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DATA BRIEF

JOBS AT RISK — U.S. EMPLOYMENT IN THE NEW AGE OF AUTOMATION (PART I)

QUICK BRIEF

PURPOSE

The goal of this brief is to introduce a new approach to estimating near-term automation displacement risk for individual occupations and for U.S. employment overall. Researchers have studied the impact of new automation technologies on labor for decades. However, in recent years, there has been a swell of new studies motivated by the rapid pace of development in fields such as artificial intelligence and advanced robotics. Approaches have varied widely, leading to correspondingly disparate estimates of the exposure of U.S. workers to these technologies and the extent to which labor is at risk of displacement. This variation was highlighted in a June 2023 *New York Times* article titled "The AI Revolution Will Change Work. Nobody Agrees How."

In response to these developments, SHRM has launched a new line of research in 2025 aimed at developing a novel method for measuring near-term automation displacement risk for the current population of U.S. workers. Critically, *this work does not attempt to forecast future job losses stemming from automation*; rather, our aim is to assess how exposed the current U.S. workforce is to automation displacement risk. By doing so, we seek to understand the extent to which current employment is exposed to risk, the types of occupations that are most and least exposed, and the types of workers who are most and least likely to be affected by automation displacement in the foreseeable future.

As indicated in the title of this brief, the work discussed here represents a first step in assessing the distribution of automation displacement in current U.S. employment using publicly available data. This data provides valuable insights but also has some limitations. Consequently, our follow-up work will focus on leveraging a large-scale SHRM survey to improve and extend these estimates.

DEFINITIONS

In this section, we will discuss the features of this method and the data used. The following terms will be especially important:

1. **Automation**: The use of any process to complete a task without human input. Typically, automation occurs when machines and/or software are used to complete tasks that were previously completed by human labor.
2. **Automation displacement risk**: The risk that human labor will be displaced by automation technology. In this study, our focus is on understanding the automation risk that individual occupations face.
3. **Automation displacement risk distribution**: The distribution of automation displacement risk within an occupation. In this work, we use five levels of risk:

   a. Negligible b. Slight c. Moderate d. High e. Very high

An automation displacement risk distribution for any given occupation reports the share of employment within the occupation that faces each level of risk. For example, the automation displacement risk distribution for a hypothetical occupation A might report that 20% of employment in A faces negligible risk, 30% faces slight risk, 35% faces moderate risk, 14% faces high risk, and 1% faces very high risk.

4. **Near-term**: In this study, we talk about automation displacement risk in the near term. This concept is not attached to any specific period of time (e.g., within "X" years). Rather, it is simply meant to capture the idea that we are focusing on displacement that could occur in the near future.

METHODS AND DATA

A detailed review of our methods and data sources is provided in the methodological appendix. However, a cursory explanation of our approach is that we estimate automation displacement risk distributions for individual occupations based on O*NET degree of automation data.[1] The O*NET survey question that generates this data is very straightforward:

How automated is your current job?

- Not at all automated
- Slightly automated
- Moderately automated
- Highly automated
- Completely automated

For 858 occupations in the O*NET data, the percentage distribution of survey responses is reported. For example, for O*NET occupation 41-3041.00 (travel agents), 9.16% of survey respondents report that their job is not at all automated, 1.48% report that their job is slightly automated, 23.59% report that their job is moderately automated, 31.27% report that their job is highly automated, and 34.5% report that their job is completely automated.

For each occupation, we assume that this distribution of current automation levels reflects the true distribution of automation levels for U.S. workers employed in the occupation. Furthermore, we assert that each occupation's distribution of future automation displacement risk relates directly to its current distribution across automation levels:

- % Not at all automated → % negligible automation displacement risk
- % Slightly automated → % slight automation displacement risk
- % Moderately automated → % moderate automation displacement risk
- % Highly automated → % high automation displacement risk
- % Completely automated → % very high automation displacement risk

Returning to the specific example of travel agents cited above, this assertion implies that a total of 31.27% + 34.5% = 65.77% of travel agents face high or very high automation displacement risk, with the remainder facing moderate (23.59%), slight (1.48%), or negligible (9.16%) risk.

