Designating Skilled Technical Workforce Using Online Job Postings

Guy Leonel Siwe, Cesar Montalvo and Vicki Lancaster

University of Virginia, Biocomplexity Institute

December 11, 2024

Abstract

The Skilled Technical Workforce (STW) are individuals without a bachelor's degree but have a non-degree credential that provides them with STEM skills. In 2015, Rothwell proposed a strategy for classifying occupations as STW using education and knowledge survey data from the Occupational Information Network (O*NET) Content Model. However, these data present a number of fitness-for-use issues such as small sample sizes, data for some occupations over a decade old, data are not available for all occupations, and the sampling error is ignored when constructing the estimate. The STW is a function of the nature of work which is rapidly changing due to emerging technologies, it follows the data used to classify this segment of the workforce be current. We propose a new approach for classifying STW occupations using labor market information such as online job postings. These data provide detailed information at the occupation level on the skills required and the technical nature of the skills. We use skills demand as a proxy for knowledge and classify occupations as STW according to the level of technical skills required. Our new classification approach shows that many additional occupations should be included in the STW.

Keywords : Skilled Technical Workforce (STW), Labor Market Information (LMI), Classification.

Funding: This research was funded by the National Center for Science and Engineering Statistics (NCSES) contract 49100420C0015. The views expressed in this report are those of the authors and not the NCSES.

Acknowledgment: Thank you to Jonathan Rothwell, Gallup, for his comments.

1 Introduction

The Skilled Technical Workforce (STW) are workers who do not possess a bachelor's degree but have acquired STEM-related skills through non-degree credentials. This segment of the labor market plays a crucial role in industries that increasingly rely on advanced technical competencies, yet it remains under-recognized in official workforce classifications (Burke, 2019).[1] Traditionally, the definition of STW has been based on knowledge and education levels, with Rothwell (2015)'s framework serving as the primary methodology for identifying STW occupations. Rothwell's approach uses survey data from the O*NET Content Model and classifies an occupation as part of the STW if it does not require a bachelor's degree for entry but demands a knowledge score of 4.5 or higher in one of 14 knowledge domains (Table 1).

Table 1: Fourteen Knowledge Domains Listed by Rothwell.

Biology	Economics and Accounting	Medicine and Dentistry
Building and Construction	Engineering and Technology	Physics
Chemistry	Food Production	Production and Processing
Computers and Electronics	Mathematics	Telecommunications
Design	Mechanical	

Source: Rothwell (2015).

O*NET, sponsored by the U.S. Department of Labor, is a key resource for occupational classification and is aligned with the Standard Occupational Classification (SOC) system. The O*NET Content Model provides detailed information on the characteristics and requirements of occupations, organized into six major domains: worker requirements, worker characteristics, experience requirements, occupational requirements, workforce characteristics, and occupation-specific information. For Rothwell (2015)'s framework, the knowledge domain scores from O*NET serve as the critical input for determining whether an occupation should be classified as part of the STW.

While Rothwell's framework was innovative at its inception, several limitations now hinder its applicability. First, the O*NET data used in the framework are often outdated, with some data points being over a decade old. This presents a challenge in fast-evolving industries where the skills required for a given occupation may change rapidly. Second, O*NET data suffer from small sample sizes for many occupations, which compromises the

[1] In the latest Okrent and Burke (2021) science and engineering (S&E) indicators report from NCSES, *The STEM Labor Force of Today: Scientists, Engineers, and Skilled Technical Workers*, skilled technical workers are divided into three categories, middle-skill, S&E-related, and S&E. In 2019, STEM jobs comprised 23 percent (36,094 million) of the U.S. workforce and of these a little over half (19,853 million) did not have a bachelor's degree; this includes 12,657 million in middle-skill jobs; 5,180 million in S&E related jobs; and 2,017 million in S&E jobs.

reliability of the knowledge scores used in the classification. For instance, survey sample sizes used to calculate the knowledge mean range from [10, 76]. Since the sampling variability of the mean is ignored when compared to the knowledge score of 4.5, the risk of making an incorrect decision when the variability is large (Lancaster et al., 2021). Third, for the 2010 SOC system, 12 percent of the occupations have no Content Model data. Fourth, the reliance on knowledge domains overlooks the growing importance of specific technical skills that are now integral to many occupations previously considered outside the scope of the STW.

Technological advancements in sectors like manufacturing and construction illustrate the inadequacies of the current STW definition. For example, occupations such as stonecutters have transitioned from manual techniques to the use of sophisticated tools such as Computer Numerical Control (CNC) machines and Computer-Aided Design (CAD) software. These technological shifts necessitate new skills, but the traditional knowledge-based framework, as employed by Rothwell, fails to recognize such changes. As a result, many technically skilled occupations remain excluded from the STW classification, limiting the ability of policymakers and educators to develop targeted workforce training programs.

In this paper, we propose an updated methodology for classifying the STW that addresses the shortcomings of the Rothwell framework. Instead of relying solely on knowledge scores from O*NET, we incorporate real-time labor market information derived from job postings, which reflect the skills that employers actively seek. By shifting from a knowledge-based to a skills-based approach, we aim to capture the dynamic and rapidly evolving skill requirements in today's labor market, driven by rapid technology adoption. This approach enables more accurate and timely classification of STW occupations and supports better-informed decisions regarding workforce development, particularly in response to technological and energy transitions. Real-time job postings have virtually no lag time and now the National Labor Exchange Research Hub scrapes tens of thousands job posting websites a day and provides the data free to researchers.

Our methodology builds on Rothwell's original work but integrates modern data science techniques and real-time labor market data to offer a more robust framework for defining and supporting the Skilled Technical Workforce. Using Lightcast job postings data from Virginia in 2019 across the four main major occupation groups (MOGS): Construction & Extraction; Transportation & Material Moving; Production; and Installation, Maintenance & Repair, we propose a new skill-based classification of occupations into the STW. We found that more than 49% of occupations not designated into the STW based on Rothwell should be listed into the STW, including Stonecutter's occupation.

The remainder of this paper is organized as follows: Section 2 describes the data, the methods used to build an occupation skills profile from job postings, and our proposed models for classifying occupations into the STW based on skills. Section 3 presents and discusses the results of this skills-based classification. Finally, Section 4 concludes by examining the implications of this new approach for workforce policy.

2 Data and Methods

2.1 Data

Our new approach to classifying occupations into the STW relies on two primary data sources: the O*NET Content Model and online job postings from Lightcast. Each source contributes a unique aspect to understanding the skills profile required for STW occupations.

Table 2: O*NET Skills Classification into Skill Categories.

O*NET Skill Categories	**O*NET Skills**
Basic Skills	Active learning; Active listening; Critical thinking; Mathematics; Monitoring; Reading comprehension; Science; Writing; Learning strategy; Speaking.
Cross-Functional skills	
Technical Skills	Operations analysis; Technology design; Installation; Programming; Operation monitoring; Equipment maintenance; Troubleshooting; Repairing; Quality control analysis; Equipment selection; Operation and control.
Complex-Problem Solving Skills	Complex-Problem Solving
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.
System Skills	Judgment and decision making; System analysis; System evaluation

Source: ONET-SOC 2019 taxonomy, which aligns with the 2018 Standard Occupational Classification. (SOC) system. Only 873 occupations have Content Model data. For references on this O*NET skills classification use the two following URLs: Basic skills https://www.onetonline.org/find/descriptor/browse/2.A or cross-functional skills https://www.onetonline.org/find/descriptor/browse/2.B

First, we use data from the O*NET Content Model version 25.2, which provides detailed information on the level of skills (35 skills) and knowledge (31 knowledge domains) required for 923 occupations.[2] The O*NET data categorize these skills into six com-

[2]We use the ONET-SOC 2019 taxonomy, which aligns with the 2018 Standard Occupational Classi-

petency groups, including technical and non-technical skills (Table 2).This allows us to analyze the relationship between the knowledge level in the 14 domains listed in Table 1 by Rothwell and the technical skill levels required, and evaluate the substituability of knowledge information by skills. Table 2 summarizes the O*NET skills classification, where 11 out of the 35 listed skills are classified as technical skills, such as Operation Analysis, Technology Design, and Troubleshooting.

Second, we use job posting data from Lightcast to identify STW occupations based on employer skill demands. This data source provides real-time information on the skills required to perform tasks in specific occupations, enabling a more dynamic and current classification of the workforce. Lightcast uses a private technology to group jobs in this dataset according to the Standard Occupation Classification (SOC) 2010 system, and each job posting is associated with a list of required skills. Due to the high granularity in skills, this technology groups skills into skill clusters and skill cluster families.

Our proof of concept focuses on four Major Occupation Groups (MOGs): Construction & Extraction (47); Installation, Maintenance & Repair (49); Production (51); and Transportation & Material Moving (53) from O*NET-SOC 2010. We chose these MOGs since the majority of occupations require less than a bachelor's degree, one of the criteria for a STW designation. The O*NET-SOC occupations are supplemented with survey data from the O*NET Content Model for most occupations. The Content Model includes survey data on the mix of skills, knowledge, education, and abilities required in an occupation. We used data from O*NET Content Model Version 25.2 to construct our model.

The Lightcast data includes 91,377 job postings in these four MOGs. There are 268 unique occupations with 5,212 unique skills. Those skills were grouped into 575 Lightcast skill clusters and 29 Lightcast skill cluster families.

Table 3: Job Postings and Occupations in the Major Occupation Groups from Online Jobs Posting Data in Virginia 2019

Major Occupation Group (MOG)	Unique Job Postings (Count)	Unique O*NET-SOC Occupations Reported (Count)	Unique O*NET-SOC Occupations Requiring < Bachelor (Count)	Count & (Percent) STW Occupations (Rothwell O*NET version 25.2)
Construction & Extraction	11,707	61	61	30 (49.18%)
Installation, Maintenance & Repair	28,730	51	51	40 (78.43%)
Production	15,112	105	105	22 (20.95%)
Transportation & Material Moving	35,828	51	50	4 (7.84%)
Total	91,377	268	267	96 (35.82%)

Source: Lightcast data for Virginia, 2019

fication (SOC) system. Only 873 occupations have Content Model data.

Table 3 provides the number of 2019 Lightcast job postings in Virginia for each of the four MOGs and the number of these job postings with unique O*NET-SOC codes. It also includes the number of occupations within each MOG that do not require a bachelor's degree based on the O*NET Content Model 25.2 education survey data. The fourth column provides the number of occupations in each MOG that satisfy Rothwell's criteria. We use Rothwell's STW classification definition to benchmark our approach. For example, 78.43% of occupations in Installation, Maintenance & Repair are classified as STW, whereas only 7.84% of occupations in Transportation & Material Moving fall into this category. Table 3 also reports that, on average, we have enough job postings per occupation to build each occupation skill profile using Lightcast data.

