Received: 4 April 2024 | Revised: 1 July 2024 | Accepted: 25 July 2024

DOI: 10.1002/ajim.23641

RESEARCH ARTICLE

AMERICAN JOURNAL OF INDUSTRIAL MEDICINE WILEY

Burden and social distribution of occupational psychosocial exposures in the United States workforce, 2022

Shelley C. Stephan-Recaido MS[1] | Trevor K. Peckham MS, MPA, PhD[1,2] | Devan Hawkins PhD[3] | Marissa G. Baker PhD[1]

[1]Department of Environmental and Occupational Health Sciences, University of Washington School of Public Health, Seattle, Washington, USA

[2]Hazardous Waste Management Program, King County, Washington, USA

[3]Public Health Program, School of Arts and Sciences, Massachusetts College of Pharmacy and Health Sciences, Boston, Massachusetts, USA

Correspondence
Marissa G. Baker PhD, Department of Environmental and Occupational Health Sciences, University of Washington School of Public Health, 4225 Roosevelt Way NE, Suite 100, Seattle WA 98105, USA.
Email: bakermg@uw.edu

Funding information
National Institute for Occupational Safety and Health; National Institute of Environmental Health Sciences; King County Hazardous Waste Management

Abstract

Objective: To characterize the burden and social distribution of occupational psychosocial exposures in the United States (US).

Methods: We merged 2022 US employment and demographic data from the Current Population Survey (CPS) with occupational characteristic data from the Occupational Information Network (O*NET), wage data from the Occupational Employment and Wage Statistics Survey, and hours worked from the CPS, to estimate the number and proportion of US workers at risk of exposure to 19 psychosocial hazards. We additionally estimated the number and proportion of US workers over- or underrepresented in exposure burden.

Results: Of the exposures examined, US workers were most commonly employed in occupations with high time pressure (67.5 million US workers exposed; 43.2% US workers exposed), high emotional labor (57.1 million; 36.6%), and low wages (47.8 million; 30.6%). The burden of exposures was uneven across sociodemographic strata, attributable to occupational segregation. The full data set is available online at https://deohs.washington.edu/us-exposure-burden.

Conclusions: Work-related psychosocial exposures are ubiquitous and should be considered in occupational and public health research, policy, and interventions to reduce the burden of disease and health inequities in the United States.

KEYWORDS

exposure burden, occupational justice, occupational surveillance, O*NET, psychosocial exposures

1 | INTRODUCTION

Mental health and substance use disorders, musculoskeletal disorders, and cardiovascular disease are among the leading causes of death and disability in the United States (US).[1] Marked disparities in the morbidity and mortality from these conditions have been consistently identified across sociodemographic strata.[2,3] There is substantial evidence that work-related exposures, including certain organizational factors and other psychosocial hazards, are important contributors to these and other adverse health conditions.[4–6] There is additional evidence of racial and ethnic, socioeconomic, and sex differences in the prevalence of and vulnerability to certain psychosocial exposures, possibly contributing to the observed health disparities.[6–8]

Psychosocial hazards are aspects of work related to its organization and management, social context, and environment that can increase the risk of work-related stress and contribute to decreased well-being.[9,10] Examples include low job control, high job demands, high job strain, long work hours, interpersonal conflict, bullying, poor working conditions, and low wages.[9,10] Psychosocial exposures have been associated with various negative mental (e.g., depression), physical (e.g., cardiovascular disease), and behavioral (e.g., smoking) health outcomes, as well as higher rates of absenteeism, presenteeism, and mortality.[4,10] In Europe, 7.88% of cardiovascular disease and 25.95% of depression in the working population was found to be attributable to five psychosocial exposures.[11] In the United States, 120,000 deaths per year and 5%–8% of annual healthcare costs may be attributable to certain psychosocial exposures.[12] It was also estimated that the societal cost of work-related stress is $200–$300 billion per year in the United States.[4]

Changes in the nature and organization of work resulting from technological advances, globalization, and other economic, political, and social forces in recent decades have led to increased job insecurity, competitive pressure, and other work-related psychosocial exposures.[6,10,13,14] While occupational health has historically focused on chemical, physical, and biological exposures, the nature of modern work has led to increased attention on psychosocial exposures.[4,13] However, psychosocial exposures are still largely unrecognized for their contributions to workers' mental and physical health in the United States, which is reflected in the absence of practices and policies targeted toward prevention of such exposures.[4]

An important component of prevention is occupational exposure surveillance, identified as an important area for development in a 2018 report by the National Academies of Sciences, Engineering, and Medicine.[15] Surveillance of occupational exposures is advantageous over surveillance of health outcomes to identify opportunities for intervention before the onset of illness or injury.[15] This is especially important for the prevention of diseases that may be latent, chronic, or multicausal in nature, such as those related to stress, and which are largely underreported in occupational health-outcome-based surveillance systems.[16] Exposures may be easier to identify and occur more frequently than diseases, allowing for greater opportunity for detection and reduction of health risks.[17] Characterizing the distribution of exposures across different working populations can also help identify who is most at-risk, which is important for shaping priorities, developing effective interventions, and improving our understanding of how work-related exposures contribute to health inequities. Occupational exposure surveillance efforts have typically focused on chemical exposures, with an emphasis on the psychosocial aspects of the workplace being historically underemphasized.[18]

