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The Potential Impact of AI Exposure on Black Workers

The Risks of Automation and Displacement, and the Opportunities of Augmentation and Adaptation

William J. Congdon, LesLeigh D. Ford, Claire Cusella, and Fernando Hernandez-Lepe

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Artificial intelligence (AI) represents a seismic technological shift that has potentially transformative economic implications. With widespread adoption of AI among workers, the nature of work is changing at an unprecedented pace (Bick et al. 2026). As with past technological changes, the expected impacts are likely to be uneven. Given the disproportionate negative economic impacts of past technological disruptions on Black workers in particular in the US, understanding the potential effects of AI on Black workers is critical. According to some estimates, Black workers are overrepresented in roles that are likely to be affected by automation, which may leave them at risk of displacement and may contribute to a widening of the racial wealth gap.[1]

In this brief, we provide updated evidence of the relative exposure of Black workers to AI and its potential consequences, with a focus on Black middle-class workers. We find that Black workers are, by some measures, overrepresented in roles that are relatively less exposed to AI, a pattern driven in part by the association between AI exposure and educational attainment and that may reflect occupational segregation. We also find that Black middle-class workers are somewhat more exposed to AI than Black workers overall. Finally, we find evidence that, among occupations that are more exposed to AI, Black workers tend to be overrepresented in roles that may be at greater risk of

automation and displacement. These early findings suggest directions for both further research and policy responses to ensure that Black workers are protected from the risks and share in the benefits of AI.

Work, Wealth, Technology, and the Black Middle Class

Understanding the potential impacts of AI on Black workers is essential in part because of the possible role this technology will play in shaping opportunities and outcomes that are central to building the Black middle class, including not only the returns to education and work and the paths provided by the labor market to economic mobility but also the importance of building wealth for economic security. Experiences from past technological revolutions and early research on the potential effects of AI suggest that, in the absence of countervailing policy intervention, middle-class Black Americans may not share in the economic benefits of these new technologies; in fact, many Black workers may be at risk of economic harm.[2]

The Risks and Challenges AI Poses for the Black Middle Class

As the Black middle class experiences changing economic conditions and policies—including technological innovation; local, state, and federal policy shifts; and policy debates to address the affordability crisis—the advent of AI and its economic impacts will compound existing challenges. Education and work help to move Black workers into the middle class, but staying there remains challenging (Cole and Omari 2003). At the same time, research shows that the returns to education and employment are uneven between Black and white workers, with Black workers receiving lower wages relative to their educational attainment (Meschede et al. 2017). Black workers are more likely to face structural barriers, including labor market discrimination, and Black women face distinct penalties for possessing identities at the intersection of race and gender (Paul et al. 2022).

Among the primary economic risks specifically associated with AI are those related to automation, or the use of technology to perform work tasks with limited human intervention.[3] Automation potentially affects workers of color disproportionately. A recent study found that Black and Latino workers are overrepresented in jobs that are more likely to be affected by automation (Broady et al. 2023). In fact, researchers have found that Black and Latino workers were overrepresented in occupations with the highest risk of automation and underrepresented in occupations with the lowest risk of automation (Broady et al. 2021). The major risks to Black workers from automation are occupations that operate through the labor market, as automation can potentially lead to displacement, resulting in large and persistent negative impacts on employment and earnings.

In addition to affecting the labor market, AI may affect the ability of the Black middle class to accumulate stable wealth. Wealth is sometimes thought of as an individual or family pursuit, but the racial wealth gap has its basis in systems and structures of stratification (Cole and Omari 2003). Narratives are starting to demonstrate that the racial wealth gap cannot be remedied by interventions focused on personal decisions and individual behaviors. Rapid transformations like those related to AI

highlight that individual-level interventions to address racial wealth inequity are not enough. And there is some evidence that generative AI could widen racial economic gaps in the United States if long-standing and structural patterns of wealth accumulation disparities persist.[4]

How Black Workers Fared in Previous Technical Revolutions

AI and generative AI represent a significant technological innovation that can change how employers make decisions about defining and assigning tasks to employees. Understanding how Black workers have fared during previous technical revolutions and racialized labor market disruptions can guide how policymakers plan for the impacts of new technical innovations and periods of transformation.

There is evidence dating back to the industrial revolution that Black workers historically were excluded from skilled labor jobs due to racism and segregation (Marable 2015; Trotter 2000). During the rise of automation in manufacturing, Black workers were overrepresented in routine jobs that required manual labor, including assembly-line jobs. Research finds that Black workers were more likely to be displaced and less likely to be upskilled or retrained for higher-skill, more technical positions. For example, according to the US Bureau of Labor Statistics, manufacturing-related employment increased by approximately 4 million jobs between 1961 and 1969.[5] Yet the Black unemployment rate was between 2.0 and 2.5 times the white unemployment rate during this same time period, a trend that has persisted since 1954, when the federal government began tracking unemployment by race (Austin 2013).[6] In cities such as Detroit, Michigan, in 1960, the white unemployment rate was 5.8 percent, whereas the Black unemployment rate was 15.9 percent. Poor working conditions, lack of access to union protections and representations, and the loss of entry-level jobs through automation contributed to the rise of the Black labor movement in Detroit and other cities in the 1960s.[7]

Motivated in part by these historical examples, we explore the question of how the proliferation of AI might reshape employment opportunities, wages, and career mobility for Black workers. Specifically, we examine the following question: *Are Black workers more likely to be exposed to AI as a result of being represented or overrepresented in specific occupations?*

BOX 1

How Does This Study Inform Our Understanding of the Black Middle Class?

This brief is a contribution to the Black Family Thriving Initiative, which aims to develop insights and evidence that can help researchers, practitioners, funders, and other stakeholders develop policies, implement programs, and test ideas that drive economic mobility and wealth building for Black families (Ford, Cooper, et al. 2024). The initiative also seeks to ensure that middle-class Black Americans establish, grow, protect, and preserve their wealth and that as many Black Americans as possible are able to move into the middle class via education, homeownership, quality jobs, small-business ownership and acquisition, and other pathways. As AI represents a significant shift in the labor market and could affect wages, economic mobility, and wealth building, we work to understand how Black workers may be impacted.

The Black Family Thriving Initiative also strives to redefine what it means to be Black and middle class in America. While there is no singular definition of what it means to be middle class in the US,[a] it is typically defined in terms of income: either being in the middle of the income distribution (Reeves et al. 2018; Cashell 2008) or having an income between two-thirds and twice the national median income (Kochhar 2024).[b] Achieving or maintaining the middle-class status often includes some combination of income, education, and homeownership, and some consideration of net worth (assets minus debts). It is important to account for the presence or absence of wealth, as it provides a more accurate conceptualization of one's class position. Nationally, 1 in 10 households have no wealth or negative wealth; this share is 1 in 4 among Black households, with approximately 25 percent of Black households having zero wealth or experiencing debt in 2021 (Kochhar and Moslimani 2023). Simply put, wealth can be defined as the difference between what an individual owns and owes, or the difference between an individual's assets and liabilities. In fact, some argue that wealth is a stronger indicator of economic security than income, as wealth gives a person something to draw on or fall back on in case of an economic crisis (Addo and Darity 2021).

We use earned income in this brief because of the availability of reliable income data (and conversely the absence of equally reliable, publicly available wealth data), and because we believe income data are informative when considering class position (Weeden et al. 2007), purchasing power (Diamond and Moretti 2021), and how individuals self-identify their class position (Kim and Sommet 2025).

To make progress on increasing household wealth for Black families and move more Black Americans firmly into the middle class, it is imperative to have accurate documentation of the interventions and policies that can help improve the Black middle class's economic situation now and in the future.

[a] Jonathan Schwabish, "How We Define 'Middle Class' Has Broad Implications," *Urban Wire*, Urban Institute, September 10, 2019, https://www.urban.org/urban-wire/how-we-define-middle-class-has-broad-implications#:~:text=The%20Pew%20Research%20Center%20defines,150%20percent%20around%20the%20median.
[b] Howard Gleckman, "Who Is Middle Class Anyway?" *Tax Vox*, Tax Policy Center, December 10, 2018, https://taxpolicycenter.org/taxvox/who-middle-class-anyway.

