The first set of figures focuses on AI applicability. Figures 1 through 4 describe how employment and wage outcomes evolved between 2019 and 2024 across occupations with the highest and lowest AI applicability scores. Read together, the figures test a simple but important question: are the occupations most exposed to AI already showing signs of broad labor-market decline, or are the early patterns more consistent with task augmentation and uneven adjustment?

Figure 1 shows that employment in occupations with the lowest AI applicability scores declined sharply between 2019 and 2020, followed by a sustained recovery beginning in 2021. Total employment in these occupations fell from 3,966,570 in 2019 to 3,588,630 in 2020, representing a decline of approximately 9.5 percent. Employment continued to decline slightly in 2021 before increasing in each subsequent year, reaching 3,914,130 in 2024. Despite the recovery, total employment in these occupations remained slightly below its 2019 level at the end of the period.

The year-over-year percentage changes show that the strongest employment growth occurred during the recovery period. Employment increased by 4.11 percent in 2022 and by an additional 3.23 percent in 2023 before moderating to 2.38 percent growth in 2024. Many of the occupations with low AI applicability scores involve manual, physical, or machine-monitoring tasks that are less susceptible to assistance or substitution from generative AI systems. While employment in these occupations had not fully returned to its 2019 level by 2024, the figure shows a clear pattern of employment growth following the declines observed in 2020 and 2021. These results suggest that occupations with low AI applicability scores experienced substantial labor-market disruption early in the period, followed by several years of steady employment recovery.

Figure 1. Total employment and percentage change in total employment from the previous year for occupations with the lowest AI applicability scores. 2019 to 2024

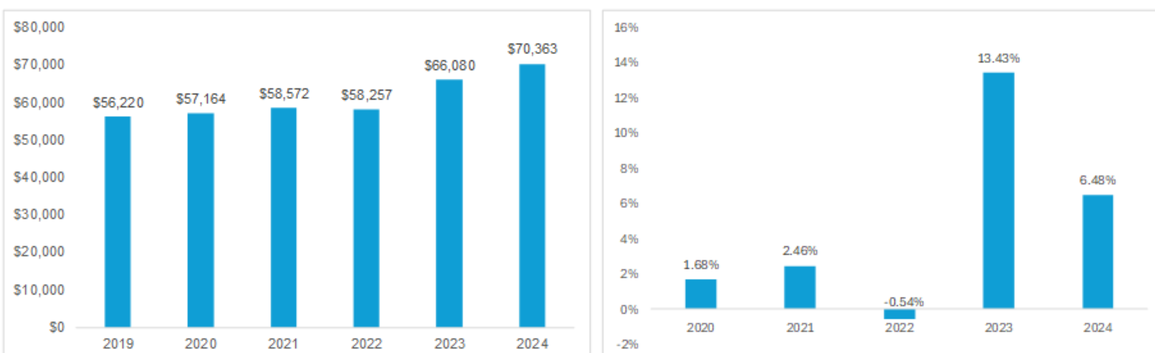


Source: Tomlinson et al. (2025); O*NET (2026), U.S. Bureau of Labor Statistics (2025); and staff calculations. *Note: This figure is based on the 35 occupations identified by Tomlinson et al. (2025) that have matches to occupations listed in Frey and Osborne (2017).

Figure 2 shows that average annual wages in occupations with the lowest AI applicability scores increased overall between 2019 and 2024, rising from $56,220 to $70,363, an increase of approximately 25 percent. Unlike total employment in these occupations, which declined sharply at the onset of the COVID-19 pandemic, wages did not exhibit a comparable decline.

Wage growth year-over-year, however, was uneven. Wage increases were relatively modest between 2020 and 2022, including a slight decline of 0.54 percent in 2022. Wage growth accelerated substantially in 2023, when average annual wages increased by 13.43 percent, before moderating to 6.48 percent growth in 2024. Many occupations with low AI applicability scores involve physical labor, equipment operation, maintenance, transportation, or in-person service tasks that remain difficult to replicate using generative AI systems. The strong wage growth observed later in the period may reflect, inflationary pressures, labor shortages in manual and service-oriented occupations, or increased competition for workers in occupations less directly exposed to generative AI substitution

Figure 2. Average annual wages and percentage change in annual wages from previous year for occupations with the lowest AI applicability scores. 2019 to 2024