2.2 Occupation Skill Profile from Job Postings

To develop a skill-based classification of occupations, it is essential to construct occupation skill profiles where technical skills are identified and used as input for classification models (Fee et al., 2020). An occupation's skill profile is represented by a vector $(x_{oi})_{i \in M}$ where x_{oi} is the level of skill i required to perform tasks in occupation o. For the O*NET Content Model, these profiles are predefined. This section details the methodology used to generate skill profiles from online job postings.

Step 1 - Extracting Skills from Job Postings

Job postings provide detailed insights into the skills employers seek for specific occupations. Using data from Lightcast, we extract all skills listed in job postings and link them to the corresponding occupations based on the Standard Occupational Classification (SOC) system. These skills form the foundation for each occupation's skill profile.

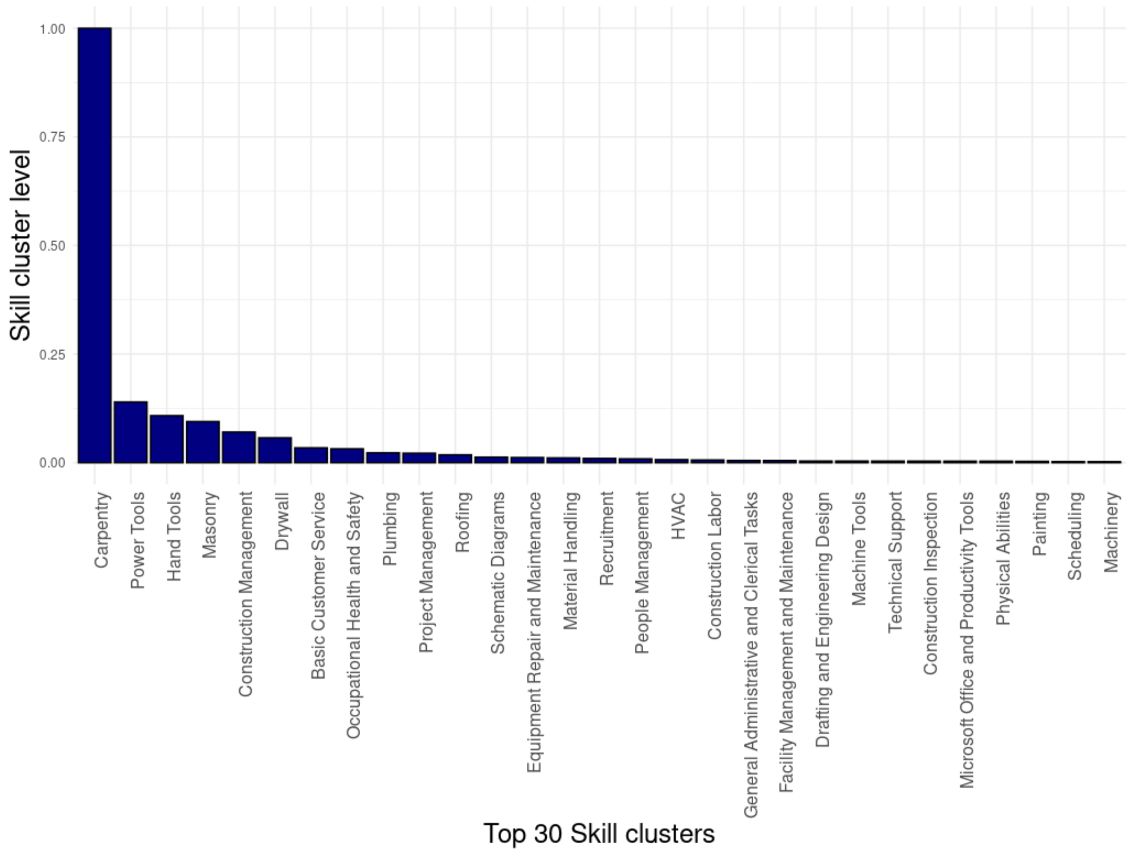
Skills listed in job postings can be highly granular. For instance, Appendix Figure 5 shows that for the occupation "Carpenter" (SOC: 47-2031.00), more than 298 unique skills are listed across job postings, including "Carpentry," "Power Tools," and "Framing." The variation in skills across postings for the same occupation creates a high level of detail that needs to be standardized. To manage this granularity, we group similar skills into clusters using Lightcast's proprietary methodology. For example, "Microsoft Excel" and "Microsoft PowerPoint" are grouped into the "Microsoft Office" skill cluster. This grouping reduces redundancy and produces a more structured, comparable skill profile across occupations.

Step 2 - Constructing the Skill Cluster Profile

After grouping individual skills into skill clusters, we construct a skill profile for each occupation based on these skill clusters. The profile reflects the skill clusters required for tasks within the occupation and the level of importance of each skill cluster.

The proficiency level within a skill cluster is indicated by the number of associated skills in the skill cluster. A higher level suggests that many skills in the cluster are essential for performing tasks in that occupation. For instance, in the case of "Carpenter" (SOC: 47-2031.00), the "Carpentry" skill cluster includes five specific skills: precision cutting, blueprint reading, tool handling, material selection, and surface finishing. In contrast, the "Construction Laborers" skill cluster lists three skills: precision cutting, safety consciousness, and tool handling. Thus, the "Carpentry" skill cluster requires a higher proficiency level than the "Construction Laborers" skill cluster.

Figure 1: Example of Skill Cluster Profile from 2019 Lightcast Online Job Postings: SOC: 47-2031.00, Carpenter.



Source: Lightcast data for Virginia, 2019.

Step 3 - Mapping Job Posting Skill Clusters to O*NET Categories

To formalize this, let $\hat{l}_{io}$ represent the level of skill cluster i required for occupation o, measured as the normalized number of skills in that skill cluster i across job postings:

$$l_{io} = \frac{f_{io} - \min_o(f_{io})}{\max_o(f_{io}) - \min_o(f_{io})} \tag{1}$$

Where f_{io} is the number of skills in skill clusters i for occupation o. This normalization ensures comparability of skill levels across occupations, with values ranging from 0 to 1, where 1 represents the most critical skill clusters for a given occupation. Appendix Figure 5 illustrates an example of a skill profile for the occupation "Carpenter" (SOC: 47-2031.00), displaying the top 30 skill clusters and their corresponding levels of importance. The "Carpentry" cluster has the highest required level, followed by clusters such as "Power Tools," "Hand Tools," and "Masonry".

While job postings provide real-time skill demand data, the O*NET Content Model offers a structured classification of skills across occupations. O*NET groups skills into six broad categories, including technical skills (see Table 2). This established framework serves as the foundation for our classification, allowing us to categorize skill clusters from job postings into technical and non-technical categories (Lassébie et al., 2021).

To classify skills from job postings into O*NET categories, we apply a Natural Language Processing (NLP) approach using the Bidirectional Encoder Representations from Transformers (BERT) model. BERT generates numerical vector representations of skill clusters from job postings and O*NET skills, enabling a semantic similarity analysis.

BERT is a transformer-based machine learning model for NLP developed by Google, pre-trained on large text corpora, including Wikipedia. It produces dense numerical vector embeddings for words or tokens in a text, capturing rich semantic information and contextual relationships (Devlin et al., 2019).[3]

We measure the semantic similarity between a job posting skill cluster and an O*NET skill using cosine similarity. For instance, if the skill cluster "Programming in Python" has a high cosine similarity to the O*NET skill "Programming," we classify it as a technical skill. This approach allows us to map skill clusters from job postings systematically to O*NET skill categories.

Table 4 shows that nearly half of the skill clusters identified in job postings are technical. Of the 575 skill clusters extracted, 256 (44%) are classified as technical. The share of technical skill clusters exceeds 40% in each of the four major occupational groups (MOGs), supporting the assumption that these occupations intensively use technical skills. The most important non-technical skill clusters are Basic Skills (113 skill clusters) and Management Skills (106 skill clusters). In the absence of ground truth data that can be used as a test set, we were unable to evaluate the performance of our NLP similarity model based on BERT.

Next, we match Lightcast skill clusters to O*NET skills to reduce the dimensionality

[3]BERT is trained on large amounts of text data in an unsupervised manner, learning to predict missing words in a sentence bidirectionally. As a result, it develops a deep understanding of the contextual relationships between words. We didn't use pre-trained models of skills classification such as SkillBERT (Nigam et al., 2020).

Table 4: Lightcast Skill Clusters by O*NET Category Groups

O*NET Skill Categories	Mean Cosine Similarity	Skill Clusters in Job Postings	Skill Clusters by MOG (47)	(49)	(51)	(53)
Basic skills	0.4425	113	77	106	96	99
Complex Problem Solving skills	0.4449	3	2	3	3	3
Management skills	0.4738	106	86	99	99	91
Social skills	0.4175	65	47	62	60	55
System skills	0.3965	32	23	28	29	25
Technical skills	0.4332	256	184	237	224	212
Total	-	575	419	535	511	485

Source : Lightcast data for Virginia, 2019.
Notes: MOG codes are 47=Construction & Extraction, 49=Installation, Maintenance & Repair, 51=Production, and 53=Transportation & Material Moving.

of the skill profiles. Our skill profiles, initially constructed from 575 skill clusters in job postings, can be reduced by mapping them to the 35 O*NET skills. We calculate the average skill level $\hat{l}_{io}$ for each O*NET skill within each occupation based on the associated skill clusters. To validate the new skill profiles, we analyze the correlation between skill levels derived from job postings and those provided by the O*NET Content Model.

The skill levels built from job postings are significantly and positively correlated with those from the O*NET Content Model within the same occupation. We introduce occupation-fixed effects (FE) to remove occupation-specific effects, and Table 9 reports the partial correlation between job posting skill levels (both scaled and non-scaled) and the O*NET skill levels. Our job posting-based skill levels are positively and significantly correlated with O*NET skill levels (p-value $<$ 5%), supporting the validity of our skill profile construction methodology.[4]

By matching Lightcast skill clusters to O*NET skills, we can systematically classify skills from job postings into O*NET categories, providing a robust, real-time measure of skill demand across occupations.

2.3 Empirical Methodology

We aim to address two key questions in this study: (1) Can skill-based data be used in place of knowledge information to classify occupations into the Skilled Technical Workforce (STW)? (2) Can job postings, which reflect evolving skill demands due to technological change, be utilized to classify occupations into the STW?

[4]The low significant partial correlation between our estimated skill level and the O*NET skill level may traduce technological changes in skill level required to operate in some occupations but may also reflect some differences in skill-level measurements.

