OCTOBER 2025

Occupational Exposure to Generative Artificial Intelligence in the Third Federal Reserve District

COMMUNITY DEVELOPMENT & REGIONAL OUTREACH

Adam Scavette Danielle Jenkins Lei Ding

The authors thank Enghin Atalay, Shigeru Fujita, Daniel Rock, and Theresa Singleton for helpful comments and Theresa Dunne for excellent research assistance. The views expressed in this report are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Any errors or omissions are the responsibility of the authors.

Introduction

The accelerating adoption of generative artificial intelligence (AI) tools has introduced both optimism and anxiety regarding the future of work. The ability of large language models (LLMs) such as ChatGPT to produce text, code, and insightful analysis through training on existing databases can allow workers to become more productive across various tasks. For example, an LLM can reduce the amount of time needed for a paralegal to draft a memo by utilizing their law firm's existing universe of documents. However, by reducing task completion time (or automating certain tasks entirely), LLMs may reduce the demand for workers. For example, a law firm may decide to hire fewer paralegals if one LLM-enabled paralegal can now complete the same amount of work as two pre-LLM paralegals. Ultimately, along with the number of jobs automated by AI adoption, the overall labor market consequences of AI adoption will depend on numerous factors such as the number of new jobs generated by the AI technologies (e.g., LLM developers at OpenAI or engineers at Nvidia), the percentage of firms implementing AI, and the degree to which the technology is labor-substituting versus labor-complementing. Nevertheless, for better or worse, some jobs will be more exposed to the effects of AI than others, conditional on the percentage of an occupation's tasks that can be AI-enhanced or automated.

In this report, we explore which occupations are most exposed to AI based on their respective task distributions and how this exposure varies geographically based on recent employment patterns across metropolitan areas in the Third Federal Reserve District. We use the methodology outlined by Eloundou et al. (2024), which measures AI exposure across occupations. We find that occupations tending to require more education and paying higher wages are disproportionately exposed to AI, such as technical research, writing, and administrative roles. We compute the most common AI-exposed occupations, such that their AI exposure ranks in the top quartile on the Eloundou et al. (2024) score, for the Philadelphia metro area and other Third District metros. We find that the Trenton-Princeton and State College metro areas contain the highest percentage of AI-exposed jobs, while Vineland and Gettysburg contain the lowest percentage. Last, by exploring worker characteristics data, we find that White and female workers are more likely to be employed in an AI-exposed occupation. We conclude by discussing how our findings may have implications for higher education, migration, and workforce training needs.

Surveys Indicate Rising AI Adoption, Productivity Benefits, and Worker Unease over Future Employment Impacts

The debut of OpenAI's ChatGPT "chatbox" application in late 2022 (followed by Google's Gemini in 2023 and DeepSeek in 2025) marked the start of a period of widespread accessibility of LLM tools for the general public. As the adoption of these generative AI tools has accelerated over the past few years, researchers have leveraged surveys to better understand these tools' use in the workplace. Based on a survey of over 4,000 workers in December 2024, Hartley et al. (2025) find that about 30 percent of respondents had used generative AI tools at work. Most of the AI-user respondents used the tools to finish tasks faster rather than to complete the tasks in their entirety, such that they were able to reduce task completion times by two-thirds on average (i.e., a 90-minute task without AI was reduced to 30 minutes with AI). Workers were more likely to use generative AI tools if they were more educated, higher-income, male, and employed in the "information services" and "management of companies" industries.

Surveys of firms tend to suggest increasing use of generative AI to automate worker tasks has limited impacts on current staffing levels, with large firms leading small firms in adoption rates. In a national survey of over 250 chief financial officers in 2024, the Federal Reserve Bank of Richmond (2024) found that the majority of firms (60 percent) had not used AI to automate tasks previously completed by employees, but that large firms (55 percent) were nearly twice as likely to have used AI to automate worker tasks compared with small firms (29 percent). Moreover, 76 percent of large firms planned to use AI to automate worker tasks in the next 12 months, compared with 44 percent of small firms. Findings from a large-scale business survey by the U.S. Census Bureau from 2023 to 2024 suggest that while 27 percent of firms had used AI to automate tasks, only 5 percent had experienced employment change due to AI use (Bonney et al. 2023). More recently, a May 2025 survey by the Dallas Fed found that 59 percent of responding Texas firms reported using AI, compared with only 38 percent the previous year (Yousuf and Leigh, 2025). Therefore, it seems possible that even though the adoption of generative AI has led to few layoffs at most firms, it may impact future staffing plans. Tellingly, a recent report in the Boston Fed's Beige Book, which surveys firms in New England, indicated that "A growing number of employers, across diverse industries, sought to increase labor productivity using AI and other technologies, reducing the need for hiring" (Federal Reserve Bank of Boston, 2025).

The rise in AI adoption in the workplace over the past couple years has coincided with general worker unease about future employment prospects in the U.S. labor market. A survey of employed adults by the Pew Research Center found that 52 percent are worried about the future impact of AI use in the workplace, and 32 percent believe its use will result in fewer job opportunities for them in the long run (Lin and Parker, 2025). Similarly, a 2023 Gallup Poll found that 75 percent of Americans believe that AI will reduce the number of jobs over the next decade (Marken and Nicola, 2023). Furthermore, PYMNTS (2025) found that workers who frequently used generative AI tools were more likely to be concerned about their own job security, as they could see first-hand how the technology could replace specific tasks within their own job.

Generative AI Can Augment, Automate, and Create New Worker Tasks

While most Americans believe that AI will reduce jobs (Marken and Nicola, 2023), the net effect of AI on employment is uncertain since AI can have both positive (e.g., enhancing productivity for existing workers and generating jobs with AI skills) and negative (e.g., automating tasks and occupations) effects on labor demand. Ultimately, the effects of AI on the labor market will depend on whether technologies are adopted by companies in a manner that complement and enhances workers' skills (i.e., augmentation) or whether they are used to perform human tasks independently (i.e., automation) (Septiandri et al., 2024; Johnston and Makridis, 2025). An example of AI used for augmentation could be a financial analyst asking ChatGPT to calculate metrics and summarize the key takeaways of a company's quarterly earnings report to prepare for an upcoming presentation. On the other hand, AI is used for automation when a bank replaces a human customer service representative with a virtual chatbot to respond to customer questions.

When economists study the potential impact of AI on occupations, they tend to use exposure metrics which measure the percentage of a job's tasks that can be enhanced or automated (Felten et al., 2021; Eloundou et al., 2023; Kochhar, 2023; Schendstok and Wertz, 2024), as we will explore in the next section. However, Autor and Thompson (2025) argue that the percentage of an occupation's tasks exposed to AI is not as relevant as the degree to which an occupation's level of expertise is exposed to automation, especially when it comes to evaluating the future employment and wage prospects of specific occupations. The authors find that when automation eliminates inexpert tasks within an occupation (e.g., data entry for a proofreader), the work may become more specialized and raise the barrier to entry, which may result in higher wages and lower employment as its remaining tasks still require expertise. However, when technology automates expert tasks (e.g., taxi driving with navigation technology) the barrier to entry is lowered, which may lower wages and increase employment as more people are able to perform the remaining tasks that have not been automated (i.e., drive a motor vehicle).

