Potential Labor Market Impacts of Artificial Intelligence: An Empirical Analysis

Introduction

Recent advancement in the development of artificial intelligence (AI) systems has been rapid, and the role of these systems in the economy continues to grow. While AI adoption is already commonplace in many aspects of daily life, much of its potential for broader economic transformation has not yet been realized. Moreover, there remains vast uncertainty about how AI technology will develop, where it will be adopted, and how it will impact the economy and society. A broad economic framework for understanding AI is necessary, because only by understanding the incentives around a technology's development and adoption can one reasonably predict its uses in the future and the impacts it may have. And, since the impacts of technological change are not a foregone conclusion, a future-oriented economic framework can inform deliberate policy choices at the technology's onset, increasing those policies' eventual impact. Thoughtful policy, informed by an evidence-based economic framework, can help to ensure that AI's economic benefits are felt broadly and its risks to workers and others are addressed.

In this year's *Economic Report of the President (ERP)*, CEA provided such an economic framework. It took a detailed look at the key features of AI technology, and it related those features to core economic concepts that might help predict future impacts. The report then used those concepts to motivate a thorough discussion of how the government can prepare its institutions and laws for AI, including by updating its existing regulations, adapting existing safety net programs, and considering potential new programs such as expanded worker assistance. CEA also developed a novel empirical methodology to analyze the potential labor market impacts of AI, as directed by Executive Order 14110 (White House 2023). In this companion report, CEA continues its analysis of potential labor market impacts, providing a number of new results and other information that could not be included in the *ERP* because of format and length limitations. CEA's ongoing analysis continues to inform the Biden-Harris Administration's comprehensive effort to seize AI's opportunities and manage its risks.

CEA's methodology draws on several economic frameworks that have been used to analyze technological changes in recent decades, especially the task-based polarization framework that predicts how some occupations are complemented and others substituted by previous computer technologies based on the tasks they perform (Autor, Levy, and Murnane 2003). CEA's empirical framework follows those of other researchers that have developed similar measures (e.g., Frey and Osborne 2017; Felten, Raj, and Seamans 2021; Brynjolfsson, Mitchell, and Rock 2018; Ellingrud et al. 2023; Eloundou et al. 2023; Kochhar 2023) and it provides similar conclusions about occupational exposure to those alternatives. However, CEA's analysis goes further than many of these previous analyses, because it develops a measure of AI-related job performance requirements that—in conjunction with its measure of overall AI exposure—may identify occupations and workers who could be particularly vulnerable to displacement or other negative economic outcomes.

In this report, CEA furthers that analysis, finding new evidence to support the assertion that AI-related job performance requirements might accurately identify the workers who are most vulnerable to negative economic outcomes from AI. Based on these findings, CEA classifies as "potentially AI-vulnerable" the subset of workers who have both a high degree of AI exposure along with low AI-related job performance requirements.[1] In particular, CEA bases this classification on evidence that:

- Occupations identified as potentially AI-vulnerable are already growing more slowly than those that are also exposed to AI, but have higher job performance requirements;
- Workers' job transition patterns are gradually changing in ways that suggest declining demand for potentially AI-vulnerable occupations; and,
- Many potentially AI-vulnerable occupations have changed comparatively little in recent years, in clear contrast to an overall pattern of occupations' job performance requirements increasing over time.

CEA cannot directly observe whether changes in performance requirements are adaptations to technology, either in response to the rise of AI or to previous technologies like computers and the internet. More generally, CEA's classification of AI-vulnerable occupations depends on assumptions about the types of future adaptations that may take place in the future. However, the results suggest that even as many workers' existing jobs may adapt substantially to accommodate AI, the occupations that currently appear most vulnerable also do not appear to be adapting, even as they face declining demand and therefore increased potential for workers in those occupations to be displaced.

In contrast, CEA finds evidence that is consistent with increasing demand for AI-exposed workers with high job performance requirements. Employment in these occupations is growing faster than average, and workers are transitioning into them. Again, CEA cannot distinguish to what degree these patterns reflect

[1] Throughout the report, CEA also uses the more general terms "AI-vulnerable" and "vulnerable" to refer to this same set of occupations that are potentially vulnerable to AI as a result of their high degree of AI exposure and low AI-related job performance requirements.

the impacts of AI above and beyond the continued effects of previous technologies—it may still be too soon to observe the direction of AI's impact on labor demand for these workers. A comparison of CEA's measure to previous task-based frameworks suggests that AI exposure and AI-related job performance requirements correlate substantially with measures of how computerization has impacted workers in the past. This makes it particularly difficult to assess the extent to which AI's impacts are meaningfully distinct from those of previous technologies. However, CEA's finding of increasing demand for AI-exposed occupations with high performance requirements is consistent with complementary usage of technology. If this pattern of demand continues, then workers who already perform complex and difficult tasks may also be more likely to benefit from AI adoption in the future.

The potential benefits from AI are substantial. Many workers are likely to benefit from use of the technology, and productivity gains could substantially improve economic wellbeing overall. Nonetheless, a subset of workers may be at risk of displacement, declining earnings, or other negative economic outcomes in response to the technology's adoption.[2] Identifying such vulnerable workers in advance—as CEA's measure attempts to do—may help to ensure that policies designed to help them transition or otherwise adapt in response to AI are efficiently targeted and executed.

Although many new empirical findings are contained in this report, the policy implications of these additional analyses differ little from those previously discussed in the *ERP*. Readers who are interested in a more thorough discussion of policy, or in the broader economic framework through which CEA evaluates AI's potential, are encouraged to review the detailed discussion therein. Instead, this report focuses on providing the necessary information, guidance, context, and transparency to permit others to assess CEA's empirical framework, and to ensure that future evaluations of its effectiveness are feasible and insightful.

The report proceeds as follows. Section 1 provides a more detailed description of the construction of CEA's AI exposure measure, and the basic principles motivating its approach. Section 2 provides the core results on predicted worker exposure to AI. Several of these results are reproduced from the *ERP*, but this section also includes new analyses on worker age, geography, and union status. Section 3 provides a series of robustness checks and comparative analyses, including a comparison to several measures of AI exposure produced by other researchers, as well as a comparison to the task-based measures of Autor and

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[2] Another important potential risk to workers from AI is declining job quality due to changes in working conditions. Although a high degree of AI exposure may be predictive of this risk, changes to working conditions can harm workers regardless of whether a technology is complementing or substituting their work. Therefore, CEA's more detailed measure of AI-vulnerable occupations does not predict potential harm from changing working conditions. Employer adoption of principles and best practices—such as those recently released by the Department of Labor (2024)—can help to minimize these harms to workers.

Dorn (2013), commonly used in the literature on labor market polarization. Section 4 provides a variety of analyses of trends over time that many provide insights into how AI could affect different workers differently. This includes new analysis on how job switching patterns and occupational tasks have changed over time. Section 5 concludes the report. Finally, an included Appendix provides several additional tables that may help with interpretation of the report's main results.

Section 1: Motivation and Measure Construction

Sometimes, it can be easy to predict how a new *specialized* technology can be used to automate specific tasks and affect labor markets. For example, the Luddites foresaw that new textile machinery such as the power loom would negatively impact wages and labor standards among skilled textile workers, and they destroyed that machinery in response (Thompson 2017). The actions of the Luddites failed to prevent technology adoption, and many of the Luddites' predictions did come to pass. Predicting some immediate labor market impacts of some specific technologies can be straightforward.

However, predicting the labor market impacts of *general-purpose* technologies like AI is challenging. General-purpose technologies are distinguished not only by the breadth of their potential applications, but by the way in which they create new opportunities for improvements in other sectors (Bresnahan and Trajtenberg 1995). For example, underpinning the adoption of technologies like the power loom was the steam engine, a general-purpose technology that could be adapted to many different purposes throughout the economy. Even as some use cases like the power loom negatively impacted some skilled craftspeople, a major effect of the steam engine was to draw farm workers into factory labor, and this likely increased the overall demand for skill in the economy (de Pleijt, Nuvolari, and Weisdorf 2020). Additionally, the new opportunities created by general-purpose technologies may lead them to be "augmentation innovations," increasing labor demand through new forms of work (Autor et al. 2024). The impacts of new forms of work may be particularly difficult to assess in advance.

Ideally, researchers would be able to use economic data to precisely identify a single technology's impacts in isolation from other factors. However, measurement issues mean that this is usually not possible, even after the fact.[3] So, economists have traditionally relied on a series of broad frameworks, using a mixture of theory and available empirical evidence to assess the labor market impacts of a technology. These frameworks look at changes in patterns of economic activity across workers over time,

[3] Often, researchers cannot directly measure the use of the technology. In many other cases, they cannot disentangle its use from that of other technologies that are adopted at the same time, or from other economic forces that might affect the decision to adopt. On balance, economic evidence can be suggestive, but attempts to neatly identify the overall labor market impacts of a particular technology are comparatively rare, because it is simply too difficult to rule out other explanations (e.g., DiNardo and Pischke 1997).

and then correspond those changes to salient characteristics of workers. When these patterns align with an underlying characterization of how a technology works, and with the timing of that technology's adoption, it suggests that the technology played a role in bringing the changes about. A useful framework not only fits the data well, but it also makes assumptions that succinctly characterize the relevant economic relationships.

In recent decades, economic analyses of technological change have been characterized by multiple such influential frameworks.[4] The first is the framework of skill-biased technical change (SBTC). The typical SBTC implementation considers changing patterns of earnings across the educational distribution, in effect using education as a proxy for skills whose value changes in response to technological advancement (e.g., Goldin and Katz 2007; Autor, Goldin, and Katz 2020). This framework suggests that growing education wage premia over time—especially during the latter part of the 20th century—could be a result of new technologies that increase the demand for educated workers faster than labor supply can keep up. The second is a task-based framework, which considers workers in different occupations based on simplified measures of those occupations' task content (e.g., Autor, Levy, and Murnane 2003; Autor and Dorn 2013). This framework relates increasing inequality and job polarization following the rise of the personal computer to that technology's ability to complement certain abstract tasks, while substituting for human labor in many routine tasks that were commonly found in middle-class jobs. Finally, CEA considers a recent framework based on the notion of new task formation, which builds on the previous task-based framework, but focuses on the way in which new tasks can be created and performed by workers even as old tasks may be fully automated (e.g., Acemoglu and Restrepo 2018). This framework has been used to explain the rise of new forms of work (Autor et al. 2022), and recently to make additional predictions about AI's potential productivity impacts (Acemoglu 2024). In practice, these frameworks are not mutually exclusive; they provide different useful insights that can be applied to different contexts, and researchers have sometimes incorporated features from multiple frameworks to explain specific circumstances (e.g., Autor, Katz, and Kearney 2008). And, although each framework has typically been developed to explain impacts of previous technologies such as the personal computer, they may also have relevance for the future if their underlying assumptions continue to hold.

CEA's measure of AI exposure—and its measure of vulnerable exposed occupations—reflect an underlying model of AI's effects. This model is built on the assumptions of the frameworks that have come before it, and can be seen as a refinement of those models. In particular, CEA's analysis relies on an idea that is common to all task-based frameworks: workers' likely exposure to new technologies is

[4] CEA provides additional discussion of these frameworks and their implications in the *ERP*.

associated with the specific tasks and activities that they perform, and therefore with their occupation. This assumption has been widely adopted by other researchers developing measures of AI exposure in recent literature (e.g., Frey and Osborne 2017; Felten, Raj, and Seamans 2021; Brynjolfsson, Mitchell, and Rock 2018; Ellingrud et al. 2023). The premise of the assumption is that AI may be used to automate or augment performance of certain tasks, and that those tasks are currently performed by workers in specific occupations. And, the above measures are alike in that they measure the task content of occupations using information provided by the Department of Labor's O*NET database, based on a mixture of workers surveys and analyst assessment. However, the papers make different assumptions about how best to measure AI exposure using the various types of occupational content information available.

Precise derivations of CEA's measure of AI exposure, and its measure of vulnerability based on AI-related job performance requirements can be found in Appendix A. However, among existing models of AI exposure, CEA follows most closely the specific measurement assumptions made by Kochhar (2023). In particular, CEA follows this prior research in making use of information about Work Activities, a rough proxy for tasks which are a list of 41 distinct activities about which individuals in all occupations are asked.[5] Of these activities, CEA also follows prior research in identifying 16 Work Activities as having high exposure to AI: the full list of these activities is included in Appendix Table A1. The premise of this assumption is that these are the activities where use of AI may be most feasible, given the present understanding of the technology's current and expected capabilities.[6] Finally, CEA adopts the idea that the potential exposure of an occupation to AI is captured by the importance to the job of the activities that are exposed to AI, in comparison with all other activities.

However, CEA's measure also differs from previous measures in two key respects. First, CEA differs from Kochhar (2023) and other measures in how it aggregates information about different activities to construct its overall AI exposure index. In particular, CEA standardizes all reported activity importance scores for each activity across occupations, and it defines its relative measure as the difference in average

[5] Another measure of occupational content in O*NET that has been used for this type of analysis is Tasks, which are uniquely defined for each occupation. Brynjolfsson, Mitchell, and Rock (2018) use this measure of occupational content in characterizing occupational exposure, and then perform textual analysis to convert the task measure into a measure of occupational exposure. In this report, CEA uses the terms activity and task flexibly, although it has not conducted an analysis of Tasks as measured in O*NET.

[6] AI technology has changed over time, and some Work Activities that are considered exposed based on its current and expected future capabilities may not have been exposed to previous AI implementations. Throughout the report, CEA measures AI exposure and AI-related job performance requirements using the same set of 16 exposed Work Activities, regardless of whether it is predicting future occupational changes or analyzing past ones.

standardized importance between exposed and non-exposed activities.[7] One reason for these methodological changes is that different activities have different average importance in the raw O*NET data, and so standardizing ensures that all work activities are weighted equally in the resulting index. The normalization also improves interpretability, because a unit increase in the importance of a particular activity or set of activities can be interpreted as a one standard deviation change in importance, relative to the distribution in the overall economy. While these methodological changes are helpful to specific pieces of CEA's subsequent analysis, they have little impact on the extent or composition of measured AI exposure in comparison to Kochhar. Analysis shown in Appendix B reflects the strong relationship between the two measures: the correlation between CEA's measure and the measure underlying Kochhar is 0.95. The analysis also compares CEA's AI exposure measure to several other measures in recent literature, and finds that all these measures are positively correlated at the occupation level.

CEA's other primary methodological contribution is to provide an extension of its measure of AI exposure that considers the potential for AI to complement or substitute for human performance of an occupation. Although CEA cannot predict the specific ways in which jobs and workers will adapt to the technology, the measure is intended to identify workers who are potentially most vulnerable to negative outcomes related to increased AI adoption. CEA's measure, referred to as AI-related job performance requirements, uses information from a separate O*NET question about the degree of complexity or difficulty to which each work activity must be performed in order to perform one's overall job.[8] The underlying assumption guiding this measure is that complexity and difficulty are closely related to costs of adoption. If it is more costly and difficult for AI to fully substitute for human performance of an activity, then using AI to complement performance of that activity may be more feasible or cost effective than using AI to fully automate the activity. As with the measure of AI exposure, CEA's measure of AI-related job performance requirements is based on an average of standardized values across all AI-exposed activities.

Threshold Determination

As outlined above, CEA constructs two basic measures for each occupation: an AI exposure score, and a score representing the degree of AI-related performance requirements. Along each of these two dimensions, CEA defines threshold levels of exposure and performance requirements, so that the full set of occupations can be neatly divided into three groups: AI-exposed with high AI-related performance

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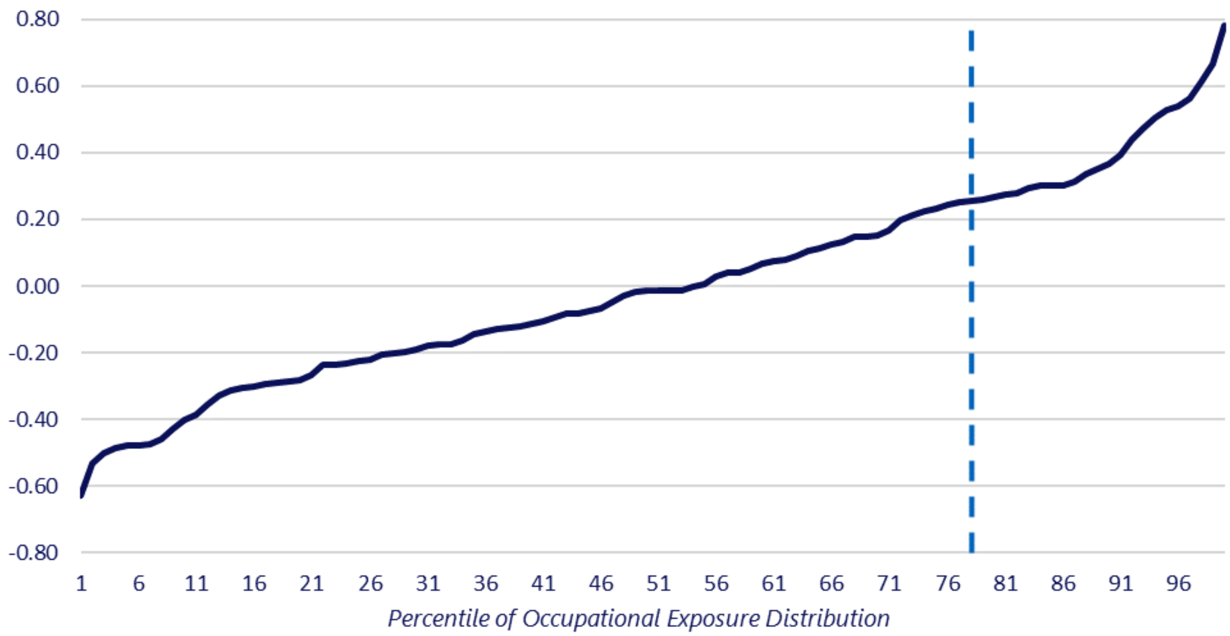
[7] The O*NET data do not provide detailed information on the distribution of survey responses, so the reported importance of a work activity to an occupation is the mean value provided by survey respondents or analysts for that occupation, recorded on a 1 to 5 scale of increasing importance.