Implications and Impacts of AI for Work and Wealth

Both economic theory and available evidence suggest that the impacts of technological advances like AI on workers' employment, earnings, and patterns of wealth accumulation are potentially profound. Evidence shows that the use of AI at work has grown rapidly but unevenly in recent years, suggesting how patterns of both disruption and opportunity might evolve. Research on the labor market impacts of AI is still preliminary and rapidly progressing but finds some evidence of changes in employment and productivity.

Quantifying AI Adoption and Exposure

To explore the evolving and likely impacts of AI advancements and improvements on the demand for labor and worker outcomes, research relies on measures of how and where AI is currently being adopted by workers and employers, and how and where it might be used in the near future. Early evidence on AI *adoption* shows that its use by workers and firms has grown rapidly in recent years, especially among workers in computer and mathematical occupations and firms in the information and

professional services sectors (Bick et al. 2026; Bonney et al. 2026). These patterns of AI adoption help explain how AI might already be affecting workers, firms, and the economy (Alikhani et al. 2025).[8]

Because these measures show that AI use is in its early stages and expected to continue and expand, research has developed and employed measures of not just employer AI adoption but also employee *exposure* to AI and occupations where AI might be employed in the future. To assess AI exposure, researchers have combined information about occupations and the tasks workers perform on the job with information about which tasks AI can perform or support (Eloundou et al. 2024; Felten et al. 2021, 2023). This line of research then characterizes occupations as more or less exposed to AI based on the share of tasks within an occupation that AI could potentially be used. Occupations considered relatively highly exposed by these measures include office and administrative support and computer and engineering occupations, while occupations such as construction and production are considered relatively less exposed.

Subsequent research has investigated associations between the degree of AI exposure and the characteristics of both the occupations themselves and the workers who hold jobs in those occupations. One finding is that workers in jobs that are most exposed to AI had higher wages on average than workers in jobs that were least exposed to AI ($33 dollars per hour versus $20 dollars per hour in 2022) (Kochhar 2023). This is due in part to the positive association between AI exposure and education levels across occupations, with more exposed occupations, such as computing occupations, more likely to require a college degree than less exposed occupations. This research also finds differences in the demographic characteristics of workers in occupations by level of AI exposure. In 2023, for example, Kochhar (2023) found that Black workers were less likely than other workers to be employed in highly exposed occupations and more likely to be employed in less exposed occupations. Our analysis extends and updates this line of research to better understand the nature and implications of differential patterns of AI exposure for Black workers, specifically Black middle-class workers.

Potential Effects of AI Exposure Are Ambiguous

It is useful to study which jobs and which workers AI is likely to affect, as well as AI's potential impacts on the Black middle class, but understanding AI's possible effects on workers requires some caution.[9] In particular, although there is much interest in AI's potential to displace workers (i.e., the risk that an individual loses their job because of AI), it is important to note that AI exposure by itself is not necessarily a measure of displacement risk.[10] As defined above, exposure refers to the extent to which AI can help automate or transform specific job-related tasks. In other words, task automation is distinct from role automation and does not necessarily mean job loss or displacement. In some exposed roles, workers might use AI and potentially become more productive in their job functions, rather than be replaced.

To try to conceptualize and identify where AI might be used in these ways—and lead to different outcomes for workers—some research has proposed distinguishing between using AI primarily to *automate* work in exposed roles and using it to *augment* the work that workers perform (Handa et al.

2025). Some workers in exposed roles may benefit as AI augments their work, while others may be harmed as their work is automated (Acemoglu and Autor 2011; Autor and Thompson 2025). This is particularly important when considering the potential effects of AI on Black workers, as research on automation conducted before the widespread use of generative AI suggests that Black workers might be overrepresented in jobs likely to be automated (Broady 2023).

Some of the early research on the likely effects of AI has attempted to complement measures of exposure with other information to distinguish between different types of potential impacts across workers and occupations. One line of research characterizes high-exposure occupations as being more or less complementary with AI, indicating whether AI exposure is more or less likely to augment rather than automate work (Lewandowski et al. 2025; Pizzinelli et al. 2023). This work suggests that occupations with high exposure to AI and low complementarity may be at the highest risk of displacement due to AI. Other work considers the relative ability of workers to adapt to AI to estimate the degree of risk associated with exposure (Manning and Aguirre 2026). As we examine the rate of AI exposure on Black workers and consider its implications, we draw on this research to interpret potential displacement risks for Black workers. We also discuss where additional inquiry is needed to better understand the potential impacts on Black workers.

For the purposes of this brief and our analysis, we use the relative level of educational attainment across occupations, in conjunction with differences in AI exposure, as a rough proxy for the degree to which AI poses varying risks of displacement. In particular, we take lower levels of education as suggesting higher risks of displacement, drawing on both emerging and historical evidence that AI and recent information technologies are often more likely to substitute for work associated with lower levels of education and that workers with higher levels of education may be more likely to have skills that are complemented by such technologies. Although lower levels of formal education are only one factor contributing to the likelihood that AI will displace exposed workers, this measure provides an initial way of considering relative risks. We describe this analysis and its limitations below.

Early Evidence of AI's Effects on Work and Wealth

Recently, AI has received a lot of attention for its potential impacts on employers (e.g., increased revenue and profitability) and workers (e.g., employment and reskilling) (Arnon 2025; Morandini et al. 2023).[11] Scholars have found early evidence that AI adoption raises worker productivity and can serve as a substitute at the task level. However, its net employment effects, at least at the firm level, appear modest due to offsetting forces, including firms' subsequent ability to scale.

This early research has found some evidence of impacts of AI adoption on worker earnings and employment outcomes as well as on firms' productivity and employment, including potential harms such as job displacement (Broady et al. 2026) and widening economic inequality (Avevor et al. 2023). Research on AI's effects on worker productivity has found some evidence of positive impacts (Cui et al. 2026; Dell'Acqua et al. 2023). Scholars have also examined the potential benefits of AI, including increases in efficiency and productivity (Al Naqbi et al. 2024; Patil 2024) as well as company revenues (Hampole et al. 2025).[12] At the firm level, much of this early evidence is mixed or limited (Babina

2026). In the labor market more widely, there is some evidence that AI has negatively affected employment for certain segments of the workforce, such as younger workers (e.g., Brynjolfsson et al. 2025).

In addition to estimating the potential effects of AI on wages and employment, scholars have considered the potential effects of AI on worker skills and other aspects of work. Related to worker skills, for example, some research suggests that AI's impact across occupations and the increasing rate of "skill obsolescence" might magnify the need for workers to acquire new skills throughout their careers (Oschinski et al. 2024). Researchers have also established that AI-driven automation will affect work-related processes and experiences, including hiring (Albaroudi et al. 2024; Kassir et al. 2023), performance assessments (Athlawy et al. 2025), and workplace training (Muehlemann 2024; Oschinski et al. 2024).

Finally, one important but still primarily theoretical strand of the research on the potential effects of AI relates closely to the interplay between work and wealth in shaping economic outcomes for workers and households. This work emphasizes the possibility that, if AI takes on a larger role in production, the economic benefits of AI will accrue disproportionately to the owners of the technology, with a smaller share of overall income flowing to workers (Restrepo 2025; Trammell and Korinek 2023). Some research has found evidence that AI produces higher returns for capital—such as business owners—than for labor (Johnston and Makridis 2025). This suggests the potential that, as the economy evolves to adopt AI more widely, wealth may play an increasingly important role in determining economic security.

Research Questions and Approach

Building on our understanding of the Black middle class and historical and structural factors that have inhibited economic mobility and wealth building, we sought to understand the potential impact of AI on Black workers and the Black middle class by exploring the following questions:

- Which occupations are most likely to be impacted by AI? Among those occupations, are there some with large concentrations of Black workers? How does AI exposure interact with occupational segregation?
  - » We specifically explore the implications this might have for job security and economic mobility, given that some occupations have historically provided strong pathways to the middle class.
- Are Black men and Black women likely to have similar experiences in terms of exposure to AI?
  - » It is well documented, for example, that women are disproportionately represented in educational, administrative, service, and care-based fields, including occupations such as customer service representatives, secretaries and administrative assistants, retail salespersons, and nursing assistants.[13] How might this explain the recent significant employment losses experienced by Black women? Recent research has found that Black

women experienced larger employment losses than other groups, including Black men; Black women's unemployment rate increased from 5.8 percent to 6.7 percent in 2025.[14] There is also some evidence that women may be relatively more exposed to AI (ILO 2026).