The adoption of AI by firms will also support the generation of new tasks and positions across organizations through developing and honing the new technology. The demand for jobs with AI skills has risen dramatically since 2010 (Acemoglu et al., 2022), which may help offset some of the decrease in labor demand for occupations with high shares of tasks that can be automated by AI. This growth in AI skills demand has been primarily driven by larger firms, where wages/salaries for AI roles tend to be higher than non-AI roles within the same company (Alekseeva et al., 2021). Additionally, Galeano et al., (2025) find that the demand for AI skills (e.g., Machine Learning and Natural Language Processing) varies by education in that "job postings that require at least a bachelor's degree are more likely to require an AI skill than postings that require an associate degree or high school diploma." According to a recent report from the Brookings Institution, Philadelphia ranked 14th out of 195 metro areas for AI adoption and AI skills in the workforce in part because of its abundance of STEM (science, technology, engineering, and mathematics) Ph.D. graduates and growing adoption of cloud-based technologies by area firms (Muro and Methkupally, 2025; Perez-Castells, 2025). Abrahams and Levy (2024) find that relatively well-educated U.S. metro areas with large concentrations of professional services jobs are most exposed to generative AI, such as Denver, San Francisco, San Jose, and Washington, D.C.

Higher-Paying and Higher-Skilled Occupations Are More Exposed to Generative AI

In this section, we evaluate occupational exposure to AI by measuring the percentage of a job's tasks that can be enhanced, expedited, or replaced by LLMs and complementary software. We utilize a metric from Eloundou et al. (2024) that leverages a rubric for exposure risk[1] based on how much LLM technology can reduce task completion time. These task ratings[2] are used to determine the share of each of 923 occupations' tasks that are exposed to LLMs, such that the time required for a human to complete the task is reduced by at least 50 percent while preserving or improving quality. Our analysis specifically uses the beta metric, rated by humans, which is an intermediate measure of exposure assuming full LLM access but where complementary technologies are not fully implemented.

[1] E1 indicates that there would be an over 50 percent reduction with the use of a simple LLM interface, E2 indicates a reduction of over 50 percent using complementary software that leverages or integrates LLMs, and E0 indicates that the time on a task will be minimally or not at all reduced by LLMs or the quality of the task's output would decrease. Each task was rated by humans and by a GPT-4 model as being E1, E2, or E0 exposed. The ratings by humans and GPT-4 were found to be quite similar.

[2] Three levels of occupational exposure calculated, the first was E1, or alpha, which was the share of the occupation's tasks that were exposed to the basic LLM. The E1+E2 level, or gamma, was the share of the occupation's tasks that were exposed with LLMs and full complementary software implementation. The E1+0.5*E2 level, or beta, which was the share of the occupation's tasks exposed while the complementary software is not yet fully invented and integrated.

TABLE 1 Median AI Exposure by Major Occupation Groups

SOC 2-Digit Code	Occupation Group	All	Typically Requires Bachelor's	Does Not Typically Require Bachelor's
00	All occupations	0.307	0.449	0.14
11	Management	0.451	0.45	0.401
13	Business and financial operations	0.504	0.52	0.48
15	Computer and mathematical	0.597	0.598	0.587
17	Architecture and engineering	0.447	0.475	0.353
19	Life, physical, and social science	0.492	0.517	0.323
21	Community and social service	0.351	0.351	NA
23	Legal	0.448	0.371	0.502
25	Educational instruction and library	0.416	0.424	0.376
27	Arts, design, entertainment, sports, and media	0.352	0.474	0.221
29	Healthcare practitioners and technical	0.293	0.319	0.19
31	Healthcare support	0.136	NA	0.136
33	Protective service	0.273	0.278	0.291
35	Food preparation and serving related	0.116	NA	0.116
37	Building and grounds cleaning and maintenance	0.06	NA	0.06
39	Personal care and service	0.233	0.25	0.232
41	Sales	0.52	0.532	0.405
43	Office and administrative support	0.5	0.637	0.486
45	Farming, fishing, and forestry	0.076	NA	0.076
47	Construction and extraction	0.026	NA	0.026
49	Installation, maintenance, and repair	0.082	NA	0.082
51	Production	0.065	NA	0.065
53	Transportation and material moving	0.143	0.273	0.139

Source
Eloundou et al. (2024), O*NET, authors' calculations. We consider any occupations within job zones 1, 2, and 3 as not requiring a bachelor's degree and occupations within job zones 4 and 5 as requiring a bachelor's degree.
Note: NAs indicate missing occupations in either job zones 1-3 or 4-5 within a group.

TABLE 2 Most AI-Exposed Occupations in U.S. Typically Requiring Bachelor's Degree (2024)

SOC Code	Title	Job Zone	Median Income	AI Exposure
19-1011.00	Animal scientists	5	$79,120	0.844
19-3022.00	Survey researchers	5	$63,380	0.844
27-3091.00	Interpreters and translators	4	$59,440	0.84
27-3043.00	Writers and authors	4	$72,270	0.808
27-3031.00	Public relations specialists	4	$69,780	0.788
19-3011.01	Environmental economists	5	$115,440*	0.776
19-2041.01	Climate change policy analysts	5	$80,060*	0.75
27-3043.05	Poets, lyricists, and creative writers	4	$72,270*	0.741
15-2041.01	Biostatisticians	5	$103,300*	0.74
19-2041.00	Environmental scientists and specialists, including health	4	$80,060	0.726

Source
Eloundou et al. (2024), O*NET, Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS), authors' calculations. We consider any occupations within job zones 4 and 5 as requiring a bachelor's degree. *Reflects income estimates from this occupation's six-digit SOC code grouping.

TABLE 3 Most AI-Exposed Occupations in U.S. NOT Typically Requiring Bachelor's Degree (2024)

SOC Code	Title	Job Zone	Median Income	AI Exposure
43-4011.00	Brokerage clerks	3	$62,940	0.800
43-6012.00	Legal secretaries and administrative assistants	3	$54,140	0.761
43-6011.00	Executive secretaries and executive administrative assistants	3	$74,260	0.743
43-4021.00	Correspondence clerks	2	$46,740	0.732
43-4051.00	Customer service representatives	2	$42,830	0.705
39-6012.00	Concierges	3	$37,320	0.700
13-2081.00	Tax examiners and collectors, and revenue agents	3	$59,740	0.677
41-2021.00	Counter and rental clerks	2	$38,540	0.677
15-1232.00	Computer user support specialists	3	$60,340	0.667
43-5032.00	Dispatchers, except police, fire, and ambulance	2	$48,880	0.652

Source
Eloundou et al. (2024), O*NET, Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS), authors' calculations. We consider any occupations within job zones 1, 2, and 3 as not requiring a bachelor's degree.

We merge occupational AI risk scores from Eloundou et al. (2024) with data on median income and job zones (education/training requirements), and occupational counts by area from O*NET[3] and the Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS) 2024 data sets.

It is helpful to keep in mind that AI exposure does not necessarily measure susceptibility to job loss. As we discussed earlier, there are several factors that will determine labor market outcomes by occupation, such as changes in expertise requirements (Autor and Thompson, 2025) and the level of labor substitutability versus complementarity that AI adoption brings per occupation.

