

### AUTOMATION, GENERATIVE AI, AND JOB DISPLACEMENT RISK IN U.S. EMPLOYMENT

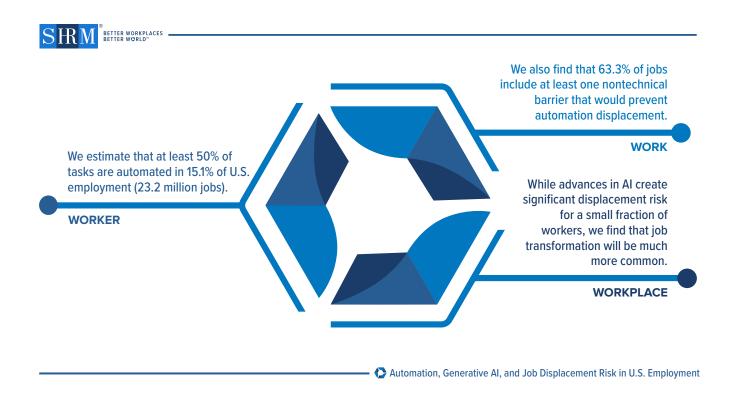


### **PURPOSE**

How will advances in automation technology and generative AI reshape the world of work? Based on recent news, one could be forgiven for concluding that human workers will soon go the way of the dinosaurs, with some headlines predicting dire outcomes such as imminent mass unemployment.<sup>1</sup> To be sure, many employers are rapidly incorporating new technology to automate tasks; however, the net effect of this technological shift will be complex and is currently poorly understood.

As a first step toward improving our knowledge in this area, SHRM fielded a large-scale survey of U.S. workers in the spring of 2025 (henceforth referred to as the SHRM 2025 Automation/AI Survey). With over 20,000 individual respondents, this survey represents a significant step forward in our understanding of current automation and generative AI use levels for individual occupations, as well as the presence of nontechnical barriers to automation displacement and worker attitudes about displacement risk. By identifying these characteristics, this work provides powerful insights about the types of jobs that are most likely to be displaced through automation technologies in the near future, as well as occupations that are more likely to be shielded from displacement.

The data gathered through these efforts will form the foundation of several SHRM publications in the near future. This data brief represents the first step along this path and focuses on using data from the SHRM 2025 Automation/AI Survey to estimate the prevalence of "high" (i.e.,  $\geq$  50%) task completion via automation and generative AI in U.S. employment, as well as the prevalence of nontechnical barriers to automation displacement.



<sup>&</sup>lt;sup>1</sup>For example, in a recent <u>Axios interview</u>, Anthropic CEO Dario Amodei said that emerging Al tools could eliminate half of entry-level white-collar jobs and drive the U.S. unemployment rate to as high as 20% within one to five years.

#### **DEFINITIONS**

One important challenge when discussing this topic is clearly defining terms. For instance, automated processes have become so ubiquitous in day-to-day life that it is sometimes easy to forget that such processes often represent critical work tasks. Similarly, AI technologies often show up in subtle ways that one may not immediately associate with AI (e.g., improved editing features in word processing software). To avoid confusion, we defined the following terms for participants in the SHRM 2025 Automation/AI Survey:

Automation: The technique of making an apparatus, a process, or a system operate autonomously (i.e., without human intervention). One example would be manufacturing processes that complete routinized tasks without human input. A task is said to be "automated" if it is completed using an automation technology. The degree to which an occupation is automated depends on the extent to which tasks completed within that occupation are done via automation.

training on an archive of content to generate brand-new, unique content (e.g., text, images). One example would be ChatGPT, which generates entirely novel and unique content based on a massive database of existing content that the AI has been trained on.

Generative Al: Any Al technology that leverages

**Artificial Intelligence (AI):** Any technology that can independently perform tasks that typically require human intelligence. One example would be self-driving vehicles.

To simplify the language of this brief and provide greater clarity to the reader, the following definitions will also be useful:

**High Automation Level:** We define a job to have a high automation level if at least 50% of tasks in that job are automated. A central value that we estimate in our results is the share of employment in a given occupation (or collection of occupations) that meets this threshold. For example, we estimate that 39.7% of employment in the "software developers" occupation is highly automated (i.e.,  $\geq$  50% of tasks automated).

High Generative AI Use Level: We define a job to have a high generative AI use level if at least 50% of tasks in that job are completed using generative AI. A central value that we estimate in our results is the share of employment in a given occupation (or collection of occupations) that meets this threshold. For example, we estimate that 23.3% of employment in the "software developers" occupation exhibits high generative AI use (i.e.,  $\geq 50\%$  of tasks completed using generative AI).

#### Nontechnical Barrier to Automation Displacement:

A nontechnical barrier to automation displacement is any barrier to displacement that does not relate to a limitation of the automation technology. In other words, nontechnical barriers to automation displacement can exist even when the technology exists to completely automate a given job. For example, client preferences for interpersonal interaction might present a barrier to displacing employment through automation.