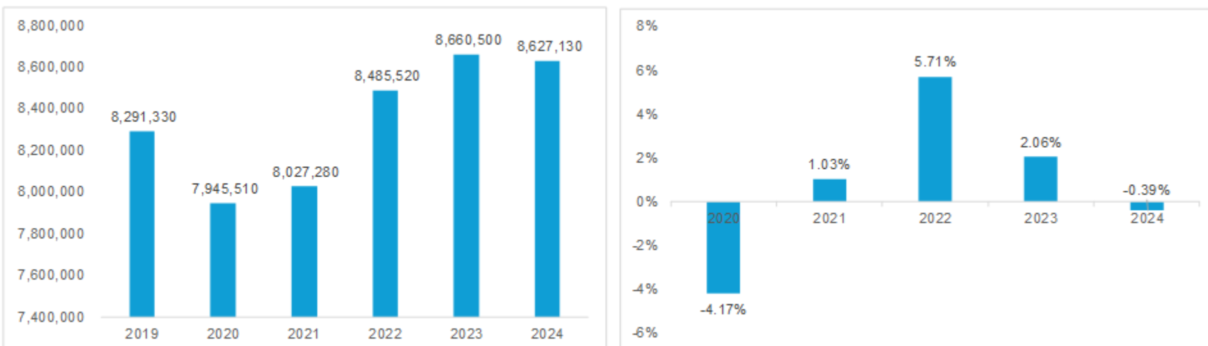
Source: Tomlinson et al. (2025); O*NET (2026), U.S. Bureau of Labor Statistics (2025); and staff calculations. *Note: This figure is based on the 35 occupations identified by Tomlinson et al. (2025) that have matches to occupations listed in Frey and Osborne (2017).

Figure 3 shows that total employment in occupations with the highest AI applicability scores declined at the onset of the COVID-19 pandemic before recovering steadily over the following three years. Employment fell from nearly 8.3 million in 2019 to approximately 7.9 million in 2020, representing a decline of approximately 4.2 percent. Employment then increased in each subsequent year through 2023, reaching a peak of 8.66 million before declining slightly to 8.62 million in 2024. Overall, employment in these occupations increased by 335,800 jobs, or 4.05 percent, between 2019 and 2024.

The year-over-year employment changes suggest a stronger post-pandemic recovery among occupations with high AI applicability scores than among occupations with low applicability scores. Employment growth accelerated to 5.71 percent in 2022 following a 1 percent increase in

2021, before moderating in 2023 and turning slightly negative in 2024. Many of the occupations with high AI applicability scores involve writing, editing, programming, sales, customer service, and other cognitively intensive tasks that can increasingly be assisted by generative AI systems. Despite their higher exposure to AI, these occupations generally experienced employment growth during the study period, suggesting that generative AI may have functioned more as a productivity-enhancing or task-augmenting technology than as a direct substitute for labor in the short run.

Figure 3. Total employment and percentage change in total employment from the previous year for occupations with the highest AI applicability scores. 2019 to 2024

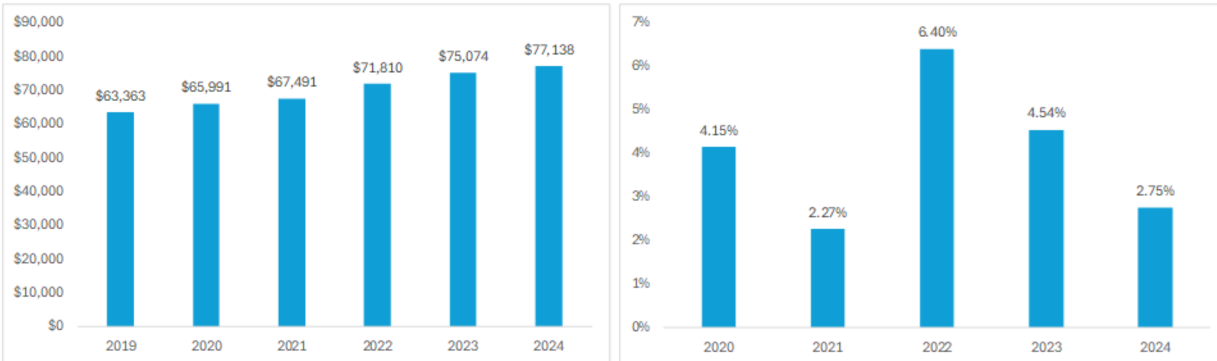


Source: Tomlinson et al. (2025); O*NET (2026), U.S. Bureau of Labor Statistics (2025); and staff calculations.
*Note: This figure is based on the 38 occupations identified by Tomlinson et al. (2025) that have matches to occupations listed in Frey and Osborne (2017).

Figure 4 shows that average annual wages in occupations with the highest AI applicability scores increased, unevenly, between 2019 and 2024. Average annual wages rose from $63,363 in 2019 to $77,138 in 2024, representing an increase of approximately 21.7 percent over the full period. Unlike employment trends, which fluctuated during and after the pandemic, wages in these occupations increased each year throughout the study period.

Year-over-year wage growth was strongest in 2022, when average annual wages increased by 6.4 percent, following gains of 4.1 percent in 2020 and 2.27 percent in 2021. Wage growth remained positive in 2023 and 2024, though at more moderate rates of 4.5 percent and 2.75 percent, respectively. Many occupations with high AI applicability scores involve analytical, communication, programming, writing, or customer-facing tasks that can increasingly be assisted by generative AI systems. Despite this exposure, the occupations shown in Figure 4 experienced both sustained wage growth and overall employment growth during the study period. These patterns suggest that generative AI may have complemented labor demand in many high-applicability occupations during the early stages of adoption rather than broadly displacing workers.