Two fundamental statistical methods were used to answer those questions. A Linear Discriminant Analysis (LDA) which is a supervised classification model and the Non-negative Matrix Factorization (NMF) which is an unsupervised classification model. Supervised and unsupervised classifiers are two fundamental approaches for pattern recognition in data. In supervised learning, the model is trained on a labeled dataset where occupations are classified as either STW or non-STW based on Rothwell's methodology. The model learns the relationship between input features and output labels, and once trained, it can predict labels for new, unclassified occupations. Unsupervised learning, by contrast, does not rely on labeled data and instead seeks to uncover inherent structures or patterns without explicit guidance.[5]

The first question is examined using the LDA where Rothwell's occupation classification into the STW was predicted using occupational skill profiles instead of knowledge information. The model was trained using O*NET skill profiles, provided across all the 923 occupations listed in the Content Model. In addition, we use the NMF model on the same data, to investigate if potential occupations may have been misclassified from Rothwell's framework.[6]

The second question is addressed through Non-negative Matrix Factorization (NMF), an unsupervised method that classifies occupations into the STW by identifying latent structures and patterns across occupational skill profiles. The advantage of the NMF model is its ability to identify occupations that may have been excluded from the STW under Rothwell's framework.

2.3.1 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is a commonly used method for classifying data by finding linear combinations of features that best separate predefined classes (Qu and Pei, 2024). In this study, LDA is employed to classify occupations into STW and non-STW categories based on their skill profiles and education requirements. The LDA projects occupational data into a one-dimensional space, aiming to maximize the difference between the mean skill profiles of STW and non-STW occupations while minimizing the variance within each group. The method estimates a set of coefficients that maximize inter-class variance (STW vs. non-STW) and minimize intra-class variance.

Formally, given a set of occupations $\{o_1, o_2, \dots, o_n\}$, each occupation is represented by a vector of skills and education requirements $Y = \{y_1 = (x_1, e_1), y_2 = (x_2, e_2), \dots, y_n = (x_n, e_n)\}$, where $x_i = (x_{ij})_{1<j<m}$ is a vector of skill level profile for occupation i and e_i is a

[5]One key distinction between the models is that LDA derives a linear classification rule, while NMF employs a non-linear approach.

[6]The idea is to develop a classification model solely based on the pattern between occupation profiles than a threshold which may vary across occupations or time.

binary variable indicating whether the occupation i requires less than a bachelor's degree at the entry, LDA estimates the following linear combination of the skill clusters:

$$z = w^T Y$$

where z is the LDA score, w is the vector of coefficients, and Y is the vector of skill profiles and education requirements. The vector w is estimated by solving the following optimization problem:

$$w = S_W^{-1}(\mu_{STW} - \mu_{\overline{STW}})$$

Here S_W is the within-class covariance matrix, defined as:

$$S_W = \sum_{i \in STW} (Y_i - \mu_{STW})(Y_i - \mu_{STW})^T + \sum_{i \in \overline{STW}} (Y_i - \mu_{\overline{STW}})(Y_i - \mu_{\overline{STW}})^T$$

where STW and $\overline{STW}$ represent the sets of technical and non-technical occupations, respectively, and μ_{STW} and $\mu_{\overline{STW}}$ are the mean vectors of skill clusters for technical and non-technical occupations.

Once w is estimated, each occupation i is projected onto the LDA axis using the linear combination $z_i = w^T Y_i$, resulting in an *LDA score* z_i for each occupation. The *LDA score* represents the position of each occupation on the linear discriminant axis. The decision boundary between STW and non-STW occupations is determined by the midpoint between the mean LDA scores of the two classes. An occupation i is classified into the STW if its LDA score z_i exceeds the threshold. If $z_i < \overline{z}$, the occupation is not classified into the STW.

$$\overline{z} = \frac{\mu^z_{STW} + \mu^z_{\overline{STW}}}{2}$$

where μ^z_{STW} and $\mu^z_{\overline{STW}}$ are the mean LDA scores for technical and non-technical occupations, respectively.

An occupation is classified as STW if its LDA score exceeds the threshold z_i. We further introduce a *technical intensity score* T_i, which measures the ratio of technical to non-technical skills for each occupation:

$$T_i = \frac{\sum_{j \in T} w_j x_{ij}}{\sum_{j \in \overline{T}} w_j x_{ij}} \qquad z_i = (1 + T_i)(\sum_{j \in \overline{T}} w_j x_{ij}) + w_{m+1} e_i$$

where T is the set of technical skills. This score allows us to analyze the intensity of technical skill usage in STW occupations.

2.3.2 Non-negative Matrix Factorization (NMF)

Non-negative Matrix Factorization (NMF) is a matrix decomposition technique used to uncover latent structures in high-dimensional data, particularly useful for dimensionality reduction (Alibasic et al., 2022). In the context of occupation classification, NMF decomposes the skill profiles and education requirements into latent factors, allowing us to classify occupations based on these underlying structures.

Let $X \in \mathbb{R}^{n\times(m+1)}$ represent the occupation-skills profile matrix added with education requirement column, where n is the number of occupations, and m is the number of distinct skills. Each entry $x_{ij(j<m+1)}$ represents the level of skill j in occupation i and $x_{i(m+1)}$ is a binary value taking 1 if the occupation i requires a bachelor degree at entry and 0 if not. NMF factorizes X into two non-negative matrices, $W \in \mathbb{R}^{n\times k}$ and $H \in \mathbb{R}^{k\times(m+1)}$, where k represents the number of latent clusters:

$$X \approx WH$$

Here, W_{ik} represents the extent to which occupation i relies on NMF cluster k, and H_{kj} represents the importance of skill j within NMF cluster k.

The goal of NMF is to minimize the reconstruction error, typically measured by the Frobenius norm:

$$\min_{W,H} ||X - WH||_F^2$$

subject to $W \geq 0$ and $H \geq 0$, where $||\cdot||_F^2$ denotes the Frobenius norm, which sums the squared differences between the elements of X and WH. After factorization, occupations are classified into the NMF cluster with the highest weight in W. We set $k = 2$ to classify occupations into two clusters, representing STW and non-STW occupations. As per Linehan et al. (2022), the weights from H are used to define the skill profiles within each NMF cluster, while W determines the classification.[7]

To identify the NMF cluster representing STW occupations, we focus on clusters that exhibit high weights for technical skills. These technical skills correspond to greater knowledge in the 14 knowledge domains identified by Rothwell (Table 1). This assertion is supported by the analysis of the correlation between skill levels and knowledge domains to build a knowledge profile for each skill. The heatmap in Appendix Figure 6 illustrates

[7]We set a seed and perform $n = 30$ runs to ensure stability from the decomposition.

the linear correlation between skills and knowledge domains based on their score levels. The heatmap, ranging from dark blue (- correlation) to red (+ correlation), ranks the correlation from the lowest to the highest.

Appendix Figure 6 highlights the knowledge profile associated with a particular O*NET skill, meaning a vector of scores measuring the association between a knowledge level in a specific domain and the skill level. For instance, skills such as installation, quality control analysis, equipment selection, repairing, operation and control, operation monitoring, and troubleshooting require a greater level of knowledge in Engineering and Technology, Design, Building and Construction, and Mechanics.

Appendix Figure 6 illustrates that skills classified as technical by O*NET generally require a higher level of knowledge across the 14 domains identified by Rothwell (2015), and these skills are central to NMF clusters that correspond to occupations classified within the STW. The top portion of Appendix Figure 6 presents a dendrogram generated from hierarchical clustering of skills, based on their associated knowledge profiles. Skills with similar knowledge profiles are grouped into clusters hierarchically.[8]

O*NET technical skills are classified into three distinct clusters based on their knowledge profiles. The first cluster includes 8 of the 11 O*NET technical skills listed in Table 2, all of which demand substantial knowledge in the 14 domains defined by Rothwell but less in the remaining domains. The other clusters do not exhibit a strong relationship with these 14 knowledge domains. Thus, the first cluster emphasizes critical technical skills such as Installation, Quality Control Analysis, Equipment Selection, Equipment Maintenance, Repairing, Operation and Control, Operation Monitoring, and Troubleshooting. These skills, characterized by their strong knowledge requirements, play a significant role in defining STW occupations.

Therefore, we identify the NMF cluster that is more likely to represent STW occupations based on the skill profile weight $(H_{kj})_j$ and education requirement weight H_{km} in each NMF cluster k. NMF cluster k with higher technical skills weights (especially in those 8 relevant technical skills) and the highest weight in education level is likely to represent a cluster where occupations belong to the STW.

2.3.3 Benchmarking

We benchmark the model predictions to Rothwell's STW designation using key-specific metrics. We use *the accuracy, precision, recall*, and *F1-score* as performance-based metrics of the LDA and NMF models. The *accuracy* represents the proportion of correctly clas-

[8]In the dendrogram, Appendix Figure 6, the height of the horizontal branches represents the distance or dissimilarity between clusters being merged. Vertical lines indicate different levels of clustering. The height of the horizontal branches serves as a measure of dissimilarity, and the analysis reveals three distinct clusters with significant dissimilarity.

sified occupations (STW and non-STW) among all occupations. The *precision* measures the proportion of occupations designated STW by Rothwell among all the occupations classified into the STW by the model. The *recall* measures the proportion of predicted STW occupations by the model among occupations listed in the STW by Rothwell. The *F1-score* summarizes both precision and recall using a harmonic mean.

Because the NMF model identifies patterns in the data and creates its classification, without using Rothwell's classification as input. Therefore, using the F1-score alone to compare the NMF model to the LDA may not be accurate. It's better to consider other metrics like precision and recall to understand the differences between your classification and the NMF model's output.

3 Results and Discussion

This section presents the classification of occupations into the Skilled Technical Workforce (STW) using Latent Dirichlet Allocation (LDA) and Non-negative Matrix Factorization (NMF) models. First, we assess the substitutability of knowledge-based information with skill data in Rothwell's framework through the LDA model. The model was trained using O*NET skill profiles, derived from the Content Model, and education requirements at the occupational entry for 923 occupations.

Next, we use the NMF model to reclassify occupations based on the underlying skill profile patterns across occupations. The NMF model was applied to both Content Model data and job posting data to identify an alternative classification system to the Rothwell framework.

