Technical Appendix: Reach for the STARs

Skills and Economic Mobility in the AI Economy

Data Sources

- Occupational Information Network Skills (O*NET), Version 30.1 Release, U.S. Department of Labor
- Occupational Information Network Skills and Tasks (O*NET), Version 30.2 Release, U.S. Department of Labor
- 2024 1-Year American Community Survey (ACS), IPUMS
- 2024 5-Year American Community Survey (ACS), IPUMS
- Current Population Survey, Annual Social and Economic Supplement (CPS ASEC), 2016–2025, IPUMS
- Lightcast Job Postings, 2021–2026

Study Population

Our study population is limited to adults aged 25 and older in the US civilian, noninstitutionalized labor force. Workers who are Skilled Through Alternative Routes (STARs), specifically, hold at least a high school diploma (or general education diploma), but no bachelor's degree. This excludes active-duty military, residents of nursing homes or correctional facilities, and individuals who are unemployed and not looking for work. Table 1 below lists estimates of the US labor force in 2024.

TABLE 1. UNITED STATES LABOR FORCE ESTIMATES, 2024

Total Labor Force	STARs	% STAR
151,934,155	75,953,016	50%

Source: Opportunity@Work analysis of the 2024 1-Year ACS, IPUMS.

Constructing Occupational Skill Profile

From the O*NET Skills Version 30.1 release, we constructed skills measure vectors for each occupation at the Standard Occupational Classification (SOC) level using the importance scores for each of the 35 O*NET skills items. These measures were converted to OCC2010-level measures by taking the weighted average of measures based on each SOC's share of the national total worker count per OCC2010 in 2024.[1,2] The OCC2010-level measures were used to identify skill-similar occupational pairs (see *Stage 1: National Pathway Screen* in "Measuring Pathways Between Occupations" below).

[1] OCC2010 is the U.S. Census Bureau's occupation classification scheme. We convert the SOC-level skills measures to OCC2010-level measures because it allows us to compare occupation-level estimates across multiple years of data from the American Community Survey and Current Population Survey.

[2] To calculate each SOC's share of the national total worker count per OCC2010, we used the counts published in the Bureau of Labor Statistics' Occupational Employment and Wage Statistics' 2024 data release. We summed worker counts across all SOCs falling under the same OCC2010 to estimate the OCC2010-level total, and divided each SOC's total by the OCC2010 total to estimate its individual weight.

Measuring Pathways Between Occupations

To identify upwardly mobile pathways between occupations, we combine two things for every pair of occupations: (1) the occupations' skill profiles and (2) the revealed preferences of employers as demonstrated by observed transitions made by STARs. We apply this in two stages. The first is a wide national screen that established the universe of plausible pathways. The second is a stricter, regional screen that determines which of those pathways count as "rising pathways" for the mobility potential analysis.

Stage 1: National Pathway Screen

Using the O*NET skill vectors we constructed for each OCC2010 (see "Constructing Occupational Skill Profile"), we compute the Euclidean distance between its skill vector measure and that of all other OCC2010s. In order to understand how closely related two occupations are, we calculate the Euclidean distance, $d_{i,j}$, between the skill vector of the worker's current occupation, $s_i = (s_{i,1}, \ldots, s_{i,k}, \ldots, s_{i,35})$ and a potential alternative occupation, $s_j = (s_{j,1}, \ldots, s_{j,k}, \ldots, s_{j,35})$, as follows:

$$d_{i,j} = \sqrt{\sum_{k=1}^{35} (s_{i,k} - s_{j,k})^2}$$

We additionally calculate skill similarity as the inverse of the skill distance (i.e., $1/(d_{i,j} + 0.1)$), such that smaller distances yield higher skill similarity values and split occupation pairs into five equal-sized quantile bins: very low, low, medium, high, and very high skill similarity.

To estimate the national volume of workers, and STARs, specifically, transitioning between occupations, we use the CPS ASEC, which asks respondents to report their current occupation and their occupation in the previous calendar year, enabling analysis of the volume of year-to-year occupational transitions. Paired with ACS-based counts of STARs per occupation and national median hourly wages per occupation, this also allows us to estimate the number of STARs per region who can move into higher-paying occupations based on the skill profile of their current occupation.

We define the pathway between a pair of occupations as similarly skilled if it meets any one of the following criteria schemes:

1. A skill distance of less than 2.25.
2. A skill distance of at least 2.25 and less than 3, and an average of at least 1,500 workers per year making the transition over the last ten years observed (2016–2025).
3. A skill distance of 3 or greater, and an average of at least 3,000 workers per year making the transition over the last ten years observed.

To limit our attention to upwardly mobile transitions, we keep only those transitions that yield a positive percent increase in both median hourly wages and median annual earnings, and an increase in median hourly wages of less than 300 percent. Pathways that clear this stage form the universe of plausible transitions carried into Stage 2.

Stage 2: Rising Pathway Screen

The requirements for a pathway to be considered plausible are stricter, and are evaluated at the worker's state and age group rather than nationally. A pathway (in which workers move from Occupation A to Occupation B) that cleared Stage 1 is a rising pathway only if it also clears all four of the following screens.

I. Accessibility. Occupation B must be one that STARs already work in; at least 10 percent of the workers in the occupation must be STARs, as estimated using the 2024 1-Year ACS.

II. Sufficient Evidence. We require each Occupation A-B pairing to have at least two unweighted CPS ASEC survey respondents observed making the transition, with at least one being a STAR.