In short, the methodology we adopt makes the central assumption that an occupation's current automation level is indicative of future automation displacement risk (i.e., the more automated an occupation is today, the more likely it is to be displaced by automation in the future). The basic intuition of this assumption is that highly automated occupations are comparatively likely to be fully displaced by automation due to minor technological advances, regulatory changes, and/or consumer preferences. In contrast, jobs that are currently not very automated would probably only face automation displacement due to groundbreaking developments.

With the O*NET degree of automation data in hand, our estimates of automation displacement risk depend on merging the O*NET data with occupation-level employment information from the U.S. Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) program. All relevant details are provided in the methodological appendix.

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[1] O*NET is a widely used database that uses survey data to describe the characteristics of over 800 occupations in the U.S. In this study, we use the "Degree of Automation" question in O*NET's Work Context module to estimate the distribution of automation displacement risk for each occupation in the O*NET data. The O*NET data is updated frequently; we use version 29.1, which was published in November 2024. The O*NET program is sponsored by the U.S. Department of Labor, Employment and Training Administration.

KEY FINDINGS

In developing and exploring this new measure of automation displacement risk, we have arrived at a number of key findings:

1. 12.6% of current U.S. employment (19.2 million jobs) faces high or very high automation displacement risk.

2. The share of employment facing high or very high automation displacement risk varies significantly by occupational group, from a low of 4.7% to a high of 19.9%.

3. Blue-collar, service, and white-collar administrative support occupations are comparatively likely to face very high automation displacement risk.

4. The share of employment facing high or very high automation displacement risk also varies significantly by industry, from a low of 8.9% to a high of 17.4%.

KEY FINDING NO. 1

12.6% OF CURRENT U.S. EMPLOYMENT (19.2 MILLION JOBS) FACES HIGH OR VERY HIGH AUTOMATION DISPLACEMENT RISK

Estimated Distribution of Current U.S. Employment Across Levels of Automation Displacement Risk