[8] The measure of AI-related job performance requirements is based on the degree of complexity or difficulty to which the 16 AI-exposed Work Activities must be performed for each occupation. Details of measure construction are provided in Appendix A.

requirements, AI-exposed with low AI-related performance requirements, and not highly AI-exposed. Specifically, the threshold exposure score is based on the 75th percentile of occupational exposure, unweighted by employment or hours, which is the same threshold used by Pew Research in its analysis (Kochhar 2023). For performance requirements, CEA's threshold for delineating high/low AI-related performance requirements is the population median, weighted by aggregate hours in the 2022 American Community Survey (Ruggles et al. 2024).

Figure 1. Measure of Standardized Relative Exposure to AI by Percentile

Standardized Avg. of high exposure activities minus Avg. of non high exposure activities



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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.

As of May 8, 2024 at 6:00pm

Figure 1 graphs the full distribution of CEA's AI exposure measure, ranked across occupations. Because of CEA's standardization procedure, the measure has the following interpretation: it is the difference between the average importance of AI-exposed activities and that of all other activities, where the importance of each activity is measured in standard deviations relative to the average in the workforce. So, for example, a value of 0 corresponds to an occupation in which AI-exposed work activities and all other activities are, on average, equally important to the job. The dotted line represents the relative importance threshold used in CEA's analysis, corresponding to the 75th percentile of occupations, unweighted by employment. As shown in the figure, 20 percent of overall employment is in occupations above the threshold. At this threshold, highly AI-exposed work activities are, on average, about a quarter of a standard deviation more important to the performance of an occupation than the average of other activities.

One concern with using any threshold-based measure such as CEA's is that the overall interpretation of results may be highly sensitive to the chosen threshold. Figure 1 illustrates a particular reason why this concern may be salient: the distribution of relative AI-exposed activity performance across the population is smooth, and no obvious discontinuity in exposure scores is apparent. So, for any chosen threshold, the difference in AI exposure between occupations immediately above and below the threshold is guaranteed to be small. And, changing the chosen exposure threshold mechanically alters the fraction of workers who are considered affected, as well as the difference in exposure between groups. On the other hand, using discrete thresholds allows for intuitive comparisons across different demographic and socioeconomic groups that may be very useful. CEA has conducted a sensitivity analysis of its selected threshold to determine the extent to which some of its primary findings might be driven by its choice of threshold, and has found that broad patterns of economic and demographic exposure are largely replicated when one chooses other thresholds within a sensible range. Portions of this analysis are included in Appendix C. So, while it is important to treat all results that use a binary threshold with caution, CEA believes that the basic conclusions of its analysis are robust to its use of binary threshold.

Relationship Between AI Exposure and Types of Tasks

As discussed above, the task-based polarization framework has been commonly used to assess the impacts of technological change during the era of widespread computerization. Implementations of this model assess occupations based on measurements of their task content along key characteristic dimensions. Typically, these are measures of routine, cognitive (or abstract), and manual task content (e.g., Autor, Levy, and Murnane 2003; Autor and Dorn 2013). AI depends on computerization, and in many cases AI adoption involves augmenting existing computerized systems with prediction, automated content generation, or other features. Therefore, it is plausible that an existing task-based framework, or refinements to one, may also be effective in characterizing the future labor market impacts of AI.

Before machine learning approaches were incorporated into automated systems, the extent of computerized automation was often limited by the need for explicit rules and codified procedures (Autor 2014). Yet, many tasks make use of tacit knowledge that is not easily codified (Polanyi 1966), and this made these tasks difficult to automate. So, modern AI systems based on machine learning—including generative AI systems—broaden the set of tasks that computers can perform by reducing the need for explicit, rules-based approaches. In the typical task-based framework, computerized automation has been characterized as capable of substituting for human performance of many routine tasks, which are likely to be codifiable (e.g., Autor and Dorn 2013). And, computerization has been suggested to complement humans in tasks which are abstract in nature. Finally, the framework suggests that workers whose tasks were sufficiently non-routine and not abstract might see their work comparatively unaffected by computer technology. If AI extends computer-led automation in ways that yield similar patterns of complementarity and substitution, then the impacts of AI may in part be predictable based on the relationship between its capabilities and these existing measures of occupational task content.

Table 1. Correlation Between AI Exposure and Measures of Occupational Task Content

AI exposure measure	*AI Exposure*	*AI-Related Performance Requirements*
AI Exposure	1.00	0.28
Performance Requirements	0.28	1.00
Autor Dorn (2013) Abstract	0.06	0.61
Autor Dorn (2013) Routine	0.29	0.00
Autor Dorn (2013) Manual	-0.09	-0.08

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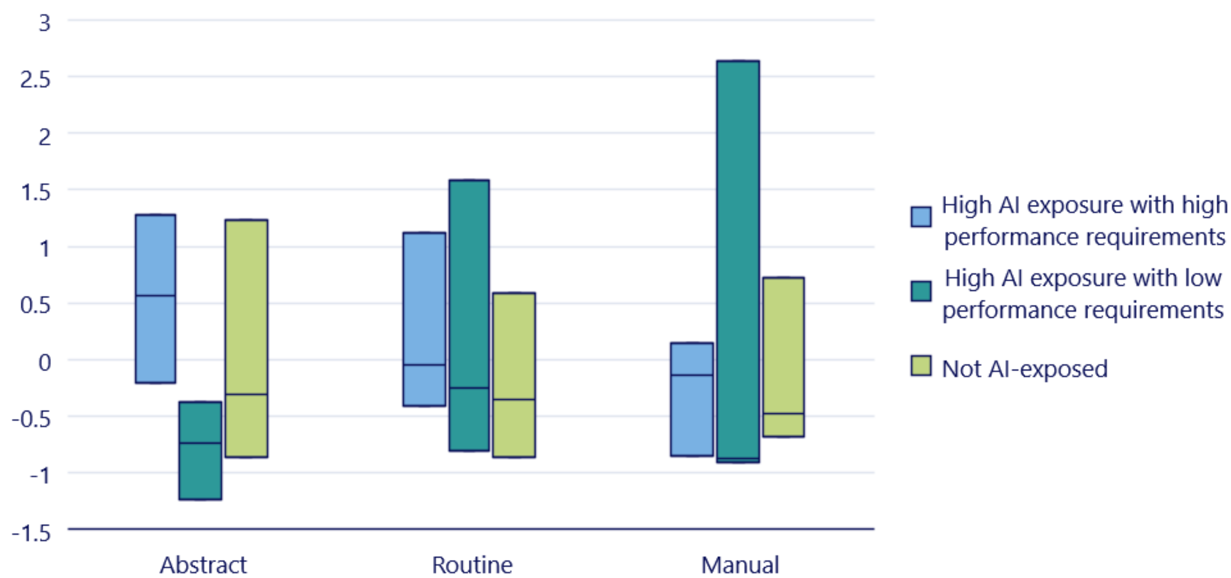
Sources: American Community Survey; Department of Labor; Autor and Dorn (2013); CEA calculations.
Note: All measures are linked to 1990 occupational codes as in Autor and Dorn (2013).
As of May 8, 2024 at 6:00pm.

Using an occupational crosswalk provided by Autor and Dorn (2013), CEA has constructed a comparison between the measures of task content that they use to implement their task-based framework and CEA's measures of AI exposure and AI-related performance requirements. Table 1 shows the correlations between these measures across occupations. Several noteworthy findings emerge. First, higher AI exposure is moderately associated with more routine task content. This is consistent with an interpretation that AI could be used in part to automate similar types of tasks as previous computer technologies. Secondly, higher abstract task content corresponds fairly strongly to CEA's measure of AI-related performance requirements. This suggests that workers who are currently observed to have high AI-related job performance requirements may have benefitted from complementarity with computer technologies in the past. And, if previous patterns hold as AI extends the scope of computer-led automation, then jobs with high AI exposure and high AI-related performance requirements could be associated with greater potential for complementarity in the future as well. Finally, both high AI exposure and high AI performance requirements are weakly associated with less manual task content.

Figure 2. Distribution of Occupational Task Content Measures by Occupational AI Exposure

Standardized occupational task content



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Sources: Autor and Dorn (2013); American Community Survey; Bureau of Labor Statistics; Pew Research Center; CEA calculations.
Notes: Measures of occupational task content from Autor and Dorn (2013) are standardized across all occupations, based on 2022 ACS employment.
As of May 5, 2024 at 6:00pm

One concern with a correlation analysis is that a positive correlation could be primarily a result of associations among occupations that are not very exposed to AI. CEA's threshold-based analysis considers only a fraction of occupations to be highly AI-exposed, and even fewer of those occupations to have the low AI-related performance requirements that might make them particularly vulnerable. So, it may be more useful to know whether these same relationships hold when considering only this subset of occupations. In Figure 2, CEA graphs distributional parameters for standardized versions of the three task content measures, across each of its three basic occupational classifications. The results confirm similar relationships to those found in the initial correlation table. Workers in occupations who are highly AI-exposed, but who have low AI-related performance requirements have substantially lower abstract task content in their work than others, while AI-exposed workers with high performance requirements have comparatively high levels of such content. The relationships along the other two dimensions are less strong, with wider within-category distributions. However, workers in both categories of AI-exposed employment also have, on average, somewhat more routineness to their tasks that other workers.

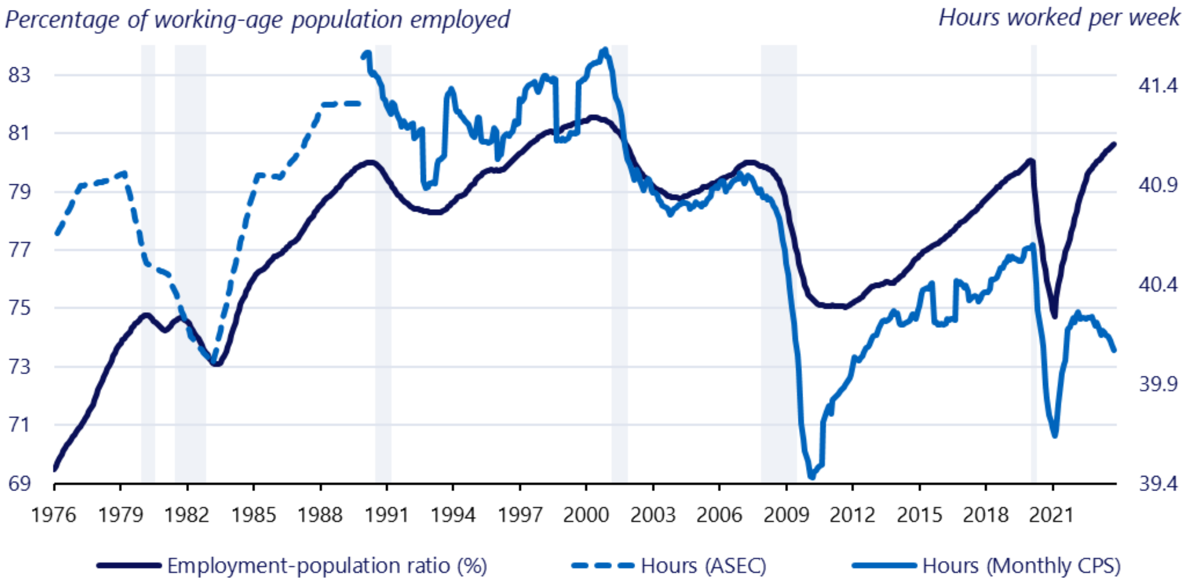
Overall, these results suggest that CEA's measure of AI exposure is substantively linked to the notions of task content developed by earlier task-based frameworks. The previous effects of computerization have been argued to be especially strong among workers who perform routine work that is not manual in nature (e.g., Autor and Dorn 2013); as Figure 2 shows, many of the workers whom CEA classifies as most potentially AI-vulnerable do appear to perform relatively routinized work. However, the implications of this analysis are perhaps more important to understanding CEA's measure of AI-related performance requirements. In developing their measure, Autor and Dorn (2013) suggested that abstractness was associated with human-computer complementarity because these tasks were largely "creative, problem-solving, and coordination tasks … for whom data analysis is an input into production." If AI continues to complement these tasks in a similar fashion as previous computer technologies, then the lack of such tasks among AI-exposed workers with low performance requirements supports CEA's assumption that those workers could be more vulnerable to AI-related displacement. Like all forward-looking predictions of labor market impacts, this interpretation is difficult to thoroughly evaluate until widespread AI adoption has taken place. However, it does suggest potential areas of focus in identifying and targeting the workers who may be most vulnerable to negative economic impacts from AI.

Predictive Scope

With the basic assumptions outlined above, CEA is able to provide numerous predictions about the potential degree of AI's impact, as well as its potential to disproportionately impact particular demographic and economic groups. These predictions are made on the premise that the workers who CEA's measure classifies as exposed to AI are those who perform the tasks that are most likely to change as a result of the technology. Such predictions, like the underlying framework, are made using the best information available at the time of their inception. However, as with many predictive AI models that incorporate continual feedback to improve their effectiveness, predictive economic frameworks generally benefit from continual evaluation. CEA anticipates that as new data become available, this framework and others like it will undergo a similar process of review and refinement.

One thing that this framework does not do, and is not designed to do, is make predictions about the future extent of employment in the economy as a whole. The reason for this limitation is found most clearly in the literature on new task formation (e.g., Acemoglu and Restrepo 2019). Task-based measures of AI exposure predict which workers are most likely to be exposed to AI in their work—they may also provide limited suggestive evidence of which activities could be most prone to labor substitution through automation. However, task-based measures do not predict what new tasks may form in the future, or whether they will be performed by workers in existing occupations or in newly-created ones. Similarly, task-based measures provide limited information about how existing tasks might change over time in response to new technology, or how occupations might adapt to these changes.[9]

Figure 3. Employment-Population Ratio and Weekly Work Hours, 1976–2022



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Sources: Current Population Survey; Bureau of Labor Statistics; CEA calculations.

Note: CPS = Current Population Survey; ASEC = CPS Annual Social and Economic Supplements. Working-age population refers to the population between the age of 25 and 54 years. The employment-population ratio is a 12-month moving average. ASEC hours are a measure of hours worked in the last week. Monthly CPS hours are a measure of hours worked in the last week from the basic monthly CPS. Gray bars indicate recessions.

As of May 8, 2024 at 6:00pm

In response to questions about the future extent of employment, the best evidence comes from the historical record. Economists and others have predicted for centuries that technological change might lead to widespread "technological unemployment" or drastically reduced hours of work. Yet, as Figure 3 demonstrates, measures of employment such as the working-age employment-population ratio and average hours of work show little evidence of decline in recent decades. In fact, the employment rate remains close to long-term highs, matched only by a period in the late 1990s in which technological change and productivity growth was also rapid, commonly associated with the previous general-purpose technologies of the personal computer and internet adoption. Even though new technologies of the past may have displaced some workers from their previous jobs, it failed to reduce employment overall.

[9] These limitations of task-based frameworks affect their ability to predict outcomes not only for employment as a whole, but also for individual workers and occupations. However, these limits pose a particular challenge to predicting macroeconomic impacts because new occupations are so prevalent. Autor et al. (2024) estimate that roughly 60 percent of work is performed in job titles that did not exist in 1940.

Similarly, the increased wealth brought about by technological change has not led workers to substantially reduce their hours or employment.

A second thing that CEA's framework does not do is predict when AI-related impacts may occur. Adopting a new technology often involves complicated changes to production processes, and these changes take time to implement. Additionally, constraints faced in different phases of an overall process can prevent a new technology from being adopted or fully utilized for long periods. Later in this report, CEA conducts a limited analysis of changes in occupations and tasks over time, providing some evidence that changes have already occurred that could plausibly be the result of existing AI uses, or of other computer-related automation. Conversely, other research has found that process innovations resulting from adoption of AI may not yet be occurring (Babina et al. 2024). Several analysts and researchers have suggested that sizeable productivity improvements from AI could begin within this decade (see Acemoglu 2024 for an overview); labor market impacts could occur on a similar time frame. However, the basic framework that CEA provides cannot provide any insights into this timing.

Section 2: Differences in Exposure by Job and Worker Characteristics

CEA's measures of AI exposure and AI-related job performance requirements predict future AI exposure and potential vulnerability at the occupation level. Using these measures, one can straightforwardly observe and rank the potential exposure of any single occupation, or of any group of occupations. By linking this measure back to survey microdata, CEA is also able to provide tabulations regarding the demographic and economic characteristics of workers who are exposed to AI. This section of the report provides the results of this exercise. Except as otherwise noted, all analyses use the 2022 American Community Survey Public-Use microdata, and examine only the characteristics of full-time, full-year workers, weighted based on the total aggregate hours of those workers.

