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Retooling the Definition of the Skilled Technical Workforce

Why don't job classification systems recognize what skills today's occupations really require?

In the early twentieth century, stonecutters relied on hand tools such as chisels, hammers, and mallets to shape and carve stones precisely. These methods demanded a high degree of manual dexterity, physical strength, and artistic skill. Artisans often acquired training through apprenticeships, where they learned the use of traditional tools and techniques from experienced workers, developing a keen eye for detail.

As technology advanced, the stonecutting industry began integrating modern machinery. By the mid-twentieth century, power tools like electric saws and grinders improved efficiency and precision. The advent of computer numerical control (CNC) machines and computer-aided design (CAD) software in the late twentieth and early twenty-first centuries further revolutionized the field. These software advances enable stonecutters to create highly detailed and complex designs with unprecedented accuracy. Stonecutters now require proficiency in advanced material properties, safety protocols, and the use of high-tech equipment such as laser scanners and water jet cutters.

Stonecutters do ongoing training and certification to maintain and update their skills. At the same time, the need to keep up with environmental regulations and sustainability practices has further increased the profession's technical complexity. Modern stonecutters blend traditional craftsmanship with cutting-edge technology, combining artistic skills with technical expertise to meet the industry's evolving demands.

For all these reasons, we—a group of researchers, social scientists and statisticians—are convinced that stonecutters should be part of the skilled technical workforce (STW). However, the STW definition adopted by the National Science Board (NSB) actually leaves them out—along with many other skilled technical jobs. The NSB's working definition is based on a framework that prioritizes education credentials and knowledge rather than specific skills to delineate STW occupations. This bias means that the definition fails to account for the evolution of skills over time, which makes the working definition less adaptable to changes in the nature of skills and skilled technical work, and consequently less effective at measuring this important segment of the workforce.

A better definition of the STW can help policymakers and industry leaders support workforce development initiatives that are connected to innovation and economic development strategies. The National Center for Science and Engineering Statistics (NCSES), the principal statistical agency within the National Science Foundation, supports research, including ours, to find better data and methodologies. Using real-time job postings and current data science and statistical techniques, we conducted a review of occupations that reveals the current STW definition is out of step, and we propose new approaches for getting it back on track.

Improving the skilled technical workforce definition

Keeping an up-to-date definition of the skilled technical workforce is important because emerging technologies are rapidly changing the nature of work. As technology changes, the skills that employers need also change, shifting occupation descriptions and titles, which in turn prompt updates to education and training programs. A lack of timely information about labor market shifts hinders effective resource allocation for workforce planning and training initiatives.

The current designation for the STW is rooted in work by the economist Jonathan Rothwell. In 2015, Rothwell prepared a commissioned paper building on his research identifying various job characteristics with STEM skills for the National Academies of Science, Engineering, and Medicine's project "The Supply Chain for Middle-Skill Jobs." His paper helped frame how skilled technical workers should be defined and analyzed. He proposed a strategy for classifying STW occupations using knowledge and education survey data from the Department of Labor's Occupational Information Network (O*NET) Content Model. O*NET maintains a framework for organizing occupational data aligned with the Bureau of Labor Statistics (BLS) Standard Occupation Classification (SOC) system, which is the federal standard for classifying workers into occupations based on work performed. Occupations must be in the SOC system for the BLS or the Census Bureau to collect and report data on them.

Today, however, the survey data in the O*NET Content Model present several fitness-for-use issues. The first is that the model uses small sample sizes and has missing or old data for some occupations. Another challenge is the way the Rothwell framework uses the survey data to define the STW cutoff. Workers responding to the O*NET survey are asked to rate the level of knowledge needed to perform their job on a scale of 1–7, across a range of "knowledge domains" including biology, chemistry, and mathematics. Occupations with mean scores equal to or above 4.5 across 14 STEM-related knowledge domains are considered by the Rothwell framework to require a sufficiently high level of technical knowledge to be included in the STW. But occupations with a mean below 4.5—even, say, 4.4—are not. This empirical approach does not accommodate for rapidly evolving skill sets, and it introduces uncertainty about occupations on the margins. Continuing to rely on these data sources and methodology risks overlooking a substantial segment of workers contributing valuable technical expertise to the STEM ecosystem.

In the past, when jobs were advertised in classified ads, it was difficult to make assumptions about skill levels. But today, when many jobs are listed in vast online job repositories and include details on qualifications for machines, software, and processes, it's possible to get both an aggregate and a granular sense of what a job entails. New online job posting data aggregators such as the National Labor Exchange (NLx) or Lightcast reflect the changing nature of work in real time, making it easier to identify an occupation's technical requirements, including skills. The volume of online job opening data is huge—NLx data include 300,000 employers and 1.8 million daily job postings. This kind of rich dataset offers a more detailed and current picture of the labor market and thus could serve as a more reliable basis for assessing the STW than the O*NET surveys.