U.S. Employment: A central goal of this research effort is to estimate the share of U.S. employment that meets certain conditions (e.g., highly automated, high generative AI use, presence of nontechnical barriers to automation displacement). In all cases, we measure U.S. employment at the occupational level using the May 2024 Bureau of Labor Statistics (BLS') Occupational Employment and Wage Statistics (OEWS) employment data. These employment figures are available in this table and can be downloaded directly here. Note that we only use the employment values for individual occupations (i.e., "detailed occupations"), as these can be aggregated to reflect employment levels in larger sets (e.g., occupational groups or overall employment). For simplicity, the text of this data brief discusses U.S. employment in the present tense.

#### METHODS AND DATA

A detailed review of our methodology and data sources is available in the associated methodological appendix. However, a cursory review of our approach is provided here for reference:

The Survey — The SHRM 2025 Automation/Al Survey was fielded in March and April of 2025, with a final sample size of 20,262 U.S. workers. From a demographic point of view, the sample is broadly representative of the overall American workforce, though certain groups are slightly overrepresented or underrepresented. In addition to providing basic occupational information and demographic characteristics, respondents were asked a series of questions related to automation, generative Al use, and nontechnical barriers to automation displacement in their current job. This data brief focuses on four topics captured in the survey data:

- 1. The share of tasks currently automated in the respondent's current job.
- 2. The share of tasks currently done using generative AI in the respondent's current job.
- 3. The presence of nontechnical barriers to automation displacement in the respondent's current job.
- 4. If present, the types of nontechnical barriers to automation displacement present in the respondent's current job.

**Occupation-Level Estimates** — A central priority in the analysis underlying this data brief is to identify the following values for each of the 831 occupations in the May 2024 BLS OEWS employment data:

- 1. The probability that a job in any individual occupation is at least 50% automated.
- 2. The probability that a job in any individual occupation is at least 50% done using generative AI.
- 3. The probability that a job in any individual occupation has at least one nontechnical barrier to automation displacement.
- 4. The probability that a job in any individual occupation is at least 50% automated and faces no definitive nontechnical barriers to automation displacement.

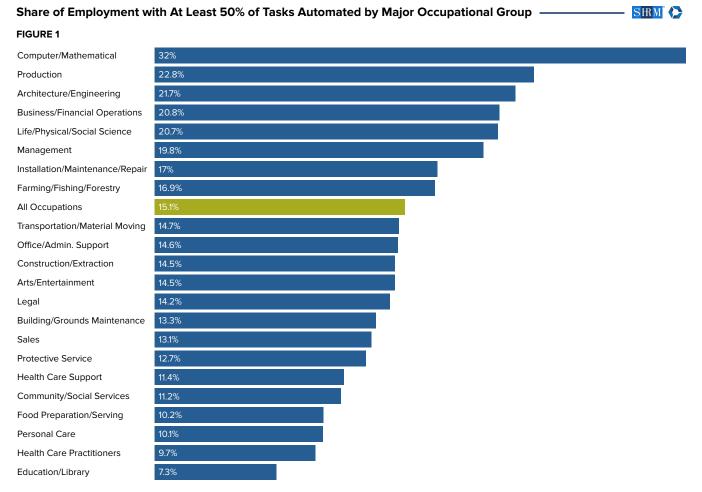
Once calculated, we combine these probabilities with occupation-level May 2024 BLS OEWS employment data, which allows us to produce estimates for the share of employment that meets any of these conditions, both for individual occupations and for aggregated groups of interest (e.g., overall employment and major occupational groups).

Unfortunately, precisely estimating the probabilities listed above generally requires a significant amount of data, so in general, we are unable to rely on direct evidence to estimate these values for each individual occupation. Instead, we adopt a "proximity-based" estimation method in which values for any given occupation are obtained by combining direct evidence (i.e., survey responses from people in the occupation in question) with data from respondents who are in similar occupations. In this approach, all final estimates for a given occupation are weighted averages in which respondents whose occupation is most similar to the occupation in question receive the most weight. The details underlying these calculations are provided in the associated methodological appendix.

### **KEY FINDINGS**

- 1. 15.1% of U.S. employment (23.2 million jobs) is at least 50% automated.
- 2. The share of employment that is at least 50% automated varies significantly by industry.
- 3. 7.8% of U.S. employment (12 million jobs) is at least 50% done using generative Al.
- 4. The share of employment that is at least 50% done using generative AI varies significantly by industry.
- 5. A significant majority of employment faces nontechnical barriers to automation displacement.
- 6. Among employment with nontechnical barriers to automation displacement, client preferences are the most common issue.
- 7. 6% of U.S. employment (9.2 million jobs) is at least 50% automated and has no definitive nontechnical barriers to automation displacement.

### 15.1% OF U.S. EMPLOYMENT (23.2 MILLION JOBS) IS AT LEAST 50% AUTOMATED



AUTOMATION, GENERATIVE AI, AND JOB DISPLACEMENT RISK IN U.S. EMPLOYMENT, SHRM, 2025. VISIT SHRM.ORG/RESEARCH TO LEARN MORE.

Source: Calculations based on data from the SHRM 2025 Al/Automation Displacement Risk Survey, O'NET 29.2 database (U.S. Department of Labor, Employment and Training Administration), and employment data from the BLS May 2024 National Occupational Employment and Wage Estimates, a product of the BLS Occupational Employment and Wage Statistics (OEWS) program.