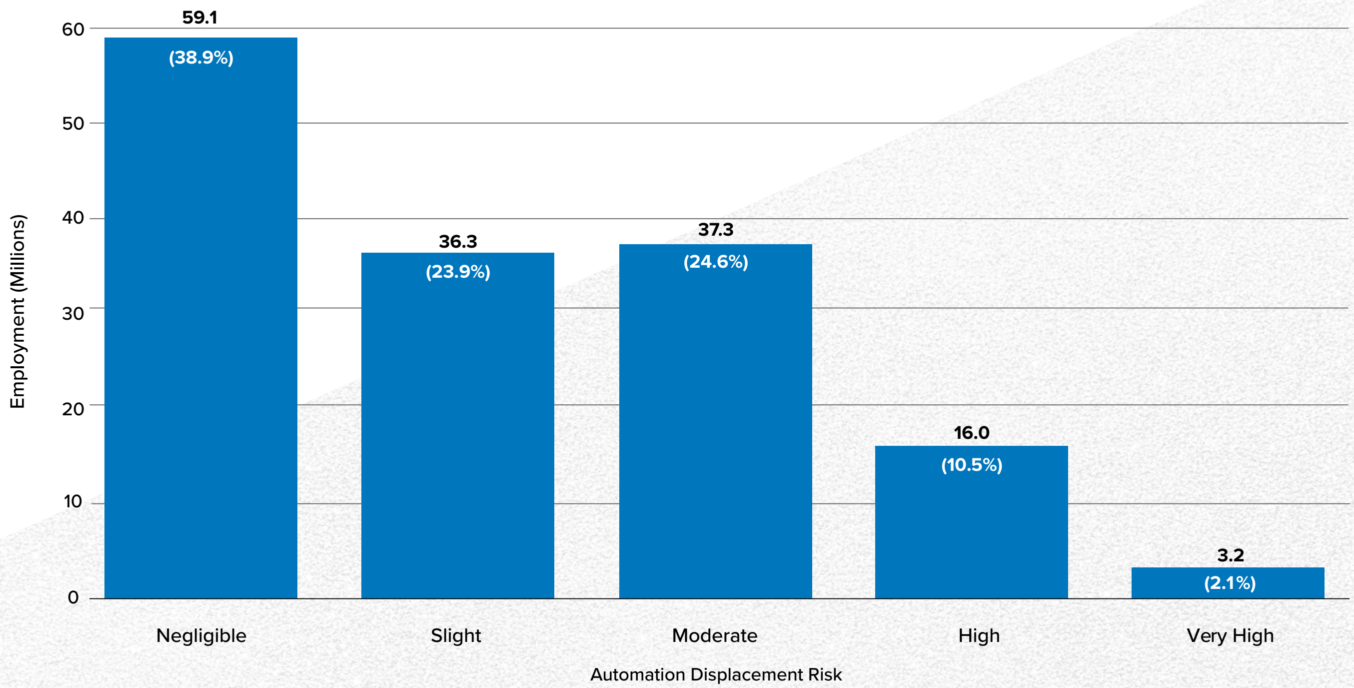


FIGURE 1

Source: Calculations based on O*NET 29.1 database (U.S. Department of Labor, Employment and Training Administration) and employment data from the BLS May 2023 National Occupational Employment and Wage Estimates, a product of the BLS Occupational Employment and Wage Statistics (OEWS) program.

In order to estimate overall automation displacement risk across current U.S. employment, we first estimate the share of employment that faces negligible, slight, moderate, high, and very high risk within each of 831 occupations covered in the BLS employment data. Having done this, we aggregate up across all occupations to obtain overall estimates.

The BLS National Occupational Employment and Wage Estimates data for May 2023 lists total nonfarm wage/salary employment at approximately 151.9 million workers.[1] Of this group, we estimate that about 38.9% of total employment (59.1 million jobs) faces negligible automation displacement risk in the near future because they are currently not at all automated. Furthermore, nearly half of total employment (roughly 73.6 million jobs) faces slight or moderate risk. The remaining 19.2 million jobs (about 12.6% of total employment) are projected to face high or very high automation displacement risk in the near term because they are already highly or completely automated.

What can be gleaned from these overall results? First and foremost, our findings suggest that the vast majority of current jobs are unlikely to be completely displaced by automation in the near term because they currently require a sufficiently high level of human input to make the leap to full displacement relatively unlikely over a short period. Having said that, it is also true that a clear majority of current jobs are already automated to some extent, so even if actual displacement risk is relatively limited, rapidly advancing automation technology (e.g., the development of generative AI tools) will almost certainly transform a large share of employment in the years ahead.

Another implication of our results is that a notable minority of current U.S. workers are likely to face relatively challenging labor market conditions in the near term because their current job is already highly or completely automated. This does not mean that all 19.2 million workers who we estimate face high or very high displacement risk will lose their jobs; in fact, as we will discuss in the caveats section below, real-world exposure to automation risk may be relatively low for many workers in this set, even if sufficiently advanced automation technology already exists.[2] Even so, the need to reskill/upskill will likely be pressing for many members of this group, particularly the 3.2 million workers we estimate to be in the very high risk category.

[1] Total nonfarm wage/salary employment is limited to wage or salary workers employed in nonfarm establishments; consequently, it excludes some employment (most notably, self-employed workers).

[2] For example, in the O*NET degree of automation data for airline pilots, roughly two-thirds of respondents described their job as "highly automated," the response we associated with high near-term automation displacement risk. In fact, from a purely technological perspective, fully autonomous commercial passenger planes are already feasible; however, a number of other barriers (e.g., legal and regulatory issues, consumer preferences) will likely shield airline pilots from substantial automation displacement risk, at least in the near future.

KEY FINDING NO. 2

THE SHARE OF EMPLOYMENT FACING HIGH OR VERY HIGH AUTOMATION DISPLACEMENT RISK **VARIES SIGNIFICANTLY BY OCCUPATIONAL GROUP**

Estimated Share of Employment at High or Very High Automation Displacement Risk by Major Occupational Group

