



August 2022

WORKFORCE AUTOMATION

Insights into Skills and Training Programs for Impacted Workers

Why GAO Did This Study

Increasingly, technology is automating tasks previously performed by people. Automation has changed some jobs and eliminated others entirely. Thus some workers have had to retrain to learn the skills needed to keep their jobs or obtain new ones. Workers with lower levels of education who perform more routine tasks have tended to experience the greatest disruptions from automation, putting at risk jobs such as cashiers or clerical workers. House Report 116-450 included a provision for GAO to examine challenges and opportunities to provide training to workers at risk of losing their jobs to automation.

GAO examined (1) what available data indicate about which workers are at risk of automation and the skills needed for in-demand jobs; and (2) what insights stakeholders offer for workforce programs to better serve displaced workers and those affected by automation.

GAO analyzed DOL data to identify occupations projected to grow over the next decade, as well as the skills associated with those growing occupations. GAO also conducted case studies in four states, diverse across jobs and geography that were also recommended by national workforce organizations and others as having promising workforce responses to automation. In those states, GAO collected information related to both objectives. Additionally, GAO interviewed stakeholders from agencies and nine workforce, labor, business, and other organizations. GAO also reviewed relevant federal laws and regulations, prior GAO reports, and literature.

View [GAO-22-105159](#). For more information, contact Dawn G. Locke at (202) 512-7215 or locked@gao.gov.

WORKFORCE AUTOMATION

Insights into Skills and Training Programs for Impacted Workers

What GAO Found

Although available data do not explicitly identify workers at risk of losing their jobs to automation, they provide insight into the skills needed for jobs projected to be in high demand over the next decade. For example, Department of Labor (DOL) data show that in-demand jobs require a mix of skills, including soft skills and process skills that help a person acquire knowledge quickly, such as active learning and critical thinking. Federal data also indicate that in-demand jobs having a higher number of skills deemed important also tend to require higher levels of education. Further, research indicates that certain jobs and skills are less likely to be automated, including those involving management and social skills. State and other data can also inform which skills are most important for in-demand jobs in a given geographic area. DOL and the Department of Commerce are seeking additional data on skills that the general worker population will need for in-demand jobs in light of automation.

Skills Deemed Important in the Top 20 In-Demand Occupations, by Education Level Required

Bachelor's and above	Some college, <i>bachelor's and above</i>	High school, <i>some college, bachelor's and above</i>
<ul style="list-style-type: none"> <input type="radio"/> Systems evaluation <input type="radio"/> Systems analysis <input type="radio"/> Learning strategies <input type="radio"/> Persuasion <input type="radio"/> Instructing <input type="radio"/> Management of personnel resources 	<ul style="list-style-type: none"> <input checked="" type="radio"/> Reading comprehension <input checked="" type="radio"/> Writing <input checked="" type="radio"/> Time management <input checked="" type="radio"/> Active learning <input checked="" type="radio"/> Complex problem solving 	<ul style="list-style-type: none"> <input type="radio"/> Active listening <input type="radio"/> Social perceptiveness <input type="radio"/> Service orientation <input type="radio"/> Speaking <input type="radio"/> Monitoring <input type="radio"/> Critical thinking <input type="radio"/> Coordination <input type="radio"/> Judgment and decision making

Source: GAO analysis of U.S. Bureau of Labor Statistics (BLS) Employment Projections program data and U.S. Department of Labor Occupational Information Network (O*NET) data. | [GAO-22-105159](#)

Note: These skills reflect a score of at least 3 in O*NET's 5-point scale of importance.

Officials in four case study states and other stakeholders GAO interviewed offered insights on how existing workforce programs could better serve displaced workers and those at risk of losing their jobs to automation who face challenges obtaining in-demand jobs. For example, several stakeholders suggested that training programs sometimes failed to focus on providing skills for in-demand jobs. Specifically, one state official said that some programs focus on interviewing and resume writing skills, rather than helping workers acquire the actual skills needed to perform the tasks for their next job. Other officials also noted that jobseekers faced barriers to accessing training, such as lack of childcare. Accordingly, stakeholders proposed strategies including (1) focusing training content on in-demand skills, (2) designing programs to maximize their accessibility, (3) increasing investment in training, and (4) collaborating with other workforce stakeholders to better serve workers displaced by automation.

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Abbreviations

BLS	Bureau of Labor Statistics
DOL	Department of Labor
O*NET	Occupational Information Network
SD	standard deviation
WIOA	Workforce Innovation and Opportunity Act

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August 17, 2022

The Honorable Patty Murray
Chair
The Honorable Roy Blunt
Ranking Member
Subcommittee on Labor, Health and Human Services, Education, and
Related Agencies
Committee on Appropriations
United States Senate

The Honorable Rosa L. DeLauro
Chair
The Honorable Tom Cole
Ranking Member
Subcommittee on Labor, Health and Human Services, Education, and
Related Agencies
Committee on Appropriations
House of Representatives

In recent decades, technological advancements have allowed automation to perform tasks traditionally done by human workers—changing or eliminating some jobs on the one hand, and creating entirely new occupations and industries on the other.¹ In addition, several researchers have argued that the COVID-19 pandemic could have accelerated the adoption of certain technological changes in the nature of work, which could result in more robots in manufacturing and warehouses or more self-service kiosks in stores, for example.² These changes may also alter the types of skills needed for current and future jobs.

¹In this report, we use “automation” to mean modifying processes to become more automatic by reducing human involvement.

²See, e.g., McKinsey Global Institute, *The future of work after COVID-19* (Feb. 2021); World Economic Forum, *The Future of Jobs Report 2020* (Switzerland: Oct. 2020); Burning Glass Technologies, *After the Storm: The Jobs and Skills that will Drive the Post-Pandemic Recovery* (Boston, MA: Feb. 2021). Moreover, there are a variety of factors that might affect a firm’s decision to automate. For example, Acemoglu, Manera, and Restrepo (2020) argue that the U.S. tax system favors excessive automation. In particular, the study notes that the heavy taxation of labor and low taxes on capital encourage firms to automate more tasks and use less labor than is socially optimal. Daron Acemoglu, Andrea Manera, and Pascual Restrepo, “Does the U.S. Tax Code Favor Automation?” *Brookings Papers on Economic Activity*, Spring, 231-300.

The current U.S. workforce faces challenges to adapt to this evolving labor market. Automation may result in the elimination of certain jobs or require workers to retrain in order to keep their jobs or to obtain new ones. We use the phrase “at-risk workers” to describe those workers whose jobs are at risk of being partially or fully automated.

Federal, state, and local governments play a role in helping to ensure that the workforce is equipped to meet current and future labor market demands. The Department of Labor (DOL) creates projections to anticipate which jobs will grow the fastest—what we term “in-demand jobs”—and the skills needed for those jobs—what we term “in-demand skills.”³ However, research has highlighted a widening gap between the skills needed for certain jobs and the skills of workers available for these jobs.⁴ This gap is especially apparent in industries with high degrees of automation, such as health care, information technology, and manufacturing. Historically low unemployment has increased difficulties for employers looking to fill jobs involving skills needed for in-demand jobs. Additionally, it is unclear whether existing training opportunities can close this skills gap. One survey of warehouse workers found that 35 percent of participants were concerned that inadequate training resources would reduce their ability to succeed in a digital environment.⁵

House Report 116-450 of the Committee on Appropriations, to accompany H.R. 7614, Departments of Labor, Health and Human Services, and Education, and Related Agencies Appropriations Act, 2021

³Based on DOL data, we identified “in-demand jobs” as those occupations that were projected to add more than 7,600 jobs over the 2019 through 2029 period—i.e., the average job gain across all occupations over this period. Of these, we selected the 20 fastest-growing occupations. This eliminated occupations that are growing quickly but will add relatively few jobs. For example, the occupation of wind turbine service technicians is projected to grow by about 60 percent from 2019 to 2029, but will add fewer than 5,000 jobs over the period.

⁴See, for example, Boston Consulting Group, *Towards a Reskilling Revolution: A Future of Jobs for All*, World Economic Forum (Geneva: January 2018) and Craig Giffi et al., 2018 *Deloitte and The Manufacturing Institute Skills Gap and Future of Work in Manufacturing Study* (Washington, D.C.: Deloitte Insights, 2018).

⁵Joe Lui et al., “Research: How Do Warehouse Workers Feel About Automation?” *Harvard Business Review* (Boston, MA: Feb. 11, 2022).

included a provision for GAO to examine challenges and opportunities to provide training to workers at risk of losing their jobs to automation.⁶

This report examines (1) what available data indicate about which workers are at risk of automation and the skills needed for in-demand jobs; and (2) what insights stakeholders offer for workforce programs to better serve displaced workers and those affected by automation.⁷

For our first objective, we analyzed DOL data to identify occupations projected to grow the fastest over the period 2019 through 2029, as well as the 2020 DOL data on skills associated with those growing occupations. We established the reliability of these data by reviewing DOL documentation and interviewing knowledgeable DOL staff. In addition, we used information from selected case study states, described below, to provide examples of data available on a state and local level with regard to in-demand jobs and skills needed.

To help address both objectives, we conducted case studies in four states, including those with a high concentration of jobs susceptible to automation based on a prior GAO report, diverse urban and rural geographies, a variety of in-demand jobs, and that were recommended to us by workforce stakeholders in early interviews as having promising workforce responses to automation. The states were California, Kentucky, Pennsylvania, and Washington. In each state, we conducted semi-structured interviews with state workforce boards, which included representation from government agencies, business, labor, and training providers.⁸ We asked questions related to how the states collect data on in-demand jobs and any challenges to obtaining in-demand jobs within their state. We also asked for examples of workforce training programs to serve at-risk workers.

⁶H.R. Rep. No. 116-450, at 22 (2020).

⁷Unless otherwise noted, the word “stakeholders” refers to anyone or any group we interviewed, including state and local workforce boards, academics, and representatives of other organizations. In addition to individual interviews, we interviewed a number of stakeholders in group settings, and not all stakeholders offered thoughts on every question. As used in the report, the term “several” indicates that three to four stakeholders gave a particular response, while the term “many” indicates that five or more stakeholders gave a particular response. We also sometimes refer to the number of states represented by stakeholders to provide another sense of breadth for the comments.

⁸We obtained information from several local workforce boards recommended to us by state workforce board representatives as having particularly noteworthy programs.

Additionally, we interviewed stakeholders, including officials from DOL and the Census Bureau, as well as nine other organizations, such as national organizations of state workforce boards and agencies, business, labor, industry, and academic organizations, to obtain their perspectives on skills needed for in-demand jobs and the challenges workers face in obtaining those jobs. We selected these stakeholders based on our prior work on automation and workforce issues, as well as additional suggestions from initial outreach. The views of the stakeholders we interviewed provide illustrative examples on these topics and are not generalizable.

We also reviewed prior GAO reports and other literature to understand skills required for in-demand jobs; programs that provide workers with in-demand skills; challenges to obtaining in-demand jobs; and any lessons to consider as agencies respond to changes in the labor market due to automation. For additional information about our methodology, see appendix I.

We conducted this performance audit from April 2021 to August 2022 in accordance with generally accepted government auditing standards. Those standards require that we plan and perform the audit to obtain sufficient, appropriate evidence to provide a reasonable basis for our findings and conclusions based on our audit objectives. We believe that the evidence obtained provides a reasonable basis for our findings and conclusions based on our audit objectives.

Background

The Changing Composition of Jobs and Skills as a Result of Automation

Historically, new technologies have enhanced productivity and improved societal standards of living. Many workplace technologies have been designed to save labor through automation. However, as automation has replaced tasks performed by some types of workers, it has also created a greater demand for other types of workers.

Automation continues to affect the workforce landscape, as advanced technologies change the composition of jobs and skills demanded by employers. In March 2019, we found that technology adoption is likely to lead to increased demand for certain types of jobs, while reducing

demand for other jobs—both in the short and long term.⁹ That report also noted that multiple tasks comprise a job and multiple jobs comprise an occupation. If automation simplifies a few tasks, for example, it will change the nature of the job and perhaps allow a worker to take on more or different tasks. Likewise, if automation replaces some tasks, the skills needed to perform those tasks might also become unnecessary and could lead to declines in the number of jobs requiring those skills.¹⁰ If automation eliminates enough tasks in a given job, the job might be eliminated. Finally, if enough of those jobs are eliminated, the occupation consisting of those jobs might also be eliminated. For example, one study noted that an occupation that features basic use of numbers, such as a cashier, might be replaced with self-checkout machines, leading to decreased demand for that occupation. In addition, workers with lower levels of education who perform more routine tasks have tended to experience the greatest disruptions from automation, putting workers such as cashiers or clerical workers at risk.

On the other hand, where automation requires new skills, such as monitoring an automated process, it can lead to a skills gap in the labor market, with employers unable to find enough workers with the new skills needed. Several studies have attempted analyses of the skills gap in the labor market. For example, a 2018 study concluded that the skills gap had widened, and estimated that the gap could account for approximately 2.4 million skilled manufacturing job vacancies from 2018 through 2028.¹¹ In the same study, surveyed manufacturers cited a “shifting skill set due to the introduction of new advanced technology and automation” as the greatest cause of their skills shortage.¹² Another study that analyzed the skills associated with job openings noted similar dynamics, stating that technological advancement has caused the skills required for common job postings to change up to 40 percent in the last decade.¹³ Other

⁹GAO, *Workforce Automation: Better Data Needed to Assess and Plan for Effects of Advanced Technologies on Jobs*, [GAO-19-257](#) (Washington, D.C.: Mar. 7, 2019).

¹⁰The Occupational Information Network (O*NET) defines skills as “the ability to perform a task well,” and notes that skills are “usually developed over time through training or experience.”