Figure 4. Average annual wages and percentage change in annual wages from previous year for occupations with the highest AI applicability scores. 2019 to 2024



Source: Tomlinson et al. (2025); O*NET (2026), U.S. Bureau of Labor Statistics (2025); and staff calculations. *Note: This figure is based on the 38 occupations identified by Tomlinson et al. (2025) that have matches to occupations listed in Frey and Osborne (2017).

To compare these recent AI applicability patterns with earlier automation forecasts, we matched 70 of the 80 occupations identified by Tomlinson et al. (2025) with automation risk scores from Frey and Osborne (2017). Occupations with automation risk probabilities of 0.70 or higher were classified as high risk; occupations with scores between 0.30 and 0.699 were classified as moderate risk, and; occupations with scores lower than 0.30 were classified as low risk.

Table 1 reports percentage changes in employment and annual wages between 2019 and 2024 for occupations classified as having high probabilities of computerization by Frey and Osborne (2017). On average, employment in high-risk occupations declined by 3 percent over the period, though outcomes varied considerably across occupations. The largest employment declines are concentrated in relatively routine administrative, clerical, and transactional occupations. Of the occupations listed, employment of telemarketers saw the steepest decrease, 51 percent, followed by 47 percent for switchboard operators, 42 percent for helpers – roofers, and 34 percent for dredge operators. These, and other occupations on the list align closely with Frey and Osborne's framework because many of their core tasks can increasingly be automated or completed by artificial intelligence applications. But not all jobs in this category experienced losses. Employment of models increased by 131 percent, followed by 49 percent for Gas Compressor and Gas Pumping Station Operators, and 28 percent for Industrial Truck and Tractor Operators.

The relatively large wage increase among occupations with high probabilities of computerization should be interpreted cautiously. Although average employment declined in this group, wages increased by 26 percent, the largest increase across the three automation-risk categories. This pattern may reflect several overlapping forces. In some occupations, employment declines may have changed the composition of remaining workers, leaving a smaller but more experienced or specialized workforce. In others, employers may have raised wages to recruit or retain workers in physically demanding, low-wage, or difficult-to-staff jobs that remained necessary despite automation exposure. The high-risk group also includes occupations with unusually large wage gains, including models, which may affect the group average. More broadly, the wage pattern reinforces the point that automation exposure does not translate mechanically into declining wages. In some cases, automation may reduce employment while changing the task content, skill requirements, or composition of the remaining jobs.

Table 1. Percentage change in employment and annual wages for occupations with high probabilities of computerization. 2019 to 2024

SOC Code	Job Title	Computerisable Prob.	Coverage	Cmpltn.	Scope	Score	% Δ Change in Employment	% Δ Change in Wage
41-9041	Telemarketers	0.990	0.66	0.86	0.60	0.40	-51%	22%
43-2011	Switchboard operators, including answering service	0.960	0.68	0.86	0.52	0.35	-47%	28%
47-3016	Helpers--Roofers	0.720	0.02	0.94	0.37	0.01	-42%	26%
53-7031	Dredge Operators	0.920	0.00	0.99	0.22	0.00	-34%	9%
47-3014	Helpers--Painters, Paperhangers, Plasterers, and Stucco Masons	0.940	0.04	0.96	0.38	0.03	-33%	24%
43-9081	Proofreaders and copy markers	0.840	0.91	0.86	0.49	0.38	-33%	22%
53-7063	Machine Feeders and Offbearers	0.930	0.05	0.89	0.36	0.02	-26%	30%
43-2021	Telephone Operators	0.970	0.80	0.86	0.57	0.42	-17%	13%
43-4011	Brokerage Clerks	0.980	0.74	0.86	0.57	0.41	-16%	23%
47-2043	Floor Sanders and Finishers	0.870	0.00	0.94	0.34	0.00	-16%	20%
47-2072	Pile Driver Operators	0.820	0.00	0.98	0.24	0.00	-14%	12%
53-6011	Bridge and Lock Tenders	0.970	0.00	0.93	0.39	0.00	-14%	18%
45-4022	Logging Equipment Operators	0.790	0.01	0.95	0.36	0.01	-13%	24%
43-4141	New accounts clerks	0.990	0.72	0.86	0.51	0.36	-12%	24%
53-6061	Passenger attendants	0.750	0.80	0.86	0.62	0.47	-10%	31%
35-9021	Dishwashers	0.770	0.03	0.95	0.30	0.02	-8%	36%
39-6010	Baggage porters, bellhops, and concierges	0.830	0.70	0.86	0.56	0.40	-7%	25%
49-3093	Tire Repairers and Changers	0.700	0.04	0.95	0.35	0.02	-4%	29%
41-2021	Counter and rental clerks	0.970	0.62	0.86	0.52	0.36	-3%	34%
51-9111	Packaging and Filling Machine Operators and Tenders	0.980	0.04	0.91	0.39	0.02	-2%	30%
25-4010	Archivists, curators, and museum workers	0.760	0.66	0.88	0.49	0.35	-1%	16%
47-2071	Paving, Surfacing, and Tamping Equipment Operators	0.830	0.01	0.96	0.29	0.01	0%	31%
47-4051	Highway Maintenance Workers	0.870	0.03	0.96	0.32	0.02	1%	21%
51-9197	Tire Builders	0.940	0.03	0.93	0.40	0.01	1%	25%
35-9031	Hosts and hostesses, restaurant, lounge, and coffee shop	0.970	0.60	0.86	0.57	0.37	1%	33%
47-4061	Rail-Track Laying and Maintenance Equipment Operators	0.890	0.00	0.96	0.27	0.00	2%	19%
47-2051	Cement Masons and Concrete Finishers	0.940	0.03	0.92	0.39	0.01	5%	23%
47-2181	Roofers	0.900	0.02	0.94	0.38	0.01	5%	25%
27-3042	Technical writers	0.890	0.83	0.86	0.54	0.38	9%	20%
41-3091	Sales representatives of services, except advertising, insurance, financial services, and travel	0.850	0.84	0.86	0.57	0.46	14%	22%
51-9161	Computer numerically controlled tool operators	0.860	0.90	0.86	0.53	0.44	17%	23%
51-8099	Plant and System Operators, All Other	0.860	0.05	0.93	0.38	0.03	23%	8%
31-9093	Medical Equipment Preparers	0.780	0.04	0.96	0.31	0.02	28%	24%
53-7051	Industrial Truck and Tractor Operators	0.930	0.03	0.94	0.28	0.01	28%	26%
53-7071	Gas Compressor and Gas Pumping Station Operators	0.910	0.01	0.96	0.47	0.01	49%	14%
41-9012	Models	0.980	0.64	0.86	0.53	0.35	131%	124%
	Average	***0.885***	***0.32***	***0.91***	***0.43***	***0.17***	***-3%***	***26%***