Revising the methodology to capture the rapidly changing set of STW skills can inform policymaking, improve the allocation of resources for training, and enable the creation of new tools to support equitable and efficient labor market outcomes. Anticipating shifts in demand for skilled technical workers in real time—especially those related to the energy transition and other technological advancements—enables targeted educational and training programs, which support social mobility by empowering individuals to obtain nondegree credentials that can provide a path to the middle class. Improved access to such programs can help people integrate into the labor market more rapidly and at a lower cost per person per year. Enhancing the STW definition is the kind of proactive approach that can help mitigate potential skills shortages while strengthening the economy's capacity to innovate and compete globally.

Better data for a stronger definition

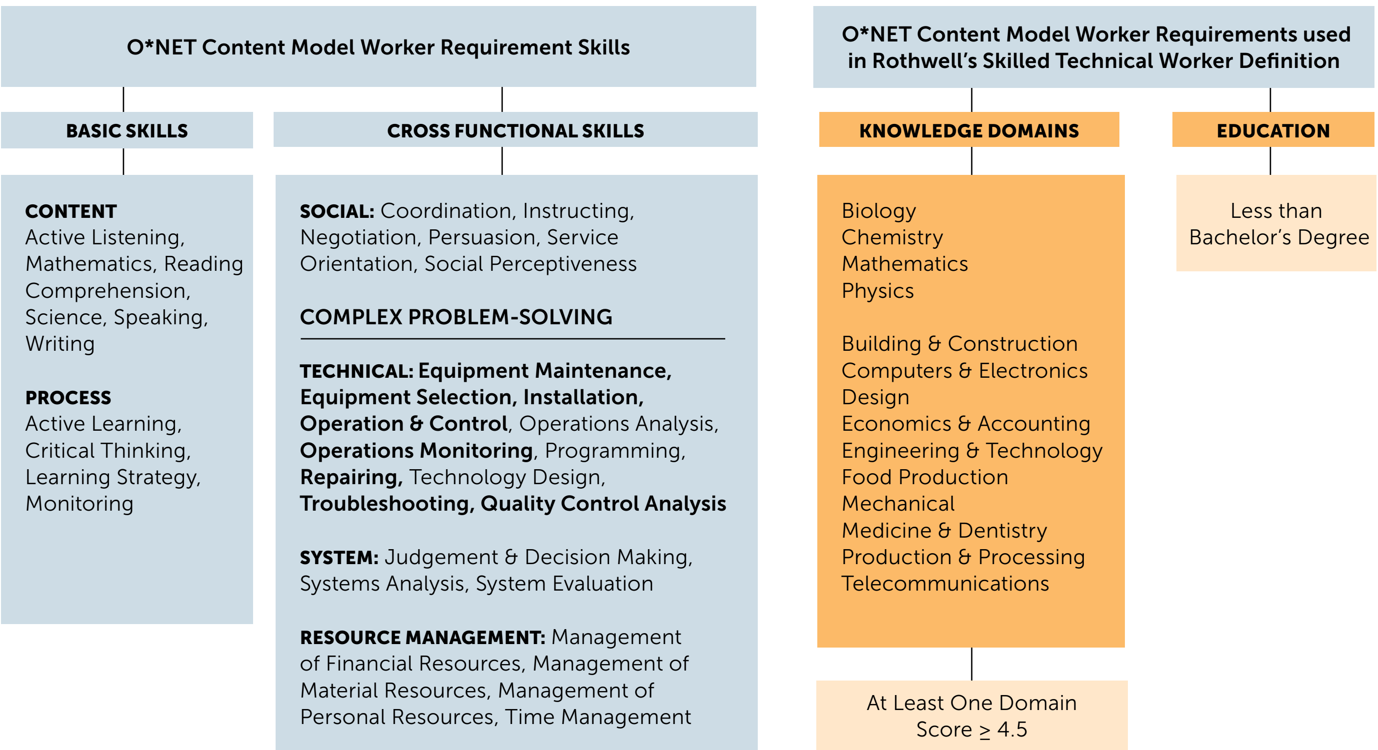
Two changes are required to address the data issues contributing to the narrow interpretation of the skilled technical workforce. First, the O*NET Content Model's occupation skills requirements should be reconfigured to focus on basic and cross-functional job skills across categories related to content, process, social, complex problem-solving, technical, systems, and resource management skills (Figure 1). Shifting away from the Rothwell framework's focus on degree attainment and "knowledge domains" enables more comprehensive engagement with a variety of modern, high-demand skills. As the workforce landscape changes rapidly, focusing on skills instead of knowledge domains can help capture how technological changes are affecting individual occupations.

For example, aircraft systems assemblers have technical skills that include reading and interpreting blueprints and engineering drawings to assemble components according to quality specifications; fitting and installing mechanical systems, electrical systems, hydraulic systems, and avionics systems; using pneumatic and precision tools; and team collaboration and attention to detail. The level of specificity in learning and skills application needed to be an aircraft systems assembler gives a more complete representation of the occupation's requirements than the average O*NET knowledge domain scores can. Aircraft systems assemblers are not counted as part of the STW under the Rothwell framework because they do not meet the knowledge domain criteria.