¹¹Giffi et al., *2018 Deloitte and The Manufacturing Institute Skills Gap*.

¹²Giffi et al., *2018 Deloitte and The Manufacturing Institute Skills Gap*.

¹³Burning Glass Technologies, *After the Storm*.

research noted that the current speed of change can leave large segments of the population with obsolete skills.¹⁴

Federal and Other Data on Jobs and Skills

To help understand workforce changes, including job trends and skills needed for specific occupations, DOL provides data on the workforce. For example, DOL's Bureau of Labor Statistics (BLS) publishes annual, 10-year employment projections for the U.S. These projections analyze changes in the economy, among other things, to predict how employment levels across about 800 occupations may change during the next 10 years. The projections incorporate factors that can affect occupational employment. These include how automation might limit employment demand in the manufacturing sector (as machines perform more tasks that human workers previously did), or how automation might reduce demand for administrative support occupations (as new software programs automate administrative tasks).

For skills needed for specific occupations, DOL's Employment and Training Administration oversees the Occupational Information Network (O*NET). O*NET collects data on skills needed for occupations, including the degree of importance of a particular skill for a given occupation.¹⁵ O*NET groups 35 skills into seven categories: content; process; complex problem solving; resource management; social; systems; and technical.¹⁶ O*NET organizes the information about occupations in a similar way to the BLS employment projections, which allows job projections information to be matched with occupational skill information. This matching can identify skills needed for in-demand occupations.

In addition to DOL's data efforts, the Census Bureau also collects data on automation. As we noted in March 2019, the Census Bureau has long measured the impact of technology, and obtains information through

¹⁴Melanie Arntz, Terry Gregory, and Ulrich Zierahn, "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis," *OECD Social, Employment and Migration Working Papers*, no. 189 (Paris: OECD Publishing, 2016).

¹⁵O*NET is sponsored by the Employment and Training Administration through a grant to the North Carolina Department of Commerce, according to DOL. O*NET also collects information on knowledge and abilities, as well as more specific job tasks. O*NET has a 5-point scale of importance for its 35 skills, with ratings ranging from "Not Important" (1) to "Extremely Important" (5). See appendix I for additional information on O*NET.

¹⁶O*NET groups content and process skills together as "basic" skills, and refers to the other five skill categories as "cross-functional" skills. See appendix I for additional information.

surveys such as its Annual Business Survey.¹⁷ The Census Bureau also collects capital expenditure data on industrial robotics in the Annual Survey of Manufactures and on industrial, as well as service, robotics in the Annual Capital Expenditures Survey.¹⁸

Beyond federal efforts, states capture data related to labor market conditions and projections, as well as the demand for particular skills and occupations in their respective geographic areas. States and employers can use this information to help plan for their area's future workforce needs, including those for in-demand jobs.

Workforce System and Training Programs

State and local workforce development boards—key components of the workforce system that include representatives from area businesses, labor organizations, government, and training providers, among others—help direct employment and training in their respective geographic areas. The boards coordinate between DOL and local American Job Centers to optimize services for jobseekers and employers.¹⁹

Training programs, also known as workforce development programs, seek to provide participants with education and training to prepare them for work and help them improve their prospects in the labor market. Programs may focus on some combination of job-search assistance, career counseling, occupational skill training, classroom training, or on-the-job training. While training programs may support individuals who are unemployed with the goal of facilitating reentry into the job market, programs may also provide skills to already employed individuals, also known as incumbent workers. Incumbent worker training can have several benefits: it can help workers gain skills needed to maintain

¹⁷[GAO-19-257](#).

¹⁸According to Census Bureau officials, these surveys do not directly make inferences about the impact of automation on work, but do produce experimental statistics on the share of workers at establishments (or firms) with robotics, a measure of exposure to automation technologies, including robotics. Officials also noted that agency efforts at collecting data on advanced technology have not been continuous, but have more recently been restarted.

¹⁹GAO, *Economic Adjustment Assistance: Experts' Proposed Reform Options to Better Serve Workers Experiencing Economic Disruption*, [GAO-21-324](#) (Washington, D.C.: Apr. 19, 2021).

employment, avert layoffs, and promote development of skills to help workers progress in their careers.²⁰

Within the workforce system, training programs can use a variety of methods. Some programs offer training that results in a credential or certificate to signal the skills participants have mastered. The Workforce Innovation and Opportunity Act (WIOA) affirms the importance of effective credentialing by stating that one of the purposes of the act is to provide workforce investment activities, through statewide and local workforce development systems, that increase participants' attainment of recognized postsecondary credentials.²¹ Other programs are centered on a "career pathways" approach—a workforce strategy designed to bolster long-term earnings and self-sufficiency for workers by combining high-quality education, training, and other services to support participants' success. As part of this strategy, workers would have multiple opportunities to enter and exit training and jobs in a specific industry.²² This can mean encouraging workers to find new jobs in "adjacent" careers that require similar skills or tasks to their previous jobs.²³ Programs can also help participants not just by teaching skills, but by providing "wraparound" services—comprehensive supports such as basic education, and supportive services such as childcare support or transportation—that enable participants to concentrate on their learning.²⁴

²⁰[GAO-21-324](#).

²¹29 U.S.C. § 3101(6).

²²ABT Associates, *Building Better Pathways: An Analysis of Career Trajectories and Occupational Transitions* (Rockville, MD: Dec. 2021). This study, funded by and prepared for DOL, noted that the career pathways approach has four main tenets: (1) offers multiple places to enter and exit training and jobs in a specific industry; (2) results in recognized credentials intended to lead to better jobs with higher pay; (3) uses support services and flexibility for nontraditional students; and (4) relies on employer partnerships.

²³Burning Glass Technologies, *After the Storm*.

²⁴[GAO-21-324](#).

Available Data Do Not Explicitly Identify Workers at Risk of Losing Their Jobs to Automation, but Indicate Skills Needed for In-Demand Jobs

Federal and other data do not explicitly identify U.S. workers who are at risk of losing their jobs to automation, and recent estimates attempting to identify the number of workers affected have varied widely. DOL and the Census Bureau are seeking additional data on skills that the general worker population will need for in-demand jobs in light of automation. Currently available federal data show that in-demand jobs require workers to have a mix of skills, including soft skills; process skills that help a person acquire knowledge quickly (e.g., active learning and critical thinking); and technical expertise (e.g., equipment maintenance).²⁵ The data also indicate that the number of skills required for in-demand jobs increases with education and pay level. Further, research indicates that certain jobs and skills are less likely to be automated. In addition, in some states, state, local, and private data are used to inform which skills are most important for in-demand jobs in a given geographic area.²⁶

Federal Data and Other Research Do Not Explicitly Identify At-Risk Workers, and Agencies Are Seeking Additional Information on Automation's Workforce Effects

Existing federal data do not explicitly identify, or provide detailed occupational characteristics about, workers that are most at risk for job loss. DOL officials noted that one of the primary challenges of collecting information on at-risk workers is accurately identifying who is at risk. Further, officials said any additional agency efforts would require significant resources and yield uncertain results. Officials also noted the large degree of uncertainty in academic estimates on the effects of automation on employment.²⁷ Our prior work corroborates this perspective. For example, in 2019 we found that academic research quotes anywhere from 9 to 47 percent or more of the workforce could hold jobs at risk of being automated. Additionally, we noted that workforce data do not identify the causes of employment shifts; so even for workers who have actually lost jobs, the data do not specify whether automation was the cause.²⁸

²⁵O*NET defines soft skills as interpersonal and thinking skills needed to interact successfully with people and to perform efficiently and effectively in the workplace.

²⁶Descriptions and terms for skills vary across data sources such as O*NET or private research, making it difficult to directly compare different research studies' conclusions about specific skills required for in-demand jobs.

²⁷DOL officials said that the agency is tracking a range of studies that use different datasets and methodological approaches to assessing automation's effect on the workforce.

²⁸As noted in [GAO-19-257](#), federal data do not provide a comprehensive picture of the causes of employment shifts or the skills needed for in-demand jobs.

Moreover, DOL officials noted that some occupations may be considered at risk of automation and yet still be projected to grow. For example, DOL officials noted that the number of truck driving jobs is projected to grow by about 3 percent from 2019 through 2029, but studies have also predicted those jobs are among the most at risk of automation further in the future.²⁹ DOL does not currently—and has no plans to—produce any public statistics on particular occupations’ vulnerability to automation, due to the uncertainty and complications of creating such data.³⁰

Like DOL, the Census Bureau collects data on the impact of automation on the workforce, but does not specifically identify at-risk workers. The Census Bureau’s efforts include the Annual Business Survey, which Census Bureau officials said collected qualitative data at a high level and did not identify the subset of workers impacted by automation. Officials said other Census Bureau efforts likewise did not identify at-risk workers.³¹

DOL and the Census Bureau are expanding their efforts to collect and analyze data on skills needed by the workforce in light of automation. For example, BLS officials said they plan to conduct case studies of employers to examine how automation is affecting jobs and to inform potential future data collection efforts on automation. The agency plans to focus the studies on three sectors: retail trade, health care, and transportation and warehousing.³² Additionally, in fiscal year 2020, DOL submitted a study to Congress on ways to supplement DOL data collection to understand the impact of changing technology on the

²⁹See, for example, GAO, *Automated Trucking: Federal Agencies Should Take Additional Steps to Prepare for Potential Workforce Effects*, [GAO-19-161](#) (Washington, D.C.: Mar. 7, 2019), which noted that widespread use of self-driving trucks was still years to decades away.

³⁰As noted earlier, although BLS does not produce these statistics, BLS nonetheless incorporates technological impacts—such as automation—into its employment projections. Those projections examine automation along with other factors, such as changes in consumer preferences, demographic changes, and outsourcing, according to BLS officials. BLS’s Occupational Outlook Handbook discusses automation for occupations when the BLS research concludes that automation has a significant impact on the expected future number of workers in an occupation.

³¹Census Bureau officials noted that they have an ongoing effort with BLS to combine establishment level data with worker skill data from O*NET.

³²BLS officials said they plan to prioritize advanced technologies with the largest effects on jobs, and will review automation that is part of each sector’s production. They anticipate publishing findings from the case studies in 2023.

workforce.³³ That study identified additional data needed on the demand for skills, including soft skills such as collaboration and more technical proficiencies such as coding. BLS has created working groups to evaluate the study's recommendations and plan next steps. DOL officials also said they are evaluating additional ways to collect data through surveys to further identify automation's effects on worker skills.

Likewise, researchers from the Census Bureau and others analyzed the 2019 Annual Business Survey data, which asked companies about their employment outcomes attributable specifically to adopted advanced technologies.³⁴ Among other findings, preliminary analysis showed the following:

- Most respondents—about 75 percent—reported no employment change attributable to technology, and of the respondents reporting change, more reported employment increases than decreases.³⁵
- About half of respondents reported changes in skill levels due to adoption of technology, and, of those, firms generally reported that adopting technology resulted in increasing firms' demand for skills.
- Respondents that reported greater adoption of new technologies (e.g., high degree of use for robotics or specialized equipment) were more likely to report a greater increase in the skills needed to work at the respondent's company.

The Census Bureau is continuing to validate the results of the 2019 Annual Business Survey, and plans to release a final paper in September

³³This study, among other efforts, helped DOL implement our recommendation to gather additional data on automation's effect on the workforce. See Gallup, *Assessing the Impact of New Technologies on the Labor Market: Key Constructs, Gaps, and Data Collection Strategies for the Bureau of Labor Statistics* (Omaha, NE: Feb. 7, 2020). DOL has also studied the feasibility of using its O*NET system to track changes in occupations over time and concluded that it was not feasible. DOL is also monitoring additional studies to assess the effects of automation.

³⁴The Census Bureau specifically asked firms about the adoption of five technologies: artificial intelligence, cloud computing, dedicated equipment, robotics, and specialized software.

³⁵Census Bureau officials noted that firms that reported greater use of robotics were just as likely or more to report a decrease in employment as to report an increase (conditional on a change in employment in either direction).

2022. Currently, the Census Bureau plans to repeat the workforce related questions in the 2023 Annual Business Survey.³⁶

Data Indicate That In-Demand Occupations with More Skills May Require More Education and Offer Higher Pay, and Research Suggests These Jobs Are Less Likely to Be Automated

We analyzed BLS employment projections for the period 2019 to 2029 and 2020 O*NET skills data and found that in-demand occupations with more “important” skills (as indicated by O*NET) tend to require higher levels of education and offer greater pay.³⁷ Specifically, from the set of occupations with above-average changes in employment levels, we analyzed O*NET data on skills for the 20 fastest-growing occupations overall—regardless of education level—and also for the top 20 fastest-growing occupations according to three education levels needed for them:

- a high school degree or less;³⁸
- some college;³⁹ or
- a bachelor’s degree or higher.⁴⁰

We found that in-demand occupations at every education level share many “important” skills. Further, as the education requirement increases,

³⁶In addition, the Census Bureau plans to collect data on technology adoption through its Economic Census in 2022, but no questions on worker effects will be included, according to agency officials. The Economic Census collects data on businesses and economic impact every 5 years.

³⁷O*NET uses a 5-point “importance scale” to quantify the importance of a particular skill to a particular occupation (such as the importance of the skill of speaking to the occupation of nursing). In this report, we used O*NET’s average score of 3 or above to identify a skill as “important.” Projections about future job growth and skills needed have limited certainty, as with any projections, and are subject to error because of the many unknown factors that may affect the economy over the projection period. Moreover, our analysis is at the national level, and the set of jobs projected to grow and the skills needed for them might differ across localities. For example, even if an occupation is projected to grow at the national level it does not mean that it will be growing in all localities. Additionally, given that these are national-level data, the characteristics of the selected occupations, such as median wages, might differ across localities. For additional information about O*NET and our analyses, see appendix I.