After estimating the share of employment that is at least 50% automated for all 831 detailed occupations in the May 2024 BLS OEWS data, we can aggregate those estimates to calculate the share of employment meeting the same automation threshold for any subgroup of interest. Figure 1 does so, both overall and for employment in each of the 22 major civilian occupational groups in the Standard Occupational Classification (SOC) system.

Overall, we estimate that 15.1% of U.S. employment is at least 50% automated, a share that translates to about 23.2 million jobs. However, the estimated share of employment meeting or exceeding this automation threshold varies significantly by major occupational group, from a low of 7.3% (education and library occupations) to a high of 32% (computer and mathematical occupations).

Looking at the ranking of occupational groups in Figure 1, some important patterns emerge: First, groups that tend to have a large share of highly automated employment tend to emphasize advanced software/hardware tools that are becoming increasingly autonomous over time. For example, computer and mathematical occupations stand out as being especially transformed by the recent emergence of generative AI, and production occupations have become increasingly automated through advanced robotics.

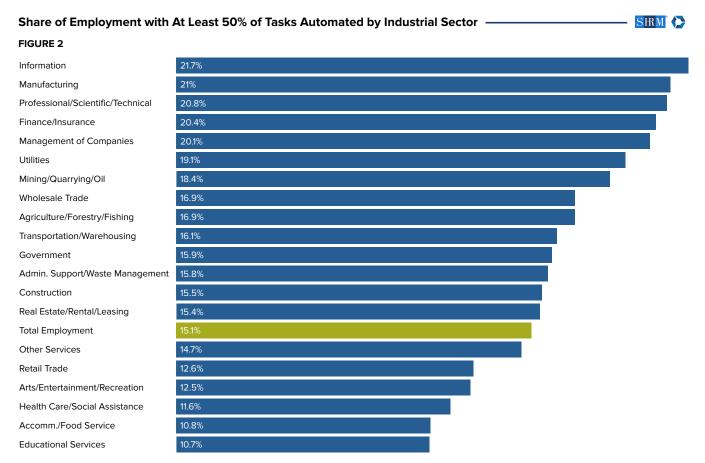
On the opposite end of the spectrum, groups that have low shares of highly automated employment tend to strongly emphasize interpersonal skills and/or relatively low-tech tools. For instance, interpersonal engagement is fundamental in many education and health care occupations.

One could interpret the results above as capturing the degree of automation displacement risk in U.S. employment, both overall and by occupational group. If interpreted this way, the findings outlined above suggest that a relatively large fraction of U.S. jobs face significant risk of displacement through automation, since a job that is 50% or more automated already could presumably be fully displaced by near-term technological advances and/or a redistribution of nonautomated tasks among workers in other occupations. Although this pathway will not be the outcome for every job that currently meets this automation threshold, it seems likely that many occupations that are currently highly automated will see some workers displaced as more tasks become automatable.

Having said this, there are notable reasons to doubt such a forecast, or at least to believe that it may only hold for a narrowly defined set of occupations. For example, it might be that a clear majority of the tasks in a given job are already automated, but that all or some of the remaining tasks are both nonautomated and require highly skilled human input. A job such as this would probably face limited risk of full displacement in the immediate future because the skill requirements associated with some or all of the nonautomated tasks make them difficult to redistribute among other workers or automate through near-term technological advances.

Another reason to doubt that tens of millions of jobs that are highly automated today will shortly be displaced by complete automation is that there are likely to be nontechnical barriers that prevent such displacement. The SHRM 2025 Automation/Al Survey explored the prevalence of such barriers directly, resulting in several key findings that will be discussed below. In particular, Figure 7 will examine our estimates for the prevalence of jobs that are simultaneously highly automated and face no definitive nontechnical barriers to automation displacement. As will be discussed, those estimates likely provide a more detailed (albeit still imperfect) view of automation displacement risk in U.S. employment.

### THE SHARE OF EMPLOYMENT THAT IS AT LEAST 50% AUTOMATED VARIES SIGNIFICANTLY BY INDUSTRY



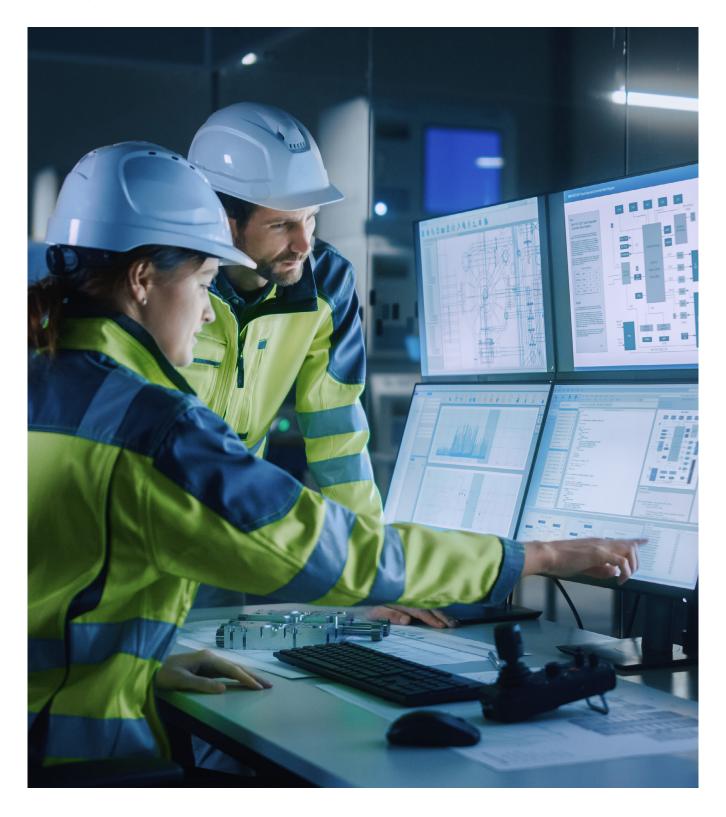
AUTOMATION, GENERATIVE AI, AND JOB DISPLACEMENT RISK IN U.S. EMPLOYMENT, SHRM, 2025, VISIT SHRM, ORG/RESEARCH TO LEARN MORE.