Table 1 displays median AI exposure across 22 major categories of occupations. Additionally, AI exposure is measured within each occupational category (when possible)[4] by whether a bachelor's degree is typically required using job zone status, which measures the level of education and training preparation needed for an occupation on a scale from 1 to 5.[5] The median AI exposure score across all occupations is .307, indicating that roughly 31 percent of its tasks will be exposed to LLMs. However, median AI exposure is over three times higher for occupations generally requiring a bachelor's degree compared with those not requiring one (.449 versus .140). The highest AI exposure scores appear to be concentrated within computer and mathematical (.597), sales (.520), business and financial operations (.504), and office and administrative support (.500) occupational groups. Measuring within categories, median AI exposure scores tend to be higher for occupations typically requiring a bachelor's degree with two exceptions (legal and protective services). The lowest AI exposure scores are exhibited by construction and extraction (.026), production (.065), farming, fishing, and forestry (.076), and installation, maintenance, and repair (.082) occupational groups.

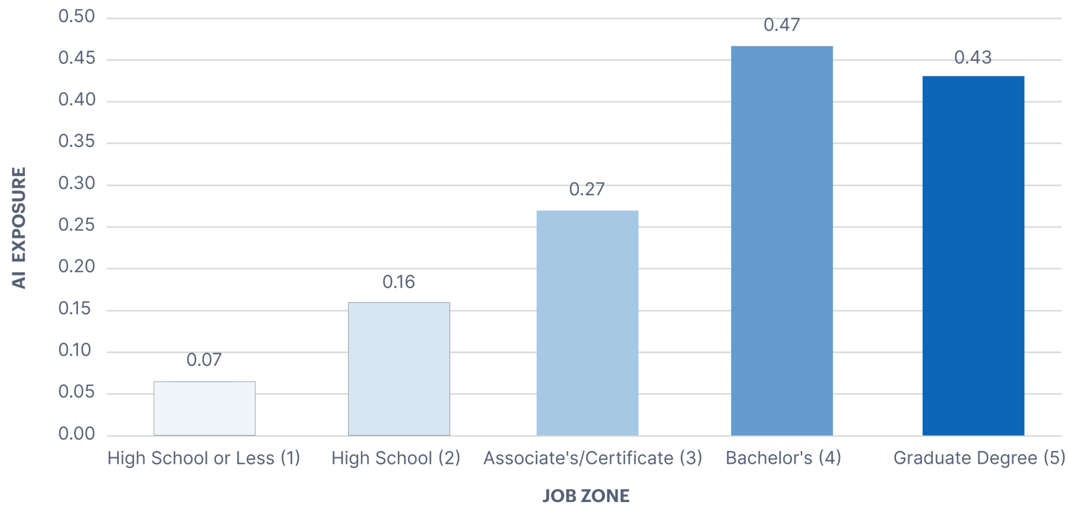
Table 2 provides the top 10 most AI-exposed occupations in the United States typically requiring a bachelor's degree. We report the median income for each of these occupations along with their job zone status. We can see that these 10 highest exposed occupations tend to involve technical, scientific research, and writing functions, and range from "environmental scientists" with 73 percent of their tasks exposed to LLMs to "animal scientists" at 84 percent. All these occupations pay above the overall median income across all occupations in 2024 of $49,500. Table 3 shows the top 10 most AI-exposed occupations not requiring a bachelor's degree along with their associated job zones and median income measures. Most of these occupations are concentrated in administrative and customer support roles and pay near the median income. See Tables A1 through A2 in the Appendix for the top 10 least AI-exposed occupations typically requiring a bachelor's degree and not typically requiring a bachelor's degree, respectively.

[3] The O*Net database is created by a partnership between the Department of Labor and the Employment and Training Administration. The data includes descriptive information about almost 1,000 occupations, with eight-digit SOC code specificity. This descriptive information includes abilities, skills, tasks, work activities, and job zones. The tasks and designated work activities (DWAs) were used in Eloundou et al. (2023) to determine which tasks can be augmented by LLMs and complementary software . The job zone variable groups occupations by the level of preparation needed for an occupation. This involves the level of education, experience, and on-the-job training. There are five job zones, and occupations in job zones 4 and 5 are considered to require a bachelor's degree.

[4] As indicated by "NA"s in the table, there are several major categories that do not contain both occupations requiring bachelor's degree and not requiring them (e.g., community and social service, production).

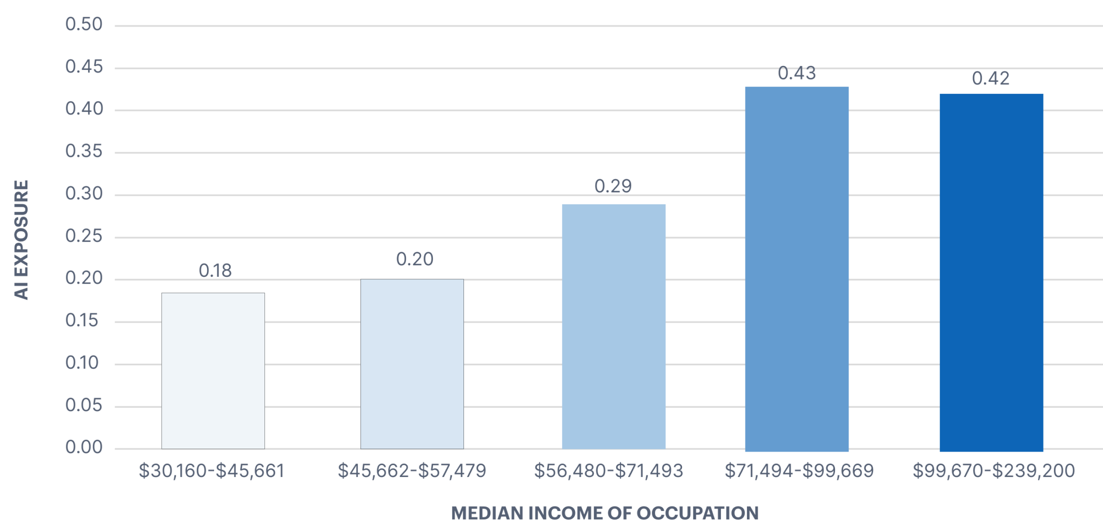
[5] Job zone 1 indicates the lowest level of preparation needed, which typically requires minimal formal education and little or no formal education (e.g., dishwashers, maids), whereas job zone 5 tends to require graduate or professional degrees with extensive experience (e.g., doctors, lawyers). See the O*NET Job Zone Description at www.onetonline.org/help/online/zones#:~:text=Job%20Zone%201%20%2D%20occupations%20that,and%20maids%20and%20housekeeping%20cleaners.

FIGURE 1 **AI Exposure by Occupation Education Level (2024)**



Source
Eloundou et al. (2024), O*NET, authors' calculations.

FIGURE 2 **AI Exposure by Occupation Median Income (2024)**



Source
Eloundou et al. (2024), Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS), authors' calculations.