³⁸We defined occupations needing “a high school degree or less” as those occupations with a typical entry-level education, based on BLS’s projections data, of “high school diploma or equivalent” or “no formal educational credential.”

³⁹We defined occupations needing “some college” as those occupations with a typical entry-level education, based on BLS’s projections data, of “associate’s degree” or “postsecondary nondegree award” or “some college, no degree.”

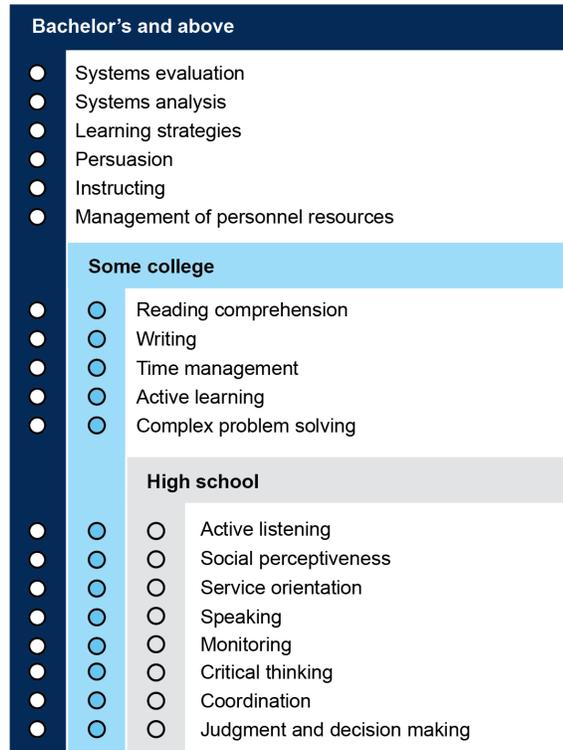
⁴⁰We defined occupations needing “a bachelor’s degree or higher” as those occupations with a typical entry-level education, based on BLS’s projections data, of “bachelor’s degree” or “doctoral or professional degree” or “master’s degree.”

so does the number of “important” skills.⁴¹ Specifically, in-demand occupations across all education levels share eight “important” skills—including critical thinking and service orientation. Occupations requiring at least some college or a bachelor’s degree or higher have an additional five skills in common.⁴² Similarly, we found that skills for occupations requiring a bachelor’s degree or higher have six additional “important” skills that were not associated with skills listed for the other two levels of education, as shown in figure 1.

⁴¹In addition, we regressed the total number of skills deemed important for each occupation on the education level and found a positive and statistically significant relationship in the sample of our top 20 jobs as well as in the overall dataset. This relationship represents a correlation, and we did not control for other factors. Thus, it could be driven by factors related to both the total number of skills deemed important and to the education level. For a full list of occupations and skills, see appendix I.

⁴²In order to identify the skills deemed important for each education group, for each skill in that group we calculated the weighted average importance score (weighted by 2019 employment) and selected the skills with a weighted average importance score of 3 or above. While our analysis of O*NET data identifies skills required for the top 20 in-demand occupations collectively, those data also include skills unique to each in-demand occupation. For example, among our top 20 in-demand occupations where the typical education needed for entry is high school or less, “equipment selection” is a skill deemed important only for the occupation of industrial machinery mechanic. Likewise, “installation” is a skill deemed important only for solar photovoltaic installers. For the list of weighted average importance scores for each education group, see appendix I.

Figure 1: Skills Deemed Important in the Top 20 In-Demand Occupations, by Education Level



Source: GAO analysis of U.S. Bureau of Labor Statistics (BLS) Employment Projections program data and U.S. Department of Labor Occupational Information Network (O*NET) data. | GAO-22-105159

Notes: We restricted our study of the fastest-growing, "in-demand" jobs to those occupations that were projected to gain an above-average number of jobs in the 2019-2029 period for each of the three education groups. Then, using O*NET's skills and "importance scores," we identified the most important skills for the 20 fastest-growing occupations by calculating the weighted average importance score (weighted by 2019 employment) and selecting the skills with a weighted average importance score of 3 or above for each education level. For additional information on how O*NET describes skills, see: [basic skills](#) and [cross-functional skills](#).

The number of skills deemed important in each education category were similar for in-demand occupations and all other occupations. (See table 1.)

Table 1: Number of Skills Deemed Important by Occupational Information Network (O*NET) Data, According to Education Level Required for Occupations

Education level	Number of “important” skills for in-demand occupations	Number of “important” skills for other occupations
High school or less	8	9
Some college	13	13
Bachelor’s degree or more	19	20

Source: GAO analysis of U.S. Bureau of Labor Statistics (BLS) Employment Projections (EP) program data and U.S. Department of Labor Occupational Information Network (O*NET) data. | GAO-22-105159

Notes: We identified in-demand occupations as those occupations that were projected to gain an above-average number of jobs during the 2019–2029 period for each of the three education groups, and then chose the 20 fastest growing occupations for each education group. We also identified occupations outside of the top 20 in-demand occupations in the relevant education group. For each category, in order to determine if one of O*NET’s 35 skills was deemed important for a particular education level, we first calculated the weighted average importance score (weighted by 2019 employment) for the top 20 in-demand occupations and for the occupations outside of the 20 in-demand occupations in that education group and selected the skills with a weighted average importance score of 3 or above. O*NET uses a 5-point “importance scale” to quantify the importance of a particular skill to a particular occupation (such as the importance of the skill of speaking to the occupation of nursing). We used O*NET’s average score of 3 or above to identify a skill as “important.”

In addition, in-demand jobs that require a greater number of “important” skills also have higher average pay, according to our analysis of BLS and O*NET data. For example, those top-20 overall in-demand jobs in the highest quartile—with median pay of nearly \$110,000—have about 18 skills deemed important, while jobs in the lowest quartile—with median pay of about \$30,000—have about eight skills deemed important.⁴³

Research suggests that many of the skills needed for in-demand occupations at the higher levels of education—including more abstract skills and those involving judgment and adaptability—might protect individuals from the effects of automation. For example, one study noted that the skills most vulnerable to automation are routine cognitive and physical skills, such as operating machinery or collecting and processing data, while the least vulnerable are skills such as creativity, social skills,

⁴³We divided our top 20 in-demand occupations into quartiles based on median wage data (in 2020 dollars) from BLS’s Occupational Employment and Wage Statistics program. We also regressed the total number of “important” skills on median annual wages and found a positive and statistically significant relationship in the sample of our top 20 jobs, as well as in the overall dataset. This relationship represents a correlation, and we did not control for other factors. Thus, it could be driven by factors related to the total number of skills deemed important and to wages.

management, and planning.⁴⁴ That study noted that nursing and home health support are good examples of occupations with tasks that are difficult to automate because they involve high levels of social and emotional interaction. Those occupations are growing and were included in our analysis of in-demand occupations.⁴⁵

O*NET Has additional Resources for Individual Job Seekers

O*NET has additional information on jobs and the skills required for them. For example, O*NET lists “Bright Outlook” occupations, which, like in-demand jobs, are projected to grow faster than average or to have more than 100,000 openings over a 10-year period, nationally. For each occupation, O*NET provides detailed information, including particular tasks common to the occupation; skills ranked by importance; and specific technology skills such as cloud-based software or spreadsheet skills. For example, for home health aides, O*NET details 11 common tasks such as maintaining records of patient care and checking patients’ pulse and temperature. O*NET also lists active listening, service orientation, and social perceptiveness as the top three most important skills for those aides. DOL officials noted that American Job Center staff work with job seekers to identify their skills and abilities, and advise them on in-demand jobs and potential training opportunities available in their local areas based on local labor market information.

Source: GAO analysis of Occupational Information Network (O*NET) data and Department of Labor interviews. | GAO-22-105159

Other studies have suggested that paths for obtaining new skills might help with performing new jobs in the future. For example, one study stated that workers have found some success in meeting changing job demands by acquiring new skills through formal educational attainment, such as obtaining a bachelor’s or associate’s degree.⁴⁶ That study noted that new and emerging jobs may have a high demand for analytical skills. Another study stated that formal educational attainment will not be the only path, noting that automation will also create other jobs that do not require a college degree, such as robotics technicians.⁴⁷

Workers who acquire additional skills may be able to leverage those skills to obtain jobs that offer higher pay. For example, one report observed that a retail worker could acquire some basic computer skills to become a “help desk” specialist.⁴⁸ Another study stated that workers at risk of automation could, with reskilling, expand their career options and increase their income.⁴⁹ Moreover, without reskilling, a quarter of at-risk workers could see their income drop, according to the same study.

⁴⁴See Conor McKay, Ethan Pollack, and Alastair Fitzpayne, *Automation and a Changing Economy, Part I: The Case for Action* (Washington, D.C.: Aspen Institute, April 2019).

⁴⁵For example, nurse practitioners, occupational therapy assistants, home health and personal care aides, and physical therapy assistants all made the list of top 20 in-demand occupations. See appendix I for the complete list.

⁴⁶Anthony P. Carnevale, Megan L. Fasules, and Kathryn Peltier Campbell, *Workplace Basics: The Competencies Employers Want 2020* (Georgetown University Center on Education and the Workforce, 2020).

⁴⁷Burning Glass Technologies, *After the Storm*.

⁴⁸Burning Glass Technologies, *After the Storm*.

⁴⁹The Boston Consulting Group, *Towards a Reskilling Revolution: A Future of Jobs for All* (Geneva: World Economic Forum, January 2018)

Likewise, one group of researchers noted that occupations requiring intellectual knowledge, skills, and abilities yield the highest pay.⁵⁰

State Data and Other Research Provide Additional Information on Skills Needed for In-Demand Jobs in Specific Geographic Areas

States Have Flexibility to Identify In-Demand Jobs

States can identify in-demand jobs in different ways, including taking into account factors such as predicted job growth, wages, stability, and future outlook. For example, all of our case study states incorporated projected job growth rates and job openings to determine their in-demand jobs. In addition, California, Pennsylvania, and Washington analyzed supply and demand to determine their in-demand jobs, while California, Kentucky, and Pennsylvania included wages and education levels as part of their determinations.

Source: Department of Labor data and interviews. | GAO-22-105159

Stakeholders we interviewed in our case study states said that many state and other entities—such as governments, business organizations, training providers, unions, and private companies—collect data on the in-demand jobs and skills needed in their specific geographic areas.

State governments. State governments collect data on in-demand jobs and skills needed in their states and, according to DOL, are able to do so because of the nationwide workforce and labor market information system that is authorized and funded under the Wagner-Peyser Act as amended by the Workforce Innovation and Opportunity Act (WIOA).⁵¹ In addition, states must include an analysis of economic conditions in their state as part of their WIOA state plan.⁵² Each of our case study states maintains data online that provide information on occupational projections within their states, as well as skills and training or education needed for specific occupations. For example, California publishes data by occupation at a regional level, along with an interactive tool that shows occupational profiles of job skills needed and training requirements for high-growth occupations, which officials said workers could use to identify “adjacent” jobs that can build on skills a worker already has. Likewise, Washington maintains data on in-demand occupations by county, as well as employment projections, pay, and skills information. Washington officials noted that the local workforce development boards finalize the lists of in-demand jobs in their regions. For skills information in particular, Washington uses private data to identify skills from online announcements. Kentucky has created a workforce dashboard showing 5-year projected job growth by region, wage estimates, and skills self-assessments for all occupations collectively or specific occupations. The dashboard can present information on occupations by education, experience level, growth, and typical on-the-job training, among other

⁵⁰Anthony P. Carnevale, Megan L. Fasules, and Kathryn Peltier Campbell, *Workplace Basics: The Competencies Employers Want 2020*.

⁵¹See 29 U.S.C. § 491(2).

⁵²See 29 U.S.C. § 3112(b)(1)(A). In order for states to be eligible for WIOA funding for adult and dislocated worker employment and training activities, states must submit a unified state plan outlining a 4-year strategy for the core programs defined under the act. 29 U.S.C. § 3112(a). See also 34 C.F.R. § 361.105. The determination of whether an industry sector or occupation is in-demand for purposes of WIOA is made by the state board or local board, as appropriate, using state and regional business and labor market projections, including the use of labor market information. 29 U.S.C. § 3102(23)(B).

characteristics. Pennsylvania officials said their state labor department uses data from research organizations within the state to obtain information pertaining specifically to workers at risk of losing their jobs to automation.

Business organizations. Business organization representatives on state boards said they took various approaches regarding collecting information on skills needed for in-demand jobs, as well as information on the effects of automation. For example, officials from a business organization in one state said it tracks jobs that could be lost to automation, and reports these data to the governor's office during monthly meetings. The organization collects information from thousands of businesses in its region through questionnaires and calls, and asks questions such as whether jobs at the business will exist in 5 years or if the company is considering automating jobs. The officials said they research potential trainings that could support workers whose jobs may soon be automated. In contrast to collecting their own data, an official representing businesses on another state workforce board said that their association relies on outside sources for data and worked closely with a local economist to study automation in their state. The study found, among other things, that automation is creating new tasks for workers to perform, which may require specific training. Similarly, business representatives in another state said that their state used a public-private partnership to collect data from businesses and employers to report on jobs in high demand.

Training providers. Training providers in our selected states presented a range of data collection efforts, from collecting data themselves on skills needed for in-demand jobs to relying on outside information. One training provider, for instance, said it gathers data on projected automation, digital skills, and job openings and shortages. Specifically, the provider said it examined the degree to which tasks within certain health care jobs are likely to be automated, and found that from 30 to 60 percent of those tasks are likely to be automated. The study also found that the percentage of tasks subject to automation decreases as a worker moves further up the career ladder. Another training provider said it collects data on in-demand jobs and skills by surveying industry partners, as well as reviewing projected retirement data and state community college data. One training provider noted that it relies significantly on state and regional workforce development board data, as well as private data, which the provider uses to identify demand for training.