- Are there any insights into potential displacement of Black workers that can be seen by examining AI exposure in combination with other occupational characteristics, such as the average level of education among workers in an occupation?

Data Sources and Methods

To investigate the relative degree of AI exposure among Black workers and its potential implications, we conduct an analysis that combines data on AI exposure at the occupation level with data on worker demographics and labor force details.

The measure of AI exposure in this analysis is one developed by Eloundou and colleagues (2024), which assigns degrees of AI exposure to occupations based on standardized descriptions of the tasks that constitute each occupation.[15] The result is a score for each occupation ranging between 0 and 1 that represents the degree of AI exposure.[16] Table 1 shows relative exposure across major occupational categories, and the results, at least in relative terms, align with both prior research and intuition.

To associate AI exposure with occupation and worker characteristics, and in particular to identify Black workers across occupations, we use data from the 2024 American Community Survey.[17] We characterize occupations' demographic, earnings, and educational profiles using employed workers with nonzero earnings in those occupations.[18] As shown in table 1, this allows us to characterize, for example, computer and related occupations as not just relatively highly exposed but also occupations in which Black workers are underrepresented, accounting for 7.3 percent of workers in the occupation compared with around 12.0 percent of all employed workers. Conversely, Black workers compose 14.0 percent of office and administrative support workers, which is a relatively high-exposure occupation. Overall, with the exception of office and administrative support, occupational categories with the highest shares of Black workers tend to exhibit relatively lower degrees of AI exposure.

Table 1 shows the variation in relative education levels among even relatively exposed occupations and how these levels covary with the share of Black workers. While office and administrative support as well as computer and science occupations are relatively high exposure, the share of workers with college or higher levels of education is much higher for the latter (where Black workers are underrepresented) than the former (where Black workers are overrepresented). In general, table 1 shows the variation across major occupational categories in the extent to which Black workers are over- or underrepresented; degree of AI exposure; typical level of education (as shown by the share of workers with a college education or higher); and size of each category, indicated by the total number of workers and number of detailed occupations in each category.

TABLE 1

Occupational Characteristics and Degree of AI Exposure

For major occupational categories, from highest to lowest share of Black workers

Occupation category	Black workers (percentage)[a]	AI exposure (index)[b]	College or higher (percentage)[c]	Workers (total)[d]	Detailed occupations (count)
Transportation and material moving	18.5	0.187	17.7	11,688,006	31
Service occupations	16.0	0.157	23.6	24,247,079	70
Office and administrative support	14.0	0.589	37.9	16,574,296	48
Production occupations	12.7	0.175	18.6	8,192,284	59
Health care practitioners and technical	10.9	0.343	81.5	10,108,247	42
Sales and related occupations	10.3	0.430	37.8	13,316,612	17
Education, legal, community service, arts, and media	10.1	0.392	79.9	16,386,874	57
Management, business, and financial	9.0	0.479	70.2	26,921,709	58
Installation, maintenance, and repair	8.0	0.124	22.1	4,716,622	30
Computer, engineering, and science	7.3	0.634	80.7	11,491,053	59
Construction and extraction	5.7	0.105	13.8	6,837,158	33
Farming, fishing, and forestry	4.0	0.108	13.6	855,677	7
All occupations	**11.7%**	**0.359**	**47.7%**	**151,335,617**	**511**

Source: Authors' calculations using 2024 five-year American Community Survey and data from Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock, "GPTs Are GPTs: Labor Market Impact Potential of LLMs," *Science* 384, no. 6702 (2024): 1306–08, http://doi.org/10.1126/science.adj0998. American Community Survey data are retrieved from Steven Ruggles, Sarah Flood, Matthew Sobek, et al., IPUMS USA: Version 16.0. Minneapolis, MN: IPUMS, 2025, https://doi.org/10.18128/D010.V16.0; and Eloundou et al., "GPTs Are GPTs."

Note: Table presents the characteristics of occupational categories, including their degree of AI exposure.

[a] "Black workers (percentage)" is the share of workers in each category who are Black.

[b] The AI exposure values are the GPT-4–classified beta exposure measure from Eloundou et al., "GPTs Are GPTs"; the value for each occupational category is the (unweighted) average of the AI exposure value across the detailed occupations that compose the category.

[c] "College or higher (percentage)" is the share of workers who have a college degree or higher.

[d] The number of workers in the occupational category is all employed workers, self-employed or otherwise, who are not living in group quarters or in the armed forces and who have nonzero earned income.

Limitations

This approach of examining differences in estimated exposure at the occupational level together with occupation-level demographics provides some early indications of the potential impacts of AI on Black

workers but also has some limitations. These limitations are in part a function of the early stage of AI adoption, such that available data are incomplete and impacts have only begun to emerge.

While the AI exposure measure we employ has been commonly used in broadly similar analyses, it is only one among a number of recently developed measures—and although different measures tend to generally correlate, they do not perfectly agree (Yin et al. 2026).[19] For this reason, which can be interpreted both as a form of measurement error and as a function of uncertainty around the nature of AI applications at work, we generally interpret results in relative and ordinal terms rather than absolute or cardinal terms. Using this interpretation, the generally intuitive ranking of the degree of AI exposure across occupational categories shown in table 1 provides some reassurance. But we caution against overinterpreting specific AI exposure values.

In addition, AI exposure does not reflect current or actual adoption or use of AI at work. In one sense, this is a relative strength of AI exposure for considering the likely future impacts of AI, given that AI adoption is still in relatively early stages and that forward-looking questions are of interest. For this same reason, however, it is necessarily prospective and uncertain. Only time will tell whether exposure translates into adoption or economic impact. One way to contextualize these findings is to consider research on AI adoption, which tells a consistent story. Adoption data have found, for example, that AI use is relatively high in computer and management occupations (Bick et al. 2026). And research on the use of generative AI tools has found that they appear to be applied to the types of computer-related tasks common in these occupations (Handa et al. 2025; Tomlinson et al. 2025).

The most important conceptual limitation of the use of AI exposure measures, discussed above, is that exposure alone has an uncertain and potentially ambiguous relationship with worker outcomes, possibly putting some workers at risk for displacement while creating opportunities for others (Autor and Thompson 2025; Pizzinelli et al. 2023). To help interpret our findings, we tabulate exposure and Black worker representation across occupations alongside other occupational characteristics, including levels of educational attainment, and consider results in the context of the literature on both AI exposure and the causes and consequences of occupational segregation. As we discuss more in our findings below, the relative exposure of Black workers across occupations and its potential consequences may reflect long-standing labor market inequities and, without policy intervention, risk perpetuating them. However, as with this literature in general, substantial uncertainty necessarily remains as to whether and how AI exposure will ultimately translate into adoption, changes in business practices, and economic impacts. We therefore present findings to offer a sense of potential directions and disruptions, not to predict change.

Analyses and Findings

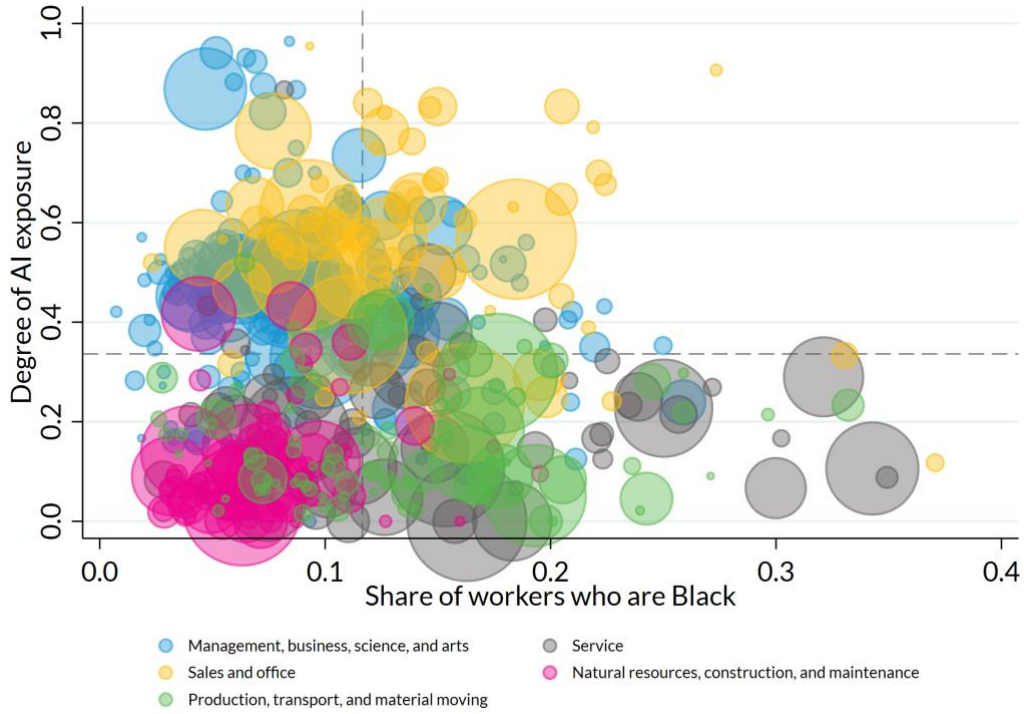
To look at the relative degree of AI exposure among Black workers, we first examine AI exposure and Black worker representation across detailed occupations. Figure 1 plots the degree of AI exposure and share of workers who are Black. Each circle represents a single occupation, and the size of each circle is proportional to the total number of workers in that occupation.