TABLE 4 Top 20 Most Common AI-Exposed Occupations in the Philadelphia MSA (2024)

SOC Code	Title	AI Exposure	Median Income in Philadelphia MSA	Job Zone	Total Jobs in Philadelphia MSA
43-9061	Office clerks, general	0.500	$46,020	2	51,570
43-4051	Customer service representatives	0.705	$45,280	2	47,010
43-6014	Secretaries and administrative assistants, except legal, medical, and executive	0.567	$47,800	2	34,970
43-1011	First-line supervisors of office and administrative support workers	0.531	$69,690	3	31,320
13-2011	Accountants and auditors	0.520	$84,080	4	29,180
43-4171	Receptionists and information clerks	0.583	$37,610	2	21,730
41-3091	Sales representatives of services, except advertising, insurance, financial services, and travel	0.567	$63,800	NA	19,340
41-4012	Sales representatives, wholesale and manufacturing, except technical and scientific products	0.707	$74,170	4	19,060
23-1011	Lawyers	0.475	$148,030	5	18,270
13-1071	Human resources specialists	0.589	$72,670	4	17,470
13-1161	Market research analysts and marketing specialists	0.577	$76,950	4	17,200
43-6013	Medical secretaries and administrative assistants	0.611	$45,530	2	16,500
15-1232	Computer user support specialists	0.667	$61,540	3	12,950
11-3021	Computer and information systems managers	0.561	$170,330	4	12,820
13-1111	Management analysts	0.500	$101,150	4	12,810
13-2051	Financial and investment analysts	0.500	$99,170	NA	9,950
41-3031	Securities, commodities, and financial services sales agents	0.519	$78,010	4	9,890
11-2022	Sales managers	0.483	$144,910	4	9,020
13-1041	Compliance Officers	0.614	$81,730	4	8,690
41-3021	Insurance Sales Agents	0.530	$75,350	4	8,190

Source
Eloundou et al. (2024), O*NET, Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS), authors' calculations.

Although occupations across all income and education levels are exposed to generative AI to some degree, AI-exposed tasks tend to be concentrated in higher-paying and higher-skilled jobs. Figure 1 shows that there is a positive relationship between job zone and AI exposure across all occupations with those typically requiring a bachelor's degree (job zones 4 and 5) having considerably higher AI exposure than occupations not tending to require a bachelor's degree (job zones 1, 2, and 3). Figure 2 shows a similar positive relationship between the median income of an occupation and its AI exposure score, such that the average occupation in the top income quintile ($99,670-$239,200) has 42 percent of its tasks exposed to AI, compared with only 18 percent in the bottom quintile ($30,160–$45,661).

High AI-Exposure Occupations in the Philadelphia Metro Area Concentrated in Administrative, Sales, and Technical Roles

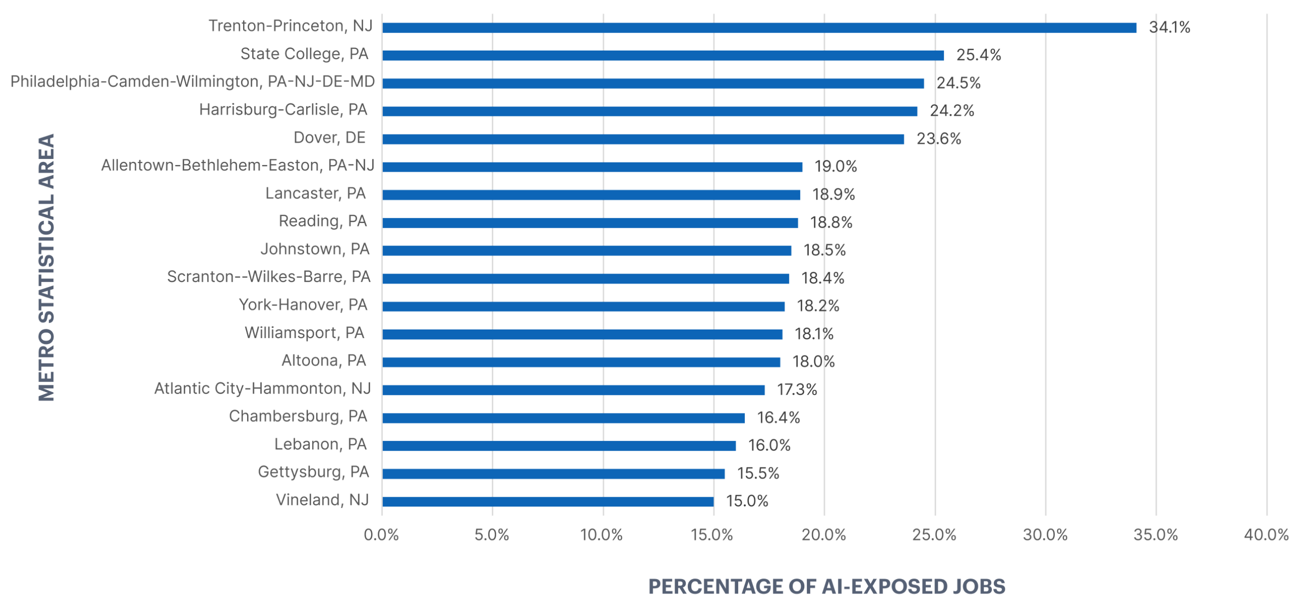
We proceed by defining AI-exposed occupations as those in the top 25 percent (top quartile) by AI exposure. We clarify that the risk to these occupations posed by AI exposure could be positive or negative. Positive risk could indicate increasing productivity and wage growth for an occupation, and negative risk might be associated with diminishing job opportunities via automation. Table 4 indicates the 20 most common AI-exposed occupations in the Philadelphia metropolitan area by the number of jobs in the metro area, median income, job zone, and AI exposure[6]. The three most common AI-exposed occupations in the Philadelphia metro area are office clerks, customer service representatives, and administrative assistants, which tend to have lower pay and require some preparation for entry (job zone 2). However, there are several high-paying positions in the top 20 most common AI-exposed jobs in the region, such as accountants, lawyers, and sales managers. Overall, administrative, sales, and computer occupations appear to be the most represented among these common AI-exposed occupations in the Philadelphia metropolitan area. See Figure A1 in the appendix for counts of the most common AI-exposed occupations across all Third District metro areas versus the Philadelphia metro area.

[6] When a job consists of multiple O*Net occupations using different AI exposure scores, employment counts from the OEWS are divided up evenly between them. For example, property appraisers in the SOC data are made up of 2 O*Net occupations, one of which is AI-exposed and the other not AI-exposed. For this SOC occupation, half of the employment gets counted as AI-exposed and the other half as not-AI-exposed, despite this not reflecting the actual share of the o-net occupation in the overarching soc code. This method is used for 75 SOC occupations in the study.

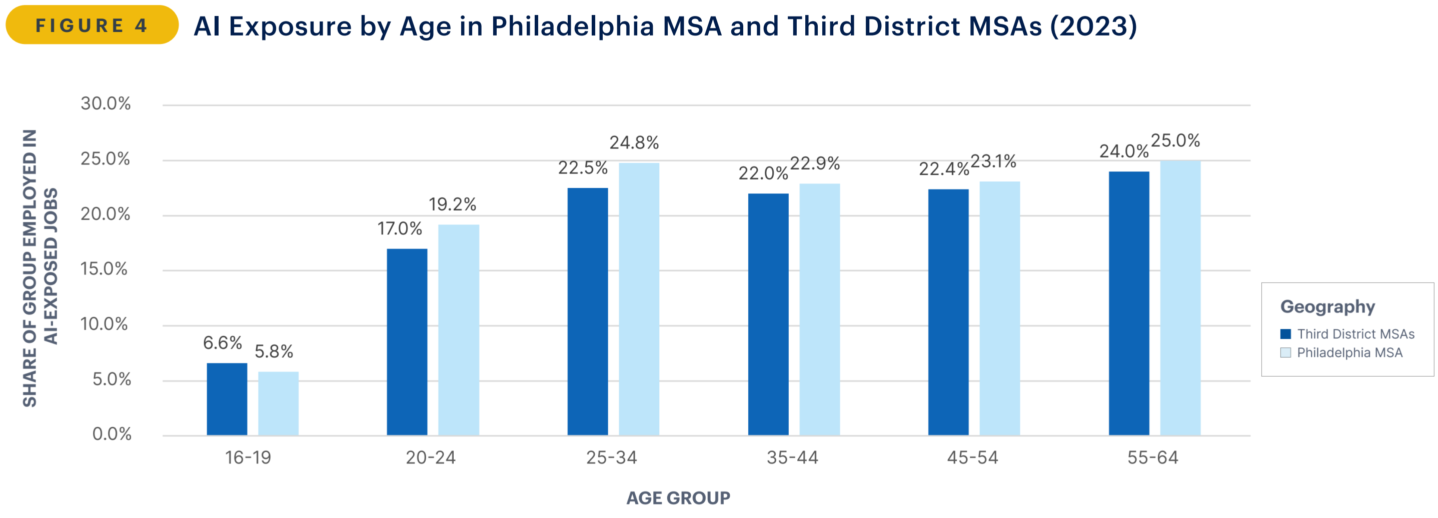
Among Third District MSAs, Trenton-Princeton, State College, and Philadelphia-Camden-Wilmington Labor Markets Are More Exposed to Generative AI