Source: Frey and Osborne (2017), Tomlinson et al. (2025); O*NET (2026), U.S. Bureau of Labor Statistics (2025); and staff calculations.

Table 2 reports percentage changes in employment and annual wages between 2019 and 2024 for occupations classified as having moderate probabilities of computerization. Employment in these occupations declined by 6 percent on average, compared to a 3 percent decline among jobs that Frey and Osborne (2017) classified as having high probabilities of computerization. Occupations that experienced the greatest employment declines were Helpers – Production Workers (-45 percent), Statistical Assistants (-40 percent), Foundry Mold and Coremakers (-28 percent), and Advertising Sales Agents (-25 percent). Jobs in this category that experienced the highest rates of employment growth were Personal Financial Advisors (29 percent), Market Research Analysts and Marketing Specialists (27 percent), and Hazardous Materials Removal Workers (14 percent).

The larger average employment decline among moderate-risk occupations should be interpreted with caution. This pattern does not necessarily imply that occupations with moderate probabilities of computerization were more exposed to automation-related displacement than occupations with high probabilities of computerization. Instead, it reflects the heterogeneity of employment changes within each risk category. Several high-risk occupations experienced large employment gains between 2019 and 2024, which offset steep declines among other high-risk jobs. By contrast, the moderate-risk group included several occupations with sizable employment losses and fewer occupations with unusually large employment gains. These results reinforce the point that automation-risk scores are best understood as measures of technological exposure rather than linear predictions of employment decline. Observed employment changes over this period likely reflect a combination of automation risk, pandemic-era disruption, industry-specific demand shifts, occupational restructuring, and other labor-market forces.

While employment outcomes generally weakened as automation risk increased, wage growth did not follow the same pattern. Average annual wages increased by 21 percent between 2019 and 2024. This increase was lower than the 26 percent wage growth observed among occupations with high probabilities of computerization and slightly below the 22 percent increase observed among occupations with low probabilities of computerization.

Table 2. Percentage change in employment and annual wages for occupations with moderate probabilities of computerization. 2019 to 2024

SOC Code	Job Title	Computerisable Prob.	Coverage	Cmpltn.	Scope	Score	% Δ Change in Employment	% Δ Change in Wage
51-9198	Helpers--Production Workers	0.660	0.04	0.93	0.36	0.02	-45%	31%
43-9111	Statistical assistants	0.660	0.85	0.86	0.49	0.36	-40%	7%
51-4071	Foundry Mold and Coremakers	0.670	0.00	0.95	0.36	0.00	-28%	27%
41-3011	Advertising Sales Agents	0.540	0.66	0.86	0.53	0.36	-25%	18%
47-5071	Roustabouts, Oil and Gas	0.680	0.01	0.95	0.39	0.01	-23%	19%
39-4011	Embalmers	0.540	0.07	0.55	0.22	0.03	-12%	15%
31-9011	Massage Therapists	0.540	0.10	0.91	0.32	0.01	-10%	34%
27-3091	Interpreters and translators	0.380	0.98	0.86	0.57	0.49	-9%	14%
37-2012	Maids and Housekeeping Cleaners	0.690	0.02	0.94	0.34	0.01	-8%	35%
43-4051	Customer Service Representatives	0.550	0.72	0.86	0.59	0.44	-7%	22%
49-3022	Automotive Glass Installers and Repairers	0.550	0.04	0.93	0.34	0.03	-2%	32%
43-4181	Reservation and transportation ticket agents and travel clerks	0.610	0.71	0.86	0.56	0.41	3%	8%
19-3093	Historians	0.440	0.91	0.86	0.56	0.48	3%	14%
43-5031	Public safety telecommunicators	0.490	0.66	0.88	0.53	0.35	6%	24%
53-5022	Motorboat Operators	0.620	0.01	0.93	0.39	0.00	12%	13%
47-4041	Hazardous Materials Removal Workers	0.530	0.04	0.95	0.35	0.03	14%	17%
13-1161	Market research analysts and marketing specialists	0.610	0.71	0.90	0.52	0.35	27%	21%
13-2052	Personal financial advisors	0.580	0.69	0.88	0.52	0.35	29%	34%
	Average	***0.574***	***0.40***	***0.88***	***0.44***	***0.21***	***-6%***	***21%***