The results show a broadly negative relationship between the degree of exposure and the share of Black workers at the occupation level. This is in part because the upper-right portion of the figure—where occupations are highly exposed and have a relatively high share of Black workers—is relatively underpopulated. The circles are color-coded to identify major occupational categories, showing how differences across occupational categories help explain the relationship between AI exposure and the share of Black workers, consistent with table 1. Sales and office jobs, which have relatively high AI exposure, tend to have lower shares of Black workers, while production and transportation jobs, which have relatively low AI exposure, tend to have higher shares of Black workers.

FIGURE 1

Exposure to AI and Black Employment Shares Across Occupations

Occupations with higher shares of Black workers tend to have lower levels of AI exposure overall



Source: Authors' calculations using 2024 five-year American Community Survey and data from Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock, "GPTs Are GPTs: Labor Market Impact Potential of LLMs," *Science* 384, no. 6702 (2024): 1306–08, http://doi.org/10.1126/science.adj0998. American Community Survey data are retrieved from Steven Ruggles, Sarah Flood, Matthew Sobek, et al., IPUMS USA: Version 16.0. Minneapolis, MN: IPUMS, 2025, https://doi.org/10.18128/D010.V16.0, and Eloundou et al., "GPTs Are GPTs."

Note: Figure shows the degree of AI exposure and the share of workers who are Black by detailed occupation. The mean values of exposure and share of Black workers are indicated by dashed lines. Size of circles is proportional to the number of workers in the occupation (all employed workers, self-employed or otherwise, who are not living in group quarters or in the armed forces and who have nonzero earned income). Color of circles indicates broad occupational categories as shown. The AI exposure values are the GPT-4–classified beta exposure measure from Eloundou et al., "GPTs Are GPTs."

Because total employment and representation of Black workers is uneven across occupations, we characterize the AI exposure of occupations with large numbers of Black workers. Table 2 presents the degree of AI exposure among the largest occupations by employment counts for all Black workers overall, Black women, and Black middle-class workers (workers earning more than two-thirds but less than twice the median wage). We use only earned income to identify middle-class workers, primarily due to data availability. Although informative, these tabulations are limited because they do not account for the importance of wealth for defining class.[20] These 10 largest occupations represent an important share of employment among Black workers—for example, they employ more than 4 million Black workers.

TABLE 2

Exposure of Occupations with Largest Numbers of Black Workers

Occupations with large numbers of Black workers exhibit a range of AI exposure levels

Occupation	Black Workers (count)[a]	Occupation AI exposure (index)	Occupation share Black (percentage)	College or higher in occupation (percentage)[b]
Panel A: All Black workers				
Driver/sales workers and truck drivers	618,744	0.297	17.7	14.9
Customer service representatives	550,254	0.567	18.5	35.6
Manual laborers and freight, stock, and material movers	486,581	0.052	19.3	14.0
Cashiers	473,894	0.237	16.2	14.5
Nursing assistants	449,214	0.106	34.3	21.1
Registered nurses	420,959	0.380	12.0	94.1
Other managers	368,712	0.468	8.5	66.7
Personal care aides	365,072	0.227	25.0	23.6
Janitors and building cleaners	359,578	0.000	16.3	12.8
Cooks	319,560	0.106	15.4	10.7
Panel B: Black female workers				
Nursing assistants	402,377	0.106	34.3	21.1
Customer service representatives	400,718	0.567	18.5	35.6
Registered nurses	371,645	0.380	12.0	94.1
Cashiers	352,900	0.237	16.2	14.5
Personal care aides	292,686	0.227	25.0	23.6
Elementary and middle school teachers	233,378	0.327	9.8	96.7
Other managers	191,111	0.468	8.5	66.7
Secretaries and administrative assistants, except legal, medical, and executive	179,382	0.625	9.3	41.8

Occupation	Black Workers (count)[a]	Occupation AI exposure (index)	Occupation share Black (percentage)	College or higher in occupation (percentage)[b]
Retail salespersons	170,147	0.375	11.0	31.0
Teaching assistants	158,528	0.378	13.5	44.3
Panel C: Black middle-class workers				
Driver/sales workers and truck drivers	381,479	0.297	17.7	14.9
Customer service representatives	271,436	0.567	18.5	35.6
Registered nurses	256,398	0.380	12.0	94.1
Elementary and middle school teachers	210,175	0.327	9.8	96.7
Nursing assistants	207,767	0.106	34.3	21.1
Laborers and freight, stock, and material movers, hand	197,838	0.052	19.3	14.0
Other managers	193,705	0.468	8.5	66.7
First-line supervisors of retail sales workers	146,018	0.500	9.2	36.5
Security guards and gaming surveillance officers	141,299	0.290	32.1	27.0
Personal care aides	130,517	0.227	25.0	23.6

Source: Authors' calculations using 2024 five-year American Community Survey and data from Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock, "GPTs Are GPTs: Labor Market Impact Potential of LLMs," *Science* 384, no. 6702 (2024): 1306–08, http://doi.org/10.1126/science.adj0998. American Community Survey data are retrieved from Steven Ruggles, Sarah Flood, Matthew Sobek, et al., IPUMS USA: Version 16.0. Minneapolis, MN: IPUMS, 2025, https://doi.org/10.18128/D010.V16.0. and Eloundou et al., "GPTs Are GPTs."
Note: Table presents the characteristics of occupations, including their degree of AI exposure, for occupations with the largest numbers of Black workers, Black female workers, and Black middle-class workers, respectively. Middle-class workers are those earning more than two-thirds and less than twice the median wage; this translates to between $32,616 and $97,800 in the previous year. The number of workers is all employed workers, self-employed or otherwise, not living in group quarters or in the armed forces and who have nonzero earned income. The AI exposure values are the GPT-4–classified beta exposure measure from Eloundou et al., "GPTs Are GPTs." Occupations and labels are based on Census occupation codes and titles in the American Community Survey. "Industry and Occupation Code Lists & Crosswalks," US Census Bureau, revised May 6, 2025, https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html.
[a] "Black workers (count)" is the share of workers in each occupation who are Black.
[b] "College or higher in occupation" is the share of workers who have a college degree or higher.

Table 2 shows some of the differences in AI exposure across detailed occupations that include the largest number of Black workers, Black female workers, and Black middle-class workers, respectively. For Black workers overall, these include a mix of high- and low-exposure occupations. Consistent with the relationship in figure 1, most of these largest occupations have below-average AI exposure; some, including nursing assistants and laborers, have very low levels of AI exposure. These occupations are characterized by relatively lower levels of formal education and, correspondingly, lower wages (not shown). One interpretation of this pattern is that many Black workers are employed in occupations

that might be less affected by AI but that might not be high-wage or high-quality jobs. In contrast, occupations with relatively high AI exposure values have quite different educational characteristics. While both customer service representatives and registered nurses, for example, are relatively highly exposed, education levels are very high for the latter and relatively low for the former. As a result, any eventual effects of AI for these two groups of workers might differ in important ways.