Figure 3 displays the percentage of jobs that are exposed to AI across metropolitan statistical areas (MSAs) in the Third Federal Reserve District. We calculate the share of AI-exposed jobs by dividing the total number of AI-exposed jobs by the total employment count in each MSA. We find that the Trenton-Princeton MSA has the highest share of AI-exposed jobs, at 34 percent, followed by State College and Philadelphia-Camden-Wilmington (both at 25 percent). Although ranked third by percent of AI-exposed jobs, the Philadelphia MSA ranks first in the number of AI-exposed jobs and contains the vast majority of AI-exposed jobs across Third District Metro Areas (see Figure A2 in the Appendix). MSAs with the lowest percentages of jobs at risk to AI exposure include Vineland (15 percent) and Gettysburg (16 percent). See Figure A3 in the appendix for a map of the share of AI-exposed jobs across the Northeast Corridor. The map indicates that all major metro areas in this super region (e.g., Washington, D.C., Baltimore, Philadelphia, New York, and Boston) rank in the top 20 percent across all U.S. metro areas by share of AI-exposed jobs.

FIGURE 3 Share of AI-Exposed Jobs Across Third District MSAs (2024)



Source
Eloundou et al. (2024), Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS), authors' calculations.



Source
Eloundou et al. (2024), 2023 American Community Survey one-year estimates via IPUMS, authors' calculations.

White and Female Workers Are Most Exposed to AI

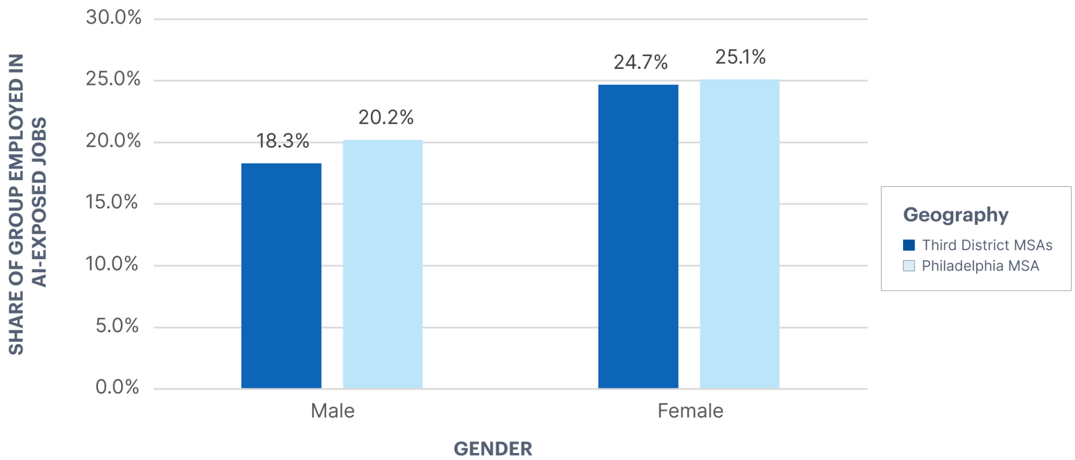
As Figure 4 shows,[7] smaller shares of younger workers hold AI-exposed occupations compared with those in their prime working years and older workers. In the Philadelphia MSA, about 6 percent of workers ages 16–19 and 19 percent of workers ages 20–24 hold AI-exposed jobs, lower than workers ages 25–34 (25 percent), 35–54 (23 percent), and 55-64 (25 percent). As Figure 5 shows, women (25 percent) are more likely to be employed in an AI-exposed occupation than men (20 percent) in the Philadelphia MSA.

In the Philadelphia MSA, about 25 percent of occupations held by White workers are AI-exposed, higher than the 24 percent for Asian workers, 19 percent for Black workers, and 16 percent for Hispanic workers

[7] We extracted data on age, race, ethnicity, and gender from the 2024 American Community Survey five-year estimates microdata via IPUMS. Because the IPUMS demographic data uses only Census OCC codes to identify each occupation, the AI exposure scores had to be aggregated to the less specific OCC code level. Using the OEWS employment totals, we created a weighted mean AI exposure score for each OCC code occupation. The weights used were the proportion of each OCC occupation's workers that each SOC occupation within it made up.

FIGURE 5

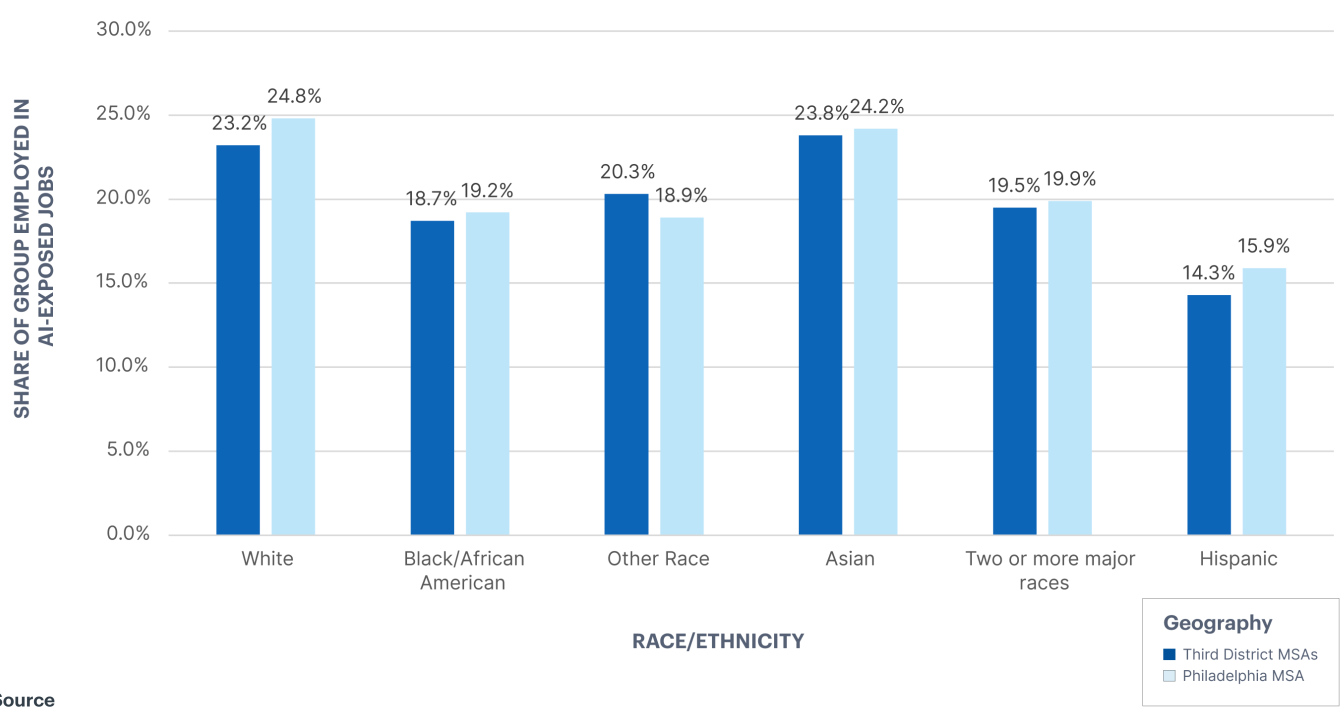
AI Exposure by Gender in Philadelphia MSA and Third District MSAs (2023)