Source: Calculations based on data from the SHRM 2025 Automation/Al Survey, O\*NET 29.2 database (U.S. Department of Labor, Employment and Training Administration), and employment data from the BLS May 2024 National Occupational Employment and Wage Estimates, a product of the BLS Occupational Employment and Wage Statistics (OEWS) program.

The May 2024 BLS OEWS data also includes tables reporting occupational employment by industry, which allows us to aggregate our occupation-level results to produce estimates for the 20 sectors in the North American Industrial Classification System (NAICS).<sup>2</sup> For simplicity, we will refer to these sectors as "industries" henceforth.

Figure 2 reports these results, which demonstrate that the share of employment that is at least 50% automated also varies significantly by industry, from a low of 10.7% (educational services) to a high of 21.7% (information).<sup>3</sup> As one would expect, industries with larger shares of highly automated employment are those in which highly automated occupations are very common; conversely, industries with low shares of highly automated employment tend to be associated with occupational groups in which highly automated jobs are comparatively rare.

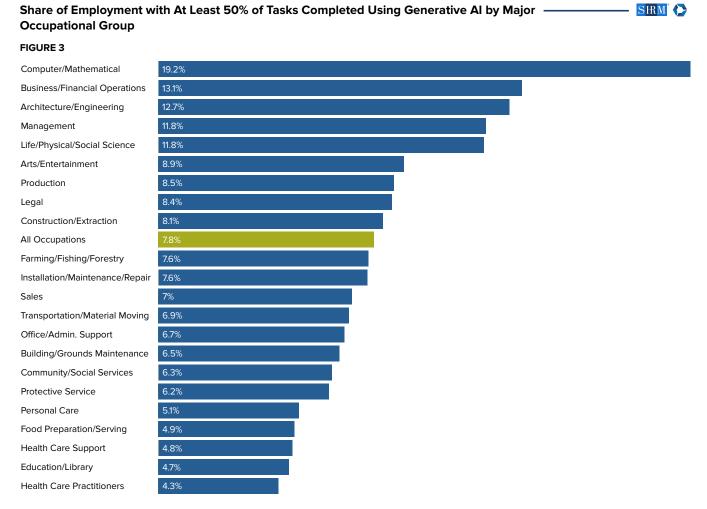
Due to this connection between occupational groups and industries, the takeaways in Figure 2 broadly align with those of Figure 1. More specifically, the share of employment that is at least 50% automated tends to be high in industries that heavily rely on computer and/or software systems that are becoming increasingly sophisticated and autonomous, whereas the share of employment that is at least 50% automated tends to be low in industries in which direct interpersonal engagement with clients is especially important.



<sup>2</sup>In NAICS terminology, a "sector" is the broadest industrial classification, with each sector representing a collection of smaller industries that share close ties. In this way, NAICS sectors are analogous to major occupational groups in the SOC system.

<sup>3</sup>When discussing the prevalence of a particular characteristic (e.g., the share of employment that is at least 50% automated), it is generally the case that there is greater variation across occupational groups than across industries, with occupational groups exhibiting lower minimums and higher maximums. The reason for this is that industries employ workers across a range of different occupational groups; as such, the characteristics of employment within an industry are more diverse which tends to mute inter-industry differences in employment characteristics.

### 7.8% OF U.S. EMPLOYMENT (12 MILLION JOBS) IS AT LEAST 50% DONE USING GENERATIVE AI



AUTOMATION, GENERATIVE AI, AND JOB DISPLACEMENT RISK IN U.S. EMPLOYMENT, SHRM, 2025. VISIT SHRM.ORG/RESEARCH TO LEARN MORE.

Source: Calculations based on data from the SHRM 2025 Automation/Al Survey, O\*NET 29.2 database (U.S. Department of Labor, Employment and Training Administration), and employment data from the BLS May 2024 National Occupational Employment and Wage Estimates, a product of the BLS Occupational Employment and Wage Statistics (OEWS) program.