Given the different occupations that account for the largest shares of employment among Black women, some patterns are similar, while others emerge. Overall, the degree of AI exposure is somewhat higher for Black women than for Black workers in general, as some of the lowest-exposure occupations (e.g., laborers, janitors, and cooks) are not among those with large numbers of Black women workers. Occupations employing large shares of Black women, such as elementary and middle school teachers, teaching assistants, and administrative assistants, have moderate to high levels of AI exposure. For Black women, employment across occupations with relatively high AI exposure but substantially different educational and earnings characteristics is a prominent feature of these tabulations: Customer service representatives and registered nurses are the second- and third-largest occupations for Black women, and both have high exposure. However, the former is a relatively low-education occupation, and the latter is a relatively high-education occupation. occupations with large employment shares tend to have somewhat higher AI exposure than those among Black workers overall.

For Black middle-class workers, as for Black women, occupations with large numbers of workers tend to have somewhat higher exposure than occupations employing large numbers of Black workers overall. This is consistent with some of the very lowest-exposure occupations overall being relatively lower-education, lower-wage occupations. Customer service representatives and registered nurses, along with first-line supervisors of retail sales workers and other managers, represent important middle-class occupations and have relatively higher levels of AI exposure. Again, the variation across these higher-exposure occupations in terms of education profiles—higher for registered nurses and other managers, and lower for customer service representatives and first-line supervisors of retail sales workers—suggests the potential for differential workforce impacts among even high-exposure occupations.

To summarize and further characterize the relationship between AI exposure and the share of Black workers across occupations, table 3 shows occupational characteristics by AI exposure terciles.

TABLE 3

Occupational Characteristics by AI Exposure Tercile

Patterns of demographic and economic characteristics by AI exposure categories

	Lowest exposure	Middle exposure	Highest exposure
AI exposure (index)	0.089	0.340	0.569
Demographics (%)[a]			
Black workers	13.0	12.8	9.6

	Lowest exposure	Middle exposure	Highest exposure
Black female workers	5.4	7.1	5.9
Black middle-class workers	5.4	6.6	5.5
White workers	49.8	60.2	63.6
Education and earnings[a]			
College or higher (%)	18.9	53.1	63.0
High school or less (%)	58.9	27.3	17.7
Mean wage income ($)	40,827	68,857	88,595
Counts			
Workers	40,273,198	54,251,123	56,811,296
Occupations	171	170	170

Source: Authors' calculations using 2024 five-year American Community Survey and data from Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock, "GPTs Are GPTs: Labor Market Impact Potential of LLMs," *Science* 384, no. 6702 (2024): 1306–08, http://doi.org/10.1126/science.adj0998. American Community Survey data are retrieved from Steven Ruggles, Sarah Flood, Matthew Sobek, et al., IPUMS USA: Version 16.0. Minneapolis, MN: IPUMS, 2025, https://doi.org/10.18128/D010.V16.0. and Eloundou et al., "GPTs Are GPTs."

Note: Table presents the characteristics of occupations grouped into terciles of AI exposure. The number of workers is all employed workers, self-employed or otherwise, who are not living in group quarters or in the armed forces and who have nonzero earned income. Middle-class workers are those earning more than two-thirds and less than twice the median wage; this translates to between $32,616 and $97,800 in the previous year. The AI exposure values are the GPT-4–classified beta exposure measure from Eloundou et al., "GPTs Are GPTs." The exposure value for each tercile is the unweighted average AI exposure of the detailed occupations that compose each tercile.

[a] Demographics as well as education and earnings values are shares and means, respectively, across workers in the occupations in each tercile.

Looking across occupations grouped in this way shows the apparent occupation-level association between AI exposure and the share of Black workers: Black workers are overrepresented in the lowest-exposure category and underrepresented in the highest-exposure category. For comparison, table 3 shows the analogous relationship for white workers, which shows a pronounced opposite pattern with a relatively smaller share of white workers in the less-exposed category. These demographic patterns are noteworthy given the associations between AI exposure and education and earnings across groups: The average levels of education and wages increase consistently across AI exposure terciles, with the highest-exposure category showing higher levels of both measures than the lowest-exposure category.

For Black women and Black middle-class workers, this relationship is slightly different. They are somewhat overrepresented in the middle exposure tercile and somewhat underrepresented in both the lowest- and the highest-exposure terciles. For example, Black women compose 6.2 percent of the overall workforce (not shown), but they compose 7.1 percent of the middle-exposure tercile. This is consistent with the observation that many of the lowest-exposure occupations with large numbers of Black workers often employ relatively smaller shares of women. For middle-class workers, this pattern is consistent with the positive association between exposure and earnings and education.

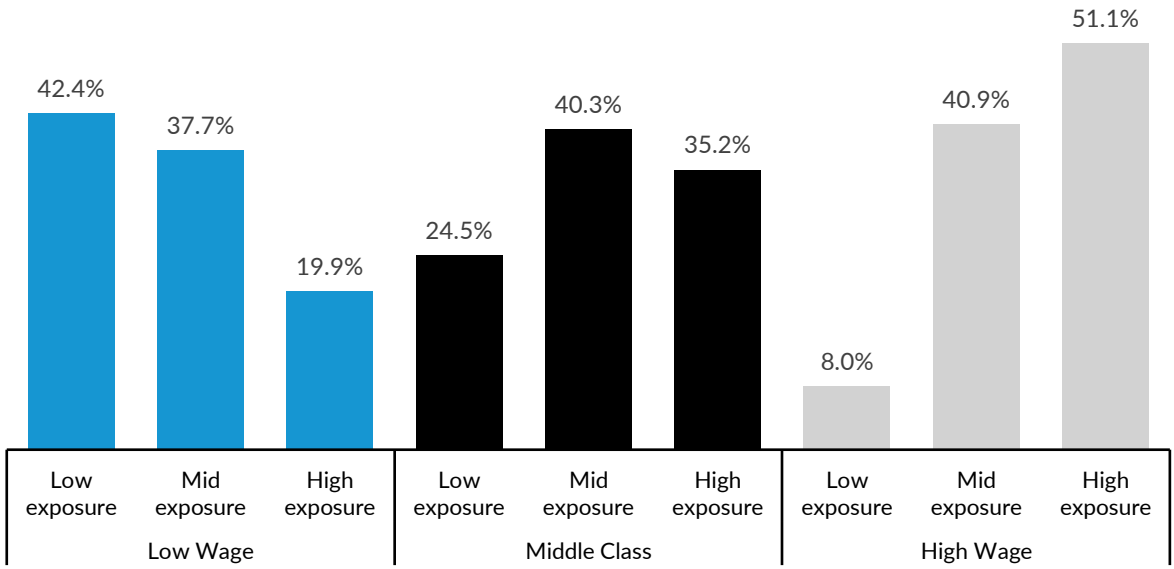
Figure 2 compares the distribution of Black middle-class workers across exposure categories with the distribution for low-wage and high-wage Black workers, respectively. Consistent with the findings shown in table 3, it shows that middle-class Black workers are predominantly in the middle-exposure category. It also shows how middle-class Black workers contrast with low-wage Black workers, who are predominantly in the lowest-exposure category, and high-wage Black workers, who are predominantly in the highest-exposure category.

FIGURE 2

Earnings Levels and AI Exposure

Low-wage, middle-class, and high-wage Black workers are distributed differently across exposure groups

Share of Black Workers (percent)



Source: Authors' calculations using 2024 five-year American Community Survey and data from Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock, "GPTs Are GPTs: Labor Market Impact Potential of LLMs," *Science* 384, no. 6702 (2024): 1306–08, http://doi.org/10.1126/science.adj0998. American Community Survey data are retrieved from Steven Ruggles, Sarah Flood, Matthew Sobek, et al., IPUMS USA: Version 16.0. Minneapolis, MN: IPUMS, 2025, https://doi.org/10.18128/D010.V16.0. and Eloundou et al., "GPTs Are GPTs."
Note: Figure presents the distribution of Black workers in three earnings categories across terciles of AI exposure. Low-wage workers are defined as those earnings less than two-thirds of the median wage; middle-class workers are defined as those earning between two-thirds and twice the median wage; and high-wage workers are defined as those earnings more than twice the median wage.