Unions. Union representatives in two case study states said that they collect workforce information. Of those, one representative said that their

union’s apprenticeship program collects information from its contractors to determine the demand for its programs, while the other said that their union provides labor demand data to state officials. Separately, a union representative in another case study state said that their organization does not collect data, and instead relies on the state’s employment data.

Private data. Some companies collect workforce data such as skills for in-demand jobs, credentials, and training needs. These companies can obtain the data from job postings and other data, which can provide more insight than federal data alone.⁵³ For example, these data

- provide skills data that are more up to date than O*NET because the job postings are current. This allows private data collection companies to readily observe workforce effects of current events, such as the COVID-19 pandemic. One such company published the trends it saw in jobs and skills coming out of the pandemic, including a greater push toward automation.⁵⁴ A company representative also said that O*NET job data can be slow to identify emerging trends; the representative noted that, for example, “data scientist” was added to the O*NET jobs list in 2018, despite being an identifiable occupation for a decade prior to then.⁵⁵
- identify more specific skills than O*NET’s set of 35 skills because job postings have more specific requirements. For example, skills could include mastery of specific software or familiarity with social media platforms. However, O*NET also uses private data to compile and update a list of “Technology Skills,” which identify the general skill (e.g., “spreadsheet software”), as well as the specific software technology. O*NET lists these skills on its website by occupation.

⁵³A representative from one company, for instance, testified to Congress that it monitors nearly 50,000 job sites daily and at any given time tracks over 3 million current job openings. The representative said that the company’s database holds more than a billion current and historical job postings, which allows the company to identify trends and see changes in the market quickly.

⁵⁴See Burning Glass Technologies, *After the Storm*.

⁵⁵DOL officials noted that O*NET purchases job postings data from a private company and uses the data, in part, to identify alternate job titles. These alternate job titles are associated with O*NET occupations and used to make the online keyword searches more effective for users who search on job titles, rather than by federal occupational codes. However, DOL officials also said that O*NET skills and other data are generally updated every 5 years, and it is unfeasible to track changes in occupational skill requirements over time.

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- could help job seekers identify possible ways to build on existing skills to obtain a job that might be less subject to automation.
 - can identify in-demand skills for specific geographic areas.

However, two stakeholders cited concerns about relying too heavily on private data to identify skills important for in-demand jobs. One stakeholder noted, for example, that the universe of online job postings is more heavily weighted toward professional occupations in large companies and consequently may not feature occupations that are projected to have many job openings over the next decade, such as food service. Both stakeholders said that the postings may not contain the skills typically required for the occupation. For example, job postings are often quite short, the stakeholders said, so they do not describe the majority of skills needed for the job. One stakeholder also said that the process of translating the job posting text to data can yield unreliable results.

Selected Stakeholders Suggested Workforce Programs Could Better Serve Displaced Workers by Refining Content and Increasing Accessibility and Investment

Stakeholders we interviewed offered insights on how existing workforce programs could better serve displaced workers who face challenges to getting in-demand jobs, and those at risk of losing their jobs to automation. Specifically, stakeholders proposed focusing training content on in-demand skills, designing programs to maximize their accessibility, incentivizing additional training opportunities, and collaborating with other workforce stakeholders to enrich the training landscape, among other potential steps, to better serve workers displaced by automation.

State Workforce Officials Cited a Few Examples of Training Programs Serving At-Risk Workers

While selected state workforce board representatives cited very few programs that targeted workers at risk of losing their jobs to automation, some efforts do exist. In Kentucky, for example, the National Dislocated Worker Grants program was used to fund employment and training services for approximately 200 displaced workers when their plant relocated due to automation. One plant worker, facing a potential layoff after 34 years, said he found new employment as a controls engineer after completing a 12-week training program. Another worker used career services and training to eventually earn a commercial driver's license, according to Kentucky workforce officials.

In addition, California workforce board officials said that an agricultural company in California automated its manual fruit-packing processes. The company sponsored in-house training to retain about 90 percent of their affected employees, who learned how to operate, clean, and maintain the new machinery.

Source: GAO analysis of interviews with state and local workforce boards. | GAO-22-105159

Training Program Content That Includes Aligning Existing and In-Demand Skills May Help Workers Obtain In-Demand Jobs

Characteristics of Workers at Risk of Automation May Differ from General Population

Previous GAO work has found that the characteristics of workers in jobs at risk of automation may differ from those of the workforce generally. For example, at-risk workers earn less, on average, and have on average fewer years of education. Other research has observed similar dynamics, noting for example that rural workers are more likely to be negatively impacted by automation. This research has suggested that training programs centered on at-risk workers should consider how the program can respond to the particular skills, needs, and characteristics of this population.

Source: GAO, Workforce Automation: Better Data Needed to Assess and Plan for Effects of Advanced Technologies on Jobs. [GAO-19-257](#) (Washington, D.C.: Mar. 7, 2019) and GAO analysis of National Governors Association Center for Best Practices, Future Workforce Now: Reimagining Workforce Policy in the Age of Disruption (Washington, D.C.: July 2020). | [GAO-22-105159](#)

According to many stakeholders, providing in-demand skills training could help workers overcome some of the challenges they face in obtaining in-demand jobs. For example, stakeholders in three states said one challenge is that training program content does not always focus on in-demand skills. One state official said that some programs focus on interviewing and resume writing skills, rather than helping workers acquire the actual skills needed to do the tasks for their next jobs. Two other stakeholders noted that workforce programs tend to focus on getting workers new jobs quickly, rather than finding jobs that could provide a longer career or work that is less susceptible to automation. Several stakeholders reported that, as a result, such programs can lead to short-term or low-wage jobs while doing little to promote entry into jobs that provide satisfactory levels of stability and wages.⁵⁶ For example, one stakeholder mentioned a program that taught participants to operate a cash register, which, upon program completion, would likely lead to a low-wage job that the stakeholder did not believe provided enough financial stability.

A second challenge, mentioned by state board stakeholders across all four states, is that workers may struggle psychologically to accept reskilling programs or new jobs. For example, one stakeholder said that job loss can be traumatic for many workers, while another said training programs that do not adequately consider workers' psychological barriers can limit opportunities to obtain in-demand jobs. According to state board stakeholders in two states, workers may not be able to envision how their skills can translate to another occupation because they have been doing the same job the same way for many years.

Lastly, two stakeholders suggested that some training programs that do not result in an industry-recognized credential hinder access to in-demand jobs. When workers do not have a recognizable credential, or when skills associated with a credential are unclear, employers may be unsure whether workers have obtained skills relevant to their job openings. Likewise, one stakeholder noted that even when credentials are provided, workers may not understand which ones are valuable to employers. Consequently, workers may not understand which training programs are most useful for obtaining in-demand jobs.

⁵⁶According to DOL officials, states can consider stability and pay as part of the requirements for the definitions of in-demand jobs in their states.

Stakeholders offered various approaches to mitigate some of these challenges. Stakeholders and research noted that workforce organizations can adjust program curriculum in several ways to help workers obtain in-demand jobs. For example, workforce officials in one state noted the importance of teaching skills that lead to jobs that are less likely to be automated, while officials from another state said that training should help workers obtain “higher-level” skills in order to compete in the labor market; as we noted earlier, these skills may be less likely to be automated. Another state’s workforce officials suggested that workforce programs should train workers for high-growth, good quality jobs by emphasizing skills needed to perform jobs that will be automation resistant. Additionally, one labor representative stated that while training often focuses on resume writing and interviewing, training would be more useful if it identified which occupations each worker should pursue and relevant skills for that occupation.

Another strategy, suggested by two studies, emphasizes building upon existing skills to move employees to “adjacent” jobs quickly.⁵⁷ State board stakeholders in two states echoed this; one state board stakeholder who represented employers said that long-haul truckers whose jobs are at risk of automation could apply skills from that job to other trucking-related positions such as monitoring vehicles for an emergency call center tracking those vehicles. The stakeholder noted the importance of workers believing their skills will be transferrable, suggesting that transitioning to new jobs that rely on already mastered skills may alleviate psychological barriers.

A 2021 report funded by DOL includes similar insights. It suggests focusing training on occupations that are likely to lead to wage growth for workers. Accordingly, the report intends to help training providers design programs that focus on “career pathways” by providing information on career trajectories and occupational transitions (such as which occupations are associated with higher-than-average wage growth for job entrants over time). The report also suggested that programs should not focus solely on a narrow range of highly specialized skills.⁵⁸ Instead, it recommended teaching skills such as problem solving and

⁵⁷Burning Glass Technologies, *After the Storm*; and McKinsey Global Institute, *The Future of Work in America* (Washington, D.C.: July 2019).

⁵⁸DOL officials noted that programs focusing on a narrow range of highly specialized skills may still be highly desirable for certain occupations or industries, such as health care.

communication, which are associated with occupations with strong wage growth and are also transferrable to a variety of industries and occupations.⁵⁹

Washington’s “Upskill Backfill” Initiative Provides Advanced-Skill Training

Washington stakeholders cited the Upskill Backfill initiative as a potentially useful model to train workers impacted by automation, though the initiative has not served these specific workers to date. One such training sought to upskill welders and machinists for supervisory roles by advancing both technical and “soft” skills, such as communication and teamwork. At the end of the program, 255 people completed training and 28 people were promoted. While technical skills were considered important, the workforce board attributed the promotions to the soft-skills training.

Source: Washington Workforce Training and Education Coordinating Board documentation and interviews with state workforce board officials. | GAO-22-105159

Additionally, one study advised that training programs be designed to lead to widely recognized credentials that signal mastery of in-demand skills. For instance, the study highlighted one state that provides programs that result in recognized certificates, like a welding certificate from a community college. This state is also developing a way to track relevant data to signal the credentials job applicants carry.⁶⁰ Another state’s governor signed an executive order requiring the state to recommend ways to create more transparency for credentials conferred by public higher education institutions by translating them wherever possible into skills and competencies. Similarly, workforce experts we interviewed for our April 2021 report suggested providing workers with information on the quality of credentials and how credentials can be combined to help career progression.⁶¹ Moreover, another study of four sector-based training programs noted that training programs that focused on occupational skills leading to an industry-recognized credential, as well

⁵⁹ABT Associates, *Building Better Pathways: An Analysis of Career Trajectories and Occupational Transitions* (Rockville, MD: Dec. 2021).

⁶⁰National Governors Association Center for Best Practices, *Future Workforce Now: Reimagining Workforce Policy in the Age of Disruption* (Washington, D.C.: July 2019).

⁶¹[GAO-21-324](#).

as targeting high-wage sectors, among other characteristics, produced the largest and most persistent wage gains.⁶²

Finally, some workforce stakeholders have taken steps to define or broaden understandings of which credentials provide meaningful skills for in-demand jobs. For example, a state board stakeholder representing training providers stated that the community college system can be leveraged to provide many workers with credentials a variety of employers understand and value. Another stakeholder noted that an organization comprised of academic, manufacturing, technology, and government stakeholders created credentials, and members agreed that the credentials represented skills critical for working in their sector.

Improving Access to Training Can Lead to Greater Worker Participation and Opportunities to Obtain In-Demand Jobs

According to stakeholders, access to training presents a key challenge to obtaining skills needed for in-demand jobs, and workers would benefit from better solutions related to childcare concerns, scheduling, financial hardships, or geography.

- **Childcare concerns.** State board stakeholders from all four states, as well as other interviewed stakeholders, cited childcare obligations as a significant barrier to accessing job training, with stakeholders from one state noting barriers are exacerbated by a shortage of affordable childcare options for many parents. Furthermore, government representatives on one state board said childcare services had been reduced recently (and therefore childcare options diminished), and a business representative from another state board said childcare had been significantly disrupted by the pandemic. The level of concern over lack of childcare aligns with our prior work, which identified childcare as one of the two most-needed support services and was particularly challenging for rural and tribal communities.⁶³
- **Difficulties with scheduling.** Two stakeholders also said that inconvenient training program schedules can hinder access, such as when training conflicts with work hours for workers with ongoing jobs.

⁶²Lawrence F. Katz et al., “Why Do Sectoral Employment Programs Work? Lessons from WorkAdvance,” paper from *JOLE* Virtual Conference in Honor of Alan Krueger (version from December 10, 2020). This study noted that it was not clear exactly which mechanisms of the training programs studied produced these gains. The study stated that a combination of upfront screening of applicants on basic skills and motivation, training on soft skills, and wraparound support services were all characteristics of the training programs that resulted in the largest and most persistent wage gains.

⁶³GAO, *Economic Adjustment Assistance: Actions Needed to Better Address Workers’ Needs and Assess Program Effectiveness*, [GAO-20-521](#) (Washington, D.C.: July 29, 2020).

For example, one local workforce board director stated that training programs scheduled to operate over a long period of time may be unattractive to workers, who cannot put their life on hold for the duration of the program.