Table 2. AI Exposure by Occupational Groups

Rank	*Occupational group*	*Avg. AI exposure*	*Avg. AI-related performance requirements*	*% highly exposed employment*	*% exposed employment with low performance requirements*
1	Architecture and engineering	0.44	0.81	90%	4%
2	Legal	0.39	0.49	100%	1%
3	Computer and mathematical	0.33	0.36	73%	0%
4	Office and administrative support	0.32	-0.36	53%	49%
5	Transportation	0.27	-0.54	81%	75%
6	Life, physical, and social science	0.25	0.69	57%	12%
7	Business and financial operations	0.17	0.36	19%	9%
8	Installation, maintenance, and repair	0.07	0.06	10%	10%
9	Production	0.07	-0.18	6%	4%
10	Farming, fishing, and forestry	0.06	-0.91	0%	0%
11	Protective service	0.05	0.63	5%	0%
12	Arts, design, entertainment, sports and media	0.01	-0.03	18%	13%
13	Healthcare practitioners and technical	-0.05	0.52	3%	0%
14	Healthcare support	-0.08	0.31	16%	1%
15	Management	-0.11	0.46	0%	0%
16	Construction and extraction	-0.16	-0.05	0%	0%
17	Education instruction and library	-0.18	-0.21	0%	0%
18	Sales and related	-0.23	-0.39	9%	9%
19	Community and social services	-0.23	0.24	7%	0%
20	Personal care and service	-0.27	-0.74	1%	0%
21	Material moving	-0.29	-0.78	2%	0%
22	Food preparation and serving related	-0.30	-0.80	0%	0%
23	Building, grounds cleaning, and maintenance	-0.31	-0.69	0%	0%

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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.

Note: Occupation groups are ranked by their average AI exposure score. Occupations with an AI-related performance requirements score below the 50th percentile are classified as having low performance requirement. SOC code 53 has been split into two groups: transportation and material moving. All other occupation groups are in their own two digit SOC code.

As of May 6, 2024 at 6:00pm.

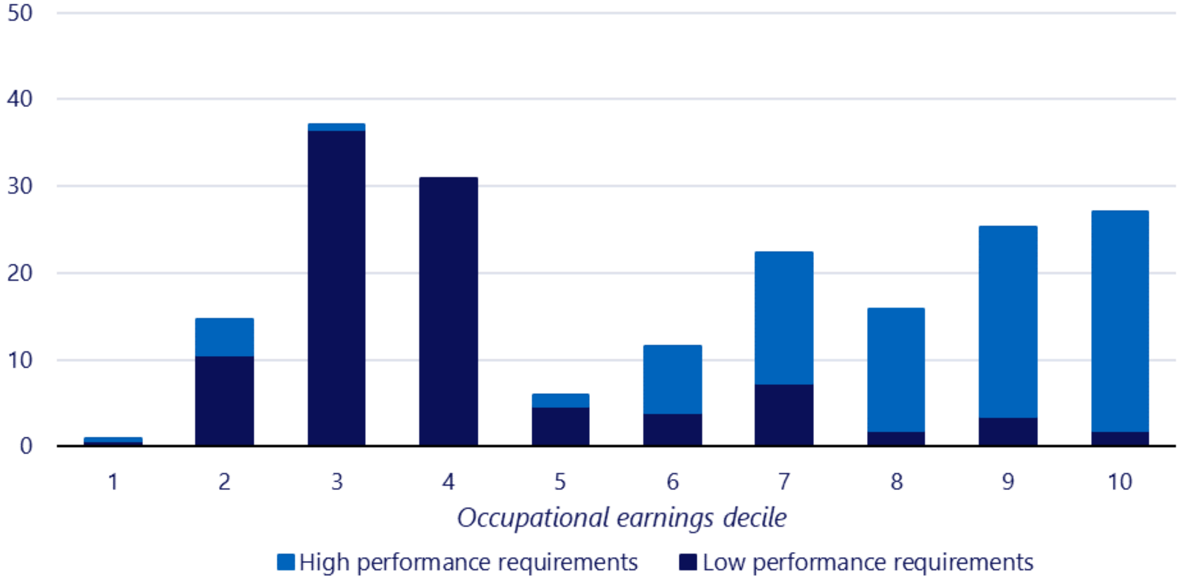
Table 2 provides a list of average occupation-level AI exposure and AI-related performance requirements by major SOC occupational group. Architecture and engineering occupations are the most exposed in CEA's measure; the score of 0.44 implies that AI-exposed activities are nearly half a standard deviation (in comparison to the population) more important to these occupations than other activities are. Notably, the top three most exposed occupational groups also have relatively high AI-related job performance requirements, suggesting that workers in these occupations may be less vulnerable than others. For example, the performance requirements score for architecture and engineering occupations of 0.81 implies that on average, AI-exposed activities of these workers must be performed with a degree of difficulty or complexity that is more than four fifths of a standard deviation above the population mean. For this reason, although 90 percent of workers in this occupation group meet CEA's threshold for high AI exposure, only 4 percent of these workers are classified as also having low performance requirements, and therefore being potentially vulnerable. In contrast, workers who have high AI exposure but low AI-related job performance requirements are comparatively vulnerable. Table 2 suggests that Office and administrative support and Transportation occupations are the groups in which potentially AI-vulnerable workers are most concentrated. However, most occupational groups have some workers who are classified as potentially vulnerable. Finally, note that many of the least AI-exposed occupations are manual in nature, and they also have very low AI-related job performance requirements. Because AI-exposed activities are relatively less important to these jobs, they are not classified as potentially vulnerable.

In Appendix Tables D1 and D2, CEA has also provided a list of the top 25 most AI-exposed occupations on this measure, as well as the bottom 25 least exposed occupations, and it has included the exposure and performance requirements scores for each. Although these rankings should be used with some caution, because exact rankings are likely to be highly sensitive to minor definitional choices, characteristic differences become apparent when comparing the two lists. Regardless of their level of performance requirements, highly AI-exposed occupations often involve tasks that have been familiar targets for computerization or automation in recent decades. Many highly AI-exposed occupations require significant amounts of information processing, as well as forms of content generation that might be automated in part or in full by generative AI. The core functions of several listed occupations, such as "Medical transcriptionists" and "Switchboard operators, including answering service" have already been targeted by commercial AI applications. In contrast, many of the occupations that are least exposed are heavily reliant on interpersonal interactions. In several cases, such as "Clergy" or "Dancers," the perceived value of outputs may be closely tied to their production by a human. In other cases, occupations involve non-routine manual activities that may simply be especially resistant to routinized automation.

Differences Across the Earnings Distribution

Figure 4. Employment in High-AI-Exposed Occupations by Earnings Decile

Percentage of employment within decile



Council of Economic Advisers

Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.
Note: Deciles are calculated using mean occupational earnings of workers who are full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high-AI-exposed work activity is performed within an occupation. High (low) indicates an average degree of difficulty above (below) the median.
As of May 8, 2024 at 6:00pm

Exposure to AI varies considerably across the earnings distribution. Figure 4 groups occupations into deciles based on workers' average earnings, and then reports the percentage of workers within each decile who are employed in an AI-exposed occupation. The highest percentage of employment in highly AI-exposed occupations occurs in the lower-middle portion of the occupational earnings distribution. In the third and fourth occupational earnings deciles, more than a third of workers are exposed to AI. However, individuals in the top two deciles are also comparatively likely to have high AI exposure.

Figure 4 also demonstrates that differences in AI-related performance requirements across the earnings distribution are substantial. While exposed workers in the lower-earning deciles have lower performance requirements, workers in higher-earning AI-exposed occupations have, on average, much higher AI-related performance requirements than workers in lower-earning occupations. For example, among the most exposed occupations reported in Appendix Table D1, some with high performance requirements, such as Electrical Engineers and Airline Pilots, are in the top occupational earnings decile, and several others are in the top half of the distribution. In contrast, several of the most exposed occupations with low AI-related job performance requirements, such as Proofreaders, Billing and Bookkeeping Clerks, and

Municipal Clerks, are found among those in the lower-middle portion of the occupational earnings distribution.

As discussed extensively in the *ERP*, workers and firms make decisions about whether and how they adopt new technologies based on numerous trade-offs between adoption costs and potential benefits. Figure 4 can be helpfully considered in this context. Potential benefits from AI come from its ability to assist with or perform specific tasks, and AI-exposed workers are the ones who currently perform these tasks. AI-related performance requirements are plausibly a measure of the cost of adopting AI to an extent sufficient to fully or mostly automate the task as it is now performed. Thus, to the extent that AI may be able to substitute for employment in jobs with lower performance requirements, such workers may be more vulnerable to substitution or displacement through automation. Conversely, workers with high job performance requirements may be more likely to use AI as a complementary input if full AI-based automation is too costly or difficult to achieve. If these relationships hold, then a pattern of AI substituting for human employment in middle-class occupations—while complementing higher-paying occupations—could meaningfully increase aggregate income inequality.

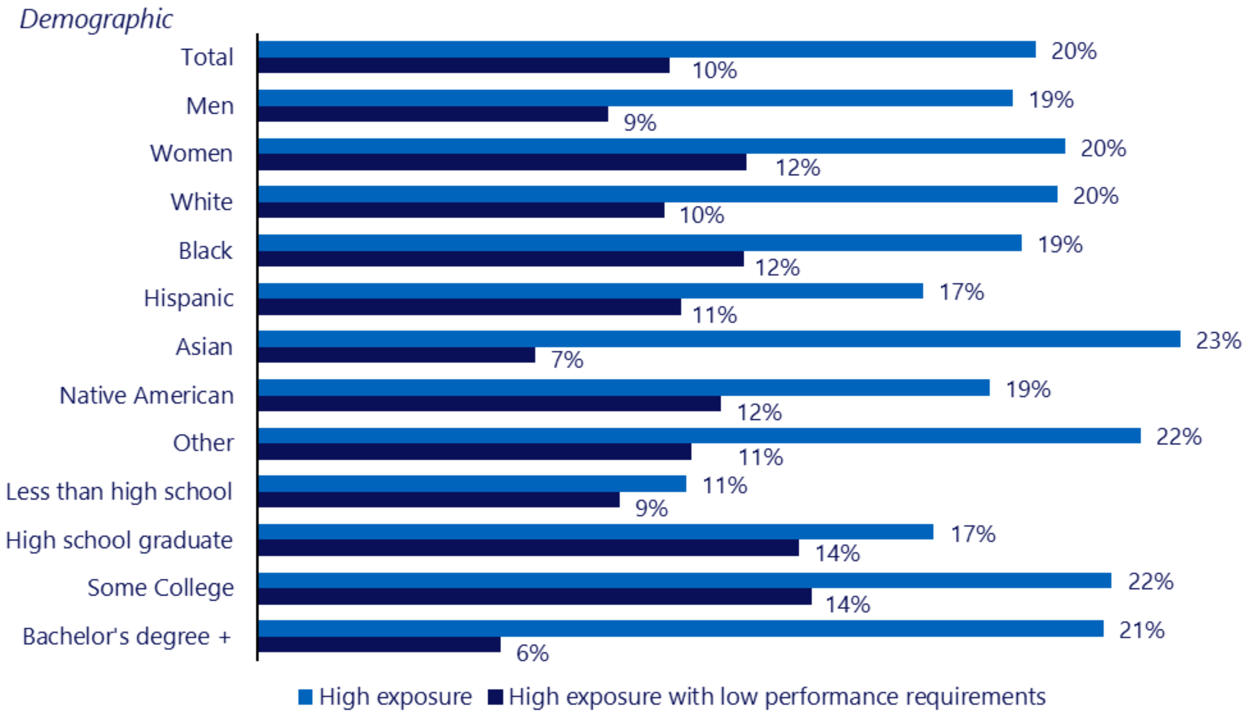
Some external evidence has begun to support the possibility that AI could impact income inequality in this way. For example, a recent survey of business executives by the Federal Reserve Bank of Dallas (2024) suggests that while most firms adopting AI do not anticipate a change in their need for workers, or for workers of different skill levels, pluralities of those that do anticipate changes plan to reduce their employment of low- and middle-skilled positions and increase their employment of high-skilled positions. Most firms adopting AI cite increased productivity as a benefit that they expect to experience as a result of AI adoption.

However, the pattern implied by a simple cost-benefit interpretation Figure 4 is by no means guaranteed. For example, the greater savings from automating tasks of highly-paid workers could spur additional use of AI to substitute for workers in the upper deciles. Or, AI-led automation could lead workers in exposed occupations to perform more difficult and complex tasks than they do now, raising their jobs' performance requirements and their productivity without displacing them. Workers might also change their focus entirely, increasing their focus on tasks that AI is not well-suited to perform. Finally, government policies could meaningfully alter AI's impacts across the earnings distribution, either through regulations that impact how AI is used, or through broader fiscal policies.

Differences in Exposure by Gender, Race/Ethnicity, and Education

It is well established that while the gender composition of many occupations has become more equal over time, many occupations continue to have highly gendered employment patterns. For example, elementary and middle school teachers are 79 percent female while construction supervisors are 95 percent male (Bureau of Labor Statistics 2024). Similarly, the racial and ethnic composition of occupations varies substantially across the workforce. As such, one might expect that AI may have differential effects by gender and ethnicity, as well as differential effects across the educational distribution.

Figure 5. Share of Workers in High-AI-Exposure Occupations by Demographic



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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.
Note: Analysis uses full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high-AI-exposed work activity is performed within an occupation. Low indicates an average degree of difficulty below the median.
As of May 8, 2024 at 6:00pm

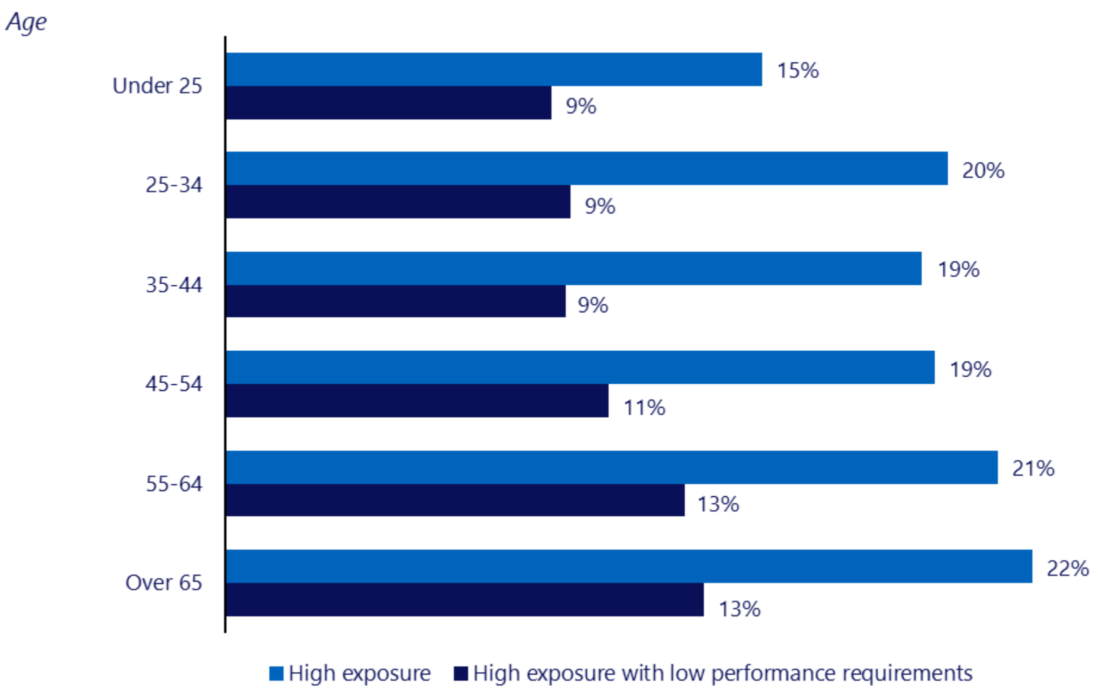
Figure 5 examines AI exposure across major demographic groups, including sex, race/ethnicity, and education. Although substantial fractions of workers from all major demographic groups are exposed AI, this analysis does suggest some demographic differences in the composition of the AI-exposed labor force. Women are slightly more likely to have high AI exposure in their jobs than men, and Asian workers are also somewhat more likely to be employed in an AI-exposed occupation. However, the most substantial differences in exposure occur across the education distribution—workers with higher levels of education are considerably more likely to have high exposure to AI.

Additionally, the demographic patterns observed among all AI-exposed workers are somewhat different than those observed among the subset of AI-exposed workers whose jobs' lower performance requirements may make them more vulnerable to AI. Workers in these jobs are disproportionately likely to have only a high school diploma, or to have some college but less than a Bachelor's degree. Conversely, workers with four-year degrees tend to be employed in jobs with higher performance requirements, making them potentially less at risk of displacement, and potentially more likely to have AI as a complementary input. Also of note, women are substantially more likely than men to be employed in high AI-exposed occupations with low performance requirements. This suggests that women may have a higher risk of displacement from AI.

Differences in Exposure by Age

Another dimension along which differences in AI exposure may be particularly important is worker age. Workers often make costly investments in education and other forms of human capital when young, in anticipation that those investments will pay off in the long run. As workers age, the time frame over which they can recoup these costly investments shortens. So, while the youngest workers may still be able to adapt their educational and occupational choices to reflect expectations about AI, older workers may not find it worthwhile to adapt, even in cases where they are negatively impacted.

Figure 6. Share of Workers in High-AI-Exposure Occupations by Age



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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.
Note: Analysis uses full-time, full-year workers age 16 and over. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high-AI-exposed work activity is performed within an occupation. Low indicates an average degree of difficulty below the median.
As of April 17, 2024 at 3:00pm

Figure 6 evaluates AI exposure over the age distribution. AI exposure is lowest among workers under 25 years of age. This may be, in part, driven by young workers who work in certain low-exposure service occupations or industries temporarily before moving on to other employment opportunities. Among workers over the age of 25, rates of high AI exposure are comparatively flat. However, rates of high exposure with low AI-related performance requirements are increasing with age. One contributor to this pattern may be higher rates of college completion among younger workers (U.S. Census Bureau 2023), since workers with at least a Bachelor's degree are more likely to work in jobs with high performance requirements.

Higher job vulnerability among older workers may be of particular concern if job displacement has more negative impacts on older workers. Earlier evidence from the United States has suggested that the negative effects of job displacement vary only modestly by age (Jacobson, Lalonde, and Sullivan 1993), but more recent evidence from Europe suggests that older workers are particularly negatively affected by job loss, including job displacement that is linked to automation (Deelen, de Graaf-Zijl, and van den Berge 2018; Bessen et al. 2023). Research in the tax literature also suggests that the extent of differential effects on new versus existing workers determines whether automation technologies should be taxed above and beyond other forms of capital (Guerrreiro, Rebelo, and Teles 2022).