Source
Eloundou et al. (2024), 2023 American Community Survey one-year estimates via IPUMS, authors' calculations.

FIGURE 6

AI Exposure by Race in Philadelphia MSA and Third District MSAs (2023)



Source
Eloundou et al. (2024), 2023 American Community Survey one-year estimates via IPUMS, authors' calculations

Implications and Closing Thoughts

While Ding et al. (2018) find that generalized automation by robotics, AI, and technological advancements would disproportionately impact lower-wage and lower-skilled workers, our results suggest that generative AI exposure will likely impact those on the upper end of the wage and skill spectrum. In further contrast with the findings from the previous automation report, we observe that metro areas in the Northeast Corridor of the Third District (e.g., Trenton-Princeton and Philadelphia) will be more impacted by generative AI than less population-dense metros such as Atlantic City-Hammonton and Williamsport.

There may be some downstream effects of generative AI adoption in the labor market for regions that are highly exposed. In a recent working paper, Abrahams and Levy (2024) contrast the disparate potential regional effects of AI with the manufacturing decline of the 1980s that took a heavy toll (e.g., job loss, outmigration) on many industrialized regional economies in the Midwest (sometimes referred to as the Rust Belt). While deindustrialization led people to obtain more education and migrate to dense coastal metropolitan areas, the AI revolution could bring a reversal of this phenomenon. If AI adoption tends to be more labor-substituting than labor-complementing for highly educated occupations, the demand for postsecondary education may decline, and more affordable lower-exposure metro areas may become more desirable. Recent research suggests that generative AI adoption has already impacted the labor market for some graduates since 2022. Brynjolfsson et al. (2025) find that early career workers (ages 22–25) in occupations with high AI exposure (e.g., software development, customer support) have experienced a 13 percent relative decline in employment, while their more experienced colleagues have seen no change or positive job growth.

While exposure to generative AI may pose threats to current and future workers through its automation effects, there are reasons to be optimistic about its positive labor-augmenting effects. Johnston and Makridis (2025) find that highly AI-exposed sectors experienced increases in employment and wages following ChatGPT's introduction, and that only those in which AI could directly substitute for human labor saw declines. Additionally, Autor (2024) suggests that through extending the reach of human expertise, AI could rebuild middle-skill jobs in the U.S. that were previously eliminated by automation and globalization.

It will be crucial for community stakeholders (policymakers, companies, higher education institutions) to stay connected with their local workforce as the labor market is shaped by transformational technologies like generative AI. As the demand for skills in the labor market shifts, collaborative solutions may allow current and future workers to take advantage of AI-enabled opportunities while avoiding displacement. Any disruptions to regional labor markets due to AI adoption will necessitate a role for job retraining. Workforce development can aid the transition of workers from automated jobs to in-demand jobs to meet the shifting needs of local producers, which have been traditionally facilitated through community colleges (Hobor, 2013, Yamashita and Cummins, 2021, Van Noy et al., 2023), temporary help firms (Autor 2001), and other nonprofit workforce organizations. Several postsecondary institutions are already shifting their educational offerings to accommodate the AI skill needs of major employers through industry-led partnerships (Brumer and Garza, 2024, Carullo, 2025).

References

Abrahams, Scott, and Frank S. Levy. "From San Francisco to Savannah? The Downstream Effects of Generative AI." Working paper, 2024. Available at dx.doi.org/10.2139/ssrn.4874104.

Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo. "Artificial Intelligence and Jobs: Evidence from Online Vacancies." *Journal of Labor Economics* 40:S1 (2022), pp. 293–340.

Alekseeva, Liudmila, José Azar, Mireia Giné, Sampsa Samila, and Bledi Taska. "The Demand for AI Skills in the Labor Market." *Labour Economics* 71 (2021), 102002.

Autor, David. "Why Do Temporary Help Firms Provide Free General Skills Training?" *Quarterly Journal of Economics* 116:4 (2001), pp. 1409–48. Available at doi.org/10.1162/003355301753265615.

Autor, David. "Applying AI to Rebuild Middle Class Jobs." NBER Working Paper No. 32140, 2024.

Autor, David, and Neil Thompson. "Expertise." NBER Working Paper No. 33941, 2025. Available at www.nber.org/papers/w33941.

Bonney, Kathryn, Cory Breaux, Catherine Buffington, et al. "The Impact of AI on the Workforce: Tasks Versus Jobs?" *Economics Letters* 244 (2024).

Brumer, Delilah, and Jeremy Garza. "California Students Want Careers in AI. Here's How Colleges Are Meeting That Demand." *Cal Matters*, October 29, 2024, calmatters.org/education/2024/10/california-community-colleges-ai-careers/.

Brynjolfsson, Erik, Bharat Chandar, and Ruyu Chen. "Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence." Stanford University Digital Economy Lab working paper, 2025.

Cerullo, Megan. 2025. "Google to Spend $1 Billion on AI Education and Job Training in the U.S." *CBS MoneyWatch*, August 6, 2025, www.cbsnews.com/news/google-ai-education-college-job-training-1-billion/.

Ding, Lei, Elaine Leigh, and Patrick T. Harker. *Automation and Regional Employment in the Third Federal Reserve District*. Philadelphia: Federal Reserve Bank of Philadelphia, 2018.

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock. "GPTs Are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models." *Science* 384:6702 (2024),1306–8.

Federal Reserve Bank of Boston. *Boston (First District) Beige Book Report*. Boston: Federal Reserve Bank of Boston, July 16, 2025. Available at www.bostonfed.org/news-and-events/news/2025/07/beige-book-july-2025-economic-activity-flat-retail-tourism-down-signals-mixed.aspx.

Federal Reserve Bank of Richmond (2024). "U.S. Companies Ramp Up Automation and AI as Inflation Persists." *The CFO Survey*, June 20, 2024. Available at www.richmondfed.org/research/national_economy/cfo_survey/data_and_results/2024/20240620_data_and_results.

References

Felten, Edward, Manav Raj, and Robert Seamans. "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses." *Strategic Management Journal* 42:12 (2021), pp. 2195–217.