- **Financial hardships.** Several stakeholders also said that workers who would benefit from training may face financial hardships, especially if they struggle to cover living expenses while enrolled in unpaid training. For example, state board stakeholders from two states and other stakeholders said that income insecurity was a major challenge for at-risk or unemployed workers. Faced with a decision about whether to engage in training that may boost job prospects and earnings long term on the one hand, or work in a job that offers low but immediate pay on the other hand, potential participants may choose the latter. Unpaid training can worsen financial hardships since time spent in training may erode savings a participant might have.
- **Transportation and geographic barriers.** Several stakeholders also noted barriers relating to transportation or geography, including lack of consistent transportation to training or job sites. For example, representatives from three state boards and other stakeholders interviewed said that available jobs might be far away from some local areas. Likewise, three stakeholders noted that some areas with more employment opportunities were difficult to reach for some job seekers, creating transportation and geographic barriers to employment. We have also found that job automation varies significantly by geographic location, with certain areas of the country more reliant on occupations susceptible to automation.⁶⁴ This could exacerbate automation's effects on the labor market in particular geographic locations.

Programs that respond to these challenges can help Americans access training aimed at entry into in-demand jobs, according to stakeholders. For example, several stakeholders stated they saw wraparound services as useful for mitigating access challenges. A state agency representative said that a community college had helped job seekers experiencing homelessness through comprehensive wraparound services that included connecting them with housing support and helping them apply for COVID-19-related grants. Stakeholders also said that training participation rates may improve as a result of wraparound services (such as substance

⁶⁴GAO-19-257. Census Bureau officials said the agency has recently produced new maps that show the concentration of robotics adopters in manufacturing across states and the susceptibility of workers to automation.

abuse counseling) that address participants' personal struggles. Likewise, one study noted that wraparound services may be particularly important for training participants who may find it difficult to thrive in more traditional postsecondary educational institutions.⁶⁵

Two state board stakeholders stated that training programs should consider optimal schedules for their target population. Specifically, scheduling training outside of normal work hours and for relatively short periods may enable attendance for workers with schedule conflicts stemming from their ongoing jobs or other obligations. For example, a state workforce board labor representative credited the short length (15 weeks) of a general industrial training program with its success in placing participants in employment.

Another strategy to promote greater access to job training is for programs to offer financial support. Several stakeholders, as well as experts interviewed for a prior report, said training programs that pay stipends or combine work with training could help increase enrollment of at-risk workers.⁶⁶ This financial support may alleviate pressure to find immediate work that may come at the expense of obtaining in-demand skills. Stakeholders from several state boards spoke favorably of the federal Registered Apprenticeship program because it provides participants with income while it offers training. However, two stakeholders cautioned that these apprenticeship programs face barriers themselves, such as cost and administrative burden (as discussed further in the next section).

To lessen geographic barriers, state workforce board stakeholders mentioned several potential approaches. For example, stakeholders in one state suggested using technology to mitigate geographical challenges, and noted that a training provider received private funding to focus its efforts on underserved rural areas. Stakeholders in another state emphasized the need to promote more economic growth in rural areas. Other state stakeholders said that they should consider how to bring in-demand jobs to workers. Another factor to consider is the likelihood of a worker and their family choosing to relocate to a new area away from their established community. One stakeholder said relocation could be

⁶⁵Lawrence F. Katz et al., "Why Do Sectoral Employment Programs Work? Lessons from WorkAdvance."

⁶⁶[GAO-21-324](#).

complex and disruptive, and suggested that it may not be the appropriate solution to geography-related challenges.

Washington Program Helps Mitigate Challenges by Tailoring Training to Meet Employer and Trainee Needs

Workforce officials in Washington highlighted its Job Skills Program, which pairs colleges with employers on a project basis to provide employers with the necessary support to meet their specific training needs. For example, a meat processing company partnered with a local community college to enhance its in-house training for an industrial maintenance certification. Trainees were paid for a 40-hour work week that included attending training for 16 hours a week at one pay rate, while working at the company for the remaining 24 hours at a different pay rate. The company also covered 66 percent of the tuition costs of the training. A company official reported that the training provided workers with opportunities to both improve their skills and move into higher-skilled positions within the company. In all, 15 workers were upskilled through the program, and most were promoted following training.

Source: State documentation and interviews with state workforce board. | GAO-22-105159

Stakeholders Cited Importance of Greater Investment in Training and Collaboration to Facilitate In-Demand Skills and Jobs

According to stakeholders, increasing investment in training and strengthening collaboration in the workforce system can mitigate challenges with funding and developing new training programs, thereby facilitating in-demand skills and jobs. Stakeholders from all four state workforce boards said their states have struggled with funding for training in various ways. For example, stakeholders from one state said that they pursue multiple funding sources but still find it difficult to fund trainings that the industry needs. Likewise, one local workforce board director stated that developing training programs is often costly, particularly when program administrators seek to improve accessibility through features like wraparound services.⁶⁷ We previously reported expert opinion that firms vulnerable to technological advancements may not have the resources to retrain workers, and one report we reviewed similarly noted that limited funding for training may especially limit lower-wage, front-line workers who are seeking advancement opportunities and are at significant risk of displacement due to automation and other technologies.⁶⁸

Several stakeholders also noted that employers may face additional challenges in offering training, limiting the availability of programs. For example, several stakeholders from one state's workforce board said that employers hesitated to offer Registered Apprenticeships because they have burdensome administrative requirements. Another stakeholder also

⁶⁷Board stakeholders from two states said that their funding was not sufficient for wraparound services to accompany training programs, though one stakeholder emphasized that such services are meaningful components of training to get an in-demand job, rather than "just" another job.

⁶⁸GAO-21-324 and *Talent Finance: A New Consensus and Return-To-Investment*. U.S. Chamber of Commerce Foundation (Washington D.C.).

noted the significant startup and administrative costs of Registered Apprenticeships, and said limited funding can make those programs unstable. Stakeholders from one state board suggested increasing federal funding for a state training program they said has shown good results and has a waitlist. Likewise, one study suggested that government could help employers by providing financial incentives for paid work-based learning in cooperation with external education and training partners who also receive government incentives for that training.

In addition, several stakeholders noted examples of collaboration that promoted entry into in-demand jobs. For example, stakeholders on one state board said their upskilling program encouraged collaboration among workforce development organizations, community colleges, and employers to provide participants a pathway from training to an in-demand job. A business representative on another state board highlighted a similar program, where a training provider solicited the input of local employers on course work and gathered their ideas for key course content. Lastly, another board representative from that state discussed a program, in which a company collaborated with another state's community college to train workers in advanced skills, including skills necessary for technician positions that the company and other employers had been struggling to fill. The state board stakeholder said that types of collaboration like this—employers partnering with academia—could reduce problems from programs operating in separate silos.

Similarly, many stakeholders noted the benefits of collaboration through industry partnerships. For example, one stakeholder noted that collaboration across industry, trainers, and government officials helps generate new job training programs to address the region's skill gaps. Likewise, a local workforce board launched a project involving hospital systems, clinics, and health care providers to identify high-demand occupations, learn how the region was producing skilled workers for those occupations, and identify the industry sector's challenges. As a result of that collaboration, the local area obtained an H-1B grant that provided federal funding to train health care providers and close the skills gap.⁶⁹ Additionally, one study we reviewed emphasized the importance of cross-stakeholder collaboration among stakeholders, such as workforce development boards, employers, training providers, and private entities.

⁶⁹H-1B Skills Training grants fund projects that provide training and related activities to workers to assist them in gaining the skills and competencies needed to obtain or upgrade employment in high-growth industries or economic sectors. See 29 U.S.C. § 3224a.

Another study suggested that public-private partnerships may be needed to generate more comprehensive labor market information. According to the study, the information can then be used to better evaluate workers' outcomes, inform state decision-making, help employers invest in training, and help workers identify in-demand job opportunities.⁷⁰

Agency Comments

We provided a draft of this report to the Departments of Labor and Commerce for review and comment. Both agencies provided technical comments, which we incorporated, as appropriate.

We are sending copies of this report to the appropriate congressional committees, the Secretary of Labor, the Secretary of Commerce, and other interested parties. In addition, the report is available at no charge on the GAO website at <http://www.gao.gov>.

If you or your staff have any questions about this report, please contact me at (202) 512-7215 or locked@gao.gov. Contact points for our Offices of Congressional Relations and Public Affairs may be found on the last page of this report. GAO staff who made key contributions to this report are listed in appendix II.



Dawn G. Locke, Acting Director
Education, Workforce, and Income Security Issues

⁷⁰National Governors Association Center for Best Practices, *Future Workforce Now*.

Appendix I: Objectives, Scope, and Methodology

The objectives of this review were to examine (1) what available data indicate about which workers are at risk of automation and the skills needed for in-demand jobs; and (2) what insights stakeholders offer for workforce programs to better serve displaced workers, and those affected by automation.

Section 1: Analyses Using Data from the Bureau of Labor Statistics and Occupational Information Network

For our first objective, we analyzed Department of Labor (DOL) data to identify occupations projected to grow over the next decade, as well as the skills associated with those growing occupations. Interviews with officials from selected case study states (described in Section 2 in this appendix) helped us understand what data existed on in-demand jobs and skills on a state and local level, and likewise, what data were unavailable to state and local stakeholders.

This section describes our methodology for identifying “in-demand” jobs, the methodology for matching occupational data from the U.S. Bureau of Labor Statistics (BLS) Employment Projections data to the DOL Occupational Information Network (O*NET) skills data, and how we identified the skills deemed important for our “in-demand” jobs.¹ It also presents the results of the analysis, as well as the associated caveats and limitations. We established the reliability of these data through a

¹BLS’s Employment Projections (EP) program publishes 10-year projections of national employment by industry and occupation based on analysis of historical and current economic data for the labor market, the macroeconomy, and industrial activity. The projections are developed annually and present employment for approximately 300 industries and about 800 occupations covering all occupations in the U.S. economy.

O*NET is a comprehensive database of worker attributes and job characteristics. The O*NET Data Collection Program provides information on skills, knowledge, abilities, and other information on nearly 1,000 occupations covering the entire U.S. economy. According to DOL officials, O*NET data are collected through a statistically valid two-stage sampling method of selected business establishments and incumbent workers within those sampled businesses. This is supplemented with responses from occupational experts (who are not themselves incumbent workers in the occupation) and occupation analysts—both of whom have knowledge of the requirements of work in relevant occupations. The O*NET survey methodology has been approved and re-approved by the Office of Management and Budget every 3 years since 2000.

The number of occupations is higher in O*NET than in the Employment Projections because O*NET provides information on some occupations at a more detailed level than the Employment Projections. Moreover, according to BLS officials, while O*NET provides some information for all occupations in the economy, it does not provide O*NET-specific information (such as knowledge, skills, and abilities) for residual (“All Other”) occupations. Even though O*NET does not have O*NET-specific data at the residual level, it may incorporate more detailed occupations within the broader “All Other” category which have O*NET-specific data.

review of relevant agency documentation and interviews with knowledgeable agency officials.

Selection of In-Demand Jobs

Although BLS had released 2020-2030 projections at the time of our analysis and also provided a list of occupations that excluded those most affected by the pandemic, we decided to use projections for 2019-2029. We did so because the COVID-19 pandemic triggered an economic recession from February to April 2020, which led to substantial and immediate declines in output and employment during that period. Because 2020 serves as the base year for BLS's 2020–30 projections, these recession impacts translate to lower base-year employment values than seen in recent projections and, therefore, disproportionately higher projected employment growth between 2020 and 2030 among the occupations most affected by the 2020 recession. Consequently, industries most affected by the pandemic, such as accommodations and food services, would see a large change in employment, partly due to the low base and the accompanying short-term recovery. Thus the 2020-2030 employment growth projections include both short-term recovery from the pandemic and longer-term structural changes, and it is unclear what portion of the projected growth is due to the short-term pandemic recovery versus structural changes. Moreover, besides the pandemic affecting short-term changes in employment, it might have longer-term impacts (independent of or in addition to structural changes already underway before the pandemic). However it will take at least a few years or perhaps longer for those longer-term pandemic-related effects to be known and accounted for in the employment projections.²

For these reasons, we concluded that using 2020-2030 projections with all occupations would lead us to select occupations with high growth due primarily to having been more affected by the pandemic, thus the growth rate could represent short-term adjustments to the recession rather than long-term structural changes. We also concluded that using the 2020-2030 projections excluding occupations most affected by the pandemic omits almost half of all occupations—some or many of which may have had high growth due to long-term structural factors, as well as short-term adjustments—but we would be excluding them altogether because we could not distinguish what share of the growth rate was due to structural factors versus short-term adjustments. Additionally, we concluded that using 2019-2029 projections, while based on data that are 1 year older,

²For a fuller discussion, see Kevin S. Dubina, Lindsey Ice, Janie-Lynn Kim, and Michael J. Rieley, "Projections overview and highlights, 2020–30," *Monthly Labor Review* (U.S. Bureau of Labor Statistics, October 2021), <https://doi.org/10.21916/mlr.2021.20>.

represented the best option for capturing the longer-term structural changes to the economy, including those associated with trends in technological change, economic policy and other macro-economic indicators that affect employment levels.³ Thus, we used 2019-2029 employment projections to identify “in-demand” jobs.⁴

The following describes how we selected our “in-demand” occupations:

1. We excluded occupations with a lower than average 2019-2029 change in employment levels, both overall (i.e., no education filter) and by education level (high school or less, some college, and bachelor’s and above). This ensured that we did not include occupations that were adding a relatively small number of jobs over the period but with a high growth mainly due to the low base. Specifically, given this selection criteria:
 - a. For the overall list (no education filter), we restricted our “in-demand” jobs to those occupations that were projected to add more than about 7,600 jobs from 2019 through 2029 (i.e., the average job gain across all occupations for this period.)
 - b. For the “high school or less” list, we restricted our jobs to those occupations with a typical entry level education, based on BLS’s projections data, of “high school diploma or equivalent” or “no formal educational credential.” We further restricted our jobs to those occupations that were projected to add more than about 5,200 jobs from 2019 through 2029 (i.e., the average job gain during the 2019-2020 period for occupations where the typical entry level education was high school or less).
 - c. For the “some college” list, we restricted our jobs to those occupations with a typical entry level education, based on BLS’s projections data, of “associate’s degree” or “postsecondary

³Using 2019-2029 projections does not incorporate the effects of the pandemic. Given the uncertainty around the long-term effects of the pandemic, this is an important caveat of our analysis. For example, the pandemic introduced large numbers of employers and employees to remote work. If these arrangements become more frequent in the long term they could have direct effects on employment. For a more detailed discussion see Lindsey Ice and Michael J. Reiley, “Expected pandemic-driven employment changes: a comparison of 2019–29 and 2020–30 projection sets,” *Monthly Labor Review* (U.S. Bureau of Labor Statistics, February 2022), <https://doi.org/10.21916/mlr.2022.5>.