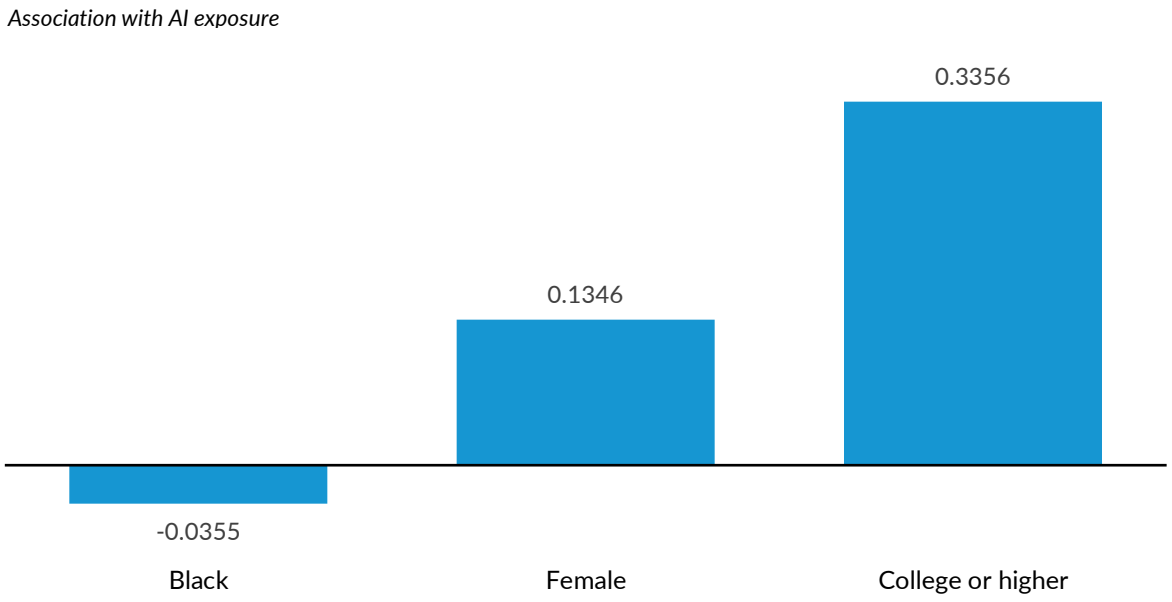
We investigate the association between AI exposure and the representation of Black workers across occupations using two linear regressions: one that quantifies the unconditional relationship between AI exposure and Black worker representation across occupations and one that examines how this relationship changes when controlling for other occupational characteristics.[21] The first regression (not shown) finds a clear negative, though only marginally statistically significant, relationship between

AI exposure and the representation of Black workers, consistent with figure 1.[22] That is, occupations with larger shares of Black workers tend to have lower levels of AI exposure. The second regression (results shown in figure 3) adds controls for other demographic characteristics and the educational composition of the occupation. After controlling for these factors, there is effectively no independent relationship between AI exposure and Black worker representation; the association is small and not statistically distinguishable from zero.

FIGURE 3

Association Between Occupational Demographics and AI Exposure

The association between AI exposure and Black representation is dependent on other factors



Source: Authors' calculations using 2024 five-year American Community Survey and data from Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock, "GPTs Are GPTs: Labor Market Impact Potential of LLMs," *Science* 384, no. 6702 (2024): 1306–08, http://doi.org/10.1126/science.adj0998. American Community Survey data are retrieved from Steven Ruggles, Sarah Flood, Matthew Sobek, et al., IPUMS USA: Version 16.0. Minneapolis, MN: IPUMS, 2025, https://doi.org/10.18128/D010.V16.0. and Eloundou et al., "GPTs Are GPTs."
Note: Figure shows selected coefficients from a linear regression of occupation-level AI exposure on worker characteristics, including the share of workers who are Black, female, have a high school diploma (not shown), have some college (not shown), have a college degree or higher, and mean log wages (not shown). Observations are occupations (n = 511).

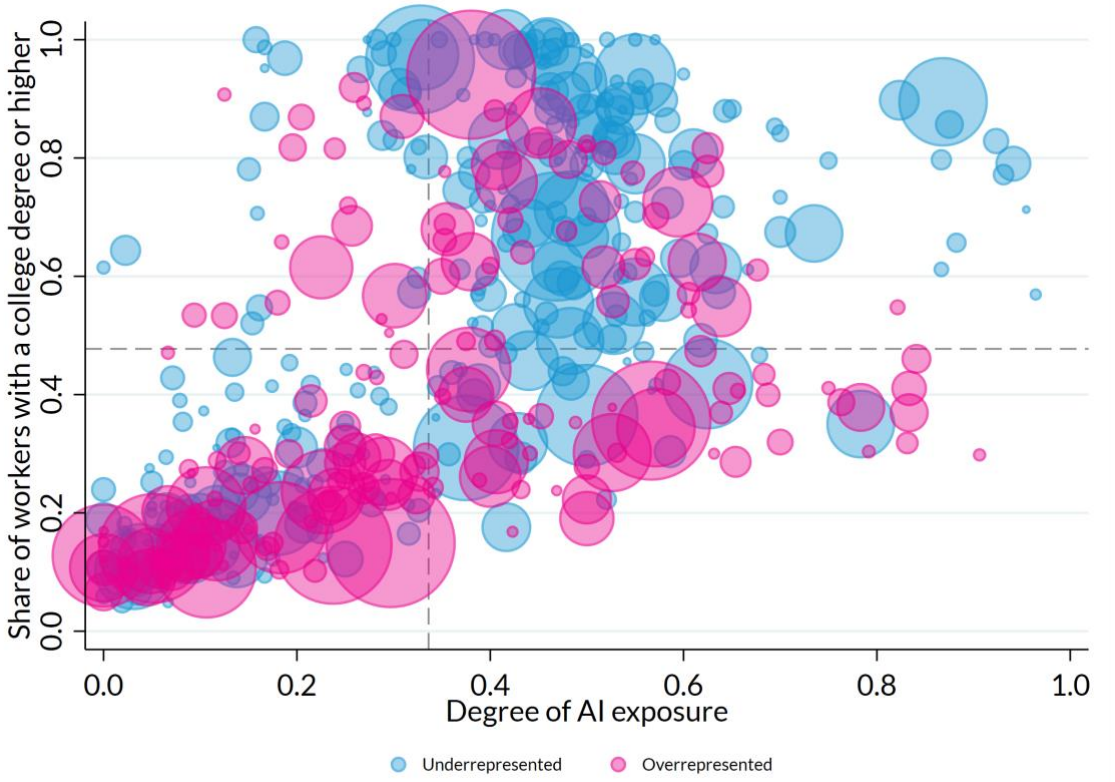
We interpret this pattern of results as broadly consistent with a possible interaction between AI exposure and occupational segregation. That is, research has found that forces associated with occupational segregation and crowding tend to crowd Black workers into occupations with lower levels of formal education and wages (Biu et al. 2023). At the same time, as shown in table 3 and consistent with other research on AI exposure as discussed above, there is a positive relationship across occupations between levels of formal education and AI exposure. The combination of these forces might have led Black workers to be overrepresented in lower-exposure occupations.

To provide some evidence of the potential degree of automation versus augmentation or adaptation for Black workers, we use the education profile of occupations to roughly categorize the extent to which AI exposure may represent work that substitutes for or complements AI. Specifically, we look at the share of workers in the occupation with a college degree or higher and interpret higher shares as suggestive of work that is more likely to be complementary with AI (Pizzinelli et al. 2023) and may be performed by workers with greater capacity to adapt to AI (Manning and Aguirre 2026). While this is a simplified version of such an assessment—augmentation and adaptation are likely to depend on this factor as well as other important factors—it provides some initial, if suggestive, evidence on this crucial question for future research.

FIGURE 4

Association Between Education, AI Exposure, and Black Worker Representation

Black workers are overrepresented in occupations with lower levels of education, regardless of exposure



Source: Authors' calculations using 2024 five-year American Community Survey and data from Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock, "GPTs Are GPTs: Labor Market Impact Potential of LLMs," *Science* 384, no. 6702 (2024): 1306–08, http://doi.org/10.1126/science.adj0998. American Community Survey data are retrieved from Steven Ruggles, Sarah Flood, Matthew Sobek, et al., IPUMS USA: Version 16.0. Minneapolis, MN: IPUMS, 2025, https://doi.org/10.18128/D010.V16.0. and Eloundou et al., "GPTs Are GPTs."

Note: Figure shows the degree of AI exposure and the share of workers with a college degree or higher by detailed occupation. The mean values of exposure and the share of workers with a college degree or higher are indicated by dashed lines. Color of circles indicates whether Black workers are over- or underrepresented in occupations. Size of circles is proportional to the number of workers in the occupation. The AI exposure values are the GPT-4–classified beta exposure measure from Eloundou et al., "GPTs Are GPTs."