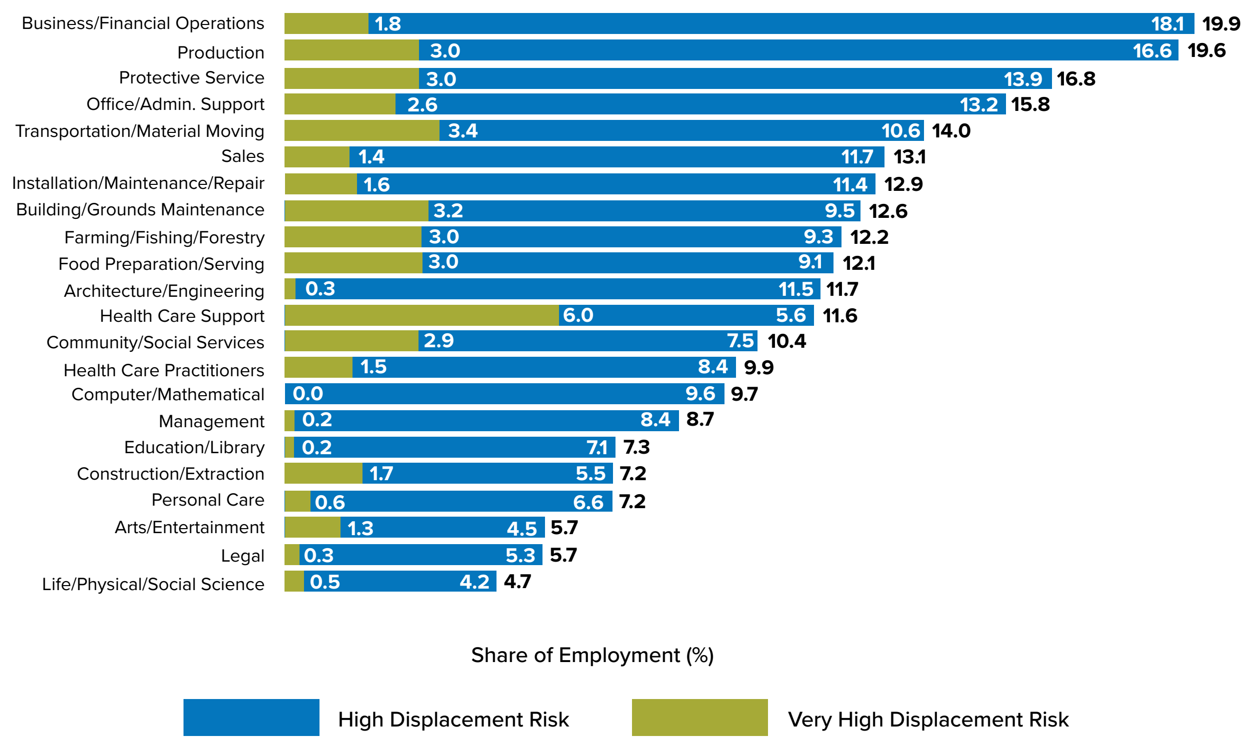


FIGURE 2

Source: Calculations based on O*NET 29.1 database (U.S. Department of Labor, Employment and Training Administration) and employment data from the BLS May 2023 National Occupational Employment and Wage Estimates, a product of the BLS Occupational Employment and Wage Statistics (OEWS) program.

Because individual automation technologies are fundamentally tied to replacing human labor for specific tasks, it comes as no surprise that our estimates of automation displacement risk vary significantly by occupation. Figure 2 illustrates this by plotting the share of employment we flag as having high or very high exposure to near-term automation displacement risk by major occupational group.

According to our estimates, the share of current employment facing high or very high near-term automation displacement risk varies from a high of 19.9% (business and financial operations) to a low of 4.7% (life, physical, and social sciences). In almost all cases, the share of workers facing high risk is much larger than the share facing very high risk; in fact, the estimated fraction of employment facing very high risk of near-term automation displacement risk is 0.6% or less in seven major occupational groups.

KEY FINDING NO. 3

BLUE-COLLAR, SERVICE, AND WHITE-COLLAR ADMINISTRATIVE SUPPORT OCCUPATIONS FACE **ELEVATED AUTOMATION DISPLACEMENT RISK**

Estimated Share of Employment Facing High or Very High Automation Displacement Risk by Worker Type

	SHARE OF EMPLOYMENT (%)		
PANEL 1 — WHITE-COLLAR	**HIGH RISK**	**VERY HIGH RISK**	**HIGH OR VERY HIGH RISK**
Overall	10.9	1.4	12.3
Professional, technical, and related	7.9	0.8	8.7
Executive, administrative, and managerial	13.2	1.0	14.2
Sales	11.7	1.4	13.1
Administrative support	13.2	2.6	15.8
PANEL 2 — BLUE-COLLAR	**HIGH RISK**	**VERY HIGH RISK**	**HIGH OR VERY HIGH RISK**
Overall	11.3	2.7	14.0
Precision production, craft, and repair	8.4	1.7	10
Machine operators, assemblers, and inspectors	16.6	3.0	19.6
Transportation and material moving	10.6	3.4	14.0
Handlers, equipment cleaners, helpers, and laborers	9.3	3.0	12.2
PANEL 3 — SERVICE	**HIGH RISK**	**VERY HIGH RISK**	**HIGH OR VERY HIGH RISK**
Overall	8.4	3.4	12.1