However, population-level exposure surveillance is challenging due to the resources required to conduct such a large-scale operation, as well as the lack of exposure information spanning the wide variety of occupations in the United States. While there is no comprehensive occupational exposure surveillance system in the United States, in particular for psychosocial exposures, piecemeal information on work organization and other psychosocial exposures can be found in various existing data sources, such as the Occupational Information Network (O*NET)[19] and the National Health Interview Survey (NHIS) Occupational Health Supplements (OHSs).[20] Recent studies utilized these sources to estimate the burden of psychosocial exposures among US workers, but they were limited in scope of exposures, geographical area, or demographics investigated.[7,21–23] NIOSH has also published prevalence estimates from the 2010 and 2015 NHIS OHSs online for a limited set of psychosocial hazards by various sociodemographic categories.[20] However, a lack of empirical information on the burden of work-related psychosocial exposures among US workers, as well as the social distribution of these exposures, still remains.

In this study, we attempt to address this gap by characterizing the burden and sociodemographic distribution of 19 psychosocial exposures among the US workforce. Information from this analysis can help identify prevalent exposures and high-risk working populations, vital for improving worker health and reducing health inequities.

2 | METHODS

2.1 | Data sources

2.1.1 | Current Population Survey (CPS)

The US Census Bureau and the US Bureau of Labor Statistics (BLS) CPS provides labor force statistics for the United States.[24] We obtained 2022 employment estimates from the National Institute for Occupational Safety and Health (NIOSH) Employed Labor Force (ELF) query system, which generates worker estimates using the CPS by 2018 Census occupation codes and sociodemographic characteristics.[24] We obtained worker estimates by race and ethnicity, sex, education, nativity and citizenship, and age. We additionally obtained data on hours worked by occupation code and sociodemographic group.

We aggregated American Indian/Alaska Native, Asian, Black/African American, multiracial, Native Hawaiian/Pacific Islander, and Hispanic/Latino workers into an additional category consisting of all racial and ethnic minoritized (REM) groups. Within the ELF query system, employment estimates less than 1000 are considered unstable. We have still included these in stand-alone groups to include small populations often omitted or aggregated in occupational health research.

2.1.2 | The Occupational Information Network

We obtained occupation-level exposure information for select psychosocial hazards from O*NET, a public-use database of job characteristics developed under the US Department of Labor/Employment and Training Administration.[19] O*NET contains detailed occupational characteristics for over 900 occupations described using Occupational Information Network-Standard Occupational Classification (O*NET-SOC) 2019 taxonomy. O*NET obtains data from job analysts, workers, and occupational experts and updates about a hundred occupations every year.[25]

We downloaded files from the O*NET 27.2 Database for 33 elements representing psychosocial work exposures.[26] O*NET respondents rate elements (i.e., psychosocial exposures) on a numerical scale representing importance, level, frequency, or other context of exposure, depending on the element. Different O*NET elements are assessed in different ways. For skill-based elements, both importance of the skill and level of the skill are assessed in the O*NET survey, with "importance" being a measure of how necessary a particular skill is to the occupation, and "level" attempting to assess the physical or cognitive level needed to undertake the skill successfully at work. Other O*NET elements ask about "context" which is a single Likert-scale question assessing how often someone does something or is exposed to something at their job, how much time they spend doing particular tasks, how responsible they are for a particular task, and so forth. The survey questions and response scales used in our analysis are detailed in Supporting Information S1: Appendix A. Previous research has found importance and level scores to be highly positively correlated, and concerns have been raised about the applicability and appropriateness of anchors used on the Likert scales for the "level" questions.[27] For this reason, our analysis used context and importance measures, but did not use level measures.

For most elements, a higher score indicated increased exposure. Responses were weighted and averaged by BLS for all respondents within the same occupation before data being publicly available for download. The scales/interpretation for each element varied, so we standardized the provided score for each occupation to a 0–100 scale and reverse coded some elements, so a higher score indicated greater exposure for all elements. Some O*NET elements were examined as individual measures, while others were combined into aggregate measures, the latter operationalized by averaging the score of multiple elements as informed by prior studies.[28–30] For each measure, we defined a threshold to represent a high level of exposure. Additional details, including exposure descriptions, thresholds, and related health outcomes are described in Supporting Information S1: Appendix A. Further information on O*NET's methodology and data collection strategy can be found in the O*NET Resource Center (https://www.onetcenter.org/).

2.1.3 | O*NET informed aggregate psychosocial exposures

As detailed in Supporting Information S1: Appendix A (Table B), we aggregated several individual O*NET elements to create five additional measures of psychosocial exposure, informed by multidimensional constructs that have been previously operationalized from O*NET elements and utilized in prior studies.[28,29] We developed an aggregate measure of Job Control, which refers to a worker's ability to have influence and decision authority over their work tasks, by averaging three individual O*NET elements as proposed by Fujishiro and Koessler.[28] We developed a measure of Psychological Job Demands, which refers to aspects of a job that require sustained cognitive or emotional efforts, by averaging four O*NET elements as proposed by Cifuentes et al.[29]