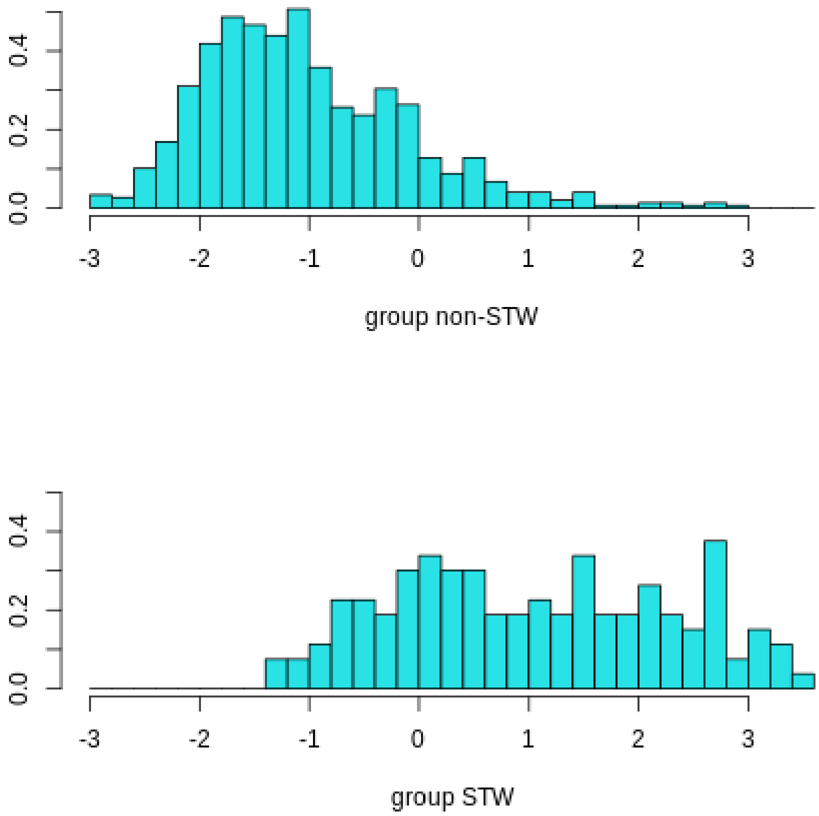
3.1 Skill-Based Definition of STW occupations

The LDA model predicts the STW classification of occupations based on skill profiles and education requirements, affirming the substitutability of knowledge with skills in Rothwell's framework. Figure 2 illustrates the distribution of the LDA scores for each Rothwell STW class, showing a right-skewed distribution for occupations listed in the STW, while non-STW occupations are left-skewed.[9]

The LDA scores reveal that STW occupations, as defined by Rothwell's framework, rely heavily on technical skills. Appendix Figure 8 further supports this, showing that most occupations labeled STW exhibit higher technical intensity score T_i than non-STW occupations, with the 25th percentile of the technical intensity score T_i for STW occupa-

[9]Appendix Figure 7 reports the LDA estimated coefficients, used to compute an LDA score for each occupation. The LDA score is measured as a linear combination of O*NET skill level and the education requirement, weighted by the LDA coefficients.

Figure 2: LDA Score Distribution for Each Class of Occupations using Rothwell's framework.

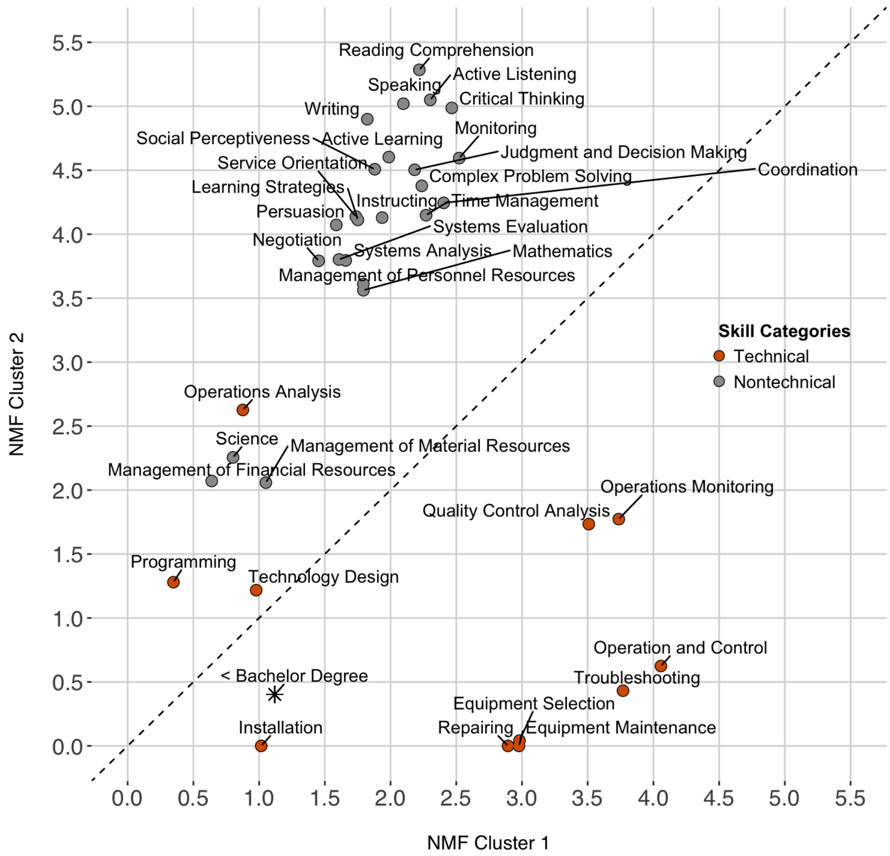


Source: O*NET Content Model version 25.2.
Notes: Each group corresponds to classification groups from Rothwell's framework.

tions exceeding the 75th percentile for non-STW occupations.

Rather than predict Rothwell's classification using skills as we did with the LDA model, we use the NMF model to classify occupations into STW based on the inherent structure across skill profiles and the intensity of using technical skills. This allows for the identification of occupations potentially misclassified under Rothwell's framework.

Figure **??** presents the weight matrix W of skills and education requirements across the two NMF clusters. A 45-degree line is used to identify the characteristics of each cluster in terms of skills and education requirements. NMF Cluster 1, characterized by a high weight in technical skills (e.g., Installation, Troubleshooting, Equipment Maintenance, etc.) and education levels below a bachelor's degree, is more likely to represent the cluster of occupations included in the STW. Those technical skills with the highest weight in the NMF Cluster 1 correspond to the 8 technical skills highly correlated with 14 knowledge



Source: O*NET Content Model version 25.2.
Notes: "< Bachelor Degree" refers to an education lower than a bachelor's degree at the occupation entry.

domains listed by Rothwell (2015).

Table 5 presents the distribution of occupations classified as STW based on the predictions from the LDA and NMF models. The NMF model classifies a larger proportion of occupations into the STW (38.03%) compared to the LDA model (11.45%). Additionally, the NMF model identifies a higher percentage of occupations designated as STW by Rothwell's framework, although it classifies fewer non-STW occupations than the LDA model. Of the 132 occupations listed within the STW according to Rothwell's framework, the NMF model correctly identified 110, while the LDA model identified only 70. For the 740 occupations not included in the STW by Rothwell, the NMF model classified 518 (70%) as non-STW, whereas the LDA model classified 710 (96%) as non-STW.

Table 5: NMF and LDA Classification of Occupations using the Content Model Data

	NMF Model		LDA Model	
Rothwell	non-STW	STW	non-STW	STW
non-STW	518	222	710	30
STW	23	110	63	70
Total	541	332	773	100
(In percent)	(61.97%)	(38.03%)	(88.55%)	(11.45%)

Source: O*NET Content Model version 25.2.

Both models accurately predict Rothwell's STW occupations. Table 6 provides metrics comparing both LDA and NMF models to the Rothwell framework. Both models predict an overall high percentage of occupations with a similar classification to the Rothwell framework (89.35% with the LDA model and 71.94% with the NMF model). However, the NMF model is more effective, identifying 82.71% of STW occupations compared to 52.63% with the LDA model. This highlights the NMF model's higher predictive power for STW occupations.

Table 6 also suggests that Rothwell's framework may have misclassified several occupations non-listed into the STW. Indeed, the NMF model has lower precision (33.33%) compared to the LDA model (70.00%), meaning that among the 332 occupations classified into the STW by the NMF model, only 33.33% were listed in the STW by the Rothwell framework. This highlights that the NMF model provides a more skill-based approach, which adapts to the occupation's education and skill profiles rather than relying on an exogenous knowledge cut-off.

Table 6: Performance-based Metrics for the LDA and NMF Models for Predicting STW Occupations

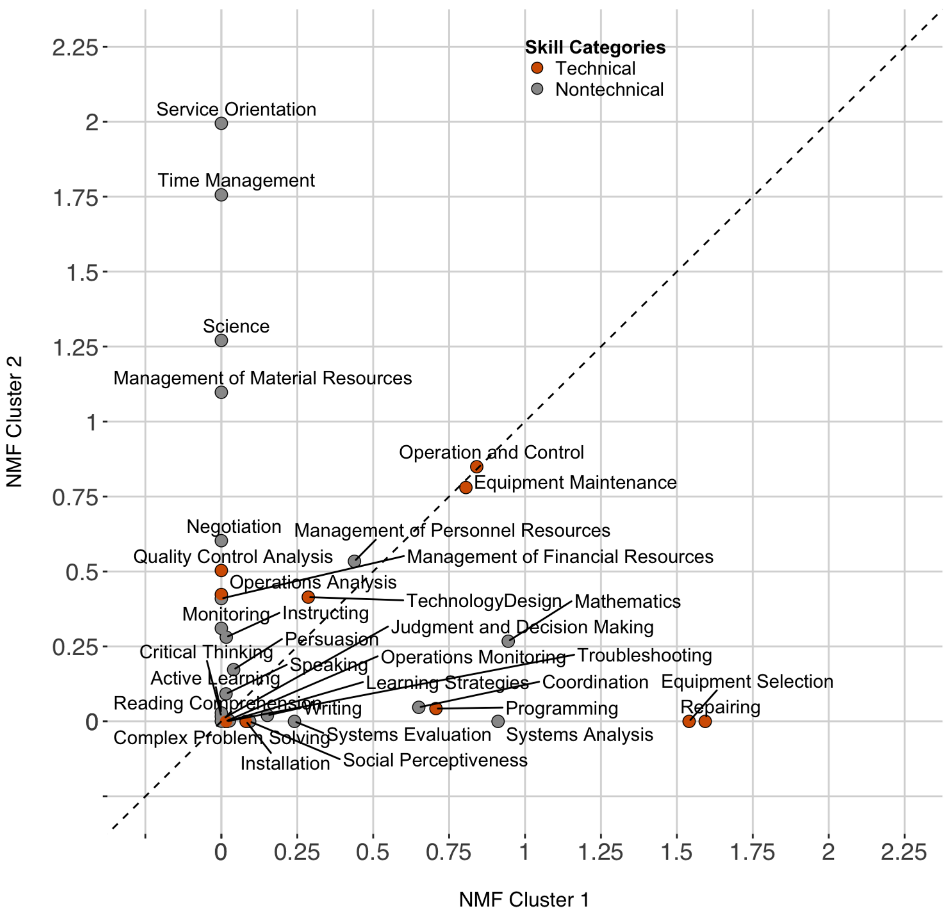
Models	Accuracy	Precision	Recall	F1-score
LDA	0.8935	0.7000	0.5263	0.6009
NMF	0.7194	0.3333	0.8271	0.4764

Source: O*NET Content Model version 25.2.