Geographic Patterns

Labor markets are often localized, and so economic forces that impact particular labor markets can also have geographically-concentrated impacts. For example, evidence has shown that previous job displacement resulting from trade liberalization spilled over into local economies, and that it has had persistent effects in those places (Autor, Dorn, and Hanson 2013; 2021). Conversely, research suggests that the rise of economically prosperous technology clusters is linked to the positive spillovers that being close to other inventors can provide (Moretti 2021). As such, the geographic distribution of AI exposure may have implications for its aggregate impacts. An understanding of the geography of AI exposure could help to target negatively affected workers through place-based policies or other means.

Table 3. Rank of Census Divisions by Percent of AI-Exposed Employment

Rank	*State*	*Percent of AI-exposed employment*	*Percent of AI-exposed employment with low performance requirements*	*Rank by AI exposure with low performance requirements*
1	Pacific	20.5%	10.1%	8
2	Mountain	20.2%	10.5%	4
3	Middle Atlantic	20.0%	10.4%	6
4	New England	20.0%	9.4%	9
5	South Atlantic	19.9%	10.3%	7
6	West South Central	19.4%	11.2%	2
7	West North Central	19.3%	11.3%	1
8	East North Central	19.1%	10.5%	5
9	East South Central	18.5%	11.0%	3

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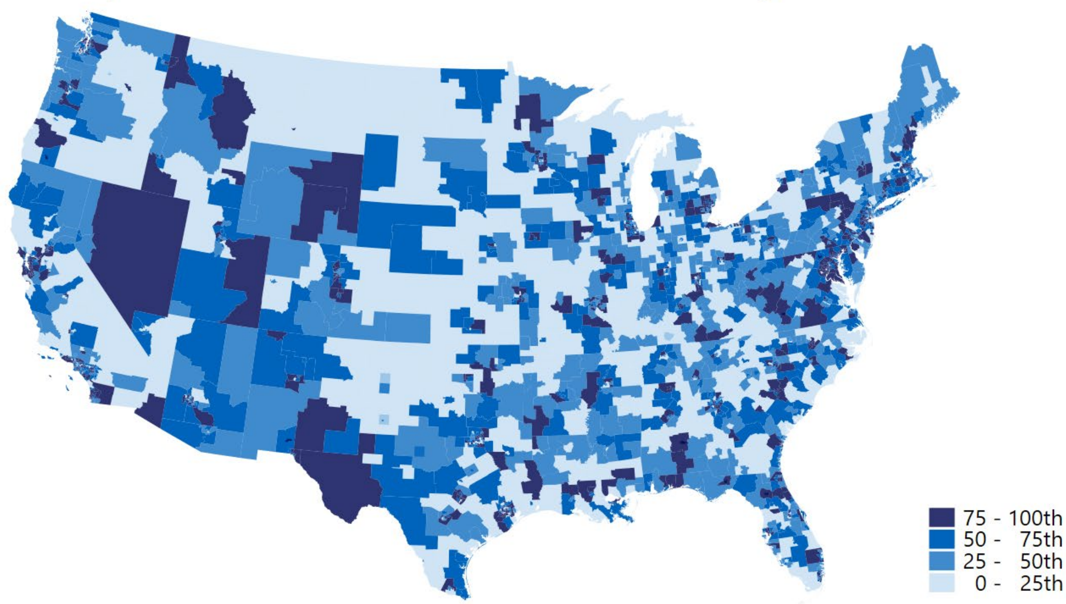
Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.

Note: Analysis uses full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high AI-exposed work activity is performed within an occupation. Low indicates an average degree of difficulty below the median.

As of May 8, 2024 at 6:00pm

Across broad geographic regions of the country, there is relatively little heterogeneity in exposure to AI. As Table 3 shows, the Census division with the largest share of AI-exposed employment has only a 2 percentage point higher share of such employment than the lowest-ranking region. And, the distribution of AI-exposed employment with low performance requirements is similarly compressed.

Figure 7. AI Exposure Across Public Use Microdata Areas by Percentile



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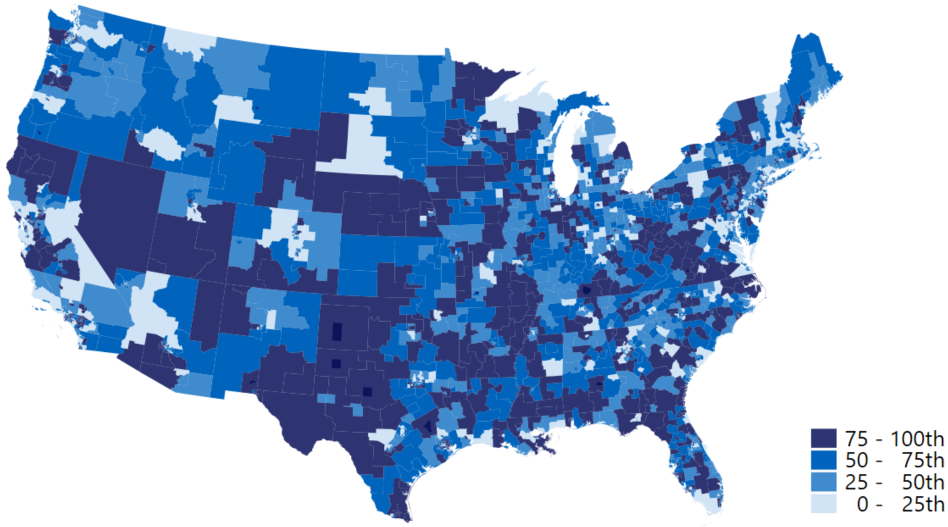
Sources: US Census Bureau; Pew Research Center; CEA calculations

Note: Public Use Microdata Areas (PUMAs) are defined as non-overlapping,statistical geographic areas that divide each state into areas with a population of at least 100,000. Analysis uses full-time, full-year workers age 16 plus.

As of June 18, 2024 at 3:50pm

Figure 8. AI Exposure with Low Level of Performance Across Public Use Microdata Areas by Percentile



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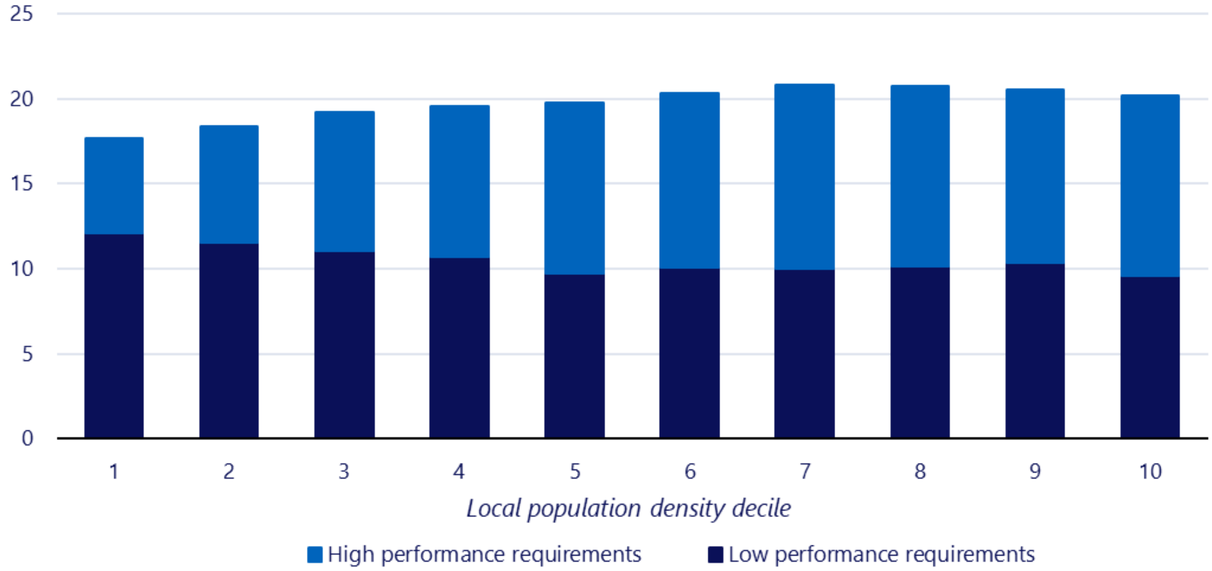
Sources: US Census Bureau; Pew Research Center; CEA calculations
Note: Public Use Microdata Areas (PUMAs) are defined as non-overlapping,statistical geographic areas that divide each state into areas with a population of at least 100,000. Analysis uses full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high AI-exposed work activity is performed within an occupation. Low indicates an average degree of difficulty below the median.
As of June 18, 2024 at 3:50pm

Nonetheless, when analyzed with finer geographic precision, there is substantial variation in exposure to AI across places. Figures 7 and 8 provides detailed maps at the PUMA level, the finest geographic level for which detailed occupation data are available in the American Community Survey. The first panel plots quartiles based on any AI-exposed employment, while the second panel shows quartiles based on AI-exposed employment with low performance requirements. While these maps suggest some regional patterns, there is no clear positive geographic correlation between overall exposure and potential vulnerability. In particular, many rural areas of the country do not rank especially high in terms of overall AI exposure, but do rank high in employing the occupations with high exposure and low AI-related performance requirements that are potentially most vulnerable. As such, rural areas could on average be more susceptible to negative spillover effects associated with increased AI adoption.

Figure 9. Employment in High-AI-Exposed Occupations by Local Population Density

Percentage of employment within decile



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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.
Note: Deciles are calculated using mean occupational earnings of workers who are full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high-AI-exposed work activity is performed within an occupation. High (low) indicates an average degree of difficulty above (below) the median.
As of May 8, 2024 at 6:00pm

Figure 9 confirms this broad pattern by plotting average rates of AI exposure across deciles of local area population density. Average rates of exposure are substantial in both the most rural areas (the lowest deciles) and the most urbanized areas (the highest deciles). Yet, overall AI exposure is highest in the densest areas. This echoes the findings of Felten, Raj, and Seamans (2021), who have previously observed a similar pattern. On the other hand, employment of potentially-vulnerable workers (highly AI-exposed and with low AI-related performance requirements) is negatively associated with local population density. The weakness of these associations suggests that population density on its own may be only modestly beneficial as a metric in identifying potentially affected workers.

In Appendix Tables D3 and D4, CEA has provided lists of the top 25 geographic regions (PUMAs) with the highest rates of employment in AI-exposed occupations, and the top 25 geographic areas with the highest rates of vulnerable employment. Notably, there is little overlap between these two lists; only a single area that ranks as having among the highest rates of AI exposure also ranks similarly high-ranking rates of exposure with low performance requirements. In fact, some regions with among the highest AI exposure—such as portions of Silicon Valley—have among the lowest rates of AI-related performance requirements in the country. This suggests that the places that may be most at risk of substantial AI-related displacement could be quite different from the places where AI is simply being widely used. Additionally, while a majority of the top regions in terms of AI-exposed employment are located in some of the nation's largest metropolitan areas, regions with high rates of AI-exposed employment with low performance requirements are often in smaller metros or outside of metropolitan areas entirely.

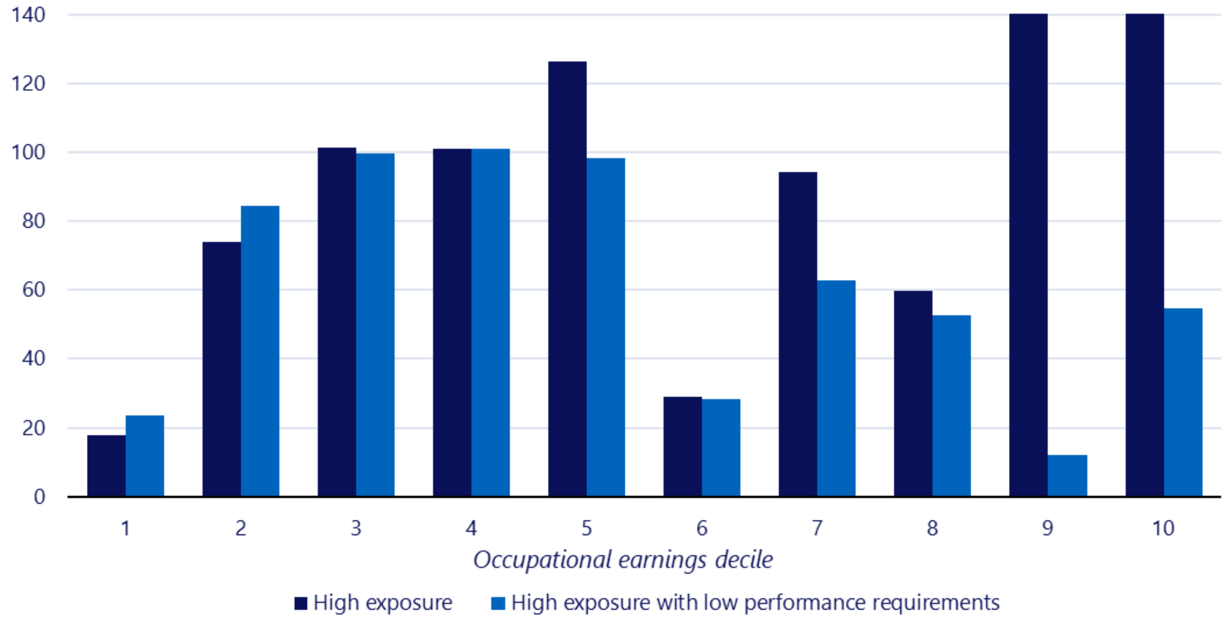
Taken collectively, this analysis suggests that both the positive and negative effects of AI on labor markets may be geographically clustered. However, it is likely that they will often not be clustered in the same places. Additional analyses and measure that can further distinguish between AI-vulnerable workers and merely AI-exposed workers may be especially useful in considering geographically-targeted assistance or other place-based policies.

Unionization and AI Exposure

Technology adoption is often characterized as a firm-level decision, but workers can play a meaningful role in determining how technologies like AI are used. There are also many ways in which workers' voices and insights can be expressed. However, the collective bargaining power of labor unions has traditionally made them a particularly important avenue for empowering workers. Unions have already had an impact on AI adoption, as workers have secured protections related to the use of AI in several recent union contracts, including those of screen writers and actors (WGAW 2023; SAG-AFTRA 2023). More generally, the knowledge that workers provide about work processes could help to improve AI implementation (Kochan et al. 2023).

Figure 10. Relative Unionization Rate of AI-Exposed Occupations Within Earnings Deciles

Exposed worker unionization rate as a percentage of non-exposed worker rate



Council of Economic Advisers

Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.

Note: Analysis uses full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high AI-exposed work activity is performed within an occupation. Low indicates an average degree of difficulty below the median.

As of May 8, 2024 at 6:00pm

Only 10 percent of wage and salary workers are union members (Bureau of Labor Statistics 2024), and CEA finds that AI-exposed workers are even less unionized: only 9.0 percent of such workers are members of a union. However, in assessing the potential role of unions, it may be useful to consider how the relative unionization rate of AI-exposed workers varies across the characteristic groups. Figure 10 plots the unionization rate of AI-exposed workers as a percentage of the rate for non-exposed workers within each occupational earning decile. The figure demonstrates that lower unionization rates for exposed workers hold across much of the earnings distribution: AI-exposed workers are substantially more likely than non-exposed workers to be unionized in only three earnings deciles. Additionally, it shows that potentially AI-vulnerable workers (highly AI-exposed workers with low performance requirements), who may be especially at risk to displacement, are not disproportionately likely to be union members. The percentage of workers who are vulnerable to AI and near the top of the earnings distribution is small, but these workers appear to particularly unlikely to be unionized.

Unions will likely continue to play a valuable role in empowering workers and ensuring that AI adoption is beneficial to them. Yet, this analysis suggests that a relatively high proportion of workers who may be displaced are not currently represented by a union. This could change if unionization becomes increasingly attractive to workers who are concerned about the role that new technology plays in their work. However, the role that unions play in empowering workers may be meaningfully complemented by a broader approach that incentivizes firms to account for the benefits and costs of AI adoption to their labor force.