⁴We consulted DOL on our approach, and DOL officials agreed that the reasoning behind our approach was sound.

nondegree award” or “some college, no degree.” We further restricted our jobs to those occupations that were projected to add more than about 8,100 jobs from 2019 through 2029 (i.e., the average job gain during the 2019-2020 period for occupations where the typical entry level education was some college).

- d. For the “bachelor’s and above” list we restricted our jobs to those occupations with a typical entry-level education, based on BLS’s projections data, of “bachelor’s degree” or “doctoral or professional degree” or “master’s degree.” We further restricted our jobs to those occupations that were projected to add more than about 11,300 jobs from 2019 through 2029 (i.e., the average job gain during the 2019-2020 period for occupations where the typical entry level education was bachelor’s degree and above).

2. From each of the four lists (overall; high school or less; some college; and a bachelor’s and above), we selected the 20 occupations with the fastest 2019-2029 growth rate.

Thus we use the phrase “in-demand jobs” to refer to occupations that, among the set of occupations with above-average change in employment levels, DOL projects will grow the fastest. In summary, in order to identify “in-demand” jobs, we restricted such jobs to those occupations that were projected to add more than the average job gain during the 2019-2029 period for that education group (i.e., overall, high school or less, some college and bachelor’s and above). Of these, we then chose the 20 fastest growing occupations for each group. Using this approach, our analyses excluded occupations that were projected to add relatively few jobs, even if they were projected to grow quickly. For example, the occupation of wind turbine technicians had the highest growth rate (61 percent), but was projected to add a total of about 4,300 new jobs over the 2019-2029 period. Thus, even though the occupation is growing quickly, it is nevertheless adding relatively few jobs over the 2019-2029 period and was therefore excluded, based on our selection criteria for “in-demand” jobs.

Matching BLS Employment Projections to O*NET Data

BLS Employment Projections data are at the six-digit Standard Occupational Classification level, and the O*NET data are at the eight-digit occupational code level. Because of differences in the purpose and methods of data collection across programs—differences that result in a different set of occupations included in each program—matching the BLS Employment Projections and O*NET data requires resolving various types of non-matches. We matched the Employment Projections data to

the O*NET skills data using the matching data provided by DOL, where the agency provided us with the BLS Employment Projections code, the associated O*NET code, and the weight assigned to each O*NET occupation code based on employment, among other variables. The matching was based on a BLS publication in which BLS outlined how to match projections data to O*NET data, such as by doing direct matches (i.e., those occupations that in the O*NET data are at the six-digit level, ending in xx-xxxx.00), and doing employment weighted scores for matches that were not directly matched, among other steps.⁵

We used O*NET skills data based on O*NET 25.0, which was published in August 2020, along the O*NET 25.0 mapping provided by DOL.⁶

Determining Skills Deemed Important for “In-Demand” Jobs

The O*NET skills database has 35 elements, broadly categorized into “basic” skills and “cross functional” skills. The basic skills are shown below:

- Content: reading comprehension; active listening; writing; speaking; mathematics; science
- Process: critical thinking; active learning; learning strategies; monitoring

The cross functional skills are further broken down into five categories:

- Complex problem solving skills
- Resource management skills: management of financial resources; management of material resources; management of personnel resources; time management
- Social skills: coordination; instructing; negotiation; persuasion; service orientation; social perceptiveness
- Systems skills: judgment and decision-making; systems analysis; systems evaluation

⁵For more information on BLS’s method for mapping occupational data from the BLS’s Employment Projections program to the U.S. Department of Labor O*NET data, see Amy Hopson, “Mapping Employment Projections and O*NET data: a methodological overview,” *Monthly Labor Review* (U.S. Bureau of Labor Statistics, August 2021), <https://doi.org/10.21916/mlr.2021.18>

⁶We did not use O*NET 26.0, published in August 2021, because skills data for some occupations, including those in the list of our “in-demand” jobs, in the 26.0 O*NET dataset were not yet available at the time of our analysis.

- Technical skills: equipment maintenance; equipment selection; installation; operation and control; operations analysis; operations monitoring; programming; quality control analysis; repairing; technology design; troubleshooting.

O*NET contains two scores for each of the 35 elements: one for *importance* and one for *level*.⁷ For *importance*, the rating indicates the degree of importance a particular descriptor is to the occupation. The possible ratings range from 1 (not important) through 5 (extremely important). For *level*, the rating indicates the degree to which a particular descriptor is required or needed to perform the occupation. The possible ratings range from 1 through 7. For our analysis, we decided to use only the *importance* score due to the high correlation between the importance and the *level* scores. According to our analysis of O*NET skills data, the correlation between the *importance* and level score was 0.97.⁸ We created two main analyses:

- For each of our 20 “in-demand” jobs, we counted the total number of skills deemed important. Specifically, we counted the skills for each top 20 in-demand occupation that had an *importance* score of 3 and above.⁹ We also present other selected characteristics for these occupations, such as median wages.
- For each of the 35 skills in the dataset, we calculated a weighted average (weighted by 2019 employment) *importance* score for each list (overall and by education level) of top 20 in-demand occupations, as well as for those occupations not in our top-20 in-demand occupations list. This allowed us to examine what skills are deemed the most important, on average, for our top 20 in-demand occupations for each education group, with the non-top 20 occupations serving as a comparison group. In order to identify the skills that are, on average, deemed important for each education group (i.e., overall, high school

⁷According to O*NET, a skill is the ability to perform a task well. It is usually developed over time through training or experience. A skill can be used to do work in many jobs or it can be used in learning.

⁸According to DOL officials, the article, “Mapping Employment Projections and O*NET data: a methodological overview,” *Monthly Labor Review* (U.S. Bureau of Labor Statistics, August 2021), <https://doi.org/10.21916/mlr.2021.18> included just “importance” of skills (and not “level”) because they noticed a high correlation between ratings of importance and level.

⁹We defined a skill as deemed “important” if the *importance* score is 3 or above given that, according to the O*NET skills questionnaire, when asked the question “How important is the skill to the performance of your current job?” the job incumbent’s answer can be: (3) if “important”, (4) if “very important” or (5) if “extremely important.”

In-Demand Jobs and Selected Characteristics, Including Total Number of Skills Deemed Important

or less, some college, bachelor's and more) of the top 20 in-demand jobs, we highlight the skills that have a weighted average score of 3 and above.

For each education category, table 2 lists the top 20 in-demand occupations we selected based on our criteria described above. The table also presents selected characteristics for each occupation, such as the typical education needed for entry; total number of skills deemed important; and median wages for that occupation and for all occupations with the associated typical entry level education.

As an additional analysis, for both the sample of top 20 in-demand occupations overall and the entire dataset, which included all occupations (i.e., top 20 and non-top 20 in-demand occupations), we examined if occupations with a higher wage or a higher education level needed for entry tended to have more skills deemed important (i.e., an importance score of 3 and above). Specifically, we regressed the total number of skills deemed important on the median annual wage and regressed the total number of skills deemed important on the typical education needed for entry. We found a positive and statistically significant relationship between the total number of skills deemed important and the education level, as well as between the total number of skills deemed important and the median annual wage in both the sample of our top 20 in-demand occupations and in the dataset which included all occupations. These relationships represent correlations, and we did not control for other factors. Thus, they could be driven by factors related to the total number of skills deemed important and to the education level, or to the total number of skills deemed important and to wages.

Table 2: Selected Characteristics of Top 20 In-demand Occupations, by Education Level

Occupation title	Occupation code	Employment, 2019 (thousands)	Projected employment, 2029 (thousands)	Projected employment change 2019-2029 (thousands)	Projected employment change 2019-2029 (percent)	Typical education needed for entry	Total number of skills deemed important	Median annual wage in dollars (2020)	Median annual wage in dollars (2020) for occupations with corresponding typical entry-level education
Top 20 in-demand occupations and selected characteristics, overall									
Nurse practitioners	29-1171	211.3	322	110.7	52.4	Master's degree	22	111,680	76,800
Statisticians	15-2041	42.7	57.5	14.8	34.6	Master's degree	15	92,270	76,800
Occupational therapy assistants	31-2011	47.1	63.5	16.3	34.6	Associate's degree	16	62,940	55,870
Home health and personal care aides	31-1120	3439.7	4599.2	1159.5	33.7	High school diploma or equivalent	10	27,080	39,070
Physical therapist assistants	31-2021	98.7	130.9	32.2	32.6	Associate's degree	15	59,770	55,870
Medical and health services managers	11-9111	422.3	555.5	133.2	31.5	Bachelor's degree	23	104,280	78,020
Physician assistants	29-1071	125.5	164.8	39.3	31.3	Master's degree	19	115,390	76,800
Information security analysts	15-1212	131	171.9	40.9	31.2	Bachelor's degree	15	103,590	78,020

Appendix I: Objectives, Scope, and Methodology

Occupation title	Occupation code	Employment, 2019 (thousands)	Projected employment, 2029 (thousands)	Projected employment change 2019-2029 (thousands)	Projected employment change 2019-2029 (percent)	Typical education needed for entry	Total number of skills deemed important	Median annual wage in dollars (2020)	Median annual wage in dollars (2020) for occupations with corresponding typical entry-level education
Data scientists and mathematical science occupations, all other	15-2098	33.2	43.4	10.3	30.9	Bachelor's degree	15	98,230	78,020
Roustabouts, oil and gas	47-5071	58.5	73.1	14.7	25.1	No formal educational credential	6	39,420	27,510
Speech-language pathologists	29-1127	162.6	203.1	40.5	24.9	Master's degree	19	80,480	76,800
Operations research analysts	15-2031	105.1	131.3	26.1	24.8	Bachelor's degree	17	86,200	78,020
Substance abuse, behavioral disorder, and mental health counselors	21-1018	319.4	398.4	79	24.7	Bachelor's degree	20	47,660	78,020
Cooks, restaurant	35-2014	1417.3	1744.6	327.3	23.1	No formal educational credential	6	28,800	27,510
Service unit operators, oil and gas	47-5013	51.7	63.6	11.8	22.9	No formal educational credential	17	47,380	27,510

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Animal caretakers	39-2021	300.7	369.5	68.8	22.9	High school diploma or equivalent	6	26,080	39,070
Marriage and family therapists	21-1013	66.2	80.9	14.8	22.3	Master's degree	20	51,340	76,800
Film and video editors	27-4032	38.3	46.5	8.3	21.6	Bachelor's degree	11	67,250	78,020
Software developers and software quality assurance analysts and testers	15-1256	1469.2	1785.2	316	21.5	Bachelor's degree	10	110,140	78,020
Physical therapist aides	31-2022	50.6	61.3	10.8	21.3	High school diploma or equivalent	10	28,450	39,070
Top 20 in-demand occupations and selected characteristics, high school or less									
Solar photovoltaic installers	47-2231	12	18.1	6.1	50.5	High school diploma or equivalent	12	46,470	39,070
Home health and personal care aides	31-1120	3439.7	4599.2	1159.5	33.7	High school diploma or equivalent	10	27,080	39,070

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Rotary drill operators, oil and gas	47-5012	20.9	26.6	5.6	26.9	No formal educational credential	17	53,820	27,510
Roustabouts, oil and gas	47-5071	58.5	73.1	14.7	25.1	No formal educational credential	6	39,420	27,510
Cooks, restaurant	35-2014	1417.3	1744.6	327.3	23.1	No formal educational credential	6	28,800	27,510
Service unit operators, oil and gas	47-5013	51.7	63.6	11.8	22.9	No formal educational credential	17	47,380	27,510
Animal caretakers	39-2021	300.7	369.5	68.8	22.9	High school diploma or equivalent	6	26,080	39,070
Physical therapist aides	31-2022	50.6	61.3	10.8	21.3	High school diploma or equivalent	10	28,450	39,070
Flight attendants	53-2031	121.9	143	21.1	17.3	High school diploma or equivalent	10	59,050	39,070
Social and human service assistants	21-1093	425.6	497.1	71.5	16.8	High school diploma or equivalent	15	35,960	39,070

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First-line supervisors of gambling services workers	39-1013	58	67.5	9.5	16.4	High school diploma or equivalent	15	50,440	39,070
Veterinary assistants and laboratory animal caretakers	31-9096	99.5	115.2	15.7	15.8	High school diploma or equivalent	10	29,930	39,070
Crematory operators and personal care and service workers, all other	39-9098	111.3	128.8	17.5	15.7	High school diploma or equivalent	13	28,420	39,070
Industrial machinery mechanics	49-9041	399.4	461.7	62.3	15.6	High school diploma or equivalent	15	55,490	39,070
Exercise trainers and group fitness instructors	39-9031	373.7	431.3	57.6	15.4	High school diploma or equivalent	10	40,510	39,070
Community health workers	21-1094	64.9	74.8	9.9	15.2	High school diploma or equivalent	20	42,000	39,070