Galeano, Sergio, Nyerere Hodge, and Alexander Ruder. "By Degree(s): Measuring Employer Demand for AI Skills by Educational Requirements." *Workforce Currents*, Federal Reserve Bank of Atlanta, 2024. Available at www.atlantafed.org/cweo/workforce-currents/2025/05/21/by-degrees-measuring-employer-demand-for-ai-skills-by-educational-requirements.

Hartley, Jonathan, Filip Jolevski, Vitor Melo, and Brendan Moore. "The Labor Market Effects of Generative Artificial Intelligence." Working paper, 2025. Available at dx.doi.org/10.2139/ssrn.5136877.

Hobor, George. "Surviving the Era of Deindustrialization: The New Economic Geography of the Urban Rust Belt." *Journal of Urban Affairs*, 35:4 (2013), 417–34.

Johnston, Andrew, and Christos Makridis. "The Labor Market Effects of Generative AI: A Difference-in-Differences Analysis of AI Exposure." Working paper, 2025. Available at dx.doi.org/10.2139/ssrn.5375017.

Kochhar, Rakesh. 2023. *Which U.S. Workers Are More Exposed to AI on Their Jobs?* Washington, D.C.: Pew Research Center, 2023. Available at www.pewresearch.org/social-trends/2023/07/26/which-u-s-workers-are-more-exposed-to-ai-on-their-jobs/.

Lin, Luona, and Kim Parker. *U.S. Workers Are More Worried Than Hopeful About Future AI Use in the Workplace*. Washington, D.C.: Pew Research Center, 2025. Available at www.pewresearch.org/social-trends/2025/02/25/u-s-workers-are-more-worried-than-hopeful-about-future-ai-use-in-the-workplace/.

Marken, Stephanie, and Tara Nicola. "Three in Four Americans Believe AI Will Reduce Jobs." *Gallup Blog*, September 13, 2023, news.gallup.com/opinion/gallup/510635/three-four-americans-believe-reduce-jobs.aspx.

Muro, Mark, and Shriya Methkupally. *Mapping the AI Economy: Which Regions Are Ready for the Next Technological Leap?* Washington, D.C.: Brookings Institution, 2025. Available at www.brookings.edu/wp-content/uploads/2025/06/Mapping-AI-readiness-final.pdf.

Perez-Castells, Ariana. "Over 10,000 Philly-Area Job Listings Required AI Skills Last Year." *Philadelphia Inquirer,* July 28, 2025. Available at www.inquirer.com/business/brookings-report-philadelphia-metro-ai-readiness-20250728.html.

PYMNTS. "54% of US Workers Wary of GenAI's Impact on Jobs, Report Finds." *PYMNTS AI*, 2025. Available at www.pymnts.com/news/artificial-intelligence/2025/54percent-united-states-workers-wary-generative-ai-impact-jobs/.

Schendstok, Matt, and Sydney Schreiner Wertz. 2024. "Occupational Exposure to Artificial Intelligence by Geography and Education." U.S. Treasury Office of Economic Policy Working Paper 2024-02. Available at home.treasury.gov/system/files/136/AI-Combined-PDF.pdf.

Septiandri, Ali Akbar, Marios Constantinides, and Daniele Quercia. "The Potential Impact of AI Innovations on US Occupations." *PNAS Nexus*, 3:9 (2024), pgae320. Available at doi.org/10.1093/pnasnexus/pgae320.

References

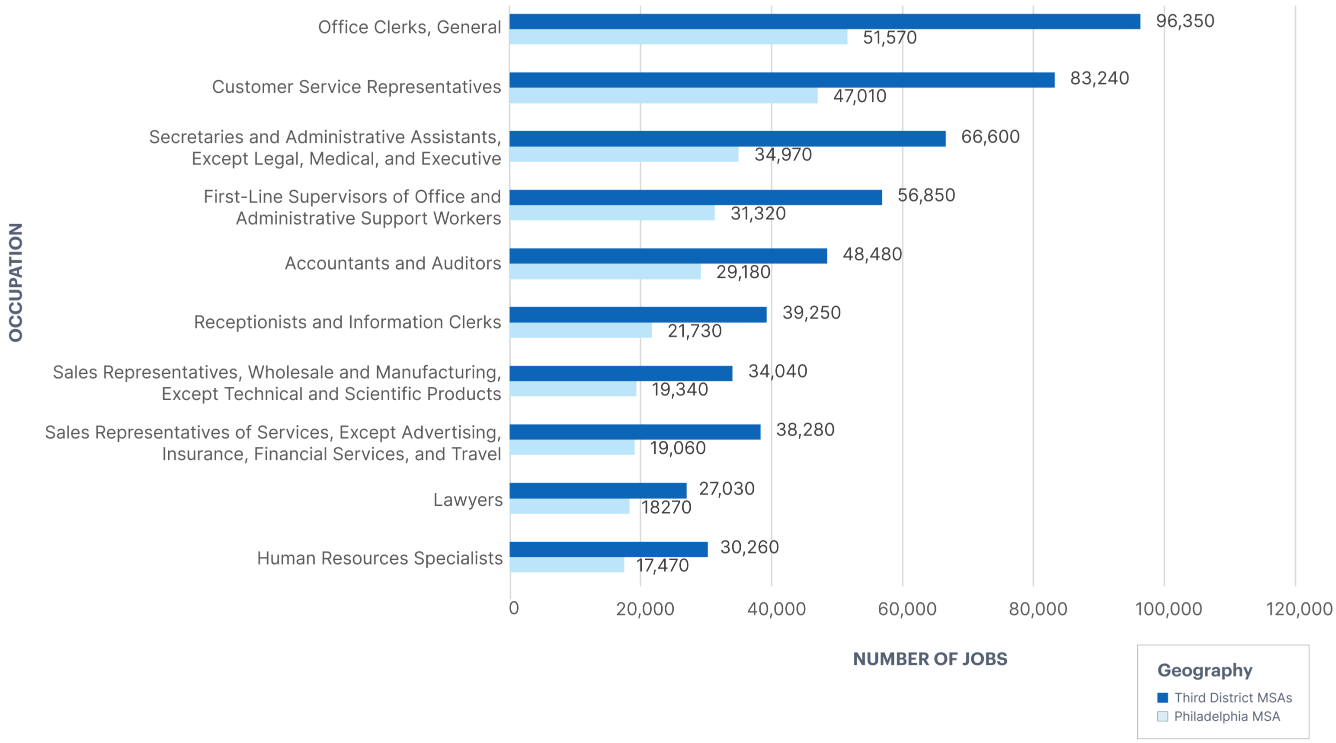
Van Noy, Michelle, Andrew Weaver, Allison Forbes, and Debra Bragg. *The Community College Role in Economic Development: A Conceptual Model*. New Brunswick, NJ: Rutgers University Education and Employment Research Center, 2023. Available at sites.rutgers.edu/eerc-hii/wp-content/uploads/sites/609/2023/12/The-Community-College-Role-in-Econ.-Dev.-EERC-12.2023.pdf.

Yamashita, Takashi, and Phyllis A. Cummins. "Jobs at Risk of Automation in the USA: Implications for Community Colleges." *Community College Journal of Research and Practice*, 46:5 (2021), pp. 374–7.

Yousuf, Mariam, and Robert Leigh. "Texas Firms Open to AI as Tariff Work-Around Strategy." *Dallas Fed Economics*, July 17, 2025. Available at www.dallasfed.org/research/economics/2025/0717.