3.2 STW Classification Using Job Postings

The classification in the previous section, using the NMF model, was based on the Content Model and then bears all the data limitations previously discussed. In this section, we use skill profiles from job postings to classify occupations into the STW using the NMF model.

Figure 4: NMF Weight Matrix (W) of Skill Profile from Job Postings Data.



Source: Lightcast data for Virginia, 2019.

Figure 4 shows presents the weight matrix W of skills and education requirements across the two NMF clusters. Although the two NMF Clusters almost have the same weight for three technical skills (Operation and Control, Equipment Maintenance; Operations Monitoring), most of the technical skills have a higher weight W in the NMF Cluster 1. Cluster 1, which includes occupations with education levels below a bachelor's degree and high technical skill intensity, is more likely to represent STW occupations.

Table 7 compares the NMF predictions from job postings with Rothwell's STW classification. The NMF model predicts a higher percentage of STW occupations (55.97%) compared to Rothwell's framework, indicating that more occupations may fit the STW definition when evaluated based on skill demands from job postings. This percentage is 20.15 points higher than the percentage of STW occupations from the Rothwell framework. However, this high percentage does not suggest that all designated STW occupations from the Rothwell approach were identified. Only 66 occupations out of the 96 STW occupations designated by Rothwell were identified. In addition, only 88 occupations out of the 172 occupations designated non-STW were also predicted as non-STW by the model.

Table 7: Occupations classification from Job Postings Data using Non-negative Matrix Factorization and Rothwell Definition

	Rothwell Definition		
NMF Model	Non-STW	STW	Total (percent)
Non STW	88	30	118 (44.03%)
STW	84	66	150 (55.97%)
Total	172 (64.18%)	96 (35.82%)	268 (100.0%)

Source: Lightcast data for Virginia, 2019.

However, only 57.46% occupations across the four MOGs have been classified similarly from the Rothwell framework. This percentage is high when using data from the Content model across those four MOGs. The difference between those accuracy values can be attributed to several factors such that the methodology used to design the occupation skills profile from job postings; the job posting sample limitations to Virginia in 2019 or new technology changing skill demands.

Table 8: Performance-based Metrics for the NMF Model from Online Job Postings Data and Content Model Data across the Four MOGs

NMF Model	Accuracy	Precision	Recall	F1-score
Job Postings Data	0.5746	0.44	0.6875	0.5366

Source: Lightcast data for Virginia, 2019.

4 Conclusion and discussion

This paper proposes a new approach to classifying occupations into the STW using job postings from Lightcast. Our framework is built on Rothwell (2015), which identifies occupations as STW using knowledge and education survey data from the O*NET Content Model. We show that skill information from the Content Model, especially technical skills, combined with less than a bachelor's degree requirement at the occupation level, can predict the Rothwell classification of occupations into the STW. We leverage that information to design an occupation skill profile from job posting data that are used to classify occupations into the STW. Our framework highlights that many occupations, especially in Production; Construction & Extraction; Installation, Maintenance & Repair; and Transportation & Material Moving should be included in the STW.

This paper offers a methodology to harmonize skills from job posting data using NLP models to match the O*NET skills profile but also provides a framework to classify occupations into the STW by leveraging big data from job postings. These data offer the advantage of studying how technology changes the technical demands of some occupations, shifting the classification of those occupations into the STW. With the advent of public data on job postings with NLx, reclassifying occupations in the STW offers an interesting opportunity to study how the technical nature of those occupations may have shifted with the technological changes.[10]

[10] National Labor Exchange Research Hub: https://nlxresearchhub.org/about-the-data.

References

A. Alibasic, H. Upadhyay, M. C. E. Simsekler, T. Kurfess, W. L. Woon, and M. A. Omar. Evaluation of the trends in jobs and skill-sets using data analytics: a case study. *Journal of Big Data*, 9(1):32, Mar. 2022. ISSN 2196-1115. doi: 10.1186/s40537-022-00576-5. URL https://doi.org/10.1186/s40537-022-00576-5.

A. Burke. The skilled technical workforce | NSF - National Science Foundation, 2019. URL https://ncses.nsf.gov/pubs/nsb20198/the-skilled-technical-workforce. Report.

J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, May 2019. URL http://arxiv.org/abs/1810.04805. arXiv:1810.04805 [cs].

K. D. Fee, K. Wardrip, and K. DeMaria. Exploring a Skills-Based Approach to Occupational Mobility. *Community Development Reports*, (20200601), June 2020. URL https://www.clevelandfed.org/community-development/opportunity-occupations/oo-20200601-skill-based-approach. Publisher: Federal Reserve Bank of Cleveland and Federal Reserve Bank of Philadelphia.

V. Lancaster, S. McDonald, C. Montalvo, and G. L. Siwe. Designating the Skilled Technical Workforce Using O*NET-SOC (2019). Report, University of Virginia, Dec. 2021. URL https://libraopen.lib.virginia.edu/public_view/41687h60p.

J. Lassébie, L. Marcolin, M. Vandeweyer, and B. Vignal. Speaking the same language: A machine learning approach to classify skills in Burning Glass Technologies data. Technical report, OECD, Paris, Nov. 2021. URL https://www.oecd-ilibrary.org/social-issues-migration-health/speaking-the-same-language_adb03746-en.

K. Linehan, E. Oh, J. Thurston, G. L. Siwe, M. Garrett, S. Keller, S. Shipp, A. Kindlon, and J. Jankowski. Technical Report - Detecting Federally Funded Research and Development Trends Using Machine Learning and Information Retrieval Methods. Technical Report BI-2022-1531, Proceedings of the Biocomplexity Institute. University of Virginia, May 2022.

A. Nigam, S. Tyagi, K. Tyagi, and A. Saxena. SkillBERT: "Skilling" the BERT to classify skills! Oct. 2020. URL https://openreview.net/forum?id=TaUJl6Kt3rW.

A. Okrent and A. Burke. The STEM Labor Force of Today: Scientists, Engineers, and Skilled Technical Workers | NSF - National Science Foundation, 2021. URL https://ncses.nsf.gov/pubs/nsb20212.

L. Qu and Y. Pei. A Comprehensive Review on Discriminant Analysis for Addressing Challenges of Class-Level Limitations, Small Sample Size, and Robustness. *Pro-*

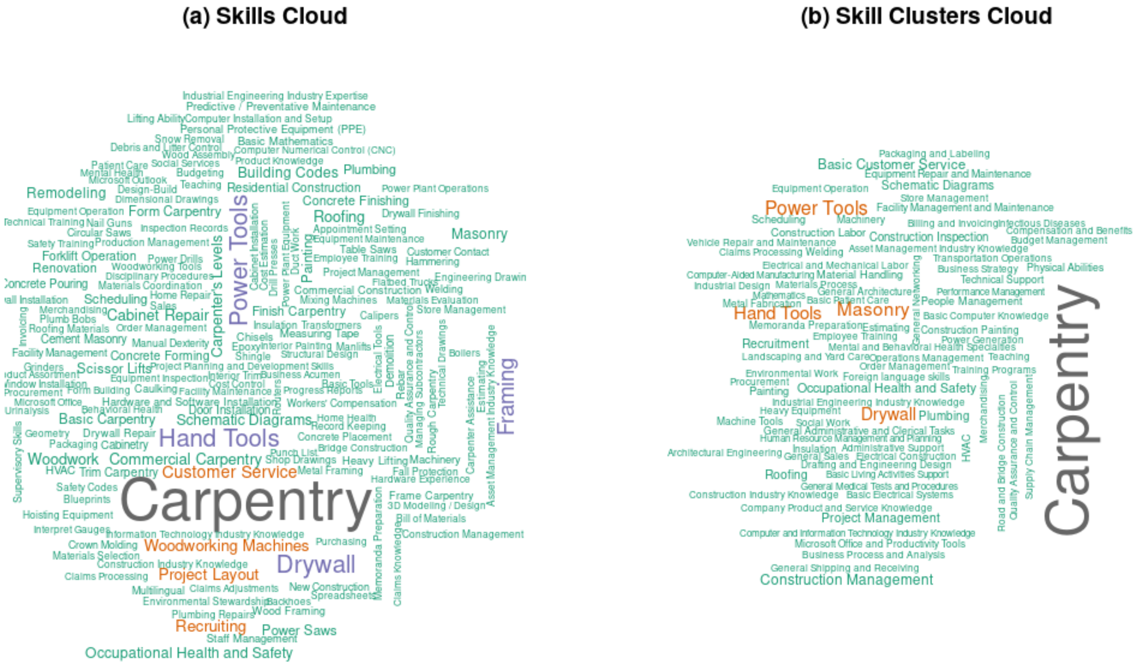
cesses, 12(7):1382, July 2024. ISSN 2227-9717. doi: 10.3390/pr12071382. URL https://www.mdpi.com/2227-9717/12/7/1382. Number: 7 Publisher: Multidisciplinary Digital Publishing Institute.

J. T. Rothwell. Defining Skilled Technical Work, Sept. 2015. URL https://papers.ssrn.com/abstract=2709141.

Appendices

Appendix A Figures

Figure 5: Word Clouds Using Lightcast Skills and Skill Clusters for SOC: 47-2031.00, Carpenter.