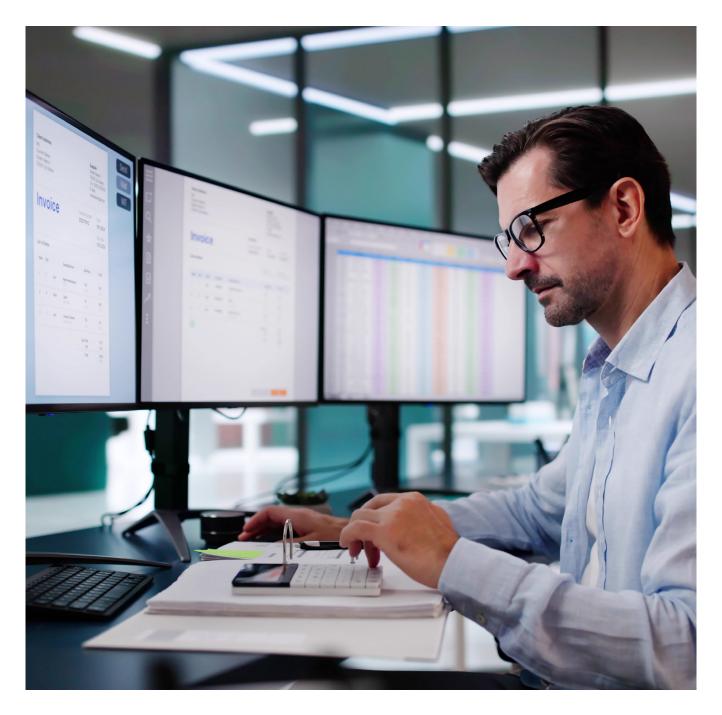
In addition to asking about the degree to which tasks in their current job are automated, we also asked respondents to report the percentage of tasks in their current job that are completed using generative Al. Aggregate estimates for the share of employment that is at least 50% completed using generative Al are reported in Figure 3, both overall and for major occupational groups.

As one would expect, the overall share of employment that is at least 50% done using generative Al is currently very small (7.8% of U.S. employment, or about 12 million jobs). However, given the novelty of these tools, it is remarkable that they have attained this level of use in so short a time. Furthermore, there is significant variation in this share across occupational groups, from a low of 4.3% (health care practitioners) to a high of 19.2% (computer and mathematical occupations).

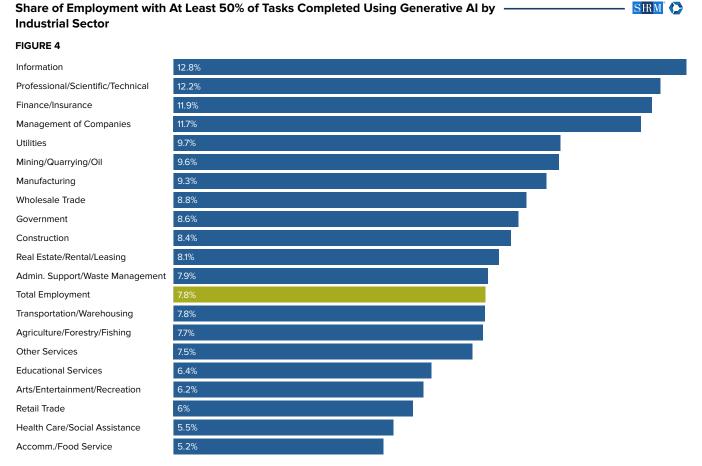
Five occupational groups stand out as being especially exposed to generative AI (computer and mathematical; business and financial operations; architecture and engineering; management; and life, physical, and social science occupations), which provides an indication of how generative AI is currently used in the workplace. For example, occupations in these five groups tend to place especially strong emphasis on gathering and analyzing data to inform decision-making, a series of tasks that many

generative AI tools are becoming increasingly proficient at. In addition, there are many occupations in these groups that historically focused on tasks that are now greatly facilitated by generative AI tools. An excellent example is the writing of computer programs, which can now be done much more efficiently with the use of certain generative AI tools.

On the other hand, the share of employment whose tasking is at least 50% done using generative AI is very low in several occupational groups, including four groups (food preparation and serving; health care support; education and library; and health care practitioners) where less than 5% of employment meets this threshold. A common theme in all of these groups is the importance of direct interpersonal engagement, which likely places a comparatively low upper bound on the share of tasks that can be done using generative AI. Relatedly, there may be a general hesitancy to use generative AI tools in some of these groups (e.g., health care occupations) due to privacy concerns or other legal issues.