We operationalized a measure of Job Strain as a function of our Job Control and Psychological Job Demands measures, with occupations in the highest quartile of both Job Demand and Job Control coded as high Job Strain occupations. We developed a measure of Emotional Labor, which refers to the labor undertaken to maintain relationships and regulate emotions, by averaging eight O*NET elements as informed by Cifuentes et al.[29] Our final aggregate exposure variable was for Substantive Complexity of the occupation, a measure of the independent critical thinking and judgment required for the work.[30] As informed by Fujishiro et al.[31] and Meyer et al.,[30] we constructed Substantive Complexity by averaging 10 O*NET elements. As noted above, for any skill-based O*NET element, we only used importance scores and did not incorporate level scores, since the latter is more difficult to interpret as a proxy of occupational exposure and is highly correlated with the importance score anyway. This approach differs from the prior studies that informed our aggregate measures, which first averaged importance and level scores at the element level before combining into aggregate measures.

2.1.4 | Occupational Employment and Wage Statistics (OEWS) Survey

The US BLS Occupational Employment and Wage Statistics (OEWS) survey produces employment and wage statistics for over 800 occupations in the United States.[32] We utilized May 2022 estimates, based on six panels of data collected over the previous 3 years, to identify low-wage occupations, and assign employment estimates for O*NET weighting purposes.[32] We defined occupations as having low wages if their median hourly wage was ranked ≤25th percentile (equivalent to $18.08). This ranked approach takes into consideration differences in minimum wage laws and cost of living across the United States, with the assumption that while median wages could geographically vary, the same set of occupations are likely to remain in the lower quartile throughout the United States.

2.2 | Data linkage and analysis

We utilized R (v4.3.0) for all data processing and analysis.[33] The three data sources utilized different occupational classification systems, requiring a multistep process to make the data compatible. Informed by Hopson,[34] we linked O*NET data with CPS data using crosswalk and definition files[32,35,36] to translate O*NET-SOC codes into 6-digit SOC codes, then into Census codes. We imputed data for residual SOC occupations (i.e., codes ending in -X9 and −99 covering "other" categories) utilizing data from related occupations. In cases when one Census code corresponded to multiple SOC codes, we used OEWS employment data to weight the SOC codes. The final data set was organized using 2018 Census occupation codes. Additional details of our data linkage processes is provided in Supporting Information S2: Appendix B.

2.2.1 | Estimates of exposure burden

All workers within an occupation were considered exposed if the average score for that occupation was at or above the predefined exposure threshold. If the score was below the exposure threshold, no workers within that occupation were considered exposed. We summed the number of workers employed across all exposed occupations to obtain the total number of exposed workers. For long work hours, we obtained the number of workers working for >48 h for each occupation, rather than a binary yes/no exposure determination. For all exposures, we then divided the total number of exposed workers by the total workforce to obtain the percent of workforce exposed. Burden estimates were calculated for all workers and separately by sociodemographic group.

2.2.2 | Estimates of over- and underrepresentation

We calculated the estimated number and percent of workers over- or underrepresented in exposure by finding the absolute and relative difference between the estimated number of exposed workers in a particular sociodemographic group and the number of workers expected to be exposed based on that group's overall proportion in the total workforce. A group is overrepresented if the estimated number of exposed workers in the sociodemographic group exceeded the expected value.

3 | RESULTS

In 2022, the CPS estimated 156.1 million employed persons aged 18 and older in the United States. Average employment estimates by sociodemographic group and major Census occupation are presented in Table 1. O*NET data were available for 510 of 525 (97.1%) Census codes in the CPS, representing 150.6 million workers (96.5% of the workforce). Wage data were available for all but one Census code, and work hours were available for all Census codes.

3.1 | Distribution of exposures by sociodemographic group

Table 2 shows the percent of US workers with estimated exposure to each psychosocial hazard by sociodemographic group. Of the exposures examined, those with the greatest burden were high time pressure (43.2% of workers exposed), high emotional labor (36.6%), and low wages (30.6%). Nearly half of the US workforce (49.4%) were employed in occupations with at least three psychosocial exposures, per the O*NET occupation-level estimates. Additionally, 12.7% of employees reported working >48 h/week (long work hours) as gleaned from the CPS.

Employment in occupations with high job strain, low substantive complexity, and many job control-related hazards tended be higher

TABLE 1 Average employment estimates of US workers 18 years and older in 2022, stratified by sociodemographic characteristics and major Census occupation codes: 2022 Current Population Survey.

Category	Employee count	Percent of workforce, %
Sociodemographic group		
Race and ethnicity[a]		
American Indian or Alaska Native	1,681,000	1.1
Asian	10,547,000	6.8
Black or African American	19,712,000	12.6
Multiracial	3,285,000	2.1
Native Hawaiian or Other Pacific Islander	701,000	0.4
White		
White, non-Hispanic	94,504,000	60.5
White, Hispanic	25,685,000	16.5
Any race		
Hispanic or Latino	28,923,000	18.5
Not Hispanic or Latino	127,192,000	81.5
Racial and ethnic minoritized groups[b]	61,611,000	39.5
Sex		
Female	72,937,000	46.7
Male	83,178,000	53.3
Education level		
Less than high school diploma	10,036,000	6.4
High school diploma or equivalent	41,037,000	26.3
Some college or associate degree	40,759,000	26.1
Bachelor's or other advanced degree	64,283,000	41.2
Nativity and citizenship status		
Foreign-born, noncitizen	14,507,000	9.3
Foreign-born, citizen	14,124,000	9.0
Native-born	127,483,000	81.7
Age		
18–24	17,201,000	11.0
25–44	69,924,000	44.8
45–64	58,407,000	37.4
65+	10,582,000	6.8
Occupation group[c]		
White-collar		