Source: Frey and Osborne (2017), Tomlinson et al. (2025); O*NET (2026), U.S. Bureau of Labor Statistics (2025); and staff calculations.

Table 3 shows the percentage change in employment and annual wages for occupations with low probabilities of computerization. Between 2019 and 2024 employment in these occupations increased by 8 percent and annual wages increased by 22 percent. Occupations in this category that experienced the largest declines were Mathematicians (-16 percent), Library Science Teachers, and Economics Teachers at postsecondary institutions, (-7 percent and -6 percent, respectively), News analysts, reporters, and journalists (-6 percent). The highest levels of job growth occurred for Prosthodontists (55 percent), First-line Supervisors of Firefighters and Prevention Workers (35 percent), and Management Analysts (26 percent).

Table 3. Percentage change in employment and annual wages for occupations with low probabilities of computerization. 2019 to 2024

SOC Code	Job Title	Computerisable Prob.	Coverage	Cmpltn.	Scope	Score	% Δ Change in Employment	% Δ Change in Wage
15-2021	Mathematicians	0.047	0.91	0.86	0.54	0.39	-16%	14%
25-1082	Library Science Teachers, Postsecondary/Postsecondary Teachers	0.032	0.65	0.90	0.51	0.34	-7%	9%
25-1063	Economics Teachers, Postsecondary/Postsecondary Teachers	0.032	0.68	0.90	0.51	0.35	-6%	12%
27-3023	News analysts, reporters, and journalists	0.067	0.81	0.86	0.56	0.39	-6%	70%
25-1011	Business Teachers, Postsecondary/Postsecondary Teachers	0.032	0.70	0.86	0.52	0.37	-3%	8%
19-3092	Geographers	0.250	0.77	0.83	0.48	0.35	-1%	20%
19-3094	Political Scientists	0.039	0.77	0.86	0.53	0.39	-1%	14%
27-3041	Editors	0.055	0.78	0.86	0.54	0.37	-1%	19%
53-5031	Ship Engineers	0.041	0.05	0.92	0.39	0.03	2%	33%
27-3043	Writers and authors	0.038	0.85	0.86	0.60	0.45	4%	16%
29-1022	Oral and Maxillofacial Surgeons	0.004	0.05	0.89	0.34	0.03	15%	52%
27-3031	Public relations specialists	0.180	0.63	0.86	0.60	0.36	15%	14%
25-9021	Farm and Home Management Educators	0.008	0.77	0.86	0.55	0.41	18%	15%
13-1111	Management Analysts	0.130	0.68	0.90	0.54	0.35	26%	20%
33-1021	First-Line Supervisors of Firefighting and Prevention Workers	0.004	0.04	0.88	0.39	0.01	35%	18%
29-1024	Prosthodontists	0.055	0.10	0.90	0.29	0.02	55%	17%
	Averages	***0.063***	***0.58***	***0.88***	***0.49***	***0.29***	***8%***	***22%***

Source: Frey and Osborne (2017), Tomlinson et al. (2025); O*NET (2026), U.S. Bureau of Labor Statistics (2025); and staff calculations.

4. Discussion

This analysis provides descriptive evidence on how employment and wage outcomes changed between 2019 and 2024 across occupations with different levels of exposure to automation and generative AI. The results complicate a simple displacement narrative. Occupations with the highest AI applicability scores experienced overall employment growth and sustained wage growth during the period, suggesting that early generative AI exposure did not correspond with broad employment decline in those occupations. Occupations with the lowest AI applicability scores experienced a sharp pandemic-era employment decline followed by recovery, though employment remained slightly below its 2019 level in 2024. When occupations are grouped by Frey and Osborne's automation risk scores, high- and moderate-risk occupations experienced average employment declines, while low-risk occupations experienced average employment growth. Across all three automation-risk categories, however, average wages increased substantially.