### THE SHARE OF EMPLOYMENT THAT IS AT LEAST 50% DONE USING GENERATIVE AI VARIES SIGNIFICANTLY BY INDUSTRY



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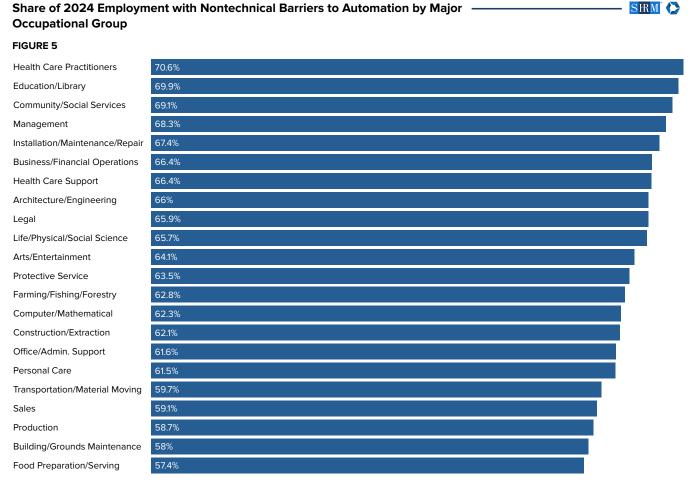
Source: Calculations based on data from the SHRM 2025 Automation/Al Survey, O\*NET 29.2 database (U.S. Department of Labor, Employment and Training Administration), and employment data from the BLS May 2024 National Occupational Employment and Wage Estimates, a product of the BLS Occupational Employment and Wage Statistics (OEWS) program.

We can also estimate the share of employment in which at least 50% of tasks are completed using generative AI by industry. The results of this analysis are presented in Figure 4.

As was the case in Figure 3, we find that the prevalence of high generative Al use (i.e., at least 50% of tasks completed via generative Al) is generally low and highly variable across industries, ranging from a low of 5.2% (accommodation and food service) to a high of 12.8% (information). Four industries (information; professional, scientific, and technical services; finance and insurance; and management of companies and enterprises) stand out as having comparatively high exposure to generative Al, with the major driver being a concentration of employment in occupational groups that are also highly exposed.

On the opposite end of the spectrum, there are five industries in which we estimate the share of employment with a high generative AI use level to be below 7.5%: educational services (6.4%), arts, entertainment, and recreation (6.2%), retail trade (6%), health care and social assistance (5.5%), and accommodation and food service (5.2%). Once again, the central issue in these industries is a high concentration of employment in occupational groups where high generative AI use is relatively low.

### A SIGNIFICANT MAJORITY OF EMPLOYMENT FACES NONTECHNICAL BARRIERS TO AUTOMATION DISPLACEMENT



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Source: Calculations based on data from the SHRM 2025 Automation/Al Survey, O\*NET 29.2 database (U.S. Department of Labor, Employment and Training Administration), and employment data from the BLS May 2024 National Occupational Employment and Wage Estimates, a product of the BLS Occupational Employment and Wage Statistics (OEWS) program.

After asking respondents about the degree to which their current job is automated and/or completed using generative AI, the 2025 SHRM Automation/AI Survey posed the following question:

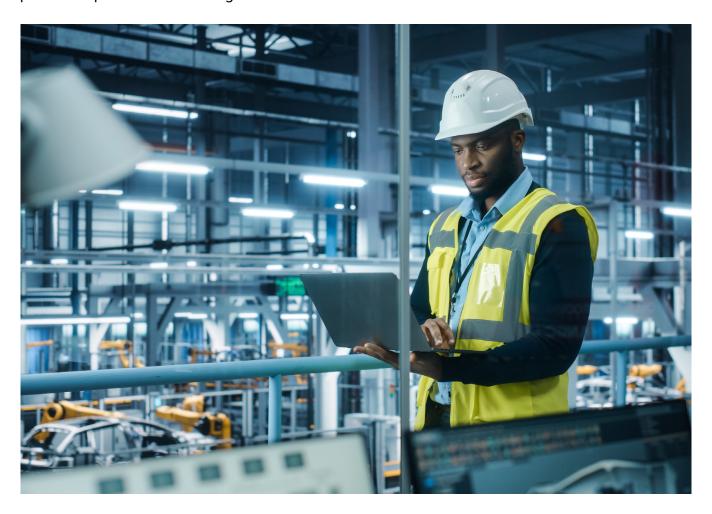
Assume that a technology existed that could do your current job completely autonomously. In such a scenario, do you think that there would still be real-world barriers that would prevent your job from being automated?

A significant majority of respondents replied with a definitive "yes," suggesting that nontechnical barriers are — at least from the perspective of workers — very common and might often shield jobs from displacement risk.

Overall, we estimate that about 63.3% of U.S. employment has at least one nontechnical barrier to automation displacement risk, with our estimates being above 50% for 829 of the 831 individual occupations in the BLS OEWS data. In fact, Figure 5 shows that the prevalence of nontechnical barriers to automation displacement in employment ranges from 57.4% to 70.6% across major occupational groups, further underscoring the idea that these barriers persist across a wide range of skill sets.

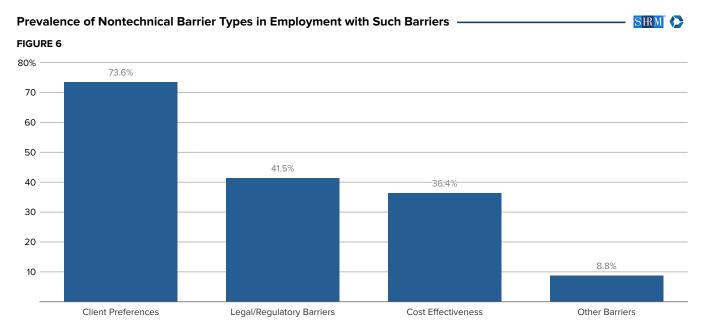
Although we estimate that nontechnical barriers to automation displacement exist for a majority of employment in every major occupational group, it is clear that certain types of occupations are more or less likely to have them. In particular, the three occupational groups with the highest prevalence of these barriers in Figure 5 (health care practitioners, education and library occupations, and community and social service occupations) all stand out as being dominated by occupations in which interpersonal engagement and communication are fundamental. For example, patients exhibit an exceptionally strong desire to directly engage with human health care providers, a preference that seems unlikely to fade in the immediate future.<sup>4</sup>