Figure 4 plots occupations by their degree of AI exposure and share of workers with a college degree or higher and shows occupations in which Black workers are underrepresented (blue circles) and overrepresented (red circles); the size of circles is proportional to the number of workers in the occupation. The figure illustrates the generally positive relationship between AI exposure and levels of formal education across occupations. It also shows a general pattern of Black workers being overrepresented in occupations with lower-than-average levels of formal education. Consequentially, large, high-exposure occupations in which Black workers are overrepresented tend to cluster in the high-exposure, low-education quadrant (bottom right); while those in which Black workers are underrepresented tend to cluster in the high-exposure, high-education quadrant (top right), with registered nurses as a notable exception.

We interpret the high-exposure, high-education quadrant (top right) as representing AI exposure that is more likely to reflect opportunities for augmentation and the high-exposure, low-education quadrant (bottom right) as representing exposure that is more likely to reflect risks of automation and potential displacement. Interpreting figure 4 in this way suggests that, among occupations with relatively high AI exposure, those with greater risk of displacement tend to be occupations in which Black workers are overrepresented. This pattern, as with the findings discussed above, is related to the general overrepresentation of Black workers in occupations with lower levels of education. This again suggests that occupational segregation and crowding may play a role in explaining the relative risks faced by Black workers. The result is that, among occupations that are exposed to AI, Black workers are overrepresented in occupations where the risks of automation and displacement may be relatively high (e.g., customer service representatives).

Conclusion and Recommendations for Future Research

Whether the adoption of AI leads to workers using the technology as jobs change, displacement due to automation, or other effects, it signifies a meaningful shift in how people work and the "economic value of their work" (Neal and Walsh 2026, 6). Given this and the preliminary state of research on its current and likely impacts, more research is needed to better understand which workers AI will affect and how. This is especially true for Black workers who are historically and structurally at risk of being left out of these gains. At the same time, given the lessons of the past and what we know about the potential impacts of AI, policymakers need not wait to take actions that evidence suggests can help not only protect Black workers against risks posed by AI but also ensure that they more fully share in its economic benefits.

Directions for Research

One essential need is continued research into the ongoing and likely impacts of AI with a focus on its potentially disparate impacts on Black workers, including its implications for the Black middle class and wealth building among Black households. The analysis above, in combination with prior research, suggests that Black workers might face a relative disadvantage in occupations that are exposed to AI. But additional work could better characterize the degree and nature of automation and displacement

risk among exposed workers, as well as the relationship between exposure and job quality. Future research could more closely investigate how occupational crowding contributes to differential exposure. There is also a need for further research on the impacts of AI on the Black middle class through wealth-building channels, in addition to labor market channels. That is, to the extent that AI disproportionately rewards capital rather than labor, it will be important to study whether and how wealth might become relatively more important for building an economically secure Black middle class.

Another line of research is interventions that might build worker resilience to AI exposure, including how to effectively train, retrain, and upskill workers so that they can share in the economic benefits of AI. As discussed above, researchers have studied workers' adaptability to AI-induced job displacement and found that "many occupations highly exposed to AI contain workers with relatively strong means to manage a job transition" (Manning and Aguirre 2026). Adaptive capacity measures a set of characteristics that are necessary for workers navigating job transitions *if* they are displaced. Researchers have found that AI exposure and adaptive capacity are positively correlated. That is, the goal is not to reduce Black workers' exposure to or use of AI but to increase the number and share of Black workers who are positioned to benefit from AI-augmented work and, thus, higher wages.

Future research could examine what happens to Black workers who experience job displacement, what types of training or on-the-job experiences are most helpful in preventing displacement, and what economic and transition supports best help ensure that Black workers who experience displacement are able to transition quickly into new roles. The private sector and federal, state, and local policymakers have dedicated resources to building AI skills into workforce development programs. By understanding the rates of AI exposure by industry and job type and mapping them to demographics, policymakers can determine whether resources are reaching the industries and workers with the greatest need to help mitigate displacement while increasing augmentation.

Future studies could also examine whether Black workers are more likely to experience reduced schedules and therefore reduced employment benefits, or whether they are losing work altogether because of outright displacement. It is important to understand whether AI-exposed workers can maintain full or partial employment and benefits or whether they are being replaced entirely.

Directions for Policy

While further research is necessary to better understand a number of these issues, available evidence suggests directions for action now. There is urgency because the potential impacts of AI on Black workers compound already well-studied labor market disadvantages that policy should seek to address. It is well documented, for example, that Black workers in the US experience racial disparities across many labor market outcomes, including unemployment, wages, and access to benefits such as paid leave. These disparities are not associated with individual choices or educational inequities, with some studies showing the most substantial gaps in labor market outcomes between Black and white college graduates (Congdon et al. 2024; Hamilton et al. 2021).

Policies that enforce equitable access to employment, offer stable employment, and guarantee fair compensation can help ensure that Black workers are not discriminated against or disadvantaged in the hiring process or while working. Researchers have advocated for the Equal Employment Opportunity Commission (EEOC) to pursue proactive hiring audits (Ford, Cusella, et al. 2024). Similarly, the EEOC could investigate instances of worker displacement based on some combination of race and/or race and gender. In 2021, for example, the commission published a report that analyzed Black workers' status in the civilian federal workforce (EEOC 2023). The EEOC could update these data and analyses to provide more information about what has happened to Black women workers in the federal workforce or expand the analyses to include Black women workers nationally across the public, private, and nonprofit sectors to evaluate whether the separations were discriminatory. Other research has shown how policies that enable workers to unionize and bargain collectively can help Black workers achieve better working conditions (Congdon et al. 2024). There is evidence that joining unions gives Black workers more bargaining power and access to higher wages and benefits. Black women, for example, are more likely than women of other races to be union members, and wage disparities are lower among union members (Ford, Cusella, et al. 2024).

There is also scope for policy action to address the potential economic impacts of AI on Black workers by drawing on research on how policy can most effectively protect workers' economic security, regardless of the specific economic or technological forces that might lead to their displacement. There are several economic policies that have helped, or could help if fully implemented, reduce the economic impacts of displacement for all workers, particularly Black workers. For example, there are gaps in the current unemployment insurance system—the primary source of economic support for dislocated workers—that policy reforms could address (Congdon and Vroman 2022). Such reforms are important for the economic security of Black workers who might be displaced by AI, because evidence shows that the existing unemployment insurance system does not adequately support Black workers in particular (O'Leary et al. 2022).

Finally, existing research suggests that local, state, and federal policymakers, along with employers, could better support all workers, including Black workers, by expanding access to retraining and reskilling programs. A recent article highlights the lack of robust investment in "active labor market policy spending," with the US ranking second to last among all 38 Organisation for Economic Co-operation and Development countries in such investments.[23] By investing more and proportionate resources in mentorships, apprenticeships, and technical training programs, workers can learn how to use new technologies, including AI, and navigate job changes and the creation of new roles. The US Department of Labor recently launched a new initiative to integrate AI into registered apprenticeships nationwide. Through its Employment and Training Administration, the Department of Labor announced a national contracting opportunity designed to speed up the adoption of AI skills into Registered Apprenticeship programs.[24] The initiative has three key priorities: "embedding AI training, tools, and curricula into existing apprenticeship programs; including AI in roles that directly build, manage, or apply AI technologies; and strengthening workforce pipelines in areas like data centers, telecommunications, and advanced manufacturing."[25]

Notes

[1] Kelemwork Cook, Duwain Pinder, Shelley Stewart, Amaka Uchegbu, and Jason Wright, "The Future of Work in Black America," McKinsey Insights, October 4, 2019, https://www.mckinsey.com/featured-insights/future-of-work/the-future-of-work-in-black-america.

[2] Jan Shelly Brown, Matthew Finney, Natasha Korgaonkar, Mark McMillan, and Chris Perkin, "The Impact of Generative AI on Black Communities," McKinsey Institute for Economic Mobility, December 19, 2023, https://www.mckinsey.com/institute-for-economic-mobility/our-insights/the-impact-of-generative-ai-on-black-communities.

[3] "What Is Automation?" IBM, accessed June 29, 2026, https://www.ibm.com/think/topics/automation.

[4] Brown et al., "The Impact of Generative AI on Black Communities."