TABLE 1

Source: Based on O*NET 29.1 database (U.S. Department of Labor, Employment and Training Administration) and BLS May 2023 National Occupational Employment and Wage Estimates, a product of the BLS Occupational Employment and Wage Statistics (OEWS) program. Categorization of occupations into white-collar, blue-collar, and service groups/subgroups based on classification scheme reported in Table 2.D at https://www.bls.gov/eci/factsheets/national-compensation-survey-classification-systems-mapping-files.htm

As informative as Figure 2 is, the 22 major occupational groups covered may represent a more detailed classification of occupations than the average person is used to. An alternative approach is to classify occupations into the well-known "white-collar," "blue-collar," and "service" categories. Table 1 reports estimated exposure of employment to high and very high automation displacement risk using this classification system.

In examining the "Overall" rows of Table 1, we find that 14% of blue-collar jobs face high or very high automation displacement risk, notably higher than the level faced by white-collar (12.3%) and service (12.1%) workers. Furthermore, we find that the share of white-collar workers facing very high displacement risk (1.4%) is much lower than what is observed for the blue-collar (2.7%) and service (3.4%) groups. One final point of note is that Table 1 reveals dramatic variation in automation displacement risk within subgroups of the white- and blue-collar categories. For example, we estimate that 15.8% of administrative support workers in the white-collar category face high or very high automation displacement risk, nearly double the share observed for white-collar workers in the professional, technical, and related subgroup (8.7%).

What do Figure 2 and Table 1 tell us about the skills associated with higher automation displacement risk? First, the most exposed groups are those with skill sets that emphasize highly routinized tasks that can increasingly be done using advanced robotics and/or software. For example, a significant fraction of employment in business and financial operations relates to the routine preparation and/or examination of financial documents (e.g., tax preparers, tax examiners, claims adjusters). On the opposite end of the spectrum, the groups we estimate to have the lowest exposure to near-term automation displacement risk generally emphasize creative and/or critical thinking, interpersonal skills, and tasks that require a degree of improvisation and ingenuity. Another feature of some (though not all) occupations in groups facing lower risk is that they rely on relatively low-cost labor, which — all else being equal — would tend to suppress the adoption of automation technologies.

KEY FINDING NO. 4

THE SHARE OF EMPLOYMENT FACING HIGH OR VERY HIGH AUTOMATION DISPLACEMENT RISK ALSO VARIES SIGNIFICANTLY BY INDUSTRY

Estimated Share of Employment at High or Very High Automation Displacement Risk by Industry