(Continues)

TABLE 1 (Continued)

Category	Employee count	Percent of workforce, %
Management, business, and financial occupations	29,298,000	18.8
Professional and related occupations	38,598,000	24.7
Sales and related occupations	13,885,000	8.9
Office and administrative support occupations	15,922,000	10.2
Service		
Service occupations	24,413,000	15.6
Blue-collar		
Farming, fishing, and forestry occupations	938,000	0.6
Construction and extraction occupations	8,387,000	5.4
Installation, maintenance, and repair occupations	4,826,000	3.1
Production occupations	8,211,000	5.3
Transportation and material moving occupations	11,637,000	7.5
Total	156,114,000	100.0%

Note: Employee counts are rounded to the nearest thousand.

[a]Ethnicity groups (Hispanic/Latino and non-Hispanic) include persons identifying as any race, and race groups include persons identifying as any ethnicity, except for persons identifying as White which has been disaggregated by ethnicity.

[b]Racial and ethnic minoritized groups include persons identifying as American Indian/Alaska Native, Asian, Black/African American, multiracial, Native Hawaiian/Pacific Islander, or Hispanic/Latino.

[c]Occupations are based on 2018 major Census occupation groups.

among workers with lower education, workers from certain REM groups, and foreign-born workers (especially noncitizens) compared with the overall workforce. One exception was repetitive tasks; compared with the overall workforce, workers with some college-level education were more likely to be exposed, and the exposure prevalence was not notably higher for any nativity group. Comparing results by age to the overall workforce, 18–24-year-olds were more likely to be exposed to low job control, low/moderate decision-making impact, little decision-making freedom, highly structured work, and low substantive complexity. Workers 65-years and older were more likely to be exposed to low/moderate decision-making impact and high job strain, and 45–64-year-olds were more likely to be exposed to machine pacing. There was little difference in exposure between age groups and the overall workforce for low decision-making frequency and repetitive tasks. Comparing results by sex, men were more likely to be exposed to machine pacing and high job strain, but women were more likely to be exposed to low/moderate decision-making impact, repetitive tasks, and highly structured work. There was little difference between sexes in exposure to low job control, low decision-making frequency, little decision-making freedom, and low substantive complexity.

For job demand-related hazards, exposures were not notably more likely for any racial, ethnic, nativity, or age group compared with the overall workforce. Men were more likely than women to be exposed to job demand-related hazards. Compared with the overall workforce, workers with high school-level education were slightly more likely to be exposed to high time pressure, but exposures to high psychological demands were not notably more likely for any education group.

Employment in occupations with social environment exposures was higher for workers with greater educational attainment compared with the overall workforce. Comparing results by race and ethnicity to the overall workforce, Black/African American workers were more likely to be exposed to unpleasant/angry people, Black/African American and REM groups as a whole were more likely to be exposed to physically aggressive people, and non-Hispanic White workers were more likely to be exposed to high emotional labor, frequent conflict situations, and high competition. Whereas women were more likely to be exposed to high emotional labor, unpleasant/angry people, and physically aggressive people, men were more likely to be exposed to high competition. There was little difference between sexes in exposure to frequent conflict situations. As for age, compared with the overall workforce, 25–44-year-olds were more likely to be exposed to physically aggressive people, workers 45-years and older were more likely to be exposed to frequent conflict situations and high competition, and exposures to high emotional labor and unpleasant/angry people were not notably more likely for any age group. As for nativity and citizenship, there was little difference between each group and the overall workforce in exposure to the social environment hazards.

Employment in occupations with low wages and irregular work schedules was higher for workers from certain REM groups, foreign-born noncitizens, workers with lower education, and 18–24-year-olds compared with the overall workforce. Whereas men had higher employment occupations with irregular work schedules, women had higher employment in low-wage occupations. Compared with the overall workforce, non-Hispanic White workers, men, 45–64-year-olds, and workers with a bachelor's degree or higher were more likely to be exposed to long hours, but no nativity group had a notably higher exposure prevalence.

3.2 | Distribution of exposures by occupation

Table 3 shows the percent of US workers with estimated exposure to each psychosocial hazard by major occupation group. The estimated proportions of workers exposed to most job demand- and control-related exposures were highest in blue-collar occupations. Social environment exposures were highest, and occurred almost exclusively, in white-collar and service

TABLE 2 Percent of US workers with estimated exposure by psychosocial hazard and sociodemographic group, 2022.