The variation within risk groupings is just as important as the averages. Of the 70 matched occupations, 21 high-risk jobs saw employment declines, compared with 11 moderate-risk jobs and 8 low-risk jobs. Employment change in low-risk occupations ranged from a 16 percent decrease among mathematicians to a 55 percent increase among prosthodontists. Moderate-risk occupations ranged from a 45 percent decrease among helpers of production workers to a 29 percent increase among personal financial advisors. High-risk occupations ranged from a 51 percent decrease among telemarketers to a 131 percent increase among models. Notably, the largest employment decline and the largest employment increase both occurred among occupations that Frey and Osborne classified as highly susceptible to automation. These findings do not prove that automation or AI caused the observed employment or wage changes, but they do show why policymakers should avoid treating exposure scores as a one-dimensional forecast of job loss. The next layer of analysis should examine how these patterns differ by worker characteristics, education, income, geography, race, and access to training, because those are the channels through which technological change becomes an opportunity issue rather than only an occupational forecasting exercise.

Here, we briefly describe just three potential threads for future research. 1): Micro-level analysis of labor market change, for firms, geographies, or sectors. As just one example, researchers could make use of difference-in-difference study designs to derive direct causal attribution of local labor market impacts. 2): Analysis of the distribution of financial returns from this technological adoption, including through both capital and wages as channels, again at varying levels (firm, sector, etc.) 3): Exploration of the interplay of K-12 and higher education, measures of community social capital, interventions around reskilling, and other such topics that are relevant to identify how different groups of workers are adapting to labor market change.

Finally, we believe both our paper and our suggested subsequent research hold lots of important implications for policymakers as it relates to both fiscal and monetary policy.

5. Conclusion

Automation and AI technologies have improved substantially over the last couple of years, and we anticipate future developments at likely non-linear rates of change. While the firms producing these technologies promise social progress, there are a wide range of material concerns about the potential effects of these technologies, ranging from water usage and environmental impact to mental health for kids and adults to consumer protections against invasive advertising to asymmetrical warfare and cybercrime vulnerability.

Meanwhile, dueling macroeconomic analyses from market players paint a future that is, by turns, dystopic or utopic, often prompting significant temporary volatility in stock prices as investors try to make sense of the headwinds (Buchanan, 2026). Given these existential questions, to say nothing about the very real concerns around job displacement, it is not surprising that 50 percent of Americans are more concerned than excited about the increased use of AI (Faverio and Kikuchi, 2026).

But amidst the dynamism of the U.S. economy, with the constant churn of firm entrants and exists and worker hirings and separations, it can be hard to separate out the signal from the noise. To help establish a framework for evaluating the implications of new automation and AI technologies, this paper has provided initial empirical analysis of the effects of these technologies on the U.S. labor market during 2019–24.

Ultimately, we see this research as establishing a methodological direction for future research that can help policymakers, business leaders, other leaders, and the general public to have a clear-eyed, data-driven view of how nascent technologies are affecting labor markets. We believe that this look-back approach provides an important complement to research that seeks to forecast AI impacts on firms and labor markets, such as recent important work from the Federal Reserve Bank of Atlanta (Barrero et al., 2026). Finally, while we have not commented heavily on the implications for this research, we believe research like this should help shape both monetary and fiscal policy, helping ensure that technological adoption is leveraged in ways that fuel economic growth while also improving career opportunities and broader material conditions for workers across the income spectrum.

References

Acemoglu, Daron, and Pascual Restrepo. "Automation and new tasks: How technology displaces and reinstates labor." Journal of economic perspectives 33, no. 2 (2019): 3-30.

Autor, David H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." Journal of Economic Perspectives 29 (3): 3–30.

Autor, David. The labor market impacts of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty. No. w30074. National Bureau of Economic Research, 2022.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. "Computing inequality: have computers changed the labor market?" The Quarterly Journal of Economics 113, no. 4 (1998): 1169-1213.

Autor, David, and Anna Salomons. Is automation labor-displacing? Productivity growth, employment, and the labor share. No. w24871. National Bureau of Economic Research, 2018.

Barrero et al. " How Much Are Firms Spending on AI (and What Will Happen to Headcounts)?" Federal Reserve Bank of Atlanta. (May 6, 2026.) Accessed May 7, 2026, from https://www.atlantafed.org/research-and-data/publications/policy-hub-macroblog/2026/05/06/how-much-firms-spending-on-ai-and-what-will-happen-to-headcounts

Berdugo, Sophie. "Scientists taught an AI-powered 'robot dog' how to play badminton against humans — and it's actually really good." Live Science. (September 3, 2025).

Broady, Kristen. "Race and jobs at high risk to automation." Joint Center for Political and Economic Studies, December 18 (2017).

Broady, Kristen E., Darlene Booth-Bell, Anthony Barr, and Aisha Meeks. "Automation, artificial intelligence, and job displacement in the US, 2019–22." Labor History (2025): 1-17.

Broady, Kristen, Darlene Booth Bell, Anthony Barr, and Ryan Perry. The Covid-19 pandemic spurred growth in automation: What does this mean for minority workers?. No. WP 2023-06. Working Paper, 2023.