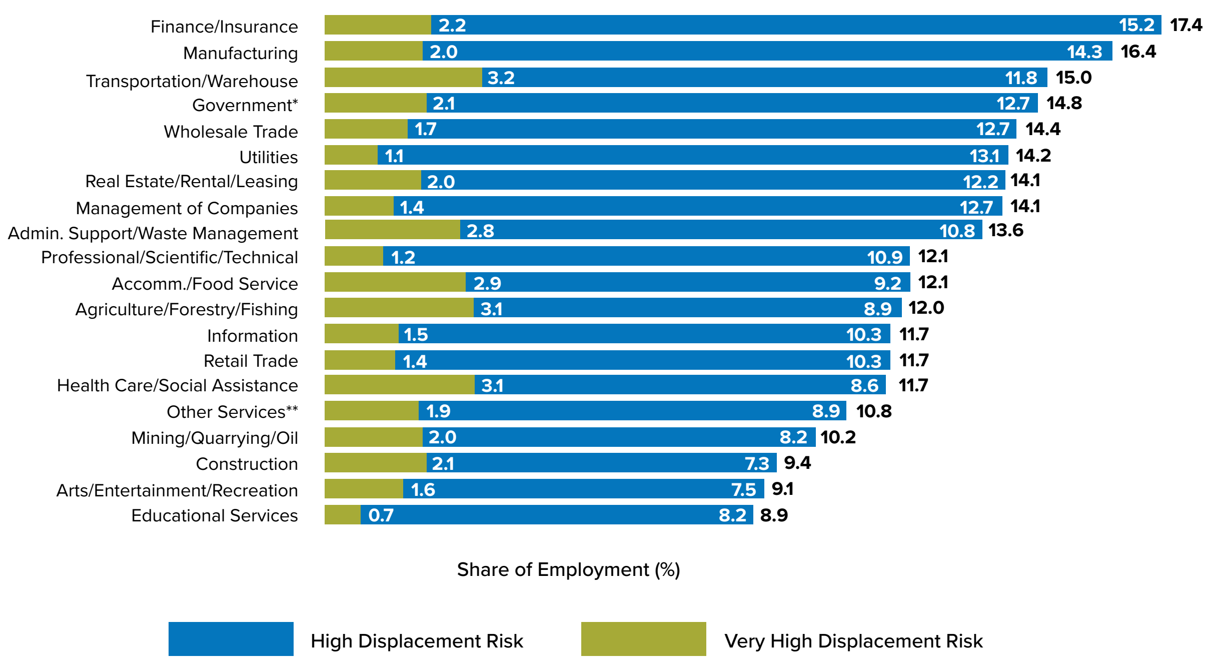


FIGURE 3

Source: Calculations based on O*NET 29.1 database (U.S. Department of Labor, Employment and Training Administration) and employment data from the BLS May 2023 National Occupational Employment and Wage Estimates, a product of the BLS Occupational Employment and Wage Statistics (OEWS) program.

*Federal, state, and local government employees excluding state and local government schools and hospitals and the U.S. Postal Service.

**Excluding public administration.

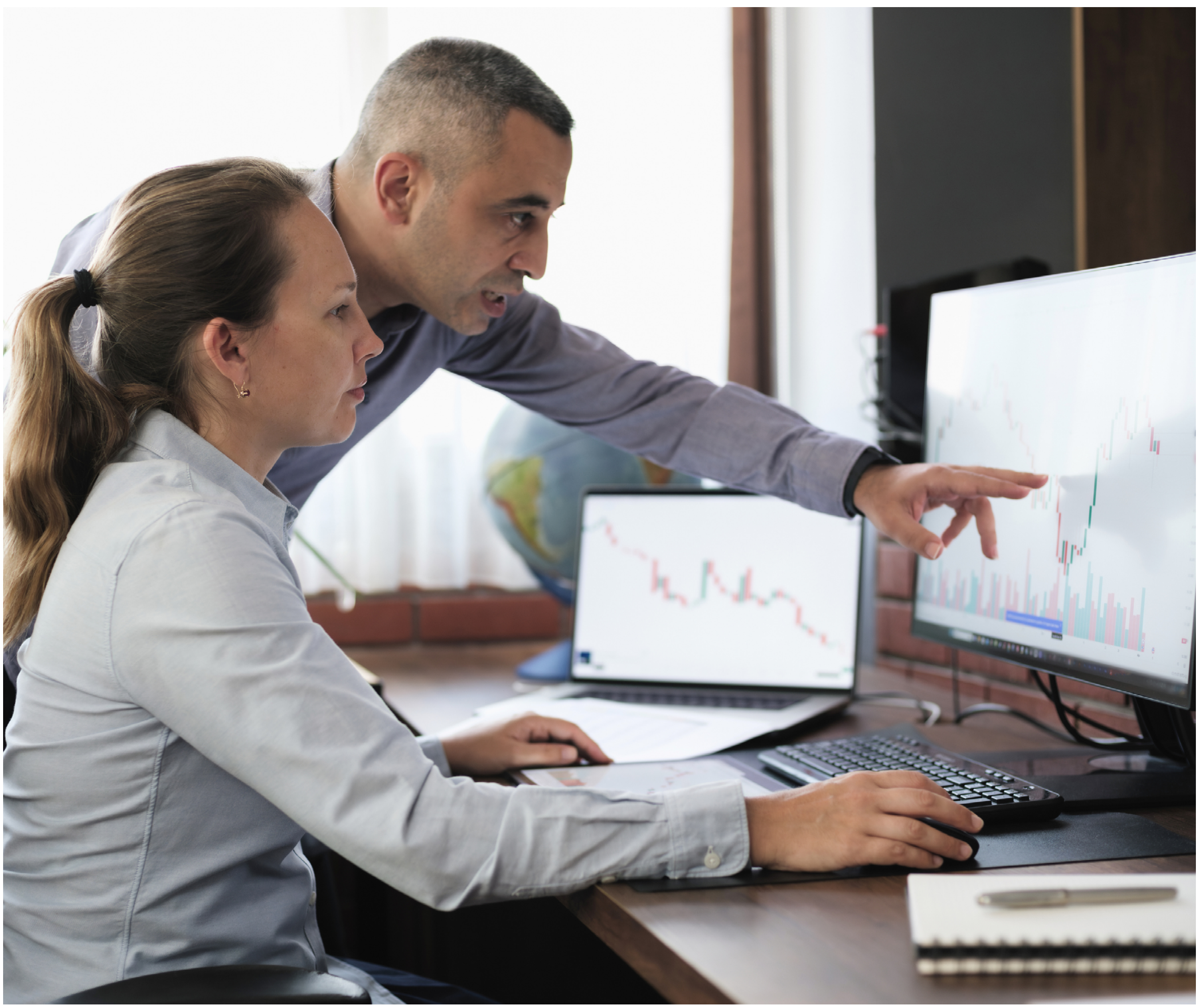
One especially attractive feature of the BLS OEWS data is that it provides occupation-level breakdowns of employment by industry. As such, our method can be used to estimate the degree to which workers in different industries are exposed to automation displacement risk. Figure 3 reports the results of this exercise by plotting the share of employment facing high or very high displacement risk by major industry.