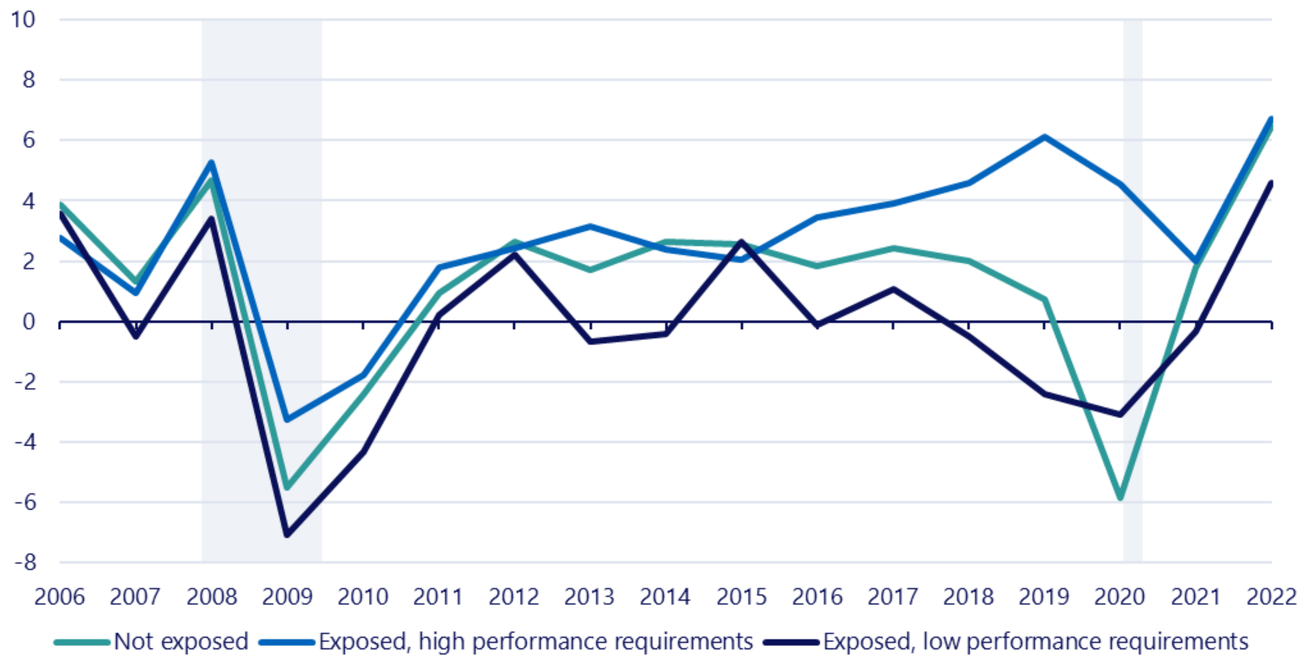
Historical Analysis

In assessing a framework that predicts potential future impacts of a new technology, it may be helpful to consider how that framework relates to the changes of the past. The analysis of the preceding subsection suggests that CEA's measures are in part linked to prominent measures of occupational task content that economists have relied upon in the past. In this section of the report, CEA looks at a variety of historical and recent employment trends that can provide clues as to how or whether AI is already impacting labor markets, and also as to how workers and labor markets may adapt to increased adoption of AI. Collectively, these results provide some additional evidence that the subset of occupations with low AI-related performance requirements identified by CEA may already be comparatively vulnerable. They also suggest some possible ways in which workers in different occupations may be adapting to technological change differently over time.

Historical Employment Trends and Recent Comparison

Figure 11. Employment Trends by AI Exposure within Occupations, 2006-22

Year-over-year percent change in employment



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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.
Note: Analysis uses full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high-AI-exposed work activity is performed within an occupation. High (low) indicates an average degree of difficulty above (below) the median.
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Figure 11 shows historic trends in annual employment growth among the three distinct occupational groups defined by CEA's measure.[10] Notably, employment growth of AI-exposed occupations with low performance requirements has been consistently slower than that of occupations with high performance requirements for nearly two decades, as well as of occupations which are not highly exposed to AI. In early periods, employment growth across these three groups was largely in parallel. They also responded similarly during the Great Recession and subsequent recovery. However, in more recent years, there has been some divergence in growth patterns across the three groups. The gap in employment group between the high- and low-performance requirement groups increased substantially in the latter portion of the last decade. And, employment in the non-exposed group declined more strongly and recovered more quickly

[10] To perform this analysis and subsequent ones in this section, occupational definitions needed to be encoded consistently over time. For this purpose, CEA used a time-consistent occupational crosswalk provided by IPUMS, based on the 2010 SOC classification. All analyses exclude occupations that did not appear in the 2022 ACS, because these occupations have not been not categorized in terms of their AI exposure.

from the pandemic recession period, potentially reflecting differences in the working environments of AI-exposed and less-exposed employment. Employment growth between 2021 and 2022 was again largely in parallel, although this finding is challenging to interpret in light of the ongoing pandemic recovery at that time.

Figure 12. Industry AI Exposure versus Payroll Employment Growth Relative to Long-Run Trends

A. AI-Exposed Employment with High Performance Requirements

Difference in growth rate of payroll employment from 2023 to annualized rate between 2007 and 2019 (percentage points)

Council of Economic Advisers

Sources: Bureau of Labor Statistics (Occupational Employment and Wage Statistics); Pew Research Center; CEA calculations.
Note: Occupations are matched to the most detailed industry data available in the Current Employment Statistics. Point sizes are proportional to industry employment and linear predictions are weighted by industry employment. These outliers are not shown: 213, support activities for mining; 313, textile mills; 3132, fabric mills; 3361, motor vehicle manufacturing; and 3212, veneer, plywood and engineered wood product manufacturing.
As of May 8, 2024 at 6:00pm

Although this historical analysis is insightful about long-run trends, it may not capture more immediate changes associated with the rapid rise of new AI systems, such as generative AI. To assess potential recent impacts of AI on employment growth, it is more useful to compare how recent changes in different groups compare to their long-run trends. For this purpose, CEA has turned to payroll employment data, as well as additional information from the Bureau of Labor Statistics that provides details on the relationship between occupation and industry patterns of employment. Although most industries employ a mix of highly AI-exposed and less-exposed workers, there are a handful of industries that employ high fractions of AI-exposed workers. A full list of these industries is included in Appendix D, and some are small, but notable examples include Legal Services, Oil and Gas Extraction, and Software Developers. Based on this information, Figure 12 compares employment growth in 2023 against long-run trends in growth for each industry from 2007 to 2019, and then plots this difference against the percentage of within-industry employment that is highly exposed to AI. The two panels of the figure separate out AI-exposed employment with high AI-related performance requirements, and AI-exposed employment with low AI-related performance requirements. As the figure shows, many of the industries that disproportionately employ exposed workers are small. And, there is relatively little evidence that changes in employment growth rates are being driven by workers' AI exposure as measured at the industry level. The relationship between changes in employment growth and employment of exposed workers with low performance requirements (the lower panel) is slightly negative. This is consistent with the more recent slowdown in employment growth among this occupational group. On the other hand, if new AI technologies were already causing substantial AI-driven substitution to take place, then the plotted relationship would likely be stronger.

A likely reason that few employment effects are currently seen in relation to AI is that it is still too early in firms' adoption process. Although many systems and processes may eventually be updated to take advantage of AI, firms may not yet have made these types of updates in all cases (McElheran et al. 2024; Babina et al. 2024).

Occupational Transitions and Career Paths

Another way in which workers may respond to the impacts of new technology is by changing jobs or occupations. For example, a worker who is displaced from an occupation whose employment is shrinking might seek employment in another occupation that is less prone to displacement. Or, in the case of AI, a worker whose tasks are automated by the technology could potentially switch to another occupation with higher performance requirements that AI cannot yet emulate. Since the human capital that workers use to perform their jobs is often task or occupation-specific (e.g., Gathmann and Schönberg 2010; Sullivan

2010), workers pay an implicit cost when they switch occupations. For this reason, occupational switching patterns reflect in part a supply response to patterns of increasing or declining demand.

To evaluate job transitions among AI-exposed workers, CEA has conducted an analysis that takes advantage of the longitudinal structure of the Current Population Survey (CPS). In this survey, the same workers are observed in two adjacent years, and this permits measurement of the same worker's employment characteristics—including occupation—at multiple points in time. From these data, CEA has constructed a one-year occupational transition matrix for each of the three main occupational categories defined by its measure. That is, for a worker is employed in a particular category in one year, this matrix provides the probability that the worker is employed in the same occupation the next year, in another occupation in the same category, in another category, or that they are not employed.

Table 4. Movement across Occupation by AI Exposure and Level of Performance in Current Occupation

	Transition rate to category one year later				
	Same occupation	*High AI exposure with high performance requirements*	*High AI exposure with low performance requirements*	*Not AI-exposed*	*Not employed*
Initial Occupational Category in 2022					
High AI exposure with high performance requirements	46.4%	15.4%	4.5%	29.2%	4.5%
High AI exposure with low performance requirements	46.5%	5.6%	10.3%	30.7%	6.8%
Not AI-exposed	46.9%	4.4%	4.0%	38.4%	6.3%
	Percentage point change from 2015-2019 transition rate				
Comparison to 2015-2019 by Initial Category					
High AI exposure with high performance requirements	*1.0%*	*1.0%*	*-0.1%*	*-1.3%*	*-0.7%*
High AI exposure with low performance requirements	*-0.4%*	*0.4%*	*-0.3%*	*0.3%*	*0.0%*
Not AI-exposed	*0.2%*	*0.1%*	*-0.1%*	*0.0%*	*-0.2%*

Council of Economic Advisers
Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.
Note: Analysis uses full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high AI-exposed work activity is performed within an occupation. Low indicates an average degree of difficulty below the median. Percentages are calculated as the average transition rates across the time-span. For example, the first row and column calculates the average share of workers who are currently in AI-exposed occupations who are in the same occupation one year later. Time period is in terms of the transition one year later.
As of May 8, 2024 at 6:00pm.

Table 4 provides this transition rate information for workers who were observed in both 2022 and 2023. It also compares these transition probabilities to rates observed in the pre-pandemic period of 2015 to 2019. In all cases, the percentage point changes in transition rates are small. Nonetheless, some notable patterns emerge when comparing 2022-2023 to the preceding period. Regardless of their initial occupations, workers are increasingly likely to have transitioned to an AI-exposed job with high AI-related performance requirements, and decreasingly likely to have transitioned to an AI-exposed job with low AI-related performance requirements. These patterns are consistent with possible changes in occupational demand. Additionally, workers who start out in a high AI-exposure, high performance-requirements job are increasingly likely to remain in the same occupation. Conversely, workers who are employed in low performance requirement jobs are increasingly likely to change occupations. Most of these switches are to occupations that are not exposed to AI, but an increasing proportion are also switching to AI-exposed jobs with higher performance requirements. Overall, workers were less likely to transition out of employment in 2023, and this was particularly true of AI-exposed workers with high job performance requirements.

This analysis is consistent with possible emergence of patterns of complementarity and substitution, but it is subject to several important data-related limitations. The first limitation is that it is based on self-reported occupations from a survey. Previous research has suggested that self-reported occupations may be imprecise, and also that occupational misreporting may systematically overstate the proportion of higher-skilled employment (Fisher and Houseworth 2013). Similarly, imprecise occupational reporting could account for the relatively low rates of workers reporting the same occupation in two consecutive years.

A second limitation of this analysis is that it only considers transitions over a one-year period of time. Career transitions may take place over longer periods, especially if workers need to obtain additional training or formal education in order to make them. Even though Federal administrative data collected from employers are increasingly used to assess differences in individuals' earnings and employment trajectories (e.g., Haltiwanger, Hyatt, and McEntarfer 2018; Foote 2022; Conzelmann et al. 2023), there are currently no U.S. administrative data sources that collect information about individual workers' occupations in a comprehensive way over multi-year periods. So, some forms of worker adaptation to AI will likely remain unobservable for now.

Changes in Task Content Over Time

One of the biggest challenges to making predictions about the labor market impacts of AI is accounting for the ways in which the tasks or activities performed by specific occupations might evolve. Occupations often change in meaningful ways as workers and firms adopt new technologies. Even in cases where automation is implemented, workers may not be displaced if they adjust the tasks they perform to increasingly emphasize other elements of the work. Similarly, workers in an occupation might benefit considerably if a new technology permits them to increase their output or capabilities. Thus, the specific nature of future adaptations to AI may determine who benefits from the technology and who does not.

For example, CEA's analysis finds that workers in the lower-middle portion of the earnings distribution are both most likely to be exposed to AI, and also most likely to have low AI-related performance requirements. This finding suggests that these workers could be particularly vulnerable to substitution and subsequent harm. However, CEA's measure is based on performance requirements today, and there is no guarantee that low performance requirements today are predictive of an inability to adapt in the future. If workers and jobs adapt to the technology over time, then potential harms may never arise. In fact, other researchers have recently suggested that AI could be especially beneficial to the middle class, by allowing them to perform work that was previously performed only by highly paid experts (Autor 2024). There is also some recent empirical evidence suggesting that the largest productivity gains from AI may go to workers who are not already performing at a high level. For example, when call center workers were given access to AI, the largest productivity gains were observed among the least experienced and least skilled workers (Brynjolfsson, Li, and Raymond 2023). If AI's specific features make it feasible for many workers to complement their own knowledge and skill with AI, then evidence of those adaptations will likely be found in future measures of job performance requirements, reflecting greater difficulty and complexity of workers' jobs. Yet, current performance requirements may not be predictive of future help or harm.

CEA continues to follow the evolving research on how workers use AI, and it has not made specific predictions about how task content will change over time in the future. However, using additional data from O*NET, it is able to provide some limited evidence on how occupations have changed over time in the past, in particular with regard to AI-exposed activities. To conduct this analysis, CEA evaluated the underlying O*NET Work Activity scores for each year going back to 2007.[11] After linking these scores to a time-consistent definition of occupations,[12] CEA researchers rescaled the work activity scores for each occupation in each year, using the methodology described in Section 2, but in all years transforming the data using means and standard deviations from the base year of 2007. Thus, CEA's measure reports how many standard deviations more or less exposed an occupation has become to AI over time, and how much higher or lower its performance requirements have become, relative to the distribution of the economy in 2007.[13] And, using this information, CEA can measure several things. First, it can provide an estimate of how much exposure and performance requirements in the aggregate economy have changed over time. Second, it can assess the extent to which these changes result from within-occupation changes in tasks as opposed to changes in occupation-level employment. Finally, it can examine how different occupational groups may have evolved differently in recent years. Changes in job performance requirements are of particular interest in this context: they reflect changes in how complex and difficult are the tasks that

[11] In each year except 2022, CEA uses the last O*NET release that was made available in that year. In 2022, CEA uses O*NET release 28.0, released in August 2023, for consistency with previous analyses. Work Activity scores are not updated for each occupation in every year, so each occupation's scores represent the most recent information available at that time. Years prior to 2007 were dropped from the analysis; in those years, Work Activity scores for numerous occupations were still recorded using legacy analyst data that predates the contemporary O*NET data collection program.

[12] Since occupational categorizations changed multiple times over the period, CEA first linked O*NET occupation information in each year to the relevant SOC occupational encoding for that year, using published crosswalks from Census and BLS. It then mapped those occupations to a longitudinally-consistent occupation encoding provided by IPUMS, based on the 2010 SOC classification.

[13] CEA has not adjusted its underlying measure of AI-exposed work activities to reflect changes in AI's capabilities over time. So, this time varying measure indicates hypothetical exposure to AI's current and expected future capabilities, not to its actual capabilities in the past.

workers are performing, and therefore they may reflect the effects of complementary adoption of new technologies over time.

Figure 13-A. Average AI Exposure By Year

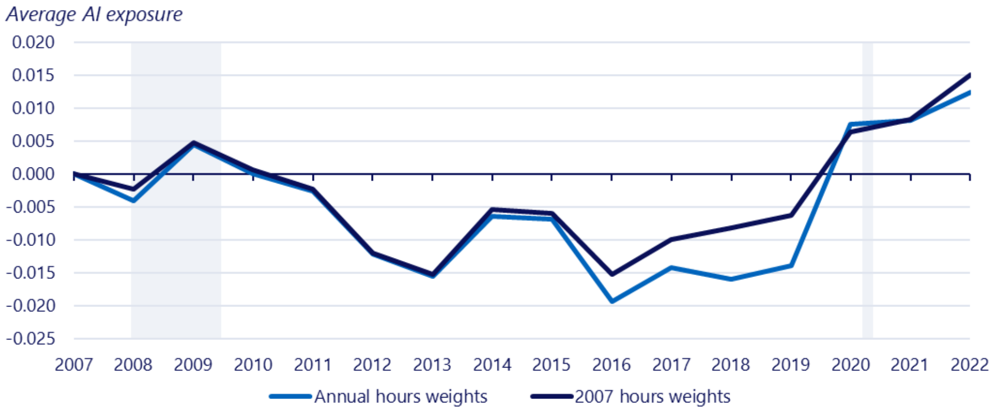


Figure 13-B. Average Performance Requirements By Year

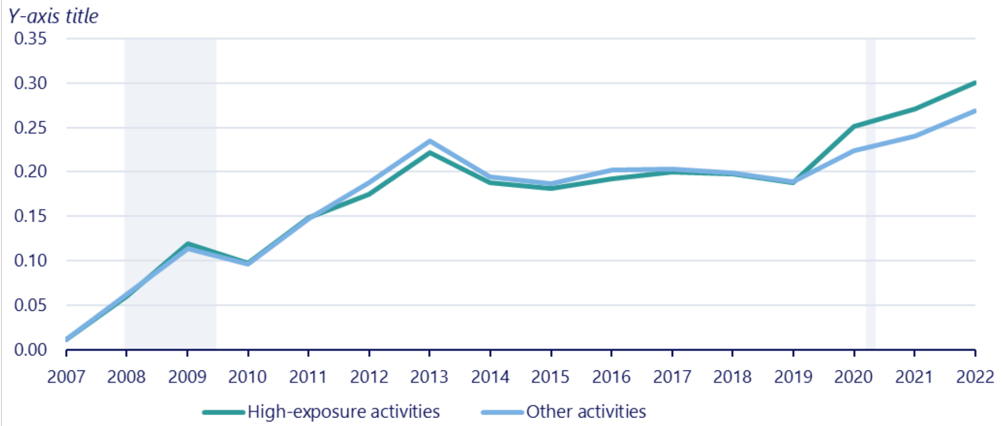
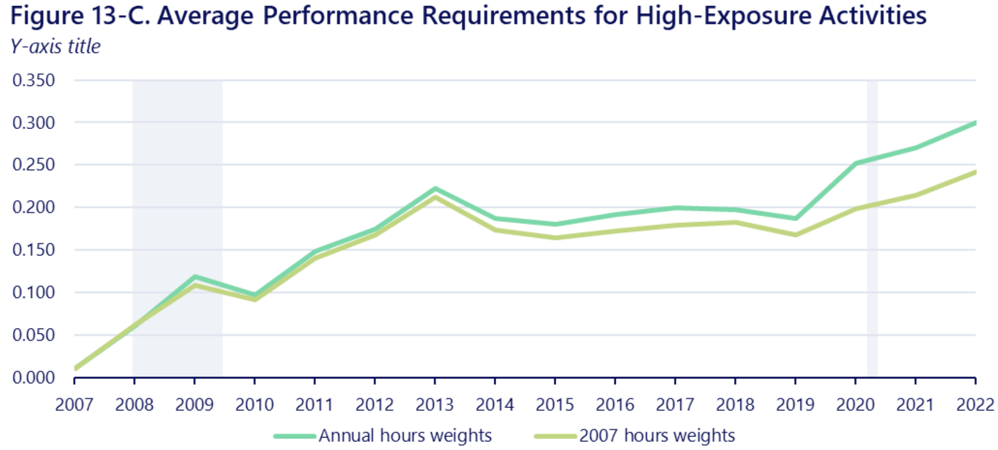


Figure 13-C. Average Performance Requirements for High-Exposure Activities



Council of Economic Advisers
Sources: American Community Survey; Bureau of Labor Statistics; Department of Labor; U.S. Census Bureau; Pew Research Center; CEA calculations.
Note: Occupational content is measured using the last available O*NET release in each year, and linked to American Community Survey using publicly available data
As of May 8, 2024 at 6:00pm

The three panels of Figure 13 show the results of this analysis across the overall economy. Taken together, the analysis of the three panels suggest that meaningful within-occupational shifts have occurred, but that they likely have not been in response to AI specifically. Instead, changes in performance requirements over time appear to reflect a more general pattern of upskilling of employment in the economy.[14]

Panel A plots average AI exposure by year, relative to the initial distribution of 2007. Exposure to AI—as measured by the importance workers have placed on activities corresponding to its present and expected future capabilities—has increased in recent years. However, even though the trend line has noticeably shifted since 2016, the magnitude of the change in aggregate AI exposure is quite small. In the second series of Panel A, CEA applies 2007 hours weights to each occupation. This additional restriction ensures that the percentage of employment in each occupation remains fixed over time. So, the second series in Panel A plots the aggregate changes in the economy that have resulted from within-occupation changes in AI exposure, rather than changes in employment composition across occupations. The 2007-weighted series confirms that not only has aggregate AI in the economy been relatively stable, but that shifts in the occupational structure over time have done relatively little to affect its path.