	Percent of workers, %																				
	All	Race and ethnicity								Sex		Education level				Nativity and citizenship status			Age			
	All	AIAN	Asian	Black	Multi-racial	NHPI	White	His-panic	REM groups	Female	Male	<High school	High school	Some college	≥Bach-elor's	FBNC	FBC	Native-born	18–24	25–44	45–64	65+
N[1] =	156,114	1681	10,547	19,712	3285	701	94,504	28,923	61,611	72,937	83,178	10,036	41,037	40,759	64,283	14,507	14,124	127,483	17,201	69,924	58,407	10,582
Job demand and control exposures																						
High psychological job demands[2]	19.8	18.8	18.5	20.6	18.7	19.5	20.1	18.6	19.3	16.3	22.9	17.9	20.1	21.1	19.1	17.3	21.5	19.9	14.6	20.4	20.6	19.7
High time pressure	43.2	43.1	37.4	43.1	41.9	46.3	43.2	45.7	43.3	36.7	49.0	45.7	48.8	43.3	39.3	42.8	42.3	43.4	38.0	43.9	44.2	42.2
Low job control[2]	28.6	38.1	22.6	37.3	33.1	37.7	22.5	44.7	37.8	27.7	29.3	66.2	46.1	31.1	9.9	49.3	30.5	26	49.2	26.5	25.5	26
Low/moderate decision impact	3.3	4.8	4.2	3.1	3.5	3.2	2.6	5.7	4.5	4.9	1.9	8.7	4.3	3.1	2.0	7.9	4.2	2.7	4.0	3.1	3.3	3.7
Low decision frequency ≤1x/mo	5.0	7.5	6.3	4.1	5.0	4.3	4.0	8.3	6.4	5.3	4.7	13.1	6.2	4.4	3.3	11.7	6.1	4.1	5.1	4.9	5.0	5.0
Limited decision freedom	2.3	3.4	2.1	1.8	2.5	2.6	1.8	4.0	3.0	2.2	2.3	6.9	3.5	2.5	0.6	5.0	2.2	2.0	5.8	2.0	1.6	1.9
Highly structured work	2.4	2.4	2.7	2.9	3.0	3.3	2.1	3.0	2.9	2.9	2.0	4.1	3.5	3.3	1.0	2.9	2.2	2.4	7.1	2.1	1.6	2.0
Repetitive tasks	12.8	12.4	12.3	14.2	13.2	14.7	12.9	11.8	12.7	19.2	7.3	4.8	12.5	17.1	11.6	6.7	11.7	13.7	12.8	12.9	12.8	12.5
Machine pacing	0.9	1.0	0.6	1.0	0.8	1.2	0.8	1.4	1.1	0.6	1.2	2.8	1.7	0.9	0.2	1.7	0.9	0.8	0.9	0.8	1.1	0.8
High job strain[2]	4.9	6.2	3.3	7.0	4.8	6.6	4.1	6.9	6.2	2.5	7.0	9.9	8.5	5.2	1.6	7.2	6.0	4.5	4.2	4.6	5.3	5.9
Low substantive complexity[2]	27.8	38.5	20.9	35.5	32.6	33.9	22.1	43.7	36.5	27.2	28.3	64.4	45.6	30.4	9.0	47.8	28.7	25.4	48.4	25.1	25.1	26.5
Social environment exposures																						
High emotional labor[2]	36.6	28.7	33.7	33.2	31.8	31.0	41.0	25.6	29.8	43.1	30.9	12.2	22.1	32.1	52.4	18.9	34.7	38.8	21.6	37.6	39.3	39.7
Conflict situations ≥1x/week	4.2	2.7	3.3	4.4	3.6	2.1	4.8	2.6	3.3	3.8	4.6	0.8	1.6	3.0	7.2	1.9	3.5	4.6	1.3	4.3	4.8	5.0
Deal with unpleasant/angry people ≥1x/week	10.0	8.1	9.2	14.4	9.9	10.8	9.8	7.7	10.2	14.2	6.3	4.1	7.4	11.6	11.5	4.9	10.6	10.5	9.5	10.9	9.4	8.1
Deal with physically aggressive people ≥1x/ month	2.5	2.5	1.6	5.2	2.7	1.2	2.2	2.1	3.0	3.3	1.8	1.2	2.1	3.3	2.5	1.1	2.5	2.7	2.4	2.9	2.3	1.4

(Continues)

TABLE 2 (Continued)

	Percent of workers, %																					
	All	Race and ethnicity								Sex		Education level				Nativity and citizenship status			Age			
	All	AIAN	Asian	Black	Multi-racial	NHPI	White	His-panic	REM groups	Female	Male	<High school	High school	Some college	≥Bach-elor's	FBNC	FBC	Native-born	18–24	25–44	45–64	65+
Highly competitive workplace	3.8	2.4	3.7	2.5	2.9	3.6	4.5	2.6	2.8	3.3	4.3	1.5	2.1	3.1	5.7	2.6	3.8	4.0	1.6	3.5	4.5	5.6
Work schedule and wage exposures																						
Irregular work schedule	13.9	20.2	8.3	11.6	15.6	14.7	12.9	20.5	15.3	8.5	18.6	30.7	19.1	13.9	7.8	23.7	12.3	12.9	17.7	13.5	12.9	15.6
Low-wage occupation	30.6	39.4	27.0	41.4	36.8	40.9	25.1	42.6	39.1	37.4	24.7	56.1	46.4	36.9	12.6	42.7	32.0	29.1	60.0	27.8	25.7	28.7
Long work hours >48 h/week	12.7	9.2	9.6	9.3	11.8	12.4	14.7	9.7	9.7	8.2	16.7	9.0	11.5	11.7	14.7	9.1	11.2	13.3	5.1	12.6	15.5	10.4

Note: With the exception of the non-Hispanic White group, race includes persons identifying as non-Hispanic or Hispanic/Latino, and the Hispanic/Latino group includes persons identifying as any race. REM groups include persons identifying as American Indian/Alaska Native, Asian, Black/African American, multiracial, Native Hawaiian/Pacific Islander, or Hispanic/Latino. For all psychosocial exposures except long work hours, the estimates reflect the percent of workers employed in occupations characterized by exposure to the respective hazards. For long work hours, the estimates reflect the percent of employees exposed to this hazard.