As is the case with occupational groups, we find that automation displacement risk varies significantly across industries. At the bottom end of the scale, we estimate that 8.9% of employment in educational services faces high or very high displacement risk; on the other end of the spectrum, we find that 17.4% of employment in finance and insurance faces high or very high displacement risk. In comparing Figures 2 and 3, a handful of key features stand out:

1. As was the case with occupational groups, we find that it is far more common for jobs in any given industry to face high (rather than very high) automation displacement risk.

2. Although automation displacement risk does vary across industries, the range observed is less extreme than what we found for occupational groups. This is to be expected, since firms in a single industry employ people in highly varied occupations (with correspondingly wide variation in automation displacement risk). The diversity of occupations within each industry will tend to reduce variation in aggregate automation displacement risk across industries.

3. Related to item 2, the variety of occupations appearing in each major industry means that some notable share of employment faces very high displacement risk in all cases. In contrast, there were several major occupational groups in which this level of risk was extremely low.



CONCLUSION

The new approach to estimating automation displacement risk explored in this brief is based entirely on publicly available data and introduces several concepts that we feel capture important characteristics of automation displacement risk (e.g., the idea that this risk can vary within an individual occupation). Although completely direct comparisons are not always possible, our finding that 12.6% of workers face high or very high automation displacement risk is roughly aligned with similar research (e.g., Arntz et al., 2016, which estimated that about 9% of U.S. employment is automatable), though the range of estimates is quite wide, as is the exact nature of what is being measured.

As promising as these initial results are, the methodological appendix highlights that our analysis to date is hampered by data limitations, particularly with respect to the O*NET degree of automation information. As such, a major SHRM research initiative in 2025 aims to improve and expand these estimates by fielding a large-scale survey aimed at understanding workers' attitudes about automation and generative AI displacement risk. By improving data quality and gathering information not previously available, this effort promises to significantly enhance our ability to measure automation displacement risk.

RELATED SHRM RESOURCES

» AI & Automation: Real Tips From Real CEOs
» Tailor AI Adoption Strategies to Meet Workforce Needs: Insights from SHRM Thought Leadership
» The New Age of Workforce Planning
» AI, Job Disruption, and Preparing for What's Next: A Conversation with Futurist Bugge Hansen
» AI's Disruption of Entry-Level Work: What HR Leaders Need to Know

CITATIONS

DATA

O*NET version 29.1. Downloaded from O*NET Resource Center. Data available at onetcenter.org/db_releases.html.

May 2023 National Occupational Employment and Wage Estimates. BLS Occupational Employment and Wage Statistics (OEWS) program. Downloaded from bls.gov/oes/tables.htm.

May 2023 National Industry-Specific Occupational Employment and Wage Estimates. BLS Occupational Employment and Wage Statistics (OEWS) program. Downloaded from bls.gov/oes/tables.htm.

O*NET-SOC to Occupational Outlook Handbook Crosswalk. Downloaded from BLS Employment Projections Classifications and Crosswalks (bls.gov/emp/documentation/crosswalks.htm).

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