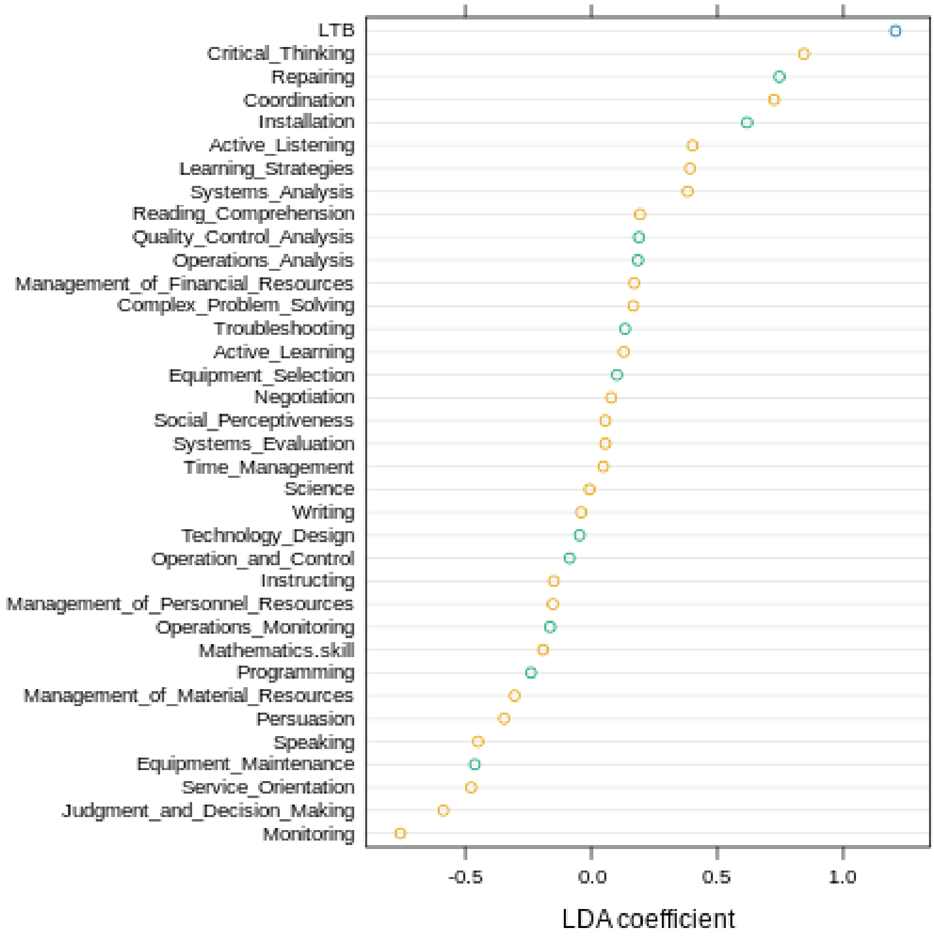


Source: Lightcast data for Virginia, 2019.

Figure 6: Correlation Between Skills and Knowledge Domains

Source: O*NET Content Model version 25.2.

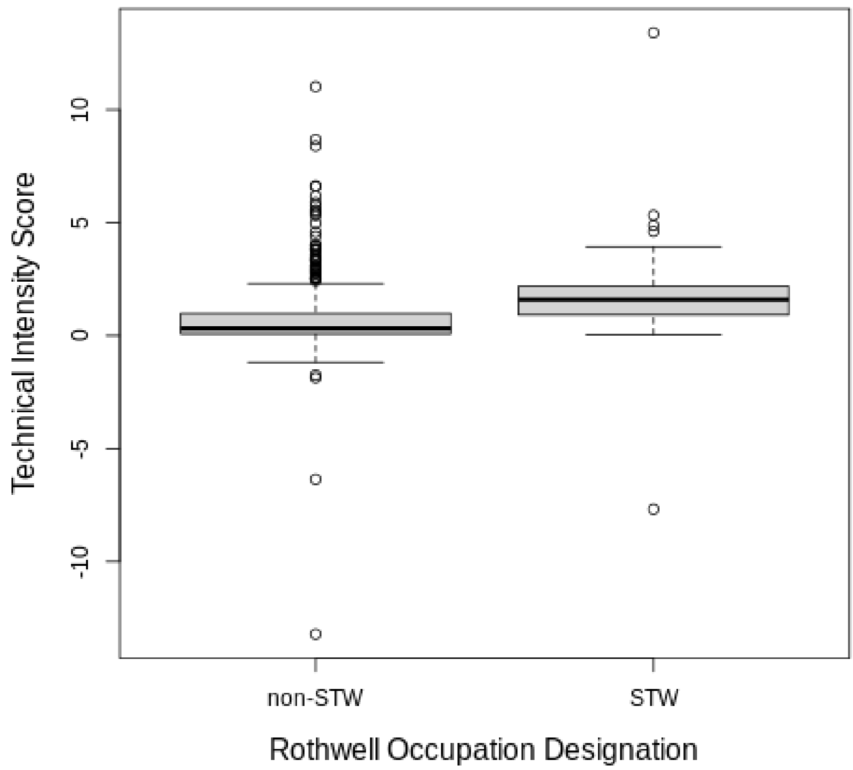
Figure 7: Linear Discriminant Analysis (LDA) Estimated Coefficients.



Source: O*NET Content Model version 25.2.

Notes: O*NET technical skills are colored in "green" while non-technical skills are colored in "yellow".

Figure 8: Technical Score Intensity Distribution by Rothwell's STW Designation.



Source: O*NET Content Model version 25.2.

Appendix B Tables

Table 9: Correlation between Skill-Level from Content Model Data and the Estimated Skill-Level from Job Postings Data within an Occupation

	Skill-level (Content Model Data)	
	(1)	(2)
Scaled Skill-level (Job postings) ($\hat{l}_{io}$)	0.2150*	
	(0.1022)	
Non scaled Skill-level (Job postings) (l_{io})		0.0573
		(0.0582)
Observations	4,281	4,281
R^2	0.1431	0.1426
Occupation FE	√	√

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Lightcast data for Virginia, 2019.

Table 10: Occupations in the Major Occupation Groups according to the Content Model

Major Occupation Group (MOG)	Number of occupations (SOC 2019)	Number of occupations requiring less than bachelor at the entry	Number of STW occupations (Rothwell)
Construction & Extraction	65	62	31 (49.18%)
Installation, Maintenance & Repair	52	52	40 (78.43%)
Production	114	114	24 (20.95%)
Transportation & Materials moving	57	56	5 (7.84%)
Total	288	284	100 (35.82%)

Table 11: Job Postings and Occupations in the Major Occupation Groups from Online Jobs Posting Data in Virginia 2019

Major Occupation Group (MOG)	Occupations Reported (Count)	Occupations with Education Less Than a Bachelor (Count)	Count & Percentage of STW Occupations (Rothwell)	Count & Percentage of STW Occupations (NMF model)
Construction & Extraction	61	61	30 (49.18%)	43 (70.49%)
Installation, Maintenance & Repair	51	51	40 (78.43%)	39 (76.47%)
Production	105	105	22 (20.95%)	48 (45.71%)
Transportation & Material Moving	51	50	4 (7.84%)	20 (39.22%)
Total	268	267	96 (35.82%)	150 (55.97%)

Table 12: Skilled Technical Workforce (STW) Occupations in Job Posting Skills Framework but NOT in Rothwell's framework, 2019, Virginia, Four Major Occupation Groups (MOG): Construction & Extraction; Transportation & Material Moving; Production; Installation, Maintenance & Repair.

STW Occupations in Job Posting Skills Framework but NOT in Rothwell's framework	**O*Net 2019**	**MOG 2019**	**No bachelor degree**	**STW (Rothwell)**	**STW (Job Posting Skills)**
Floor Sanders and Finishers	47-2043.00	47.0	Yes	No	Yes
Tile and Stone Setters	47-2044.00	47.0	Yes	No	Yes
Cement Masons and Concrete Finishers	47-2051.00	47.0	Yes	No	Yes
Terrazzo Workers and Finishers	47-2053.00	47.0	Yes	No	Yes
Operating Engineers and Other Construction Equipment Operators	47-2073.00	47.0	Yes	No	Yes
Insulation Workers, Mechanical	47-2132.00	47.0	Yes	No	Yes
Painters, Construction and Maintenance	47-2141.00	47.0	Yes	No	Yes
Paperhangers	47-2142.00	47.0	Yes	No	Yes
Sheet Metal Workers	47-2211.00	47.0	Yes	No	Yes
Helpers–Painters, Paperhangers, Plasterers, and Stucco Masons	47-3014.00	47.0	Yes	No	Yes
Fence Erectors	47-4031.00	47.0	Yes	No	Yes
Highway Maintenance Workers	47-4051.00	47.0	Yes	No	Yes
Segmental Pavers	47-4091.00	47.0	Yes	No	Yes
Excavating and Loading Machine and Dragline Operators, Surface Mining	47-5022.00	47.0	Yes	No	Yes
Roof Bolters, Mining	47-5061.00	47.0	Yes	No	Yes
Rock Splitters, Quarry	47-5051.00	47.0	Yes	No	Yes
Helpers–Extraction Workers	47-5081.00	47.0	Yes	No	Yes
Automotive Body and Related Repairers	49-3021.00	49.0	Yes	No	Yes
Automotive Glass Installers and Repairers	49-3022.00	49.0	Yes	No	Yes
Tire Repairers and Changers	49-3093.00	49.0	Yes	No	Yes
Home Appliance Repairers	49-9031.00	49.0	Yes	No	Yes
Electrical Power-Line Installers and Repairers	49-9051.00	49.0	Yes	No	Yes
Musical Instrument Repairers and Tuners	49-9063.00	49.0	Yes	No	Yes

STW Occupations in Job Posting Skills Framework but NOT in Rothwell's framework	**O*Net 2019**	**MOG 2019**	**No bachelor degree**	**STW (Rothwell)**	**STW (Job Posting Skills)**
Geothermal Technicians	49-9099.01	49.0	Yes	No	Yes
Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	51-2011.00	51.0	Yes	No	Yes
Coil Winders, Tapers, and Finishers	51-2021.00	51.0	Yes	No	Yes
Electrical and Electronic Equipment Assemblers	51-2022.00	51.0	Yes	No	Yes
Electromechanical Equipment Assemblers	51-2023.00	51.0	Yes	No	Yes
Fiberglass Laminators and Fabricators	51-2051.00	51.0	Yes	No	Yes
Team Assemblers	51-2092.00	51.0	Yes	No	Yes
Food Cooking Machine Operators and Tenders	51-3093.00	51.0	Yes	No	Yes
Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	51-4031.00	51.0	Yes	No	Yes
Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	51-4033.00	51.0	Yes	No	Yes
Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic	51-4035.00	51.0	Yes	No	Yes
Machinists	51-4041.00	51.0	Yes	No	Yes
Metal-Refining Furnace Operators and Tenders	51-4051.00	51.0	Yes	No	Yes
Pourers and Casters, Metal	51-4052.00	51.0	Yes	No	Yes
Model Makers, Metal and Plastic	51-4061.00	51.0	Yes	No	Yes
Welders, Cutters, Solderers, and Brazers	51-4121.00	51.0	Yes	No	Yes
Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders	51-4122.00	51.0	Yes	No	Yes
Laundry and Dry-Cleaning Workers	51-6011.00	51.0	Yes	No	Yes
Sewing Machine Operators	51-6031.00	51.0	Yes	No	Yes
Shoe and Leather Workers and Repairers	51-6041.00	51.0	Yes	No	Yes
Tailors, Dressmakers, and Custom Sewers	51-6052.00	51.0	Yes	No	Yes
Textile Bleaching and Dyeing Machine Operators and Tenders	51-6061.00	51.0	Yes	No	Yes
Fabric and Apparel Patternmakers	51-6092.00	51.0	Yes	No	Yes