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Animal trainers	39-2011	50.2	56.9	6.7	13.3	High school diploma or equivalent	13	31,520	39,070
Residential advisors	39-9041	115.2	128.7	13.6	11.8	High school diploma or equivalent	15	31,190	39,070
Fast food and counter workers	35-3023	4047.7	4508.6	460.9	11.4	No formal educational credential	4	23,860	27,510
Agricultural equipment operators	45-2091	70.3	78.3	8	11.4	No formal educational credential	7	32,750	27,510
Top 20 in-demand occupations and selected characteristics, some college									
Occupational therapy assistants	31-2011	47.1	63.5	16.3	34.6	Associate's degree	16	62,940	55,870
Physical therapist assistants	31-2021	98.7	130.9	32.2	32.6	Associate's degree	15	59,770	55,870
Massage therapists	31-9011	166.7	201.1	34.4	20.6	Postsecondary nondegree award	9	43,620	41,520
Respiratory therapists	29-1126	135.8	162	26.3	19.4	Associate's degree	18	62,810	55,870

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Manicurists and pedicurists	39-5092	155.3	185.2	29.9	19.2	Postsecondary nondegree award	4	27,870	41,520
Medical assistants	31-9092	725.2	864.4	139.2	19.2	Postsecondary nondegree award	14	35,850	41,520
Phlebotomists	31-9097	132.6	155.5	22.8	17.2	Postsecondary nondegree award	12	36,320	41,520
Diagnostic medical sonographers	29-2032	74.3	86.8	12.5	16.8	Associate's degree	19	75,920	55,870
Skincare specialists	39-5094	78.6	91.6	13.1	16.6	Postsecondary nondegree award	9	36,510	41,520
Veterinary technologists and technicians	29-2056	112.9	131.2	18.3	16.2	Associate's degree	14	36,260	55,870
Ophthalmic medical technicians	29-2057	59.5	67.9	8.5	14.2	Postsecondary nondegree award	10	37,940	41,520

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Psychiatric technicians	29-2053	82.8	93.8	11	13.3	Postsecondary nondegree award	19	35,030	41,520
Audio and video technicians	27-4011	91.8	103.1	11.3	12.3	Postsecondary nondegree award	16	47,920	41,520
Paralegals and legal assistants	23-2011	337.8	373.1	35.3	10.5	Associate's degree	12	52,920	55,870
Licensed practical and licensed vocational nurses	29-2061	721.7	787.4	65.7	9.1	Postsecondary nondegree award	18	48,820	41,520
Medical dosimetrists, medical records specialists, and health technologists and technicians, all other	29-2098	341.6	370.6	29	8.5	Postsecondary nondegree award	9	44,090	41,520

Appendix I: Objectives, Scope, and Methodology

Occupation title	Occupation code	Employment, 2019 (thousands)	Projected employment, 2029 (thousands)	Projected employment change 2019-2029 (thousands)	Projected employment change 2019-2029 (percent)	Typical education needed for entry	Total number of skills deemed important	Median annual wage in dollars (2020)	Median annual wage in dollars (2020) for occupations with corresponding typical entry-level education
Web developers and digital interface designers	15-1257	174.3	188.3	14	8	Associate's degree	15	77,200	55,870
Computer user support specialists	15-1232	687.2	741.9	54.8	8	Some college, no degree	13	52,690	37,770
Nursing assistants	31-1131	1528.5	1645.5	116.9	7.6	Postsecondary nondegree award	8	30,850	41,520
Radiologic technologists and technicians	29-2034	212	226.1	14.1	6.7	Associate's degree	15	61,900	55,870
Top 20 in-demand occupations and selected characteristics, bachelor's and above									
Nurse practitioners	29-1171	211.3	322	110.7	52.4	Master's degree	22	111,680	76,800
Statisticians	15-2041	42.7	57.5	14.8	34.6	Master's degree	15	92,270	76,800
Medical and health services managers	11-9111	422.3	555.5	133.2	31.5	Bachelor's degree	23	104,280	78,020
Physician assistants	29-1071	125.5	164.8	39.3	31.3	Master's degree	19	115,390	76,800

Appendix I: Objectives, Scope, and Methodology

Occupation title	Occupation code	Employment, 2019 (thousands)	Projected employment, 2029 (thousands)	Projected employment change 2019-2029 (thousands)	Projected employment change 2019-2029 (percent)	Typical education needed for entry	Total number of skills deemed important	Median annual wage in dollars (2020)	Median annual wage in dollars (2020) for occupations with corresponding typical entry-level education
Information security analysts	15-1212	131	171.9	40.9	31.2	Bachelor's degree	15	103,590	78,020
Speech-language pathologists	29-1127	162.6	203.1	40.5	24.9	Master's degree	19	80,480	76,800
Operations research analysts	15-2031	105.1	131.3	26.1	24.8	Bachelor's degree	17	86,200	78,020
Substance abuse, behavioral disorder, and mental health counselors	21-1018	319.4	398.4	79	24.7	Bachelor's degree	20	47,660	78,020
Marriage and family therapists	21-1013	66.2	80.9	14.8	22.3	Master's degree	20	51,340	76,800
Software developers and software quality assurance analysts and testers	15-1256	1469.2	1785.2	316	21.5	Bachelor's degree	10	110,140	78,020

Appendix I: Objectives, Scope, and Methodology

Occupation title	Occupation code	Employment, 2019 (thousands)	Projected employment, 2029 (thousands)	Projected employment change 2019-2029 (thousands)	Projected employment change 2019-2029 (percent)	Typical education needed for entry	Total number of skills deemed important	Median annual wage in dollars (2020)	Median annual wage in dollars (2020) for occupations with corresponding typical entry-level education
Health specialties teachers, postsecondary	25-1071	254	306.1	52.1	20.5	Doctoral or professional degree	19	99,090	110,160
Interpreters and translators	27-3091	77.4	92.9	15.5	20	Bachelor's degree	15	52,330	78,020
Physical therapists	29-1123	258.2	305.2	47	18.2	Doctoral or professional degree	19	91,010	110,160
Market research analysts and marketing specialists	13-1161	738.1	868.4	130.3	17.7	Bachelor's degree	17	65,810	78,020
Nursing instructors and teachers, postsecondary	25-1072	72.9	85.7	12.8	17.6	Doctoral or professional degree	20	75,470	110,160
Social and community service managers	11-9151	175.5	205.4	29.8	17	Bachelor's degree	20	69,600	78,020
Mental health and substance abuse social workers	21-1023	123.2	143.8	20.7	16.8	Master's degree	20	48,720	76,800

Appendix I: Objectives, Scope, and Methodology

Occupation title	Occupation code	Employment, 2019 (thousands)	Projected employment, 2029 (thousands)	Projected employment change 2019-2029 (thousands)	Projected employment change 2019-2029 (percent)	Typical education needed for entry	Total number of skills deemed important	Median annual wage in dollars (2020)	Median annual wage in dollars (2020) for occupations with corresponding typical entry-level education
Occupational therapists	29-1122	143.3	166	22.7	15.9	Master's degree	21	86,280	76,800
Veterinarians	29-1131	89.2	103.4	14.2	15.9	Doctoral or professional degree	19	99,250	110,160
Financial managers	11-3031	697.9	806	108.1	15.5	Bachelor's degree	22	134,180	78,020

Source: GAO analysis of U.S. Bureau of Labor Statistics (BLS) Employment Projections (EP) program data and U.S. Department of Labor (DOL) Occupational Information Network (O*NET) data. | GAO-22-105159

Notes: In order to identify the top 20 in-demand jobs, we restricted such jobs to those occupations that BLS projected to add more than the average job gain during the 2019-2029 period for that education group (i.e., overall, high school or less, some college and bachelor's and above). Of these, we then chose the 20 fastest growing occupations for each group. In order to calculate the total number of skills deemed important, we counted the number of skills with an importance score greater or equal to 3 based on O*NET 25.0 skills data. We chose this threshold because, according to the O*NET skills questionnaire, when asked the question "How important is the skill to the performance of your current job?" the job incumbent's answer can be: (3) if "important", (4) if "very important" or (5) if "extremely important."

Average Importance Score by Education Level

Table 3 shows the weighted average importance score and weighted standard deviation (weighted by 2019 employment) for each list of top 20 in-demand jobs as well as non-top 20 jobs for each level of typical education needed for entry. Weighted average scores with a value of greater or equal to 3 are highlighted in order to highlight the skills that are, on average, deemed important for that list based on the value of the weighted average score. Given that this is for the average occupation in that group (i.e., for the typical worker in that education group), even if a skill is not deemed important on average it might be important for particular occupations in that group. For example, even though repairing has the lowest weighted average score in the top 20 in-demand occupations (overall), it is a skill deemed important for the occupation “service unit operators, oil and gas.”

Table 3: Skills Average Importance Scores for Top 20 and Non-Top 20 In-Demand Occupations, by Education Level

Standard deviation (SD) in parentheses

Skill name	Average and SD, non-top 20 overall	Average and SD, top 20 overall	Average and SD, non-top 20 high school or less	Average and SD, top 20 high school or less	Average and SD, non-top 20 some college	Average and SD, top 20 some college	Average and SD, non-top 20 bachelor's and above	Average and SD, top 20 bachelor's and above
Active Listening	3.6 (0.5)	3.5 (0.4)	3.4 (0.4)	3.4 (0.3)	3.4 (0.4)	3.7 (0.3)	4.0 (0.2)	3.9 (0.4)
Social Perceptiveness	3.2 (0.5)	3.4 (0.5)	3.1 (0.4)	3.2 (0.4)	3.0 (0.3)	3.5 (0.4)	3.6 (0.4)	3.5 (0.5)
Critical Thinking	3.3 (0.5)	3.3 (0.4)	3.1 (0.3)	3.0 (0.3)	3.3 (0.3)	3.4 (0.3)	3.9 (0.2)	3.9 (0.2)
Speaking	3.5 (0.5)	3.3 (0.4)	3.4 (0.5)	3.2 (0.2)	3.4 (0.4)	3.6 (0.4)	4.0 (0.3)	3.8 (0.4)
Service Orientation	3.1 (0.5)	3.3 (0.6)	3.0 (0.5)	3.3 (0.6)	3.0 (0.4)	3.5 (0.5)	3.3 (0.4)	3.3 (0.5)
Judgment and Decision Making	3.1 (0.4)	3.2 (0.4)	2.9 (0.3)	3.0 (0.1)	3.0 (0.2)	3.1 (0.3)	3.6 (0.3)	3.7 (0.2)
Reading Comprehension	3.3 (0.5)	3.2 (0.4)	3.1 (0.4)	2.9 (0.3)	3.3 (0.3)	3.6 (0.4)	3.9 (0.2)	3.8 (0.3)
Monitoring	3.2 (0.4)	3.2 (0.3)	3.1 (0.3)	3.1 (0.2)	3.1 (0.3)	3.4 (0.4)	3.6 (0.3)	3.5 (0.4)
Coordination	3.2 (0.4)	3.1 (0.3)	3.0 (0.3)	3.0 (0.2)	3.0 (0.3)	3.2 (0.4)	3.5 (0.4)	3.3 (0.4)
Time Management	3.1 (0.4)	3.0 (0.3)	3.0 (0.3)	2.8 (0.3)	3.0 (0.2)	3.1 (0.4)	3.4 (0.3)	3.3 (0.4)
Complex Problem Solving	3.0 (0.5)	3.0 (0.5)	2.8 (0.4)	2.6 (0.4)	3.0 (0.3)	3.0 (0.4)	3.5 (0.3)	3.7 (0.2)
Active Learning	3.0 (0.5)	3.0 (0.4)	2.7 (0.4)	2.7 (0.2)	3.0 (0.2)	3.1 (0.2)	3.5 (0.2)	3.5 (0.4)
Writing	3.0 (0.6)	3.0 (0.5)	2.7 (0.5)	2.5 (0.5)	3.0 (0.2)	3.2 (0.4)	3.7 (0.3)	3.6 (0.4)
Instructing	2.8 (0.6)	2.8 (0.4)	2.5 (0.5)	2.8 (0.4)	2.7 (0.5)	2.8 (0.4)	3.3 (0.5)	3.1 (0.4)
Learning Strategies	2.7 (0.6)	2.7 (0.4)	2.4 (0.4)	2.6 (0.3)	2.7 (0.5)	2.7 (0.3)	3.2 (0.5)	3.2 (0.3)
Persuasion	2.8 (0.5)	2.7 (0.4)	2.7 (0.6)	2.6 (0.3)	2.6 (0.3)	2.5 (0.4)	3.2 (0.4)	3.1 (0.3)
Systems Analysis	2.5 (0.5)	2.6 (0.7)	2.2 (0.4)	2.1 (0.3)	2.4 (0.4)	2.5 (0.4)	3.1 (0.3)	3.3 (0.3)
Systems Evaluation	2.4 (0.5)	2.6 (0.7)	2.2 (0.4)	2.1 (0.3)	2.4 (0.4)	2.4 (0.3)	3.1 (0.4)	3.3 (0.3)