On the other hand, we find that the prevalence of nontechnical barriers to automation displacement appears to be lowest in occupational groups where interpersonal interaction is less essential to the ultimate perception of the good or service being provided. For example, a patron at a typical restaurant is unlikely to care much about how automated the production of their meal is, even if they do value the interpersonal interactions they have with restaurant staff. In fact, our estimates for individual occupations within the food preparation and serving group broadly support this conclusion, as customer-facing staff (e.g., bartenders) tend to be more likely to have nontechnical barriers to displacement than those with little to no customer interaction (e.g., fast food cooks). Similarly, the average consumer buys manufactured goods all the time with little thought paid to how automated the production processes for these goods are.



<sup>4</sup>Riedl et al. (2024) examined hypothetical patient preferences for different combinations of a human doctor and Al technology in an online experiment. Their findings reveal nuance in how patients perceive the use of Al technology across different medical specialties. However, in all cases, patients exhibited a strong preference for the presence of a human doctor (with or without Al technology as an aide) over Al technology alone.

# AMONG EMPLOYMENT WITH NONTECHNICAL BARRIERS TO AUTOMATION DISPLACEMENT, CLIENT PREFERENCES ARE THE MOST COMMON ISSUE



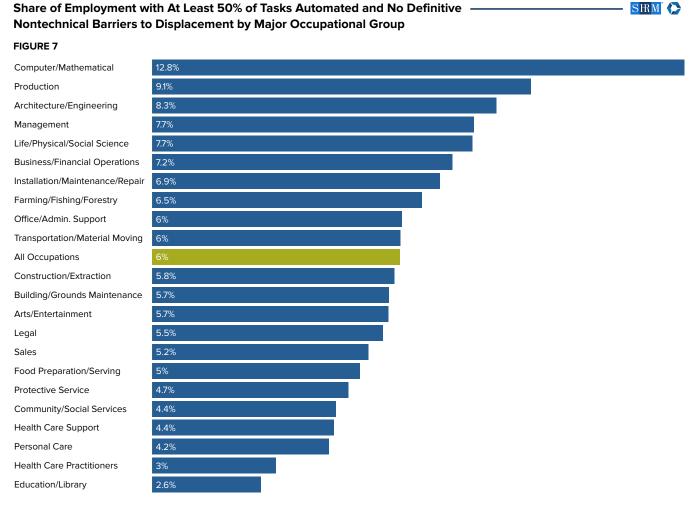
AUTOMATION, GENERATIVE AI, AND JOB DISPLACEMENT RISK IN U.S. EMPLOYMENT, SHRM, 2025. VISIT SHRM.ORG/RESEARCH TO LEARN MORE.

Source: Calculations based on data from the SHRM 2025 Automation/Al Survey, O\*NET 29.2 database (U.S. Department of Labor, Employment and Training Administration), and employment data from the BLS May 2024 National Occupational Employment and Wage Estimates, a product of the BLS Occupational Employment and Wage Statistics (OEWS) program.

For survey respondents who definitively reported the presence of at least one nontechnical barrier to automation displacement in their current job, we asked a follow-up question about the nature of these barriers. In this question, respondents were able to cite multiple barrier types from three specific categories (client preferences, legal or regulatory requirements, and cost effectiveness) and an "other" category.

The survey data from this follow-up question was used to estimate how common different types of nontechnical barriers to automation displacement are in jobs where such barriers exist, with the overall results reported in Figure 6. As the examples provided in the prior section suggest, client preferences represent the most widespread barrier of this type, with 73.6% of employment with at least one nontechnical barrier to automation displacement having a barrier (or barriers) related to client preferences. Legal/regulatory and cost effectiveness barriers are comparatively uncommon, but they still appear in a substantial fraction of employment where nontechnical barriers to automation displacement risk exist.

# 6% OF U.S. EMPLOYMENT (9.2 MILLION JOBS) IS AT LEAST 50% AUTOMATED AND HAS NO DEFINITIVE NONTECHNICAL BARRIERS TO AUTOMATION DISPLACEMENT



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Source: Calculations based on data from the SHRM 2025 Automation/Al Survey, O\*NET 29.2 database (U.S. Department of Labor, Employment and Training Administration), and employment data from the BLS May 2024 National Occupational Employment and Wage Estimates, a product of the BLS Occupational Employment and Wage Statistics (OEWS) program.