Abbreviations: AIAN, American Indian/Alaska Native; ≥bachelor's, bachelor's or advanced degree; Black, Black/African American; FBC, foreign-born, citizen; FBNC, foreign-born, noncitizen; high school, high school diploma or equivalent; <high school, less than high school diploma or equivalent; Hispanic, Hispanic/Latino; NHPI, Native Hawaiian/Pacific Islander; REM, racial and ethnic minoritized; some college, some college or associate degree; White, non-Hispanic White.

[1]Population size is expressed in thousands.

[2]Exposure is constructed from multiple Occupational Information Network (O*NET) elements.

TABLE 3 Percent of US workers with estimated exposure by psychosocial hazard and major Census occupation code, 2022.

	Percent of workers, %										
	All	White-collar				Service	Blue-collar				
	All	Management, business, financial	Professional	Sales	Office, administrative support	Service	Farming, fishing, forestry	Construction, extraction	Installation, maintenance, repair	Production	Transportation, material moving
N[1] =	156,114	29,298	38,598	13,885	15,922	24,413	938	8387	4826	8211	11,637
Job demand and control exposures											
High psychological job demands[2]	19.8	7.3	27.8	0.5	4.1	20.0	–	44.3	41.6	13.0	48.4
High time pressure	43.2	42.3	30.3	45.0	58.8	15.1	4.8	77.4	50.9	81.3	72.7
Low job control[2]	28.6	1.0	4.0	18.1	34.3	63.2	82.0	58.7	0.9	58.0	75.9
Low/moderate decision impact	3.3	–	5.0	0.5	1.2	7.7	82.0	–	0.5	3.4	0.4
Low decision frequency ≤1x/month	5.0	–	6.8	0.5	1.5	13.0	77.3	0.6	8.8	5.1	0.2
Limited decision freedom	2.3	–	–	–	0.9	12.0	4.8	–	–	3.6	1.0
Highly structured work	2.4	–	0.6	–	3.3	9.7	4.8	0.3	–	3.9	2.3
Repetitive tasks	12.8	8.1	7.9	0.8	80.0	5.2	–	0.4	0.8	1.1	3.0
Machine pacing	0.9	–	–	–	–	–	10.7	0.8	–	14.9	0.4
High job strain[2]	4.9	1.0	1.0	–	0.7	3.1	–	19.9	0.4	4.1	35.1
Low substantive complexity[2]	27.8	–	1.0	18.7	39.0	65.8	85.4	41.6	1.7	49.8	82.8
Social environment exposures											
High emotional labor[2]	36.6	73.7	46.5	75.8	11.2	21	–	–	–	–	1.0
Conflict situations ≥1x/week	4.2	7.5	6.7	–	0.8	6.2	–	–	–	–	1.3
Deal with unpleasant/angry people ≥1x/week	10.0	6.4	17.9	0.8	20.6	13.5	–	–	–	–	1.2
Deal with physically aggressive people ≥1x/month	2.5	–	2.8	–	0.5	11.2	–	–	–	–	–
Highly competitive workplace	3.8	8.5	3.0	12.1	–	2.4	–	0.8	–	–	–

(Continues)

TABLE 3 (Continued)

	Percent of workers, %										
	All	White-collar				Service	Blue-collar				
	All	Management, business, financial	Professional	Sales	Office, administrative support	Service	Farming, fishing, forestry	Construction, extraction	Installation, maintenance, repair	Production	Transportation, material moving
Work schedule and wage exposures											
Irregular work schedule	13.9	7.7	7.3	20.3	0.2	21.4	88.2	46.9	20.6	0.7	23.2
Low-wage occupation	30.6	-	8.8	37.5	53.0	81.6	83.7	0.6	1.9	49.8	50.0
Long work hours >48 h/week	12.7	20.6	10.9	13.4	6.2	7.7	17.0	13.5	15.3	13.7	14.8

Note: For all psychosocial exposures *except* long work hours, the estimates reflect the percent of workers employed in occupations characterized by exposure to the respective hazards. For long work hours, the estimates reflect the percent of employees exposed to this hazard. A dash indicates that there were no occupations characterized as having exposure to the respective psychosocial hazard within the major Census occupation group.

[1]Population size is expressed in thousands.

[2]Exposure is constructed from multiple Occupational Information Network (O*NET) elements.

occupations. Irregular schedules were highest in *Farming/fishing/forestry* occupations, low wages were highest in service and *Farming/fishing/forestry* occupations, and long hours were highest in *Management/business/financial* occupations.

3.3 | Overrepresented exposures by sociodemographic group

Figure 1 shows the percent of US workers estimated to be overrepresented in exposure to each psychosocial hazard by sociodemographic group. Working populations with notably high magnitudes of overrepresentation include workers with lower education, foreign-born noncitizens, 18–24-year-olds, and workers from certain REM groups.