Appendix I: Objectives, Scope, and Methodology

Skill name	Average and SD, non-top 20 overall	Average and SD, top 20 overall	Average and SD, non-top 20 high school or less	Average and SD, top 20 high school or less	Average and SD, non-top 20 some college	Average and SD, top 20 some college	Average and SD, non-top 20 bachelor's and above	Average and SD, top 20 bachelor's and above
Negotiation	2.7 (0.6)	2.5 (0.4)	2.6 (0.5)	2.2 (0.3)	2.5 (0.3)	2.4 (0.4)	3.1 (0.4)	2.9 (0.3)
Management of Personnel Resources	2.5 (0.5)	2.4 (0.5)	2.4 (0.5)	2.2 (0.3)	2.3 (0.3)	2.4 (0.4)	3.0 (0.4)	3.0 (0.4)
Mathematics	2.4 (0.5)	2.4 (0.5)	2.3 (0.5)	2.2 (0.3)	2.4 (0.5)	2.3 (0.3)	2.8 (0.5)	2.9 (0.6)
Operation Monitoring	2.3 (0.6)	2.3 (0.3)	2.4 (0.6)	2.3 (0.5)	2.7 (0.9)	2.5 (0.5)	2.2 (0.5)	2.1 (0.3)
Quality Control Analysis	2.2 (0.6)	2.3 (0.4)	2.2 (0.6)	2.2 (0.4)	2.3 (0.8)	2.3 (0.4)	2.2 (0.6)	2.1 (0.4)
Science	1.5 (0.7)	2.0 (0.6)	1.2 (0.4)	1.4 (0.4)	1.7 (0.6)	2.1 (0.6)	2.1 (0.8)	2.5 (0.6)
Management of Material Resources	1.9 (0.5)	1.9 (0.4)	1.8 (0.4)	1.9 (0.2)	1.9 (0.3)	1.7 (0.3)	2.2 (0.5)	2.0 (0.4)
Operations Analysis	1.8 (0.6)	1.9 (1.0)	1.6 (0.4)	1.3 (0.4)	1.9 (0.4)	1.8 (0.6)	2.4 (0.6)	2.9 (0.4)
Troubleshooting	1.9 (0.7)	1.9 (0.4)	1.9 (0.6)	1.9 (0.5)	2.3 (1.0)	1.9 (0.5)	1.6 (0.6)	1.6 (0.6)
Management of Financial Resources	1.8 (0.5)	1.8 (0.4)	1.7 (0.5)	1.8 (0.3)	1.7 (0.3)	1.6 (0.3)	2.2 (0.6)	2.1 (0.7)
Operation and Control	2.0 (0.8)	1.7 (0.4)	2.1 (0.8)	1.9 (0.5)	2.4 (1.1)	2.0 (0.6)	1.6 (0.5)	1.4 (0.4)
Technology Design	1.6 (0.3)	1.7 (0.5)	1.5 (0.3)	1.4 (0.2)	1.7 (0.3)	1.7 (0.3)	1.8 (0.3)	1.9 (0.4)
Programming	1.4 (0.4)	1.6 (0.9)	1.3 (0.3)	1.1 (0.2)	1.5 (0.3)	1.5 (0.6)	1.8 (0.5)	2.2 (0.9)
Equipment Selection	1.5 (0.6)	1.3 (0.4)	1.5 (0.7)	1.3 (0.5)	1.9 (0.8)	1.4 (0.4)	1.3 (0.4)	1.3 (0.3)
Installation	1.2 (0.4)	1.1 (0.2)	1.2 (0.5)	1.1 (0.3)	1.5 (0.7)	1.2 (0.4)	1.1 (0.2)	1.2 (0.3)
Equipment Maintenance	1.5 (0.8)	1.1 (0.3)	1.6 (0.8)	1.2 (0.7)	2.1 (1.0)	1.3 (0.5)	1.1 (0.4)	1.1 (0.2)
Repairing	1.5 (0.8)	1.1 (0.2)	1.6 (0.8)	1.2 (0.6)	2.1 (1.1)	1.3 (0.5)	1.1 (0.4)	1.1 (0.2)
Total observations	769	20	405	20	77	20	247	20

Source: GAO analysis of U.S. Bureau of Labor Statistics (BLS) Employment Projections (EP) program data and U.S. Department of Labor (DOL) Occupational Information Network (O*NET) data. | GAO-22-105159

Notes: In order to identify the top 20 in-demand jobs, we restricted such jobs to those occupations that were projected to add more than the average job gain during the 2019-2029 period for each education group (i.e., overall, high school or less, some college and bachelor's and above). Of these, we then chose the 20 fastest growing occupation for each group. We then calculated the average importance value, weighted by 2019 employment, for each of the 35 skills in O*NET 25.0 for each group of top 20 and non-top 20 in-demand jobs for each education group. Shaded scores are for the skills deemed important for that group (i.e., skills with a weighted average score value greater or equal to 3). We chose this threshold because, according to the O*NET skills questionnaire, when asked the question "How important is the skill to the performance of your current job?" the job incumbent's answer is (3) if "important", (4) if "very important" or (5) if "extremely important". Standard deviations (SD) weighted by 2019 employment are in parentheses.

Caveats and Limitations

Uncertainty exists in the projections and the skills that will be deemed important in the future. Projections are estimates of future job growth

based on a series of modeling assumptions.¹ As with any projections, the projections for individual occupations are subject to error because of the many unknown factors that may affect the economy over the projection period. Thus, due to a variety of factors, actual changes in employment might differ from projected changes. Moreover, our analysis of skills is based on the skills that are currently deemed important, while the skills deemed important in the future might differ from the skills deemed important currently.

According to BLS's documentation, its 2019-2029 Employment Projections do not include impacts of the COVID-19 pandemic and response efforts. The BLS Employment Projections are developed using models based on historical data, as well as other qualitative and quantitative information available at the time the projections are made. This set of projections covers the time period through 2019; all input data therefore precede the pandemic.

We examined national-level projections, though projections might differ across localities. Given that we used national data, the data did not allow a discussion of where the "in-demand" jobs would be located. For example, even if an occupation is projected to grow at the national level it does not mean that it will be growing in all localities. Moreover, given that these are national level data, the characteristics of the selected occupations, such as median wages, might differ across localities.

The skills needed for a particular occupation might differ across localities and firms. The data did not allow us to discuss how the skills need for a particular occupation differ across locations or firms. According to DOL officials, customers should not use O*NET data and applications as a stand-alone, off-the-shelf tool to make selection or hiring decisions. Instead, for these type of human resource activities, O*NET data can serve an important starting point for job analyses. However, the data

¹The BLS's projections of industrial and occupational employment are developed in a series of six interrelated steps, each of which is based on a different procedure or model and related assumptions: labor force, aggregate economy, final demand (GDP) by consuming sector and product, industry output, employment by industry, and employment by occupation. For example, according to DOL officials, one of the key assumptions of the projections is full employment. That is, the 10-year projections assume the economy will be operating at its full potential and the unemployment rate is equal to the nonaccelerating inflation rate of unemployment. The purpose of this assumption is to focus on the long-term trends in the economy by excluding the effects of the business cycle.

would need to be reviewed, augmented, and validated for the particular purpose and local organization context.²

Further, the O*NET skills presented are broad and may not allow for nuanced analysis in some instances, according to Employment and Training Administration officials.

Any relationships we present are correlations and, as such, could be driven by other factors. For example, the statistically significant relationship between the total number of skills deemed important and the median annual wage could be driven by factors related to both the total number of skills deemed important and to median annual wages.

Section 2: Other Analyses

To address both objectives, we conducted interviews with stakeholders from four states: California, Kentucky, Pennsylvania and Washington. For our state selection process, we sought recommendations through initial stakeholder interviews and non-GAO reports that mentioned state programs as particularly effective in supporting at-risk workers. We also sought to select states that had a high concentration of jobs susceptible to automation by referring to a prior GAO report.³ Additionally, we sought states that had diversity across urban and rural geographies using Census data on urban and rural area classifications, including one state that did not have an urban area in the top 25 most populous in the United States (Kentucky).⁴ We also sought to select states with diversity in the type of their in-demand jobs, using data submitted to DOL by states.

In each state, we conducted semi-structured interviews with state workforce boards, which generally included representation from government agencies, business, labor, and training providers. In each state, we obtained information from local workforce boards recommended to us by state workforce board representatives as having particularly

²According to DOL officials, occupation is a concept—that groups many specific jobs across specific industries, representing many specific firms, in different parts of the country—all of which likely have distinct features that cannot be captured in aggregate national occupational data.

³GAO, *Workforce Automation: Better Data Needed to Assess and Plan for Effects of Advanced Technologies on Jobs*, [GAO-19-257](#) (Washington, D.C.: Mar. 7, 2019).

⁴To qualify as an urban area under the Census Bureau classification, a territory must encompass at least 2,500 people, at least 1,500 of which reside outside institutional group quarters. Rural areas encompass all population, housing, and territory not included within an urban area. For additional information, see the 2010 Census Urban and Rural Classification and Urban Area Criteria.

noteworthy programs or experience. We asked questions related to how the states collect data on, and challenges to, obtaining in-demand jobs, and examples of workforce training programs to serve at-risk workers. The views of the stakeholders we interviewed provided illustrative examples on these topics and are not generalizable.

In addition, we asked interviewees for their views on how well federal workforce programs served at-risk workers. Specifically, we asked about four such programs: (1) WIOA Dislocated Worker Formula Program, (2) WIOA National Dislocated Worker Grants, (3) H1-B Job Training Grants, and (4) Registered Apprenticeship program. To identify these four programs, we reviewed our prior work that cataloged federal employment and training programs.⁵ To narrow this list of programs to those that could serve workers at risk of losing their jobs to automation, we narrowed it to only programs that served the general population; provided occupational training; targeted workers who were on the job, underemployed or displaced; did not base eligibility on income; and had a goal of providing skills for in-demand jobs. We also reviewed a second GAO report that reviewed economic adjustment assistance programs that could serve workers, including programs that pertained to workers laid off due to any reason (as opposed to those laid off from a specific economically disruptive event, such as trade).⁶

Additionally, we interviewed stakeholders, including officials from DOL and the Census Bureau, as well as nine other organizations, such as national organizations of state workforce boards and agencies, business, labor, industry, and academic organizations, to obtain their perspectives on skills needed for in-demand jobs and challenges to obtaining those jobs.⁷ We selected these stakeholders based on our prior work on automation and workforce issues, as well as additional suggestions from initial outreach. In the report, we use the term “other stakeholders interviewed” to specify we are referring to stakeholders not from a state or

⁵GAO, *Employment and Training Programs: Department of Labor Should Assess Efforts to Coordinate Services Across Programs*, [GAO-19-200](#) (Washington, D.C.: Mar. 28, 2019).

⁶GAO, *Economic Adjustment Assistance: Actions Needed to Better Address Workers' Needs and Assess Program Effectiveness*, [GAO-20-521](#) (Washington, D.C.: July 29, 2020).

⁷These organizations include Upskill America, Burning Glass Technologies, the Georgetown Center on Education and the Workforce, the National Association of Workforce Boards, the National Association of State Workforce Agencies, and the National Governors Association.

local workforce board. The views of the stakeholders we interviewed provided illustrative examples on these topics and are not generalizable.

In describing responses of interviewees, the report sometimes specifies the number of states or stakeholders who voiced a particular response (such as “four states,” or “two business representatives”). In other instances, the report uses other terms to describe the number of responses. As used in the report, the term “several” indicates that three to four stakeholders gave a particular response, while the term “many” indicates that five or more stakeholders gave a particular response.

In addition to the GAO reports discussed above, we reviewed other GAO reports related to automation’s effects on the labor market. These GAO reports were published in the last 5 years and focused on automation, labor market policies, or in-demand jobs or skills.⁸

Additionally, we reviewed other relevant literature for information related to our objectives. We performed a literature search based on search terms related to the engagement’s objectives, such as automation, skill, and workforce. We narrowed search results by excluding articles or studies that did not include the United States, were more than 5 years old, and did not provide information related to the engagement’s objectives. We also reviewed several reports referred to us by interviewed stakeholders. We determined the credibility of relevant literature by reviewing the methodology and conclusions of those studies. We incorporated the results of our literature analyses into the report as appropriate. We did not conduct a comprehensive review of the factors that affect a firm’s decision to automate any of its tasks, but rather focused on the labor market once the automation decision has been made.

In addition, we reviewed relevant federal laws, regulations, and guidance.

⁸GAO reports we reviewed include: GAO, *Workforce Automation: Better Data Needed to Assess and Plan for Effects of Advanced Technologies on Jobs*, [GAO-19-257](#) (Washington, D.C.: Mar. 7, 2019); *Automated Trucking: Federal Agencies Should Take Additional Steps to Prepare for Potential Workforce Effects*, [GAO-19-161](#) (Washington, D.C.: Mar. 7, 2019); *Economic Adjustment Assistance: Actions Needed to Better Address Workers’ Needs and Assess Program Effectiveness*, [GAO-20-521](#) (Washington, D.C.: July 29, 2020); and *Economic Adjustment Assistance: Experts’ Proposed Reform Options to Better Serve Workers Experiencing Economic Disruption*, [GAO-21-324](#) (Washington, D.C.: Apr. 19, 2021).

**Appendix I: Objectives, Scope, and
Methodology**

We conducted this performance audit from April 2021 to August 2022 in accordance with generally accepted government auditing standards. Those standards require that we plan and perform the audit to obtain sufficient, appropriate evidence to provide a reasonable basis for our findings and conclusions based on our audit objectives. We believe that the evidence obtained provides a reasonable basis for our findings and conclusions based on our audit objectives.

Appendix II: GAO Contacts and Staff Acknowledgments

GAO Contact

Dawn G. Locke, (202) 512-7215 or locked@gao.gov

Staff Acknowledgments

In addition to the contact named above, Meeta Engle (Assistant Director), Andrew Nelson (Analyst-In-Charge), Laura Abendroth, and Dylan Desjardins made significant contributions to this report. Also contributing to this report were Charlotte Cable, Lilia Chaidez, Sherwin Chapman, Gabrielle Crossnoe, Hayden Huang, Kirsten Lauber, Lara Laufer, Ty Mitchell, Nhi Nguyen, Stacy Ouellette, Dae Park, Moon Parks, James Rebbe, Almeta Spencer, Curtia Taylor, Adam Wendel, and Candice Wright.

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