III. Higher Earning Potential. For each pathway, we estimate potential earnings gains by calculating the percentage difference in median hourly wages between Occupation A and Occupation B, at the state-age level. Remaining pairings are kept if they meet either of the following two earnings-gain conditions:

- Occupation B's median wage is at least 10% higher than Occupation A's median wage ***and*** Occupation B's wage group is higher than Occupation A's wage group (e.g., moving from a low-wage current occupation to a middle-, upper-, or high-wage occupation) OR
- Occupation B's median wage is at least 30% higher than Occupation A's median wage, regardless of wage group.

(Wage groups are defined under "Grouping STARs by Mobility Opportunity" below.)

IV. Local Job Demand. Occupation B must show viable hiring demand in the subpopulation's state, based on annualized Lightcast Job Postings data from January 2021 to July 2026.[3] Occupation B's hiring demand is considered viable if it meets either criterion:

- an average of 0.04 annual statewide postings per worker in the state; or
- an average of 100 or more annual statewide postings.

Grouping STARs by Mobility Opportunity

To identify the available pathways to higher-wage work available to STARs, we sort STARs into three different groups based on their occupation, age, and state labor market conditions. We take a three-step approach. In the report, the peer groups defined below are referred to as *comparison groups*; here we use the technical term *subpopulation*.

1. Define the subpopulation

We first place each worker in a subpopulation of peers: those with the same current occupation, living in the same state, and in the same age group (below 25, 25 to 34, 35 to 44, 45 to 54, 55 to 64, and 65 and older). Each subpopulation is assigned a wage group, based on its median hourly wage relative to the state's median wage.

At the national level, the median wage across all occupations was $27.02 in 2024:

- **Low-wage:** median wage is less than two-thirds (67%) of the national median wage (less than $18.01)
- **Middle-wage:** median wage is greater than or equal to two-thirds (67%) of the national median wage ($18.01) and less than four-thirds (133%) of the national median wage ($36.03)
- **Upper-wage:** median wage is greater than or equal to four-thirds (133%) of the national median wage ($36.03) and less than two times (200%) the national median wage ($54.04)
- **High-wage:** median wage is greater than or equal to two times (200%) the national median wage ($54.04)

[3] Three occupation codes with no postings anywhere are treated as untestable due to a data coverage gap and passed through as viable; and where the demand screen would leave a subpopulation with zero possible destinations, its single highest-ranked pathway is retained and flagged, so no subpopulation is dropped from the analysis entirely

To estimate wage groups at the subnational level, we adapt this methodology by estimating median hourly wages per occupation per state using the 2024 5-Year ACS, and comparing those estimates to the overall median wage across the state.

STARs already in a high-wage subpopulation are considered Shining STARs. STARs in low-, middle-, or upper-wage subpopulations are analyzed for possible pathways to higher-wage work.

2. Count available rising pathways

For each remaining subpopulation, we count how many rising pathways are available from its current occupation. That is, how many destination occupations clear both the national screen (Stage 1) and the stricter regional screen (Stage 2) described under "Measuring Pathways Between Occupations."

3. Assign STAR groups

Workers are assigned to groups based on their subpopulation's wage group and the number of rising pathways available to them:

- **Shining STARs** currently work in roles earning high wages — at least two times their state's median hourly wage (The number of available rising pathways does not affect this assignment.).
- **Rising STARs** currently work in low-, middle-, or upper-wage roles and have at least three viable rising pathways to greater economic mobility.
- **Forming STARs** currently work in low-, middle-, or upper-wage roles and have two or fewer viable rising pathways available to them.

We set the threshold at three because real opportunity means having access to several paths forward, not just a single ladder. It also builds in a margin against pathways that look open in the aggregate data but may be closed for any one worker (e.g., a local employer may stop hiring, or an occupation may cool in local demand) so a Rising STAR's mobility does not rest on a single fragile route.

Nationally, this yields approximately 3 million Shining STARs, 33 million Rising STARs, and 40 million Forming STARs.

Tasks, Skills, and AI

Skills describe an occupation's general capabilities, while tasks describe the specific activities through which those skills are applied on the job. Two occupations with similar skill profiles can still differ in the tasks that make up the actual work, and in how AI is used to perform them. Examining tasks allows us to show three things: that skill-similar occupations share overlapping tasks, that performing those tasks is how workers build the skills to move up, and that AI's uneven reach across tasks could reshape those pathways.

Identifying overlapping tasks. O*NET publishes task statements for each occupation, each with importance and frequency ratings. Task statements are phrased specifically to each occupation, so no two occupations share the same statements, and task overlap cannot be measured with the Euclidean distance we use for skills. Different occupations do, however, often describe the same activity in similar phrasing. For example, licensed practical and vocational nurses "measure and record patients' vital signs, such as height, weight, temperature, blood pressure, pulse, or respiration", while registered nurses "record patients' medical information and vital signs." To identify these shared activities from the O*NET Tasks Version 30.2, we embedded task statements using the Sentence Transformers framework's all-MiniLM-L6-v2 language model, computed cosine similarity between embeddings, and used the Hungarian algorithm to find the optimal one-to-one matching of tasks between each pair of occupations.

Opportunity @Work

About Opportunity@Work

Opportunity@Work is a nonprofit social enterprise with a mission to increase career opportunities for the 75+ million adults in the U.S. who do not have a four-year college degree but are Skilled Through Alternative Routes (STARs). For STARs, the American Dream has been fading due in part to an "opportunity gap," in which access to the good jobs required for upward mobility often depends less on people's skills and more on whether and where they went to college, who they know professionally and socially, or even how they look. We envision a future in which employers hire people based on skills rather than their pedigree. We are uniting companies, workforce development organizations and philanthropists in a movement to restore the American Dream so that every STAR can work, learn and earn to their full potential.

Visit us at www.opportunityatwork.org.