3.4 | Online application

The full data set is available in an online application for use by researchers, policymakers, practitioners, and others (https://deohs.washington.edu/us-exposure-burden). The online application provides estimates of exposure and estimates of over- and under-representation by sociodemographic group for all occupations combined, as well as by major and detailed Census occupation groups. We also provide exposure determinations for each occupation-exposure combination.

4 | DISCUSSION

We estimated the proportion of US workers at risk of exposure to several psychosocial hazards and characterized the social distribution of these exposures. Our analysis estimates a substantial number of US workers at risk, highlighting the need to recognize and address psychosocial exposures in the workplace. Our analysis also shows an unequal exposure burden across sociodemographic groups. Understanding the extent of the working population at risk of exposure, as well as specific populations at increased risk, is important for shaping prevention-related research, policies, and interventions.

Workers from REM groups, workers with lower education, foreign-born workers (especially noncitizens), and younger workers had a higher exposure burden than the overall workforce to high job strain, low substantive complexity, several job control-related hazards, irregular schedules, and low wages, and the major occupation groups with the greatest proportions of exposed workers were mostly blue-collar. In contrast, non-Hispanic White workers, workers with higher educational attainment, native-born workers, and middle- and older-aged workers generally had a higher exposure burden than the overall workforce to social environment hazards and long hours, and the major occupation groups with the greatest proportions of exposed workers were mostly white-collar.