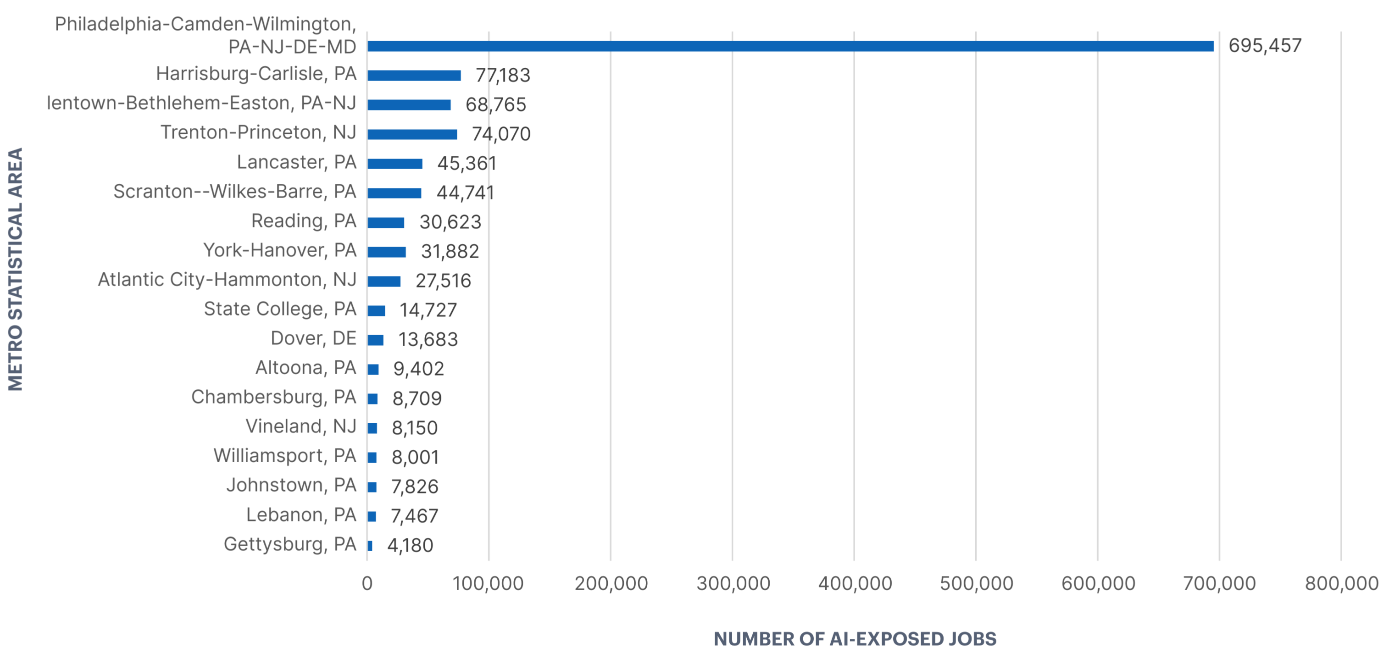
Appendix:

FIGURE A1 **Most Common AI-Exposed Occupations in Philadelphia MSA and Third District MSAs (2024)**



Source
Eloundou et al. (2024), Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS), authors' calculations.

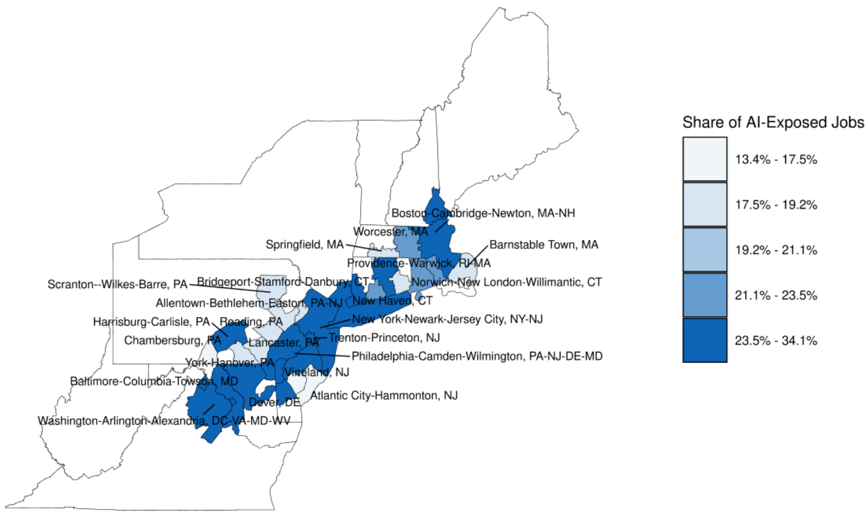
FIGURE A2 **Number of AI-Exposed Jobs Across Third District MSAs (2024)**



Source
Eloundou et al. (2024), Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS), authors' calculations.

Appendix:

FIGURE A3 Share of AI-Exposed Jobs in Northeast Corridor MSAs (2024)



Source
Eloundou et al. (2024), Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS), authors' calculations.

NOTE: The five shaded bins represent quintiles based on the distribution of AI-exposed jobs across all U.S. metropolitan statistical areas.

TABLE A1 Least AI-Exposed Occupations in U.S. Typically Requiring Bachelor's Degree (2024)

SOC Code	Title	Job Zone	Median Income	AI Exposure
29-1041.00	Optometrists	5	$134,830	0.0500
29-2011.04	Histotechnologists	4	$61,890*	0.0625
29-1022.00	Oral and maxillofacial surgeons	5	>=$239,200	0.0800
29-1024.00	Prosthodontists	5	>=$239,200	0.0909
29-1071.01	Anesthesiologist assistants	5	$133,260*	0.0952
29-1071.00	Physician assistants	5	$133,260	0.1250
29-1151.00	Nurse anesthetists	5	$223,210	0.1250
27-2042.00	Musicians and singers	4	NA	0.1327
29-1229.04	Physical medicine and rehabilitation physicians	5	>=$239,200*	0.1333
27-2022.00	Coaches and scouts	4	$45,920	0.1444

Source
Eloundou et al. (2024), O*NET, Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS), authors' calculations. *Reflects income estimates from this occupation's 6-digit SOC code grouping.

Appendix:

TABLE A2 Least AI-Exposed Occupations in U.S. Not Typically Requiring Bachelor's Degree (2024)

SOC Code	Title	Job Zone	Median Income	AI Exposure
13-1074.00	Farm labor contractors	2	$48,690	0
27-2021.00	Athletes and sports competitors	2	$62,360	0
31-9099.02	Endoscopy technicians	2	$46,050*	0
35-2015.00	Cooks, short order	2	$35,620	0
35-9011.00	Dining room and cafeteria attendants and bartender helpers	1	$32,670	0
35-9021.00	Dishwashers	1	$33,670	0
45-2091.00	Agricultural equipment operators	1	$42,580	0
47-2011.00	Boilermakers	3	$73,340	0
47-2021.00	Brickmasons and blockmasons	2	$60,800	0
47-2022.00	Stonemasons	3	$51,990	0

Source
Eloundou et al. (2024), O*NET, Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS), authors' calculations. *Reflects income estimates from this occupation's 6-digit SOC code grouping.

FEDERAL RESERVE BANK
PHILADELPHIA

PHILADELPHIAFED.ORG | @PHILADELPHIAFED