In Panel B, CEA plots the change in average performance requirements by year, comparing those for highly AI-exposed activities (as used throughout and identified in Appendix Table A1) to those for all other activities. In contrast to AI exposure, AI-related performance requirements have increased substantially since 2007. The average worker in 2022 has AI-related performance requirements that would have been nearly 0.3 standard deviations above the mean in 2007. However, performance requirements have also increased by a similar magnitude among all other activities measured. This result, in particular, suggests that upskilling has occurred broadly throughout the economy, and that upskilling is likely not in response to AI technology specifically.

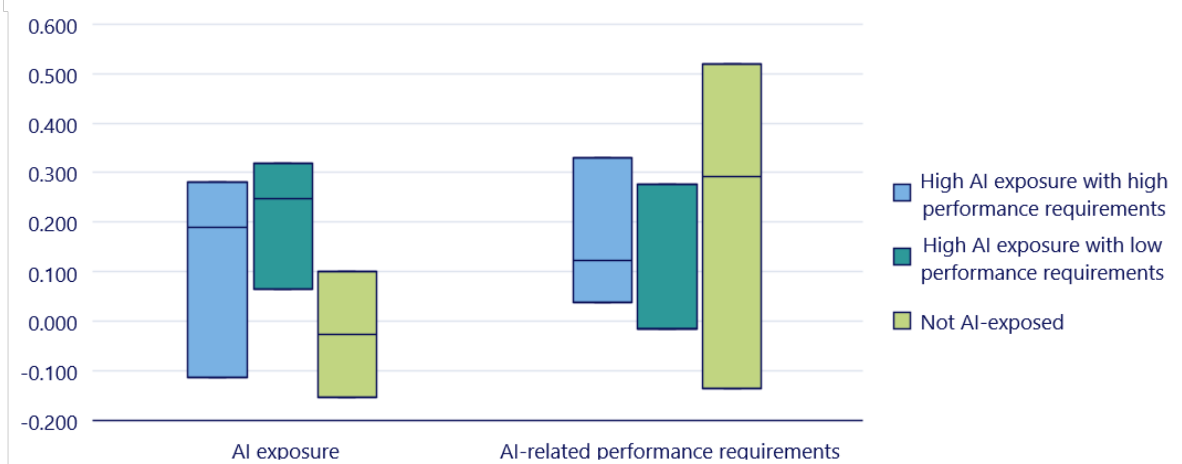
Finally, Panel C compares this change in AI-related performance requirements to the same series, with 2007 hours weights applied. As in Panel A, the fixed hours weight series is intended to reflect only within-occupation changes in performance requirements, while the baseline series also reflects the impact of compositional changes over time. This analysis implies that about 80 percent of the increase in AI-related performance requirements from 2007 to 2022 was attributable to within-occupation changes in occupational content, rather than to shifts in employment across occupations. This result confirms that

[14] CEA uses the term upskilling in this context in reference to increases in job performance requirements over time. O*NET also contains a separate measure of occupational content denoted as Skill, which CEA has not analyzed.

individual occupations have undergone considerable upskilling over time, and it also suggests that significant upskilling of the economy may not require widespread occupational transitions to occur.

Figure 14. Change in AI Exposure and AI-Related Performance Requirements 2007-2022 by Occupational AI Exposure

Percent change



Council of Economic Advisers

Sources: American Community Survey; Bureau of Labor Statistics; Department of Labor; Pew Research Center; U.S. Census Bureau; CEA calculations.

Note: Occupational content is measured using the last available O*NET release in each year, and linked to American Community Survey using publicly available data.

As of May 8, 2024 at 6:00pm

In Figure 14, CEA plots the distribution of cumulative changes from 2007 to 2022 in both AI exposure and AI-related performance requirements for each of the three occupational categories identified. This demonstrates several noteworthy differences in occupational changes among the three groups, which may reflect occupational adaptations to previous computing technologies, or to existing AI implementations. In particular, these results suggest that workers who are highly exposed to AI, but who have low AI-related job performance requirements may be vulnerable precisely because their exposure has increased, but the complexity and difficulty of their jobs has not. These results should not be interpreted to suggest that any one occupation or set of occupations cannot or will not adapt to future technological changes. However, they do suggest that the vulnerability of the high-exposure, low-performance requirements occupations that CEA identifies may be increased by their lack of previous adaptation over time.

As previously shown in Panel A of Figure 13, AI exposure in the overall economy did not increase much over the period, despite a slight uptick in recent years. However, as Figure 14 shows, the finding of little change is generally not true of the occupations that CEA classifies as currently highly AI-exposed. The median worker in these occupations in 2022 has exposure that is roughly 0.2 standard deviations higher than a worker in the same occupation in 2007, implying that AI-exposed activities have gotten more relatively important to these jobs over time. In contrast, the majority of workers in non-exposed occupations saw their AI exposure decline.

Regarding AI-related performance requirements, the largest increases have, perhaps surprisingly, often been among workers who are not exposed to AI. This could reflect underlying technological forces, such as the ability of workers to use computers to perform more complex tasks that might not be particularly central to their jobs. However, the distribution of changes among this category of workers is quite wide, making this result hard to interpret. What is clearer is that there is a sizeable difference in the extent to the two categories of AI-exposed workers have changed over time. The complexity and difficulty of many AI-exposed occupations with low performance requirements have changed little since 2007, and this is reflected in the near zero change for the median worker in that category. On the other hand, the median worker in an AI-exposed job with high AI-related performance requirements has seen those requirements increase over time.

As with the other time-series analyses that CEA has performed, there are important limitations to the analysis. Notably, O*NET does not update its estimates of each occupation's activity scores in each year, so although this analysis uses the most recent information available in each year, these measures may considerably lag underlying occupation-level changes. Additionally, the need to use a time-consistent occupational definition limits the ability to look at more finely grained patterns of occupational birth and death that may suggest changes. And, changes to task content could be mismeasured if analysts or respondents simply interpret O*NET's quantitative scales differently over time. Nonetheless, this analysis supports the notion that substantial changes within occupations have occurred in recent years, and that these patterns have been notably different for the occupations that CEA identifies as potentially AI-vulnerable.

Of course, all these patterns could change over time, and increased upskilling of vulnerable workers could mitigate the possibility of displacement or other harms. However, the occupations that CEA identifies as potentially AI-vulnerable show less evidence of upskilling despite the fact that they are already experiencing slower employment growth and other signs of reduced demand. CEA cannot observe whether these signs of declining demand are a result of labor substitution that is already taking place. However, if these occupations are particularly resistant to complementary integration of new technologies, then AI is especially likely to negatively impact workers in these occupations.

Conclusions

The potential implications of AI on workers and labor markets are large, but highly uncertain. In this report, CEA has taken an explicitly data-driven approach to consider who might be most impacted by AI, and to evaluate reasons why those impacts might be more or less positive for different groups of workers. Carefully examining the data has benefits: it ensures that any predictions are grounded in evidence to the extent possible. It also helps to identify the specific ways in which existing data may be insufficient to answer the questions being posed. The value in the CEA's framework derives, in large part, from its ability to provide a concise and interpretable lens on those underlying data, and on new data as they become available.

This approach is not without limitations or trade-offs. Many forms of AI technology are very new, and in numerous cases there is simply not enough data to evaluate how different groups of workers will be affected by the technology. All analyses of potential labor market impacts from AI should be interpreted cautiously, and CEA's is no different in this regard. As adoption of AI increases over time, CEA expects that they and others will continue to revisit these questions, and its predictions may well be proven wrong.

Nonetheless, the analyses contained in this report provide several new pieces of evidence that support the potential implications of its underlying framework. In particular, these analyses support an interpretation that a subset of AI-exposed workers are particularly vulnerable to potential negative impacts from AI and that these workers are most commonly found in the lower-middle portion of the earnings distribution. These AI-vulnerable workers may be identified by their occupations and the types of work that they do. Policies that seek to provide targeted assistance or otherwise address vulnerable workers may benefit from taking occupational information into account. However, there are also notable demographic and geographic patterns of exposure, and these may influence the overall policy response as well.

AI adoption has both many potential benefits and also a potential for harm. The potential benefits to workers could be many, including higher productivity leading to higher wages, more time spent working on the interesting and enjoyable parts of their jobs, and other improvements to working conditions. The harms to workers may include some that are associated with declining demand—such as reduced earnings or job displacement—but also many others. For example, AI could be harmful if it is used in ways that reduce workers' privacy or autonomy, undermine their rights, or that embed or enable discrimination. The Biden-Harris Administration has taken a thorough, whole of government approach to ensuring safe and responsible AI adoption. Its actions to support workers are consistent with that approach, including numerous actions outlined in Executive Order 14110 (White House 2023). Guidance from the Department of Labor will help to ensure that workers are treated fairly, employment decisions are made responsibly, and working conditions are upheld (Department of Labor 2024). The Labor Department also continues to review the government's labor market assistance programs, to ensure that they are prepared for any new demands brought about by AI. And, both the analysis of this report and the broader economic framework discussed in the *ERP* will continue to inform and guide the Administration as it considers how best to support workers.

Changes to the labor market over time are an inevitable and necessary feature of a dynamic economy. Jobs, occupations, and workers will adapt to accommodate AI, as they have done for numerous technologies over time. However, thoughtful policies and appropriate regulations can help ensure that these changes are broadly beneficial and not unnecessarily disruptive or harmful to workers. CEA will continue to analyze new developments in both data and research to help ensure that these policies are appropriately designed and effectively implemented.

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Appendix A: Detailed Measure Construction

CEA's measures of AI exposure and AI-related performance requirements are based on an analysis of Work Activity ratings in O*NET. Of 41 work activities, 16 have been designated as having high AI exposure. The full set of exposed and non-exposed activities is reported in Appendix Table A1. O*NET reports this information at a custom occupational classification that is closely aligned to the Standard Occupational Classification (SOC) system. O*NET data are periodically updated, and CEA has relied on version 28.0 for its primary analysis, released in August 2023.

Table A1. List of AI Exposed and All Other Work Activities

Panel A. AI Exposed Work Activities

Activity ID	*Activity Name*
4.A.1.a.1	Getting Information
4.A.1.a.2	Monitoring Processes, Materials, or Surroundings
4.A.2.a.2	Processing Information
4.A.2.a.3	Evaluating Information to Determine Compliance with Standards
4.A.2.a.4	Analyzing Data or Information
4.A.2.b.1	Making Decisions and Solving Problems
4.A.2.b.2	Thinking Creatively
4.A.2.b.5	Scheduling Work and Activities
4.A.3.a.3	Controlling Machines and Processes
4.A.3.a.4	Operating Vehicles, Mechanized Devices, or Equipment
4.A.3.b.1	Working with Computers
4.A.3.b.2	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
4.A.3.b.6	Documenting/Recording Information
4.A.4.a.8	Performing for or Working Directly with the Public
4.A.4.c.1	Performing Administrative Activities
4.A.4.c.3	Monitoring and Controlling Resources

Panel B. All Other Work Activities

Activity ID	*Activity Name*
4.A.1.b.1	Identifying Objects, Actions, and Events
4.A.1.b.2	Inspecting Equipment, Structures, or Materials
4.A.1.b.3	Estimating the Quantifiable Characteristics of Products, Events, or Information
4.A.2.a.1	Judging the Qualities of Objects, Services, or People
4.A.2.b.3	Updating and Using Relevant Knowledge
4.A.2.b.4	Developing Objectives and Strategies
4.A.2.b.6	Organizing, Planning, and Prioritizing Work
4.A.3.a.1	Performing General Physical Activities
4.A.3.a.2	Handling and Moving Objects
4.A.3.b.4	Repairing and Maintaining Mechanical Equipment
4.A.3.b.5	Repairing and Maintaining Electronic Equipment
4.A.4.a.1	Interpreting the Meaning of Information for Others
4.A.4.a.2	Communicating with Supervisors, Peers, or Subordinates
4.A.4.a.3	Communicating with People Outside the Organization
4.A.4.a.4	Establishing and Maintaining Interpersonal Relationships
4.A.4.a.5	Assisting and Caring for Others
4.A.4.a.6	Selling or Influencing Others
4.A.4.a.7	Resolving Conflicts and Negotiating with Others
4.A.4.b.1	Coordinating the Work and Activities of Others
4.A.4.b.2	Developing and Building Teams
4.A.4.b.3	Training and Teaching Others
4.A.4.b.4	Guiding, Directing, and Motivating Subordinates
4.A.4.b.5	Coaching and Developing Others
4.A.4.b.6	Providing Consultation and Advice to Others
4.A.4.c.2	Staffing Organizational Units

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Sources: Department of Labor; Kochhar (2023); CEA calculations.

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For formal exposition, let $\mathbb{A}$ denote the set of work activities are AI-exposed, and $\mathbb{A}^C$ denote the set of all other work activities. And, let Imp_{io} be the reported importance of work activity i to occupation o in O*NET. CEA standardizes all reported activity importance scores across occupations to account for distributional differences across activities, and to ensure that all work activities are weighted equally in the subsequent analysis. This normalized measure is expressed as $z(Imp_{io})$, and the means and standard deviations used to construct it come from the distribution of reported importance scores across all occupations in O*NET, with occupations weighted by aggregate hours of work among full-time, full-year workers in the 2022 ACS.

Using the above notation, CEA's exposure score for occupation o is the simply difference in the average normalized importance of AI-exposed activities and all other activities:

$$Exposure_o = \frac{1}{\|\mathbb{A}\|}\sum_{i\in\mathbb{A}} z(Imp_{io}) - \frac{1}{\|\mathbb{A}^C\|}\sum_{i\in\mathbb{A}^C} z(Imp_{io})$$

This measure yields an intuitive interpretation. An exposure score of 0 corresponds to an occupation in which AI-exposed activities are, on average, equally important to all other activities. A positive score implies that AI-exposed work activities are, on average, more important to performance of the occupation than other activities, while a negative score implies that they are less important. And, the value of $Exposure_o$ itself also has a specific interpretation: it reports how many standard deviations more (or less) important to the performance of an occupation are the AI-exposed activities, on average.

CEA's measure of AI-related job performance requirements uses information from a separate scale in O*NET, which reports the level of performance of each work activity that is required to perform the overall occupation. As described in Peterson et al. (1995), this scale is intended to capture the degree of difficulty or complexity with which activities are performed in each occupation. Formally, if Lev_{io} is the reported level of performance of a given work activity that is needed to work at a given occupation, and $z(Lev_{io})$ is the weighted standardized version of this information, then CEA's measure of an occupation's AI-related performance requirements is the average of this normalized measure among AI-exposed activities:

$$PerformanceRequirements_o = \frac{1}{\|\mathbb{A}\|}\sum_{i\in\mathbb{A}} z(Lev_{io})$$

As before, this measure has an intuitive interpretation: it indicates how many standard deviations more difficult or complex an occupation's performance requirements are for AI-exposed activities in comparison to the hours-weighted mean among the overall employed population.

For both the measures of AI exposure and of AI-related job performance requirements, CEA defines threshold levels, so that the full set of occupations can be neatly divided into three groups: AI-exposed with high AI-related performance requirements, AI-exposed with low AI-related performance requirements, and not highly AI-exposed. Much of the analysis in this report is based on these three groups; in some cases, AI-exposed workers with high and low performance requirements are analyzed together. For AI exposure, the threshold exposure score for delineating high AI exposure is based on the 75th percentile of occupational exposure, unweighted by employment or hours; this is the same threshold used by Pew Research in its analysis (Kochhar 2023). For performance requirements, the threshold for delineating high/low AI-related performance requirements is the population median, weighted by aggregate hours in the 2022 American Community Survey (Ruggles et al. 2024).