STW Occupations in Job Posting Skills Framework but NOT in Rothwell's framework	O*Net 2019	MOG 2019	No bachelor degree	STW (Rothwell)	STW (Job Posting Skills)
Upholsterers	51-6093.00	51.0	Yes	No	Yes
Cabinetmakers and Bench Carpenters	51-7011.00	51.0	Yes	No	Yes
Furniture Finishers	51-7021.00	51.0	Yes	No	Yes
Sawing Machine Setters, Operators, and Tenders, Wood	51-7041.00	51.0	Yes	No	Yes
Power Plant Operators	51-8013.00	51.0	Yes	No	Yes
Grinding and Polishing Workers, Hand	51-9022.00	51.0	Yes	No	Yes
Cutters and Trimmers, Hand	51-9031.00	51.0	Yes	No	Yes
Gem and Diamond Workers	51-9071.06	51.0	Yes	No	Yes
Medical Appliance Technicians	51-9082.00	51.0	Yes	No	Yes
Coating, Painting, and Spraying Machine Setters, Operators, and Tenders	51-9124.00	51.0	Yes	No	Yes
Stone Cutters and Carvers, Manufacturing	51-9195.03	51.0	Yes	No	Yes
Glass Blowers, Molders, Benders, and Finishers	51-9195.04	51.0	Yes	No	Yes
Ambulance Drivers and Attendants, Except Emergency Medical Technicians	53-3011.00	53.0	Yes	No	Yes
Driver/Sales Workers	53-3031.00	53.0	Yes	No	Yes
Heavy and Tractor-Trailer Truck Drivers	53-3032.00	53.0	Yes	No	Yes
Light Truck Drivers	53-3033.00	53.0	Yes	No	Yes
Bus Drivers, Transit and Intercity	53-3052.00	53.0	Yes	No	Yes
Rail Yard Engineers, Dinkey Operators, and Hostlers	53-4013.00	53.0	Yes	No	Yes
Railroad Brake, Signal, and Switch Operators and Locomotive Firers	53-4022.00	53.0	Yes	No	Yes
Bridge and Lock Tenders	53-6011.00	53.0	Yes	No	Yes
Parking Attendants	53-6021.00	53.0	Yes	No	Yes
Automotive and Watercraft Service Attendants	53-6031.00	53.0	Yes	No	Yes
Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	53-6051.07	53.0	Yes	No	Yes
Industrial Truck and Tractor Operators	53-7051.00	53.0	Yes	No	Yes
Cleaners of Vehicles and Equipment	53-7061.00	53.0	Yes	No	Yes
Laborers and Freight, Stock, and Material Movers, Hand	53-7062.00	53.0	Yes	No	Yes

STW Occupations in Job Posting Skills Framework but NOT in Rothwell's framework	**O*Net 2019**	**MOG 2019**	**No bachelor degree**	**STW (Rothwell)**	**STW (Job Posting Skills)**
Refuse and Recyclable Material Collectors	53-7081.00	53.0	Yes	No	Yes

Table 13: Skilled Technical Workforce (STW) Occupations Rothwell's framework but NOT in Job Posting Skills Framework, 2019, Virginia, Four Major Occupation Groups (MOG): Construction & Extraction; Transportation & Material Moving; Production; Installation, Maintenance & Repair.

STW in Rothwell's Framework but NOT in the Job Posting Skills Framework	**O*Net 2019**	**MOG 2019**	**No bachelor degree**	**STW (Rothwell)**	**STW (Job Posting Skills)**
Solar Energy Installation Managers	47-1011.03	47.0	Yes	Yes	No
Pile Driver Operators	47-2072.00	47.0	Yes	Yes	No
Construction and Building Inspectors	47-4011.00	47.0	Yes	Yes	No
Derrick Operators, Oil and Gas	47-5011.00	47.0	Yes	Yes	No
Rotary Drill Operators, Oil and Gas	47-5012.00	47.0	Yes	Yes	No
Earth Drillers, Except Oil and Gas	47-5023.00	47.0	Yes	Yes	No
Continuous Mining Machine Operators	47-5041.00	47.0	Yes	Yes	No
Electrical and Electronics Installers and Repairers, Transportation Equipment	49-2093.00	49.0	Yes	Yes	No
Electrical and Electronics Repairers, Commercial and Industrial Equipment	49-2094.00	49.0	Yes	Yes	No
Electronic Equipment Installers and Repairers, Motor Vehicles	49-2096.00	49.0	Yes	Yes	No
Security and Fire Alarm Systems Installers	49-2098.00	49.0	Yes	Yes	No
Rail Car Repairers	49-3043.00	49.0	Yes	Yes	No
Bicycle Repairers	49-3091.00	49.0	Yes	Yes	No
Watch and Clock Repairers	49-9064.00	49.0	Yes	Yes	No
Wind Turbine Service Technicians	49-9081.00	49.0	Yes	Yes	No
Manufactured Building and Mobile Home Installers	49-9095.00	49.0	Yes	Yes	No
Engine and Other Machine Assemblers	51-2031.00	51.0	Yes	Yes	No
Meat, Poultry, and Fish Cutters and Trimmers	51-3022.00	51.0	Yes	Yes	No
Patternmakers, Metal and Plastic	51-4062.00	51.0	Yes	Yes	No
Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	51-4081.00	51.0	Yes	Yes	No
Prepress Technicians and Workers	51-5111.00	51.0	Yes	Yes	No
Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	51-6064.00	51.0	Yes	Yes	No

STW in Rothwell's Framework but NOT in the Job Posting Skills Framework	**O*Net 2019**	**MOG 2019**	**No bachelor degree**	**STW (Rothwell)**	**STW (Job Posting Skills)**
Model Makers, Wood	51-7031.00	51.0	Yes	Yes	No
Water and Wastewater Treatment Plant and System Operators	51-8031.00	51.0	Yes	Yes	No
Chemical Equipment Operators and Tenders	51-9011.00	51.0	Yes	Yes	No
Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders	51-9021.00	51.0	Yes	Yes	No
Etchers and Engravers	51-9194.00	51.0	Yes	Yes	No
Ship Engineers	53-5031.00	53.0	Yes	Yes	No
Traffic Technicians	53-6041.00	53.0	Yes	Yes	No
Gas Compressor and Gas Pumping Station Operators	53-7071.00	53.0	Yes	Yes	No

Table 14: Skilled Technical Workforce (STW) Occupations in Job Posting Skills Framework AND Rothwell's framework, 2019, Virginia, Four Major Occupation Groups (MOG): Construction & Extraction; Transportation & Material Moving; Production; Installation, Maintenance & Repair.

STW in BOTH Rothwell's Framework AND the Job Posting Skills Framework	**O*Net 2019**	**MOG 2019**	**No bachelor degree**	**STW (Rothwell)**	**STW (Job Posting Skills)**
First-Line Supervisors of Construction Trades and Extraction Workers	47-1011.00	47.0	Yes	Yes	Yes
Boilermakers	47-2011.00	47.0	Yes	Yes	Yes
Brickmasons and Blockmasons	47-2021.00	47.0	Yes	Yes	Yes
Stonemasons	47-2022.00	47.0	Yes	Yes	Yes
Carpenters	47-2031.00	47.0	Yes	Yes	Yes
Construction Laborers	47-2061.00	47.0	Yes	Yes	Yes
Paving, Surfacing, and Tamping Equipment Operators	47-2071.00	47.0	Yes	Yes	Yes
Drywall and Ceiling Tile Installers	47-2081.00	47.0	Yes	Yes	Yes
Electricians	47-2111.00	47.0	Yes	Yes	Yes
Glaziers	47-2121.00	47.0	Yes	Yes	Yes
Pipelayers	47-2151.00	47.0	Yes	Yes	Yes
Plumbers, Pipefitters, and Steamfitters	47-2152.00	47.0	Yes	Yes	Yes
Reinforcing Iron and Rebar Workers	47-2171.00	47.0	Yes	Yes	Yes
Roofers	47-2181.00	47.0	Yes	Yes	Yes
Sheet Metal Workers	47-2211.00	47.0	Yes	Yes	Yes
Structural Iron and Steel Workers	47-2221.00	47.0	Yes	Yes	Yes
Solar Photovoltaic Installers	47-2231.00	47.0	Yes	Yes	Yes
Helpers–Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters	47-3011.00	47.0	Yes	Yes	Yes
Helpers–Carpenters	47-3012.00	47.0	Yes	Yes	Yes
Helpers–Electricians	47-3013.00	47.0	Yes	Yes	Yes
Helpers–Pipelayers, Plumbers, Pipefitters, and Steamfitters	47-3015.00	47.0	Yes	Yes	Yes
Elevator and Escalator Installers and Repairers	47-4021.00	47.0	Yes	Yes	Yes
Service Unit Operators, Oil and Gas	47-5013.00	47.0	Yes	Yes	Yes

STW in BOTH Rothwell's Framework AND the Job Posting Skills Framework	O*Net 2019	MOG 2019	No bachelor degree	STW (Rothwell)	STW (Job Posting Skills)
Loading and Moving Machine Operators, Underground Mining	47-5044.00	47.0	Yes	Yes	Yes
First-Line Supervisors of Mechanics, Installers, and Repairers	49-1011.00	49.0	Yes	Yes	Yes
Computer, Automated Teller, and Office Machine Repairers	49-2011.00	49.0	Yes	Yes	Yes
Radio, Cellular, and Tower Equipment Installers and Repairers	49-2021.00	49.0	Yes	Yes	Yes
Telecommunications Equipment Installers and Repairers, Except Line Installers	49-2022.00	49.0	Yes	Yes	Yes
Avionics Technicians	49-2091.00	49.0	Yes	Yes	Yes
Electric Motor, Power Tool, and Related Repairers	49-2092.00	49.0	Yes	Yes	Yes
Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	49-2095.00	49.0	Yes	Yes	Yes
Audiovisual Equipment Installers and Repairers	49-2097.00	49.0	Yes	Yes	Yes
Aircraft Mechanics and Service Technicians	49-3011.00	49.0	Yes	Yes	Yes
Automotive Service Technicians and Mechanics	49-3023.00	49.0	Yes	Yes	Yes
Bus and Truck Mechanics and Diesel Engine Specialists	49-3031.00	49.0	Yes	Yes	Yes
Farm Equipment Mechanics and Service Technicians	49-3041.00	49.0	Yes	Yes	Yes
Mobile Heavy Equipment Mechanics, Except Engines	49-3042.00	49.0	Yes	Yes	Yes
Motorboat Mechanics and Service Technicians	49-3051.00	49.0	Yes	Yes	Yes
Motorcycle Mechanics	49-3052.00	49.0	Yes	Yes	Yes
Outdoor Power Equipment and Other Small Engine Mechanics	49-3053.00	49.0	Yes	Yes	Yes
Recreational Vehicle Service Technicians	49-3092.00	49.0	Yes	Yes	Yes
Mechanical Door Repairers	49-9011.00	49.0	Yes	Yes	Yes
Control and Valve Installers and Repairers, Except Mechanical Door	49-9012.00	49.0	Yes	Yes	Yes
Heating, Air Conditioning, and Refrigeration Mechanics and Installers	49-9021.00	49.0	Yes	Yes	Yes
Industrial Machinery Mechanics	49-9041.00	49.0	Yes	Yes	Yes
Maintenance Workers, Machinery	49-9043.00	49.0	Yes	Yes	Yes
Millwrights	49-9044.00	49.0	Yes	Yes	Yes
Telecommunications Line Installers and Repairers	49-9052.00	49.0	Yes	Yes	Yes
Camera and Photographic Equipment Repairers	49-9061.00	49.0	Yes	Yes	Yes