Buchanan, Naomi. "Citadel Securities hits back at the AI doomsday scenario in the viral Substack post that tanked stocks." Business Insider. (February 26, 2026.)

Challenger, Gray, and Christmas. "May 07 Challenger Report: April Job Cuts Rise 38% from March; YTD Cuts Down 50%." (May 7, 2026). Challenger, Gray, and Christmas Job Cut Announcement Report. Accessed on May 19, 2026, from: Challenger-Report-Apr2026001249.pdf

Chatterji, Aaron, Thomas Cunningham, David J. Deming, Zoe Hitzig, Christopher Ong, Carl Yan Shan, and Kevin Wadman. *How people use chatgpt*. No. w34255. National Bureau of Economic Research, 2025.

Coughlin, Thomas. "Google's TurboQuant Compression Could Increase Demand For AI Memory." Forbes. (March 26, 2026.) Accessed May 7, 2026, from https://www.forbes.com/sites/tomcoughlin/2026/03/26/googles-turboquant-compression-could-increase-demand-for-ai-memory/

Courseiv. (n.d.) "AI in Creative Arts: How Tech Merges with Imagination." Retrieved on September 10, 2025, from https://blog.coursiv.io/blog/ai-in-creative-arts-how-tech-merges-with-imagination.

Curry, David. "Microsoft Copilot Revenue and Usage Statistics (2026)." Business of Apps. (April 13, 2026). Accessed on May 20, 2026, from: https://www.businessofapps.com/data/microsoft-copilot-statistics/

Davenport, Thomas H., and Nittin Mittal. "How Generative AI Is Changing Creative Work." Harvard Business Review. (November 14, 2022).

Deloitte. "AI goes physical: Navigating the convergence of AI and robotics." (December 25, 2026.) Accessed May 7, 2026, from https://www.deloitte.com/us/en/insights/topics/technology-management/tech-trends/2026/physical-ai-humanoid-robots.html

Fatahi, Somayeh, Mehdi Khalaj, Shahabeddin Abhari, Julita Vassileva, and Chanchal Roy. "Beyond Words: Exploring Emotional Contrasts Between Human and ChatGPT Responses in Medicine and Finance." In International Conference on Human-Computer Interaction, pp. 136-151. Cham: Springer Nature Switzerland, 2025.

Faverio, Michelle, and Kikuchi, Emma. "Key findings about how Americans view artificial intelligence." Pew Research Center. (March 12, 2026.) Accessed May 7, 2026, from https://www.pewresearch.org/short-reads/2026/03/12/key-findings-about-how-americans-view-artificial-intelligence/

Finet, Alain, Kevin Kristoforidis, and Julie Laznicka. "The Limits of AI in Understanding Emotions: Challenges in Bridging Human Experience and Machine Perception." F1000Research 14 (2025): 582.

Fišer, Nikolaj, Miguel Ángel Martín-Pascual, and Celia Andreu-Sánchez. "Emotional impact of AI-generated vs. human-composed music in audiovisual media: A biometric and self-report study." PloS one 20, no. 6 (2025): e0326498.

Frey, Carl Benedikt, and Michael A. Osborne. "The future of employment: How susceptible are jobs to computerisation?" Technological forecasting and social change 114 (2017): 254-280.

Gorenz, Drew, and Norbert Schwarz. "How funny is ChatGPT? A comparison of human-and AI-produced jokes." Plos one 19, no. 7 (2024): e0305364.

Gregory, Christina, Phil Lewis, Pamela Frugoli, and Alexander Nallin. “Updating the O*NET-SOC Taxonomy: Incorporating the 2018 SOC Structure – Summary and Implementation. The National Center for O*NET Development (August 2019). Accessed on April 20, 2021, from: O*NET-SOC 2019 Taxonomy White Paper 8.9.19

HAND ERC (n.d.). Retrieved on August 21, 2025, from https://hand-erc.org/.

Knight, Will. “This Robot Only Needs a Single AI Model to Master Humanlike Movements.” Wired. (September 3, 2025).

Lahemer, Elfituri SF, and Ahmad Rad. "An Audio-Based SLAM for Indoor Environments: A Robotic Mixed Reality Presentation." Sensors 24, no. 9 (2024): 2796.

Liu, Yan, and Wang, He. “Who on earth is using Generative AI?” World Development, volume 199. (March 2026.)

Massenkoff, Maxim and McCrory, Peter. “Labor market impacts of AI: A new measure and early evidence.” Anthropic. (March 5, 2026.)

MLQ Editorial Team. “ElevenLabs Launches Eleven Music: AI-Generated Music Platform with Licensing From Major Rights Holders.” MLQ.ai. (August 5, 2025). Retrieved on September 10, 2025, from https://mlq.ai/news/elevenlabs-launches-eleven-music-ai-generated-music-platform-with-licensing-from-major-rights-holders/#:~:text=Licensing%20Deals%20with%20Kobalt%20and,participating%20in%20AI%2Dgenerated%20content.