Appendix B: Relationship to Existing Measures of AI Exposure

In recent years, researchers have developed a number of different measures of occupational AI exposure. Each measure shares a similar goal of identifying the workers who are most likely to be impacted by AI, whether positively through increased productivity and earnings, or negatively through substitution or displacement. And, in many cases, the measures rely on similar data sources to measure underlying occupational task content, especially the Department of Labor's O*NET database. Given the extent uncertainty around AI's future capabilities, it's valuable to have multiple complementary frameworks for comparison. However, because these measures differ in the particulars of their approaches, there may be reason for concern that some core conclusions of any one analysis—including CEA's—might be heavily dependent on the unique assumptions of that individual measure.

Table B1. Correlation Between AI Exposure Measures

AI exposure measure	*Report measure*	*Kochhar (2023)*	*OpenAI measure using AI ratings*	*OpenAI measure using human ratings*	*Felten, Raj, and Seamans (2021)*
Report measure	1.00	0.95	0.43	0.25	0.30
Kochhar (2023)	0.95	1.00	0.62	0.46	0.53
OpenAI measure using AI ratings	0.43	0.62	1.00	0.87	0.83
OpenAI measure using human ratings	0.25	0.46	0.87	1.00	0.86
Felten, Raj, and Seamans (2021)	0.30	0.53	0.83	0.86	1.00

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Sources: American Community Survey; Department of Labor; Eloundou et al. (2023); Felten, Raj, and Seamans (2021); Kochhar (2023); Pew Research Center; CEA calculations.

Note: Pew methodology was followed to obtain continuous scores underlying the high AI exposure binary measure. All measures are crosswalked to ACS occupations for comparison.

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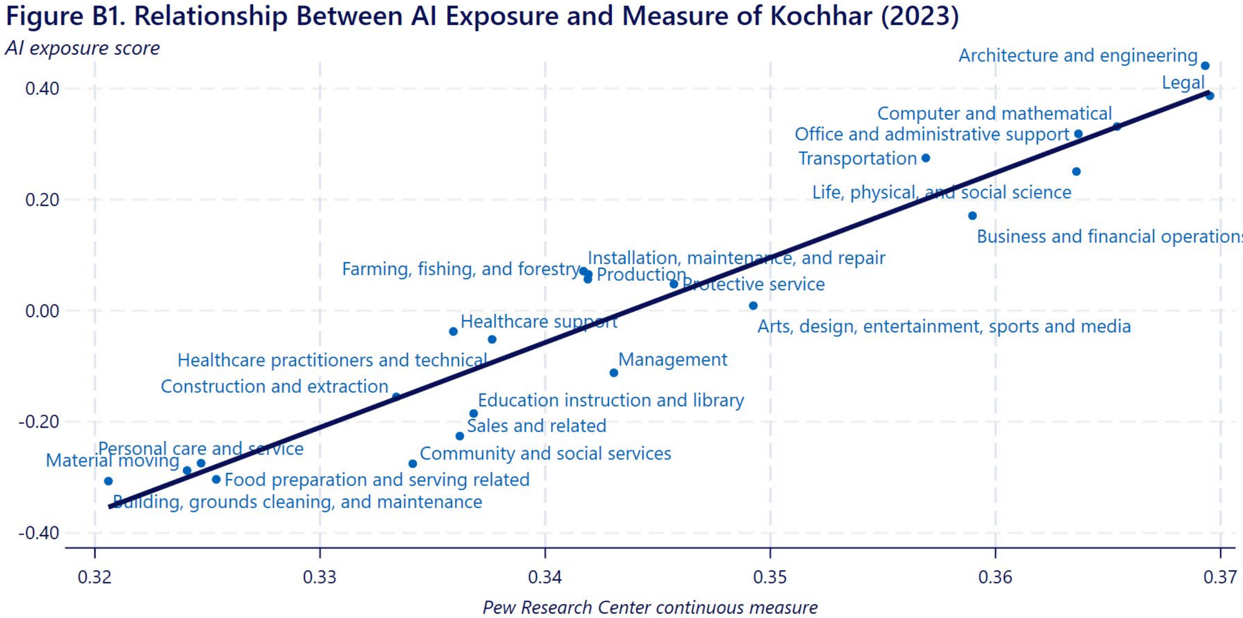
CEA has conducted a comparative analysis of its measure of AI exposure with several other prominent measures in the recent literature. Occupation-level predictions of the extent of AI exposure were linked across measures so that basic patterns could be compared. Appendix Table B1 presents results from this analysis, in the form of a correlation table. A higher positive correlation demonstrates a stronger degree of association between CEA's measure of AI exposure and the alternative measures shown.[15] Unsurprisingly, CEA's measure is most correlated with the measure on which many of its basic assumptions are based: the measure of Kochhar (2023). However, it is also notable that all examined measures are positively correlated.

In Appendix Figures B1 through B4, CEA has provided additional scatterplots that compare CEA's estimated extent of occupational AI exposure by major occupational group to each alternative analyzed. These figures confirm the positive relationship, and also provide some context about the portions of the occupational distribution in which CEA's measure and other measures may differ in part.

Overall, this analysis suggests that many basic conclusions about AI exposure are unlikely to be sensitive to the particular measure used. Occupations that are considered highly exposed in one measure are generally also recognized as highly AI-exposed in others. However, since the alternative measures evaluated here do not assess AI-related performance requirements, or other particular measures of potential vulnerability, this analysis provides only limited support to CEA's more specific predictions about the possibility of complementarity or substitution.

Figure B1. Relationship Between AI Exposure and Measure of Kochhar (2023)



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Sources: American Community Survey; Department of Labor; Kochhar (2023); Pew Research Center; CEA calculations.
Note: Pew methodology was followed to obtain a continuous socres underlying their high AI exposure binary measure. This measure is crosswalked to ACS occupations for comp
Occupations are aggregated to the occupational group level using total hours weights from the ACS. The best fit line is unweighted.
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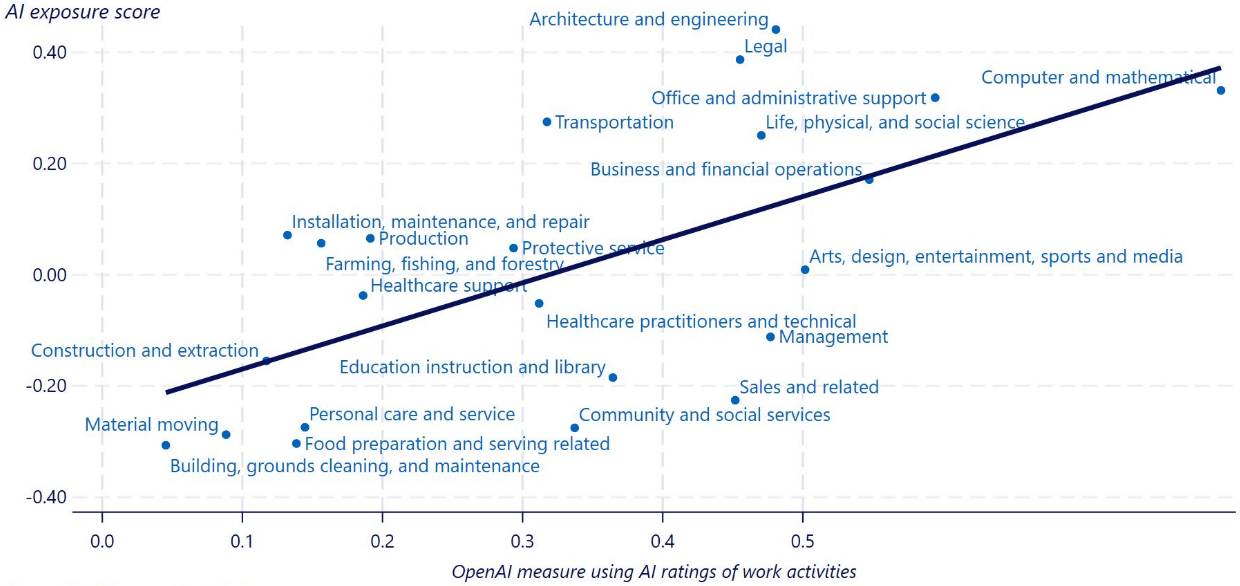
[15] In the case of Kochhar (2023), which also developed a binary indicator of occupational exposure, CEA has used the underlying methodology of that paper to produce the continuous indicator of exposure upon which its binary classification is based. All occupations for this analysis have been linked using the SOC 2018 classification, and are weighted based on 2022 employment as measured in the ACS.

Figure B2. Relationship Between AI Exposure and OpenAI Rating Measure of Eloundou et al. (2023)



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Sources: American Community Survey; Department of Labor; Eloundou et al. (2023); Pew Research Center; CEA calculations.
Note: Exposure score from Eloundou et al. (2023) is crosswalked to ACS occupations for comparison. Occupations are aggregated to the occupational group level using total hours weights from the ACS. The best fit line is unweighted.
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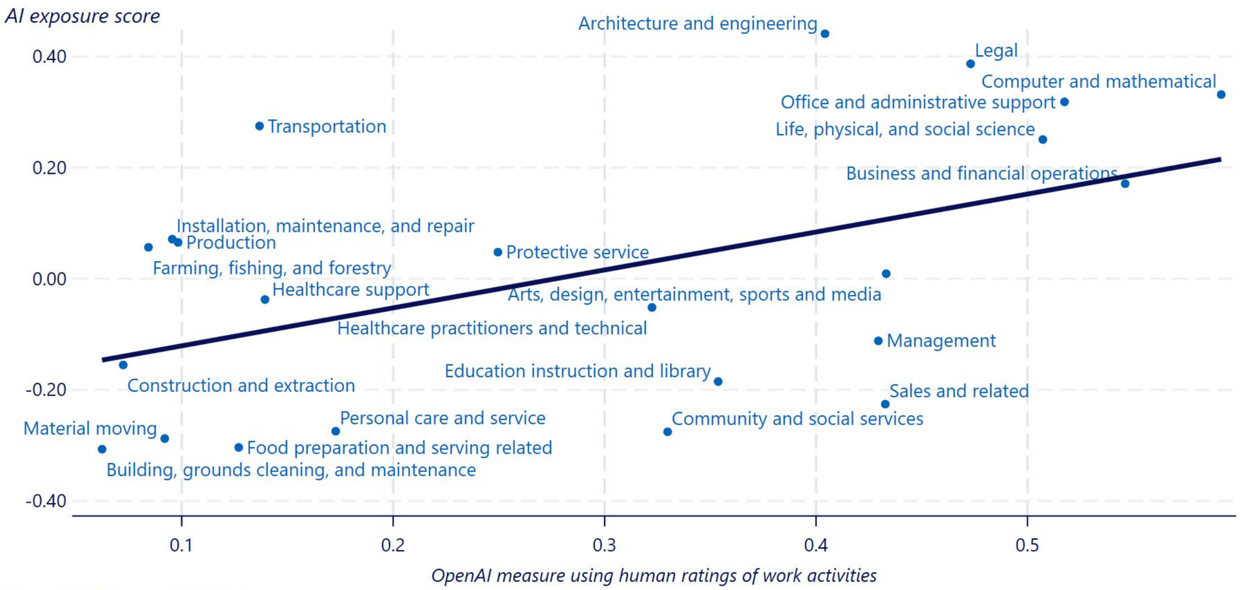
Figure B3. Relationship Between AI Exposure and Human Rating Measure of Eloundou et al. (2023)



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Sources: American Community Survey; Department of Labor; Eloundou et al. (2023); Pew Research Center; CEA calculations.
Note: Exposure score from Eloundou et al. (2023) is crosswalked to ACS occupations for comparison. Occupations are aggregated to the occupational group level using total hours weights from the ACS. The best fit line is unweighted.
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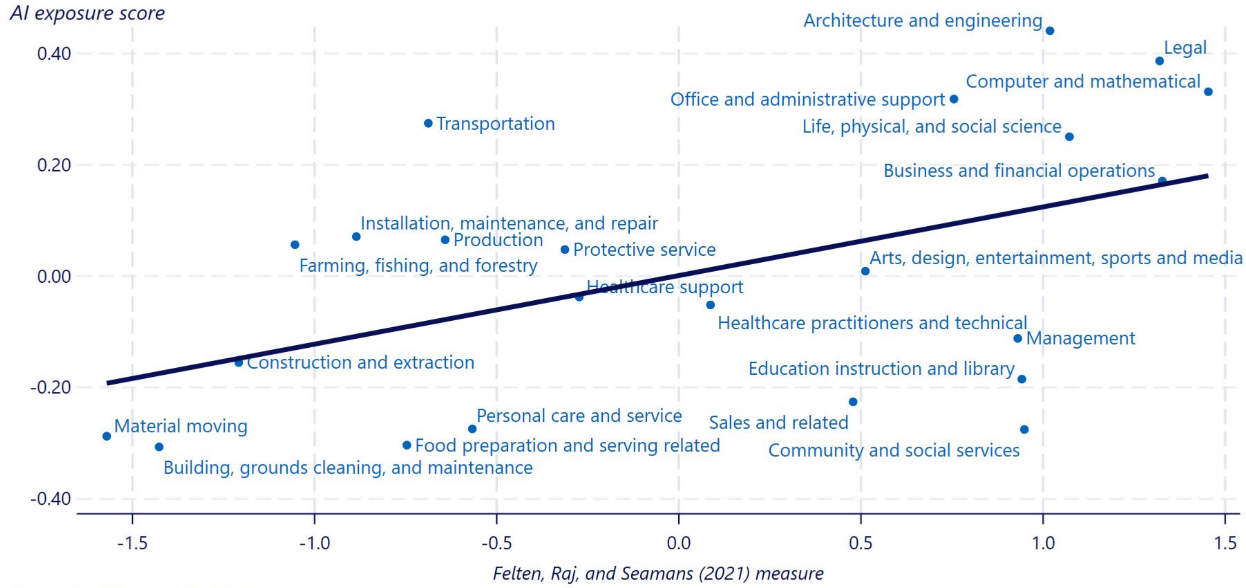
Figure B4. Relationship Between AI Exposure and Measure of Felten, Raj, and Seamans (2021)



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Sources: American Community Survey; Department of Labor; Felten, Raj and Seamans (2021); Pew Research Center; CEA calculations.

Note: Exposure score from Felten, Raj and Seamans (2021) is crosswalked to ACS occupations for comparison. Occupations are aggregated to the occupational group level using total hours weights from the ACS. The best fit line is unweighted.

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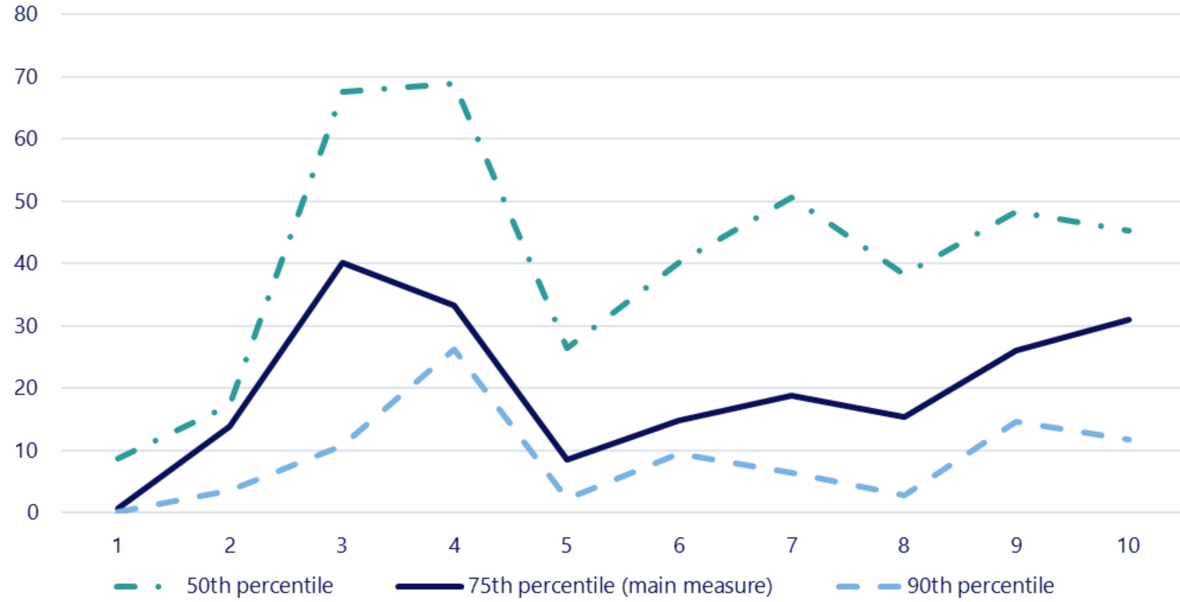
Appendix C: Alternative Threshold Analysis

As outlined in Appendix A, CEA has constructed measures of occupational AI exposure, and of AI-related job performance requirements that vary continuously across occupations. However, CEA also identifies thresholds for each measure, and it uses these thresholds to conduct much of its analysis. Above a threshold level of AI exposure, occupations are considered to be highly AI-exposed. And, below a threshold level of AI-related performance requirements, occupations are considered to have low performance requirements. Occupations that have both high AI exposure and low AI-related job performance requirements are identified as potentially vulnerable to negative impacts.

The use of discrete thresholds to define occupational categories allows for intuitive comparisons across different demographic and socioeconomic groups that may be very useful. However, one concern with using any threshold-based measure such as CEA's is that the overall interpretation of results may be highly sensitive to the chosen threshold. For this reason, CEA has conducted a set of sensitivity analysis in which it defines higher (more restrictive) and lower (less restrictive) thresholds for AI exposure and for AI-related job performance requirements. The analyses confirm that differences in economic and demographic patterns of exposed are not meaningfully affected by the choice of alternative thresholds within a sensible range.