Given that the 2025 SHRM Automation/Al Survey asks respondents about the extent to which tasks in their current job are automated and the presence or absence of nontechnical barriers to automation displacement, we are able to estimate the share of employment in individual occupations that simultaneously meets two conditions:

- 1. At least 50% of tasks are automated.
- 2. There are no definitive nontechnical barriers to automation displacement.<sup>5</sup>

<sup>&</sup>lt;sup>5</sup>In the original survey question about the presence of nontechnical barriers to automation displacement, respondents may answer "Yes," "No," or "Don't know." We classify a respondent as not having a definitive nontechnical barrier to automation displacement in their current job if they reply "No" or "Don't know."

As we discussed when reviewing the findings of Figure 1, meeting the first condition is important because it identifies jobs that are plausibly already automated enough to become fully displaced in the near future due to relatively minor technological advances and/or through the redistribution of nonautomated tasks across other positions. However, we noted that highly automated positions of this kind might be shielded from full displacement by nontechnical barriers, and in fact our survey data suggests that such barriers are very common (even in highly automated jobs). Therefore, jobs that meet both of the conditions listed above plausibly face a significantly elevated level of displacement risk.

Figure 7 reports the share of U.S. employment that we estimate meets these two conditions by major occupational group. In comparing these findings with those presented in Figure 1, we see that imposing the second condition (i.e., the absence of nontechnical barriers to automation displacement) dramatically reduces the share of employment that we would identify as facing significant displacement risk. Overall, we find that just 6% of U.S. employment is currently at least 50% automated and has no definitive nontechnical barriers to displacement (roughly 9.2 million jobs), despite the fact that 15.1% of employment is estimated to be at least 50% automated.

Although the overall percentage of employment that is simultaneously highly automated and bereft of definitive nontechnical barriers to automation displacement is relatively low, we do find that this share varies significantly across occupational groups, from a low of 2.6% (education and library occupations) to a high of 12.8% (computer and mathematical occupations). Taken together, the results reported in Figure 7 tend to support the following conclusions:

- At least in the near future, overall exposure to automation displacement risk is relatively low in U.S. employment. This does not mean that displacement driven by increasingly advanced automation technology won't occur, just that this displacement will affect a relatively small percentage of total employment.
- 2. Occupations that face the greatest exposure to automation displacement risk are generally those that rely heavily on relatively high-tech inputs to production (e.g., advanced software, robotics). The computer and mathematical occupational group stands out in this regard, as we estimate that 12.8% of employment in this group is currently at least 50% automated and has no definitive nontechnical barriers to displacement.
- 3. Conversely, occupations that face the lowest risk tend to place strong emphasis on interpersonal interaction or rely on relatively low-tech inputs to production that are unlikely to be altered (at least in the near future) by technological change.

### CONCLUSION

This brief has covered seven key findings stemming from analysis associated with the SHRM 2025 Automation/AI Survey, with a focus on current automation levels, current generative AI use, and nontechnical barriers to automation displacement in U.S. employment. Broadly speaking, our findings support the conclusion that a notable percentage of U.S. jobs are currently highly (i.e., at least 50%) automated, with a smaller (but still significant) share of employment exhibiting high generative AI use. Even so, the high automation levels seen in some jobs are a limited indicator of automation displacement risk, since nontechnical barriers to displacement are quite common. If we limit our attention to employment that is highly automated and lacks nontechnical barriers to displacement, we estimate that about 6% of U.S. employment (approximately 9.2 million jobs) meets these conditions.

This last finding suggests that — at least in the immediate future — the complete displacement of workers due to advancing automation technology is likely to be limited as a percentage of overall employment and concentrated in specific contexts. However, even in this limited case, total displacement due to automation could amount to millions of jobs in total, with some occupational groups facing significantly elevated risk. Furthermore, our findings reinforce the conclusion that automation and generative AI use are fundamentally important across a wide range of occupations. As such, many workers can expect their roles to be transformed as technological advances reshape the world of work.

### RELATED SHRM RESOURCES

- Jobs at Risk U.S. Employment in the New Age of Automation (Part I)
- Al & Automation: Real Tips from Real CEOs
- Tailor Al Adoption Strategies to Meet Workforce Needs: Insights from SHRM Thought Leadership
- The New Age of Workforce Planning
- Al, Job Disruption, and Preparing for What's Next: A Conversation with Futurist Bugge Hansen
- Al's Disruption of Entry-Level Work: What HR Leaders Need to Know

#### **DATA**

SHRM 2025 Automation/Al Survey

O\*NET version 29.2. Downloaded from O\*NET Resource Center. Data available at <u>onetcenter.org/db\_releases.html</u>.

May 2024 National Occupational Employment and Wage Estimates. BLS Occupational Employment and Wage Statistics (OEWS) program. Downloaded from <a href="https://doi.org/10.2016/bls.ncm/bls.gov/oes/tables.htm">bls.gov/oes/tables.htm</a>.

May 2024 National Industry-Specific Occupational Employment and Wage Estimates. BLS Occupational Employment and Wage Statistics (OEWS) program. Downloaded from <a href="https://document.nd/bls.gov/oes/tables.htm">bls.gov/oes/tables.htm</a>.

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#### LITERATURE

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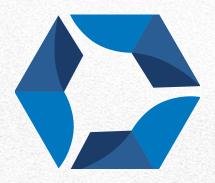
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Our mission is to empower people and workplaces by advancing HR practices and by maximizing human potential. Our vision is to build a world of work that works for all.