Second, the O*NET Content Model should be based on data sources that capture more up-to-date information about skills and education requirements demanded by employers, instead of the current O*NET knowledge and education survey data. O*NET surveys are not timely, which may hamper the efficacy and usability of O*NET-based tools. Using online job posting data from free and publicly available sources like the NLx Research Hub, where online job openings are scraped and refreshed daily and reflect local and regional demand for skills in industry clusters, would contribute to building a more comprehensive, timely, and customizable resource. The O*NET Content Model has made use of commercial job posting data from companies such as Lightcast in recent versions, but the data have been used as a secondary source for education requirements, in-demand skills, and new technologies.

To understand whether the changes we propose would be effective in real life, we did a test. We used Virginia job posting data for the major occupational groups—construction and extraction; transportation and material moving; production; and installation, maintenance, and repair—because they require a high level of technical skill and most do not require a college degree. Applying supervised and unsupervised machine learning models to the job posting data, we demonstrated that using skills from

Figure 1. **O*NET CONTENT MODEL WORKER REQUIREMENTS**



*Rothwell's framework for the STW definition selected 14 of the 35 O*NET Content Model knowledge domains as relevant to STW occupations. Domain scores are computed by averaging the rankings (1–7) reported in the questionnaires of the O*NET survey for each of the relevant knowledge domains, and are compared to the hypothetical mean value, 4.5. An occupation must require a high level of knowledge—indicated by a mean ranking above or equal to 4.5—in at least one STEM-related knowledge domain. Eight of the 11 cross-functional technical skills we derived through our analysis (in bold text) correlate with the 14 knowledge domains.*

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job posting data identifies more relevant STW occupations than the knowledge-based approach alone. We then used employer skill demands from online job postings to distribute occupations into a STW classification and remapped the skills to the O*NET classifications.

To build an occupational skill profile for each occupation listed in the job postings, we compiled a unique list of skills and skill clusters from all jobs within that occupation. The number of skills in a skill cluster is an indicator of the proficiency level within that skill cluster. For example, the carpentry skill cluster lists five skills: precision cutting, blueprint reading, tool handling, material selection, and surface finishing. The construction laborers skill cluster lists three skills: precision cutting, safety consciousness, and tool handling. We conclude that the carpentry skill cluster requires a higher level of proficiency than the construction laborers' skill cluster.

Our final sample for one year includes 91,000 job postings from 268 occupations, encompassing 5,212 skills, which we grouped into 575 clusters. Using the skills-based method, 150 (56%) occupations were classified as STW. Under the Rothwell framework, only 96 (36%) of the 268 occupations would be counted as STW. Our analysis identified 84 additional skilled technical occupations, including stonecutters; sheet metal workers; automotive body and related repairers; aircraft structure, surfaces, and rigging systems assemblers; and fiberglass laminators and fabricators. These occupations now demand advanced technical skills, including the use of software tools and digital literacy.

Our analysis demonstrates the kinds of insights that can be gained by incorporating contemporary data sources and data science methods to understand the changing composition of the labor force. The United States sorely needs these insights to support workers in a rapidly transitioning economy. The new methodology generates a picture of existing and emerging skills that is closer to real time, which could benefit decisionmakers, employers, and workers alike in the coordination of complex employment shifts. Filling the skills information gap could improve training options for career development advisors, better equipping them to guide individuals—particularly those not pursuing a traditional four-year college degree—in making more informed career decisions.

In this evolving field for data science, another area for further research is creating a standardized methodology to compare the value of nondegree credentials (including apprenticeships, licenses, certificates, certifications, and digital badges). Understanding which credentials help improve income or prospects could be invaluable for workers trying to plan long-term career pathways and choose among technical specialties. Likewise, updated data sources and new methods are needed to better assess the portability of certain skills to other job classifications, which could help to more efficiently align workers with training programs for in-demand jobs in their regions.

When it was introduced, the Rothwell framework used the best data sources available, but changes in the field of data science and new data sources have made improvements possible. To accurately capture transformations in the current labor market, the practice of defining and measuring skills and work must evolve as well.

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RECOMMENDED READING

Vicki Lancaster, Sarah McDonald, Cesar Montalvo, and Guy Leonel Siwe, "Designating the Skilled Technical Workforce Using O*NET-SOC (2019)," University of Virginia (2022), available online: https://doi.org/10.18130/142t-4976

Cesar Montalvo, Haleigh Tomlin, and Guy Leonel Siwe, "Portability: A New Measure for Comparing the Value of Career Certifications," University of Virginia, Biocomplexity Institute (2024), available online: https://doi.org/10.18130/8673-ew54

Guy Leonel Siwe, Cesar Montalvo, and Vicki Lancaster. "Designating Skilled Technical Workforce Using Online Job Postings," University of Virginia (2024), available online: https://doi.org/10.18130/pp1g-a507