STW in BOTH Rothwell's Framework AND the Job Posting Skills Framework	**O*Net 2019**	**MOG 2019**	**No bachelor degree**	**STW (Rothwell)**	**STW (Job Posting Skills)**
Medical Equipment Repairers	49-9062.00	49.0	Yes	Yes	Yes
Maintenance and Repair Workers, General	49-9071.00	49.0	Yes	Yes	Yes
Commercial Divers	49-9092.00	49.0	Yes	Yes	Yes
Locksmiths and Safe Repairers	49-9094.00	49.0	Yes	Yes	Yes
Signal and Track Switch Repairers	49-9097.00	49.0	Yes	Yes	Yes
Helpers-Installation, Maintenance, and Repair Workers	49-9098.00	49.0	Yes	Yes	Yes
Structural Metal Fabricators and Fitters	51-2041.00	51.0	Yes	Yes	Yes
Rolling Machine Setters, Operators, and Tenders, Metal and Plastic	51-4023.00	51.0	Yes	Yes	Yes
Tool and Die Makers	51-4111.00	51.0	Yes	Yes	Yes
Layout Workers, Metal and Plastic	51-4192.00	51.0	Yes	Yes	Yes
Plating Machine Setters, Operators, and Tenders, Metal and Plastic	51-4193.00	51.0	Yes	Yes	Yes
Nuclear Power Reactor Operators	51-8011.00	51.0	Yes	Yes	Yes
Stationary Engineers and Boiler Operators	51-8021.00	51.0	Yes	Yes	Yes
Gas Plant Operators	51-8092.00	51.0	Yes	Yes	Yes
Dental Laboratory Technicians	51-9081.00	51.0	Yes	Yes	Yes
Computer Numerically Controlled Tool Operators	51-9161.00	51.0	Yes	Yes	Yes
Computer Numerically Controlled Tool Programmers	51-9162.00	51.0	Yes	Yes	Yes
Pump Operators, Except Wellhead Pumpers	53-7072.00	53.0	Yes	Yes	Yes

Table 15: Non-Skilled Technical Workforce (non-STW) Occupations, 2019, Virginia, Four Major Occupation Groups (MOG): Construction & Extraction; Transportation & Material Moving; Production; Installation, Maintenance & Repair.

Non-STW Occupations	**O*Net 2019**	**MOG 2019**	**No bachelor degree**	**STW (Rothwell)**	**STW (Job Posting Skills)**
Airline Pilots, Copilots, and Flight Engineers	53-2011.00	53.0	No	No	No
Carpet Installers	47-2041.00	47.0	Yes	No	No
Floor Layers, Except Carpet, Wood, and Hard Tiles	47-2042.00	47.0	Yes	No	No
Insulation Workers, Floor, Ceiling, and Wall	47-2131.00	47.0	Yes	No	No
Plasterers and Stucco Masons	47-2161.00	47.0	Yes	No	No
Hazardous Materials Removal Workers	47-4041.00	47.0	Yes	No	No
Rail-Track Laying and Maintenance Equipment Operators	47-4061.00	47.0	Yes	No	No
Septic Tank Servicers and Sewer Pipe Cleaners	47-4071.00	47.0	Yes	No	No
Weatherization Installers and Technicians	47-4099.03	47.0	Yes	No	No
Explosives Workers, Ordnance Handling Experts, and Blasters	47-5032.00	47.0	Yes	No	No
Roustabouts, Oil and Gas	47-5071.00	47.0	Yes	No	No
Coin, Vending, and Amusement Machine Servicers and Repairers	49-9091.00	49.0	Yes	No	No
Riggers	49-9096.00	49.0	Yes	No	No
First-Line Supervisors of Production and Operating Workers	51-1011.00	51.0	Yes	No	No
Bakers	51-3011.00	51.0	Yes	No	No
Butchers and Meat Cutters	51-3021.00	51.0	Yes	No	No
Slaughterers and Meat Packers	51-3023.00	51.0	Yes	No	No
Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders	51-3091.00	51.0	Yes	No	No
Food Batchmakers	51-3092.00	51.0	Yes	No	No
Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	51-4021.00	51.0	Yes	No	No
Forging Machine Setters, Operators, and Tenders, Metal and Plastic	51-4022.00	51.0	Yes	No	No

Non-STW Occupations	O*Net 2019	MOG 2019	No bachelor degree	STW (Rothwell)	STW (Job Posting Skills)
Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic	51-4032.00	51.0	Yes	No	No
Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	51-4034.00	51.0	Yes	No	No
Foundry Mold and Coremakers	51-4071.00	51.0	Yes	No	No
Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic	51-4072.00	51.0	Yes	No	No
Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	51-4191.00	51.0	Yes	No	No
Printing Press Operators	51-5112.00	51.0	Yes	No	No
Print Binding and Finishing Workers	51-5113.00	51.0	Yes	No	No
Pressers, Textile, Garment, and Related Materials	51-6021.00	51.0	Yes	No	No
Shoe Machine Operators and Tenders	51-6042.00	51.0	Yes	No	No
Sewers, Hand	51-6051.00	51.0	Yes	No	No
Textile Cutting Machine Setters, Operators, and Tenders	51-6062.00	51.0	Yes	No	No
Textile Knitting and Weaving Machine Setters, Operators, and Tenders	51-6063.00	51.0	Yes	No	No
Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers	51-6091.00	51.0	Yes	No	No
Woodworking Machine Setters, Operators, and Tenders, Except Sawing	51-7042.00	51.0	Yes	No	No
Power Distributors and Dispatchers	51-8012.00	51.0	Yes	No	No
Petroleum Pump System Operators, Refinery Operators, and Gaugers	51-8093.00	51.0	Yes	No	No
Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders	51-9012.00	51.0	Yes	No	No
Mixing and Blending Machine Setters, Operators, and Tenders	51-9023.00	51.0	Yes	No	No
Cutting and Slicing Machine Setters, Operators, and Tenders	51-9032.00	51.0	Yes	No	No
Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	51-9041.00	51.0	Yes	No	No

Non-STW Occupations	**O*Net 2019**	**MOG 2019**	**No bachelor degree**	**STW (Rothwell)**	**STW (Job Posting Skills)**
Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	51-9051.00	51.0	Yes	No	No
Inspectors, Testers, Sorters, Samplers, and Weighers	51-9061.00	51.0	Yes	No	No
Jewelers and Precious Stone and Metal Workers	51-9071.00	51.0	Yes	No	No
Ophthalmic Laboratory Technicians	51-9083.00	51.0	Yes	No	No
Packaging and Filling Machine Operators and Tenders	51-9111.00	51.0	Yes	No	No
Painting, Coating, and Decorating Workers	51-9123.00	51.0	Yes	No	No
Semiconductor Processing Technicians	51-9141.00	51.0	Yes	No	No
Photographic Process Workers and Processing Machine Operators	51-9151.00	51.0	Yes	No	No
Adhesive Bonding Machine Operators and Tenders	51-9191.00	51.0	Yes	No	No
Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	51-9192.00	51.0	Yes	No	No
Cooling and Freezing Equipment Operators and Tenders	51-9193.00	51.0	Yes	No	No
Molders, Shapers, and Casters, Except Metal and Plastic	51-9195.00	51.0	Yes	No	No
Paper Goods Machine Setters, Operators, and Tenders	51-9196.00	51.0	Yes	No	No
Tire Builders	51-9197.00	51.0	Yes	No	No
Helpers–Production Workers	51-9198.00	51.0	Yes	No	No
Aircraft Cargo Handling Supervisors	53-1041.00	53.0	Yes	No	No
First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand	53-1042.00	53.0	Yes	No	No
Recycling Coordinators	53-1042.01	53.0	Yes	No	No
First-Line Supervisors of Material-Moving Machine and Vehicle Operators	53-1043.00	53.0	Yes	No	No
Commercial Pilots	53-2012.00	53.0	Yes	No	No
Air Traffic Controllers	53-2021.00	53.0	Yes	No	No
Airfield Operations Specialists	53-2022.00	53.0	Yes	No	No
Flight Attendants	53-2031.00	53.0	Yes	No	No
Locomotive Engineers	53-4011.00	53.0	Yes	No	No
Railroad Conductors and Yardmasters	53-4031.00	53.0	Yes	No	No
Subway and Streetcar Operators	53-4041.00	53.0	Yes	No	No

Non-STW Occupations	**O*Net 2019**	**MOG 2019**	**No bachelor degree**	**STW (Rothwell)**	**STW (Job Posting Skills)**
Sailors and Marine Oilers	53-5011.00	53.0	Yes	No	No
Captains, Mates, and Pilots of Water Vessels	53-5021.00	53.0	Yes	No	No
Transportation Inspectors	53-6051.00	53.0	Yes	No	No
Aviation Inspectors	53-6051.01	53.0	Yes	No	No
Passenger Attendants	53-6061.00	53.0	Yes	No	No
Conveyor Operators and Tenders	53-7011.00	53.0	Yes	No	No
Crane and Tower Operators	53-7021.00	53.0	Yes	No	No
Hoist and Winch Operators	53-7041.00	53.0	Yes	No	No
Recycling and Reclamation Workers	53-7062.04	53.0	Yes	No	No
Machine Feeders and Offbearers	53-7063.00	53.0	Yes	No	No
Packers and Packagers, Hand	53-7064.00	53.0	Yes	No	No
Tank Car, Truck, and Ship Loaders	53-7121.00	53.0	Yes	No	No