Naderi, Hossein, Alireza Shojaei, and Lifu Huang. "Foundation Models for Autonomous Robots in Unstructured Environments." arXiv preprint arXiv:2407.14296 (2024).

Nagle, Frank, and Yue, David. “The Latent Role of Open Models in the AI Economy.” Georgia Tech Scheller College of Business Research Paper No. 5767103. (Nov. 19, 2025.) Available at SSRN: https://ssrn.com/abstract=5767103 or http://dx.doi.org/10.2139/ssrn.5767103

Novet, Jordan. “Cisco’s stock pops 15% on surging AI orders, as company says it’s cutting almost 4,000 jobs.” (May 13, 2026) CNBC. Accessed on May 19, 2026, from: https://www.cnbc.com/2026/05/13/cisco-csco-q3-earnings-report-2026.html

Novo, Alvaro, Francisco Lobon, Hector Garcia de Marina, Samuel Romero, and Francisco Barranco. "Neuromorphic perception and navigation for mobile robots: a review." ACM Computing Surveys 56, no. 10 (2024): 1-37.

O*NET. “About O*NET.” (April 14, 2026). Accessed on April 21, 2026, from https://www.onetcenter.org/overview.html

Patel, Marcus, and Ethan Reynolds. "Robotic Perception and Manipulation in Unstructured Environments." International Journal on Mechanical Engineering and Robotics 13, no. 1 (2025): 16-22.

Paul, Katie. “Exclusive: Meta lays out details of May 20 restructuring in internal document.” (May 18, 2026). Accessed on May 19, 2026, from: https://www.reuters.com/world/meta-lays-out-plans-may-20-layoffs-restructuring-internal-document-says-2026-05-18/.

Pérez, Andrea Saravia. “Watch this robot 'cannibal' grow bigger and stronger by consuming smaller robots.” Live Science. (July 23, 2025).

Perez, Sarah. “Spotify says its best developers haven’t written a line of code since December, thanks to AI.” TechCrunch. (February 12, 2026.)

Qi, Jian, Mingzhu Lai, Zhiyuan Yang, Ning Zhao, Kai Han, Xin Sui, Jie Zhao, and Yanhe Zhu. "A Fault-Tolerant Approach for Modular Robots through Self-Reconfiguration." Advanced Intelligent Systems 6, no. 7 (2024): 2300774.

Schlegel, K., Sommer, N.R. & Mortillaro, M. Large language models are proficient in solving and creating emotional intelligence tests. Commun Psychol 3, 80 (2025). https://doi.org/10.1038/s44271-025-00258-x

Sen, Meghna. “Anthropic AI Statistics 2026: Users, Revenue & Market Share.” Panto AI (July 5, 2026). Accessed on May 20, 2026, from: https://www.getpanto.ai/blog/anthropic-ai-statistics

Singh, Chahat Deep, Botao He, Cornelia Fermüller, Christopher Metzler, and Yiannis Aloimonos. "Minimal perception: enabling autonomy in resource-constrained robots." Frontiers in Robotics and AI 11 (2024): 1431826.

Sorall, Pavel. “2D or 3D? Finding the Perfect Machine Vision Fit For Your Application.” Photone. (January 21, 2025)

Schroyer, John. “H&M Group to lay off 181 workers at downtown call center.” Crain’s Chicago Business. (February 25, 2026). Accessed on May 19, 2026, from: https://www.chicagobusiness.com/retail/hm-group-lay-181-downtown-call-center/.

Stachniss, Cyrill, John J. Leonard, and Sebastian Thrun. "Simultaneous localization and mapping." In Springer handbook of robotics, pp. 1153-1176. Cham: Springer International Publishing, 2016.

The Economist. “Why Anthropic and OpenAI are locking up their latest models.” (April 15th, 2026.) Accessed May 5, 2026, from https://www.economist.com/business/2026/04/15/why-anthropic-and-openai-are-locking-up-their-latest-models

The Washington Times AI News Desk. “Oracle begins massive layoffs to fund AI data center push.” (March 31, 2026). Accessed on May 19, 2026, from:

https://www.washingtontimes.com/news/2026/mar/31/oracle-begins-massive-layoffs-fund-ai-data-center-push/

Tomlinson, Kiran, Sonia Jaffe, Will Wang, Scott Counts, and Siddharth Suri. "Working with AI: Measuring the Occupational Implications of Generative AI." *arXiv preprint arXiv:2507.07935* (2025).

Tu, Yuxiao, Guanqi Liang, Di Wu, Xinzhuo Li, and Tin Lun Lam. "Locomotion and self-reconfiguration autonomy for spherical freeform modular robots." The International Journal of Robotics Research (2025): 02783649251360360.

U.S. Bureau of Labor Statistic, Occupational Employment and Wage Statistics (OEWS) Tables. 2019 to 2024. (May 15, 2026). Accessed on April 20, 2026, from: https://www.bls.gov/oes/tables.htm

U.S. Department of Labor, O*NET database Content Model. Employment & Training Administration (ETA). Accessed on April 21, 2026, from: https://www.dol.gov/agencies/eta/onet