Figure C1. Employment in High-AI-Exposed Occupations Using Different Exposure Thresholds

Percentage of employment within decile



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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.

Note: Deciles are calculated using mean occupational earnings of workers who are full-time, full-year workers age 16 plus.

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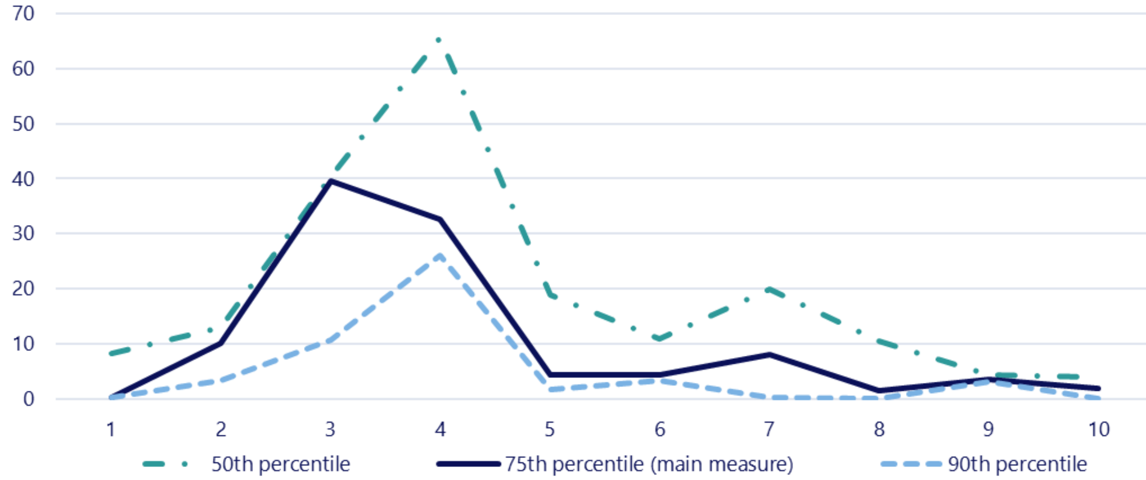
In Appendix Figure C1, CEA provides a sensitivity analysis of its earnings distribution results on overall AI exposure. The baseline threshold for AI-exposed occupations, based on the unweighted 75th percentile of occupations, is compared against a more restrictive threshold (90th percentile) and a less restrictive threshold (50th percentile). Regardless of the threshold chosen, the overall shape of exposure across the earnings distribution is little affected. The highest rates of occupational AI exposure are associated with occupations in the lower-middle portion of the earnings distribution. And, the share of employment that is AI-exposed increases over the upper half of the occupational earnings distribution, with relatively high exposure among workers in the top two deciles.

Figure C2. Employment in High-AI-Exposed Occupations with Low Performance Requirements Using Different Exposure Thresholds

Percentage of employment within decile



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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.

Note: Deciles are calculated using mean occupational earnings of workers who are full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high-AI-exposed work activity is performed within an occupation. High (low) indicates an average degree of difficulty above (below) the median.

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In Appendix Figure C2, CEA provides a similar sensitivity analysis for AI-exposed employment with low performance requirements. This analysis also confirms the baseline implication that workers in the lower-middle portion of the earnings distribution may be most vulnerable to AI.

Appendix D: Additional Tables and Figures

Table D1. Top 25 Most AI-Exposed Occupations

Rank	*Occupation*	*AI exposure score*	*AI-related performance requirements score*	*Percentile of AI-related performance requirements*
1	Eligibility Interviewers, Government Programs	0.92	0.06	53
2	Title Examiners, Abstractors, and Searchers	0.82	0.06	53
3	Medical Transcriptionists	0.81	-0.73	***18***
4	Cartographers and Photogrammetrists	0.81	0.49	79
5	Judicial Law Clerks	0.80	-0.58	***20***
6	Tax Preparers	0.78	0.26	62
7	Biological Technicians	0.77	0.19	59
8	Electrical Engineers	0.75	1.35	100
9	Compliance Officers	0.74	0.36	67
10	Proofreaders and Copy Markers	0.73	-1.23	***4***
11	Architectural and Civil Drafters	0.73	0.16	57
12	Private Detectives and Investigators	0.73	0.40	69
13	Billing and Posting Clerks	0.71	-0.98	***9***
14	Commercial and Industrial Designers	0.71	0.02	***49***
15	Production, Planning, and Expediting Clerks	0.69	-0.24	***33***
16	Drilling and Boring Machine Tool Setters, Operators, and Tenders,	0.69	-0.21	***38***
17	Airline Pilots, Copilots, and Flight Engineers	0.68	0.69	89
18	Payroll and Timekeeping Clerks	0.63	-0.39	***27***
19	Nuclear Power Reactor Operators	0.63	0.61	85
20	Court, Municipal, and License Clerks	0.63	-0.42	***26***
21	Paralegals and Legal Assistants	0.63	0.17	57
22	Switchboard Operators, Including Answering Service	0.63	-1.06	***8***
23	Bookkeeping, Accounting, and Auditing Clerks	0.62	-0.26	***32***
24	Loan Interviewers and Clerks	0.61	0.26	62
25	Surveying and Mapping Technicians	0.58	-0.05	***46***

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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.

Note: Occupations with an AI-related performance requirements score below the 50th percentile are classified as having low performance requirements. These are bolded in the last column of the table.

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Table D2. Top 25 Least AI-Exposed Occupations

Rank	*Occupation*	*AI exposure score*	*AI-related performance requirements score*	*Percentile of AI-related performance requirements*
1	Human Resources Managers	-0.67	0.60	85
2	Bicycle Repairers	-0.66	-0.55	***21***
3	Laundry and Dry-Cleaning Workers	-0.64	-1.29	***4***
4	Clergy	-0.62	-0.08	***44***
5	Demonstrators and Product Promoters	-0.60	-1.12	***6***
6	Sales Managers	-0.55	0.37	68
7	Exercise Trainers and Group Fitness Instructors	-0.53	-0.67	***19***
8	Marketing Managers	-0.53	-0.06	***45***
9	Food Preparation Workers	-0.53	-0.46	***24***
10	Dancers	-0.51	-1.79	***1***
11	Manicurists and Pedicurists	-0.50	-1.77	***1***
12	Passenger Attendants	-0.50	-1.64	***1***
13	Bartenders	-0.50	-0.95	***10***
14	Training and Development Managers	-0.50	0.58	84
15	Writers and Authors	-0.50	-1.11	***7***
16	Laborers and Freight, Stock, and Material Movers, Hand	-0.49	-1.19	***5***
17	First-Line Supervisors of Retail Sales Workers	-0.48	-0.24	***33***
18	Education and Childcare Administrators, Preschool and Daycare	-0.48	0.17	58
19	Cutters and Trimmers, Hand	-0.47	-1.09	***7***
20	Door-to-Door Sales Workers, News and Street Vendors, and Related Workers	-0.46	-1.17	***5***
21	Directors, Religious Activities and Education	-0.46	0.24	61
22	Dishwashers	-0.45	-0.16	***40***
23	Cashiers	-0.45	-1.10	***7***
24	Dining Room and Cafeteria Attendants and Bartender Helpers	-0.45	-0.87	***11***
25	Orderlies	-0.44	-1.05	***8***

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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.

Note: Occupations with an AI-related performance requirements score below the 50th percentile are classified as having low performance requirements. These are bolded in the last column of the table.

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Table D3. Top 25 Most AI-Exposed Public Use Microdata Areas

Rank	*State*	*Public Use Microdata Area*	*Metropolitan statistical area*
1	California	San Diego County (West Central)--San Diego City (Northwest/Del Mar Mesa)	San Diego-Carlsbad, CA
2	District of Columbia	District of Columbia (Central)	Washington-Arlington-Alexandria, DC-VA-MD-WV
3	California	Santa Clara County (Northwest)--Sunnyvale & San Jose (North) Cities	San Jose-Sunnyvale-Santa Clara, CA
4	New Mexico	Albuquerque City (Central) & Bernalillo County (North Valley)	Albuquerque, NM
5	California	Santa Clara County (North Central)--Milpitas & San Jose (Northeast) Cities	San Jose-Sunnyvale-Santa Clara, CA
6	Virginia	Arlington County (North)	Washington-Arlington-Alexandria, DC-VA-MD-WV
7	Texas	Dallas County (Northwest)--Irving (North), Coppell & Carrollton (Southwest) Cities	Dallas-Fort Worth-Arlington, TX
8	California	Santa Clara County (Northwest)--Mountain View, Palo Alto & Los Altos Cities	San Jose-Sunnyvale-Santa Clara, CA
9	Virginia	Fairfax County (North Central)--Vienna Town, Oakton & Fair Oaks (East)	Washington-Arlington-Alexandria, DC-VA-MD-WV
10	California	Santa Clara County (Northwest)--San Jose (Northwest) & Santa Clara Cities	San Jose-Sunnyvale-Santa Clara, CA
11	Oregon	Washington County (Central)--Hillsboro City	Portland-Vancouver-Hillsboro, OR-WA
12	Florida	Manatee County (South)	North Port-Sarasota-Bradenton, FL
13	Maryland	Anne Arundel County (Northwest)--Severn, Odenton, Crofton, Maryland City & Fort Meade	Baltimore-Columbia-Towson, MD
14	Texas	Austin City (South)	Austin-Round Rock, TX
15	Alabama	Huntsville City (Central & South)	Huntsville, AL
16	California	Alameda County (South Central)--Fremont City (East)	San Francisco-Oakland-Hayward, CA
17	California	Alameda County (North)--Berkeley & Albany Cities	San Francisco-Oakland-Hayward, CA
18	California	San Diego County (Central)--San Diego City (Central/Mira Mesa & University Heights)	San Diego-Carlsbad, CA
19	District of Columbia	District of Columbia (West)	Washington-Arlington-Alexandria, DC-VA-MD-WV
20	Maryland	Montgomery County (South)--Bethesda, Potomac & North Bethesda	Washington-Arlington-Alexandria, DC-VA-MD-WV
21	Iowa	Polk (Southwest) & Dallas (East) Counties--West Des Moines & Urbandale Cities	Des Moines-West Des Moines, IA
22	North Carolina	Wake County (West Central)--Cary Town	Raleigh, NC
23	Ohio	Columbus (Far Northeast), Gahanna & New Albany Cities	Columbus, OH
24	Massachusetts	Woburn, Melrose Cities, Saugus, Wakefield & Stoneham Towns	Boston-Cambridge-Newton, MA-NH
25	Texas	Houston City (West Central)--South of I-10 & Inside Loop I-610	Houston-The Woodlands-Sugar Land, TX

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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.

Note: Public Use Microdata Areas (PUMAs) are defined as non-overlapping,statistical geographic areas that divide each state into areas with a population of at least contain 100,000. The corresponding metropolitan statistical area (MSA) is listed when there is a
Analysis uses full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high AI-exposed work activity is performed within an occupation. Low indicates an aver

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Table D4. Top 25 AI-Exposed Public Use Microdata Areas with Low Performance Requirements

Rank	*State*	*Public use microdata area*	*Metropolitan statistical area*
1	Georgia	Atlanta Regional Commission (Southwest)--Douglas County	Atlanta-Sandy Springs-Roswell, GA
2	Florida	Manatee County (South)	North Port-Sarasota-Bradenton, FL
3	Texas	Hidalgo County (North & West)	McAllen-Edinburg-Mission, TX
4	Arkansas	Southwest Arkansas	Texarkana, TX-AR
5	Texas	Dallas City (South Central)--North of I-20 & West of I-35E	Dallas-Fort Worth-Arlington, TX
6	Florida	Sumter (North) & Lake (North) Counties	Orlando-Kissimmee-Sanford, FL
6	Florida	Sumter (North) & Lake (North) Counties	The Villages, FL
7	New Mexico	San Juan County (Northeast)--Farmington, Bloomfield & Aztec Cities	Farmington, NM
8	Texas	Bexar County (South)--San Antonio City (Far South)	San Antonio-New Braunfels, TX
9	Texas	Deep East Texas COG (East)	Beaumont-Port Arthur, TX
10	New Jersey	Middlesex County (Northeast)--Carteret Borough	New York-Newark-Jersey City, NY-NJ-PA
11	Missouri	Platte County	Kansas City, MO-KS
12	Texas	El Paso County (Outside El Paso City)--Socorro & Horizon Cities	El Paso, TX
13	Texas	East Texas COG (Southwest)--Henderson & Anderson Counties	
14	Georgia	Atlanta Regional Commission (Central)--DeKalb County (East Central)--Redan	Atlanta-Sandy Springs-Roswell, GA
15	Mississippi	East Central Region--Neshoba, Scott, Leake, Jasper, Smith & Kemper Counties	
16	Nebraska	Southwest Nebraska	
17	Missouri	St. Francois, Washington, Perry & Ste. Genevieve Counties	
18	California	Stanislaus County (Southwest)--Ceres, Patterson & Newman Cities	Modesto, CA
19	Iowa	Sioux, Clay, Dickinson, O'Brien, Lyon, Emmet, Palo Alto & Osceola Counties	
20	Arizona	Maricopa County--Goodyear, Glendale (West) & Litchfield Park (Northwest) Cities	Phoenix-Mesa-Scottsdale, AZ
21	Florida	Miami-Dade County (North Central)--Miami Gardens City (North & West)	Miami-Fort Lauderdale-West Palm Beach, FL
22	Kentucky	Cumberland Valley Area Development District (South)	
23	Arkansas	St. Francis, Poinsett, Phillips, Cross, Lee & Monroe Counties	Jonesboro, AR
24	California	San Bernardino County (Southwest)--Colton, Loma Linda & Grand Terrace Cities	Riverside-San Bernardino-Ontario, CA

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Sources: American Community Survey; Department of Labor; Pew Research Center; CEA calculations.

Note: Public Use Microdata Areas (PUMAs) are defined as non-overlapping,statistical geographic areas that divide each state into areas with a population of at least contain 100,000. The corresponding metropolitan statistical area (MSA) is listed whe population. Analysis uses full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high AI-exposed work activity is performed within an occupatio

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Table D5. Top 25 Most AI-Exposed Industries

Rank	*Industry*	*Percent of AI-exposed employment*	*Percent of AI-exposed employment with low performance requirements*
1	Legal Services	41%	23%
2	Web Search Portals, Libraries, Archives, and Other Information Services	40%	18%
3	Monetary Authorities-Central Bank	40%	16%
4	Communications Equipment Manufacturing	38%	16%
5	Credit Intermediation and Related Activities	38%	20%
6	Nondepository Credit Intermediation	38%	20%
6	Oil and Gas Extraction	37%	13%
7	Offices of Dentists	37%	26%
8	Computing Infrastructure Providers, Data Processing, Web Hosting, and Related Services	37%	18%
9	Software Publishers	37%	18%
10	Agencies, Brokerages, and Other Insurance Related Activities	37%	19%
11	Couriers and Express Delivery Services	36%	18%
12	Natural Gas Distribution	36%	13%
13	Computer Systems Design and Related Services	35%	14%
14	Pipeline Transportation	35%	13%
15	Commercial and Service Industry Machinery Manufacturing	35%	15%
16	Business Support Services	35%	22%
17	Couriers and Messengers	35%	17%
18	Medical and Diagnostic Laboratories	35%	15%
19	Electric Power Generation, Transmission and Distribution	34%	12%
20	Computer and Peripheral Equipment Manufacturing	34%	15%
21	Management, Scientific, and Technical Consulting Services	34%	14%
22	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	34%	15%
23	Scientific Research and Development Services	34%	12%
24	Architectural, Engineering, and Related Services	34%	12%
25	Media Streaming Distribution Services, Social Networks, and Other Media Networks & Content Providers	33%	15%

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Sources: American Community Survey; Bureau of Labor Statistics; Department of Labor; Pew Research Center; CEA calculations.

Note: Analysis uses full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high AI-exposed work activity is performed within an occupation. Low indicates an average degree of difficulty below the median.

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Table D6. Top 25 AI-Exposed Industries with Low Performance Requirements

Rank	*State*	*Percent of AI-exposed employment*	*Percent of AI-exposed employment with low performance requirements*
1	Offices of Dentists	37%	26%
2	Taxi and Limousine Service	33%	26%
3	Legal Services	41%	23%
4	Business Support Services	35%	22%
5	Technical and trade schools - Local government owned	30%	22%
6	Florists	24%	21%
7	Support Activities for Road Transportation	25%	21%
8	Fuel Dealers	28%	21%
9	Nondepository Credit Intermediation	38%	20%
10	Logging	20%	20%
11	Credit Intermediation and Related Activities	38%	20%
12	Drycleaning and Laundry Services	24%	19%
13	Technical and trade schools - State government owned	26%	19%
14	Other Transit and Ground Passenger Transportation	28%	19%
15	Other Textile Product Mills	24%	19%
16	Other Motor Vehicle Dealers	26%	19%
17	Death Care Services	23%	19%
18	Agencies, Brokerages, and Other Insurance Related Activities	37%	19%
19	Automobile Dealers	30%	19%
20	Computing Infrastructure Providers, Data Processing, Web Hosting, and Related Services	37%	18%
21	Web Search Portals, Libraries, Archives, and Other Information Services	40%	18%
22	Travel Arrangement and Reservation Services	32%	18%
23	Textile Furnishings Mills	26%	18%
24	School and Employee Bus Transportation	26%	18%
25	Couriers and Express Delivery Services	36%	18%

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Sources: American Community Survey; Bureau of Labor Statistics; Department of Labor; Pew Research Center; CEA calculations.

Note: Analysis uses full-time, full-year workers age 16 plus. Performance requirements are captured using the O*NET data measuring degree of difficulty or complexity at which a high AI-exposed work activity is performed within an occupation. Low indicates an average degree of difficulty below the median.

As of May 8, 2024 at 6:00pm.