[5] Katelynn Harris, "Forty Years of Falling Manufacturing Employment," *Beyond the Numbers*, US Bureau of Labor Statistics, November 2020, https://www.bls.gov/opub/btn/volume-9/forty-years-of-falling-manufacturing-employment.htm.

[6] Tiffany Ford, "Historical Unemployment for Black Women and Men in the United States: 1954–2021," Brookings Institution, February 13, 2023, https://www.brookings.edu/articles/historical-unemployment-for-black-women-and-men-in-the-united-states-1954-2021/.

[7] "Jobs and Unemployment," *Rise Up North: Detroit*, accessed June 29, 2026, https://riseupdetroit.org/chapters/chapter-2/part-1/jobs-and-unemployment/#:~:text=Using%20old%20technology%20and%20trying,its%20federally%20funded%20apprenticeship%20program.

[8] In this line of research, many early measures of AI adoption have not yet focused closely or reported extensively on any differences in AI use at work by race. See, for example, "Gen AI/ dpotionTracker," accessed July 7, 2026, https://www.genaiadoptiontracker.com/; and Luona Lin, "About 1 in 5 US Workers Now Use AI in Their Job, Up Since Last Year," October 6, 2025, Pew Research Center, https://www.pewresearch.org/short-reads/2025/10/06/about-1-in-5-us-workers-now-use-ai-in-their-job-up-since-last-year/.

[9] In addition to caveats related to interpreting how exposure might affect labor market impacts, there are some caveats related to the measures themselves, which we discuss in the "Data Sources and Methods" section.

[10] "Displacement" refers to the process through which a worker experiences a loss of employment due to the position being eliminated, an organization or site closing, or an organizational restructuring. See, for example, "Worker Displacement News Release," US Bureau of Labor Statistics, August 29, 2024, https://www.bls.gov/news.release/disp.htm.

[11] "AI's Impact Accelerates," Morgan Stanley, February 5, 2026, https://www.morganstanley.com/insights/articles/ai-adoption-accelerates-survey-find; and Michael Chui and Lareina Yee, "AI Could Increase Corporate Profits by $4.4 Trillion a Year, According to New Research," McKinsey Global Institute, July 7, 2023, https://www.mckinsey.com/mgi/media-center/ai-could-increase-corporate-profits-by-4-trillion-a-year-according-to-new-research.

[12] Mark A. Wynne and Lillian Derr, "Advances in AI Will Boost Productivity, Living Standards over Time," Federal Reserve Bank of Dallas, June 24, 2025, https://www.dallasfed.org/research/economics/2025/0624; and Seb Murray, "How Artificial Intelligence Impacts the US Labor Market," MIT Management Sloan School, October 9, 2025, https://mitsloan.mit.edu/ideas-made-to-matter/how-artificial-intelligence-impacts-us-labor-market.

[13] "Occupations with the Largest Share of Women Workers," US Department of Labor, Women's Bureau, updated April 2026, https://www.dol.gov/agencies/wb/data/occupations/largest-share-women-workers.

[14] Economic Policy Institute, State of Working America Data, "Unemployment Rate," dataset for Current Population Survey, EPI extracts for 2025, accessed June 29, 2026, https://data.epi.org/labor_force/labor_force_unemp/line/year/national/percent_unemp/race?timeStart=1976-01-01&timeEnd=2025-01-01&dateString=2025-01-

01&focuses=gender_female&highlightedLines=race_white&highlightedLines=race_black&highlightedLines=race_his.

[15] The descriptions of tasks by occupation were collected from O*NET, which keeps a repository of task descriptions. Each task was assessed based on the reduction of time required to complete the task and the quality of the output when implementing AI. In our analysis, we implement the GPT-4–classified beta exposure measure, which weighs tasks directly exposed to AI tools twice as much as tasks that require a secondary tool for AI tools to be integrated into the task.

[16] "Exposure" is defined as a measure of whether AI tools could reduce the time required to perform a task by 50 percent.

[17] We use the 2024 five-year American Community Survey (ACS) to conduct analysis of worker subgroups across detailed occupations. We connect AI exposure data to the ACS data at the detailed occupation level using a crosswalk between the Standard Occupation Codes used in the AI exposure data with the ACS occupation codes from the US Census Bureau. See "Industry and Occupation Code Lists & Crosswalks," US Census Bureau, revised May 6, 2025, https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html.

[18] To align with the Bureau of Labor Statistics's measure of the employed labor force, we exclude ACS workers in the armed forces. We include both employed-for-pay and self-employed workers.

[19] See, for example, Martha Gimbel , Joshua Kendall and Ryan Kulsakdinun, "Labor Market AI Exposure: What Do We Know?" Yale Budget Lab, February 19, 2025, https://budgetlab.yale.edu/research/labor-market-ai-exposure-what-do-we-know.

[20] For purposes of these tabulations, we define middle-class workers as those earning more than two-thirds and less than twice the median wage based on their annual wage and salary income; this translates to between $32,616 and $97,800 in the previous year.

[21] To illustrate the occupation-level relationship, the findings presented here use occupations as the unit of observation but do not weight occupations by their relative size; regressions weighted by total employment (not reported) generate qualitatively similar results.

[22] A regression of exposure on the occupation share of Black workers alone estimates a coefficient of −0.232, with a standard error of 0.144 (not shown). A regression with controls for gender and education (as in figure 3) estimates a coefficient of −0.036, with a standard error of 0.143.

[23] Sara Freuh, "Retraining Workers for the Age of AI," National Academies, December 1, 2025, https://www.nationalacademies.org/news/retraining-workers-for-the-age-of-ai.

[24] See US Department of Labor, "US Department of Labor Launches Landmark Initiative to Integrate Artificial Intelligence Skills into Registered Apprenticeships Nationwide," news release, April 1, 2026, https://www.dol.gov/newsroom/releases/eta/eta20260401.

[25] US Department of Labor, "US Department of Labor Launches Landmark Initiative to Integrate Artificial Intelligence Skills."

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About the Authors

William J. Congdon is a senior fellow in the Work, Education, and Labor Division at the Urban Institute. His research focuses on labor markets, economic policy, and social insurance. Congdon was previously a senior economist at the Council of Economic Advisers and a fellow and founding member of the White House Social and Behavioral Sciences Team during the Obama administration. He holds a PhD in economics from Princeton University.

LesLeigh D. Ford is an associate director and practice area lead in the Center for Equity and Community Impact at the Urban Institute. She leads and contributes to research and policy-advising projects that explore sources of and solutions to racial inequities. Ford has led research at Urban on topics such as diversifying the health care workforce, expanding the Black maternal health workforce, and improving access to leadership development programs for racial-equity-focused leaders of color. She currently leads a Center for Equity and Community Impact initiative that focuses on advancing wealth equity for Black Americans. Her previous work includes evaluations of philanthropic and government-funded grant programs and research and advising that inform funder decisionmaking and practice. Ford earned a BA in political science and English from the University of Michigan, an MA in education policy and management from the Harvard Graduate School of Education, and a PhD in sociology from Duke University.

Claire Cusella is an associate director in the Center for Equity and Community Impact. Her portfolio includes research and policy projects focused on scoring policy proposals to improve equity outcomes, advancing wealth building and economic mobility solutions, and supporting federal agencies in implementing their equity strategies and goals. Before joining Urban, Cusella spent seven years at Equal Justice Works, an organization dedicated to promoting lifelong commitments to public service and equal justice through legal fellowships. In her most recent role there, she served as senior manager of strategy execution, leading enterprise-level coordination to mobilize lawyers, advocates, and organizers to address a wide range of unmet legal needs. Cusella holds a BA in political science and sociology from the State University of New York College at Geneseo and a master of public administration from the Maxwell School of Citizenship and Public Affairs at Syracuse University. She is certified as a project management professional by the Project Management Institute.

Fernando Hernandez-Lepe is a research associate in the Tax and Income Supports Division at the Urban Institute. He has more than 10 years of experience conducting quantitative research on topics related to aging, health care, food access, and education workforce development. His work on simulations includes supporting the Health Insurance Policy Simulation Model and the Social Genome Model. In addition, he has conducted research assessing the impact of removing Supplemental Nutrition Assistance Program benefits after expansions expired, the decisionmaking of informal caregivers and older parents regarding where to move, and how these decisions are linked to the propensity to provide care. This work used multivariate regression modeling, including probabilistic and difference-in-difference modeling.

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