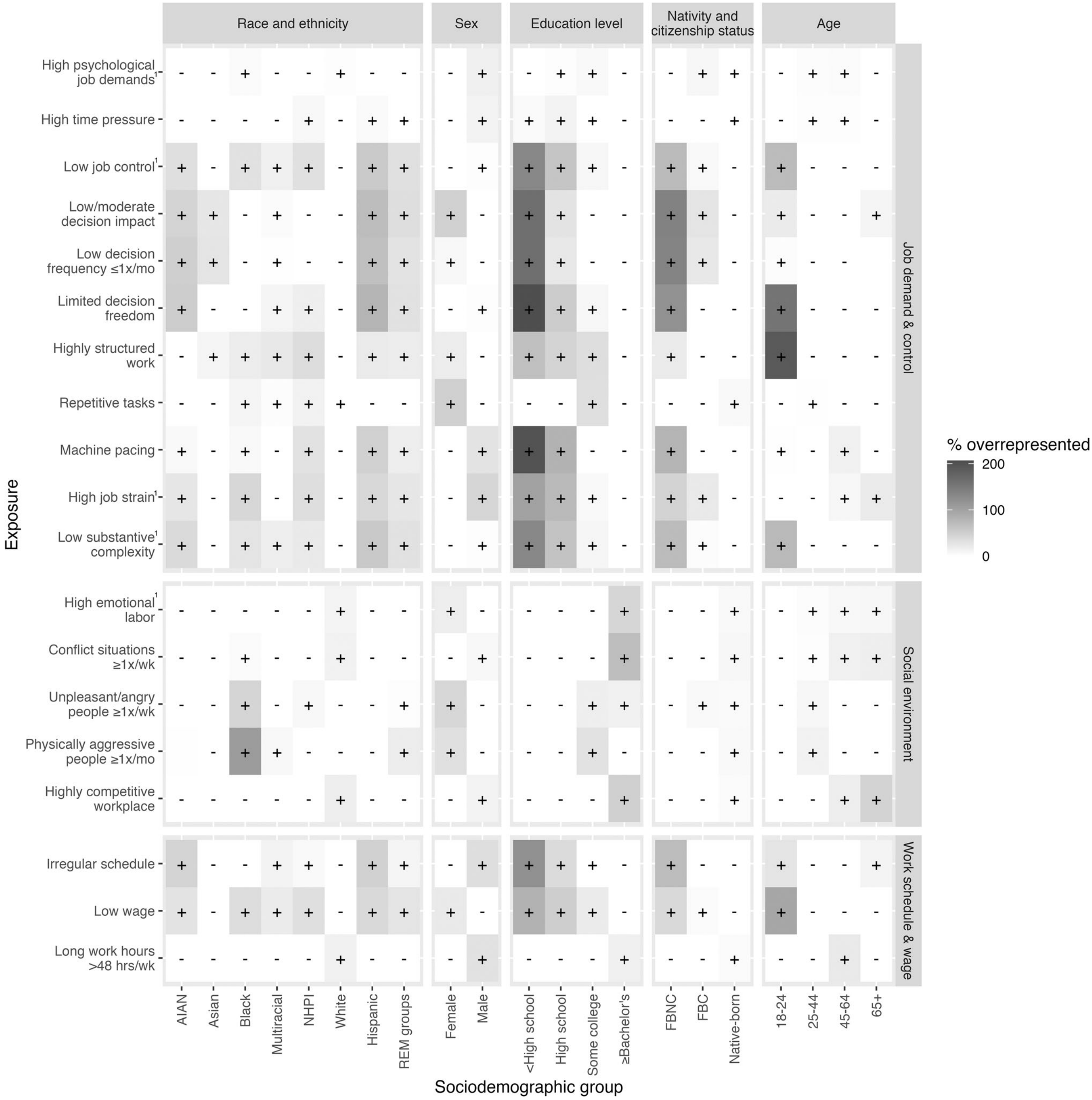

FIGURE 1 Magnitude of US workers estimated to be overrepresented in exposure by psychosocial hazard and sociodemographic group, 2022. A positive sign indicates overrepresentation, a negative sign indicates underrepresentation, and a blank cell indicates neither overrepresentation or underrepresentation. Darker shades of gray indicate greater percentages of overrepresentation. For all psychosocial exposures except long work hours, the estimates reflect the percent of workers employed in occupations characterized by exposure to the respective hazards. For long work hours, the estimates reflect the percent of employees exposed to this hazard. With the exception of the non-Hispanic White group, race includes persons identifying as non-Hispanic or Hispanic/Latino, and the Hispanic/Latino group includes persons identifying as any race. Racial and ethnic minoritized groups include persons identifying as American Indian/Alaska Native, Asian, Black/African American, multiracial, Native Hawaiian/Pacific Islander, or Hispanic/Latino. AIAN, American Indian/Alaska Native; ≥bachelor's, bachelor's or advanced degree; Black, Black/African American; FBC, foreign-born, citizen; FBNC, foreign-born, noncitizen; high school, high school diploma or equivalent; Hispanic, Hispanic/Latino; NHPI, Native Hawaiian/Pacific Islander; REM, racial and ethnic minoritized; some college, some college or associate degree; White, non-Hispanic White. [1]Exposure is constructed from multiple Occupational Information Network (O*NET) elements.

Prior research has demonstrated differential vulnerabilities between groups defined by socioeconomic position (SEP), that is, differential effects of certain psychosocial exposures on health outcomes by SEP.[6,8] Most studies found psychosocial exposures associated with worse outcomes in lower SEP workers compared with higher SEP workers, though a few found the opposite.[6,8] These differential vulnerabilities suggest that while certain exposures may be higher among relatively privileged working populations, working populations with less power and resources likely experience greater health impacts from these exposures.

Our study's prevalence estimates are largely consistent with those reported by Doubleday et al.,[21] who applied a subset of O*NET data to workers in Federal Region 10 in 2019 using similar methods. Our results are less consistent with reported prevalence estimates for comparable psychosocial exposures from the 2010 and 2015 NHIS OHSs,[7,22,23,37] though the overall social patterns of exposure are generally similar. Trends observed in our study are mostly consistent with Landsbergis et al.,[6] who conducted a review of work organization hazards and occupational health disparities. One difference is the review's finding of high psychological job demands more common among higher SEP workers than lower SEP workers, whereas we did not find a clear trend across education for this exposure. We also found workers in blue-collar occupations were more likely to be exposed to high job demands than workers in white-collar occupations. We expect some variability in findings to be due to differences in methods used to define and operationalize the exposures, as well as calculate the proportion of exposed workers. These differences highlight the need to develop greater consistency across researchers in how psychosocial exposures are defined and operationalized.

There are limitations to note. Our O*NET-informed exposures were based on analyst, occupational expert, and job incumbent responses to subjective questionnaires and are therefore subject to bias. Our analysis did not cover the entire US working population as the CPS excludes military personnel and institutionalized workers from its survey, populations that should also be considered for intervention as applicable. Our analysis also only covered a subset of all relevant psychosocial exposures. Our analysis also did not examine intersecting identities, and sociodemographic characteristics explored were limited to those capture in the CPS.

Misclassification is another important limitation. With the availability of exposure information only at the occupation-level, we assumed the same exposure for all individuals within a single occupation and were unable to account for exposure variability across individuals or groups within the same occupation. Consequently, exposure disparities estimated in this study can only be attributed to occupational segregation, that is, the uneven distribution of working populations across occupations, and not differential exposure within an occupation. Misclassification could have also been introduced from using crosswalks to merge the datasets. It should be noted that our estimates for long hours were not subject to these limitations, since they were based on worker-level data and no crosswalks were needed.

O*NET's primary purpose is to understand worker and job requirements of different occupations for use by job seekers, employers, and others, and its validity as a source of exposure assessment information is not clear.[19,38] Several studies have demonstrated the predictive validity of certain O*NET elements, but only a few have evaluated their convergent validity.[28–30,38] One such study found that O*NET may more accurately capture the job experience of non-Hispanic White workers than workers from REM groups.[28] This suggests exposures of other working populations may also be differentially captured in O*NET. Although there are still some questions to be explored regarding O*NET's validity as an exposure assessment tool, its availability, comprehensive coverage, and annual update still make it a valuable tool for exposure surveillance.

Specific limitations of our aggregate exposure variables must also be noted. Our aggregate measures are informed by existing survey-based psychosocial constructs such as the Karasek job control-demand-strain model, typically assessed via the Job Content Questionnaire (JCQ) which has been rigorously validated.[39] As such, the questions asked in O*NET do not necessarily align with the validated questions in the JCQ; rather, elements chosen from O*NET to operationalize constructs such as job demand, job control, or job strain have been based on expert judgment. In addition, many validated psychosocial constructs and surveys such as the JCQ were developed in the 1960s and 1970s, when the US workforce and conditions of work were much different than experienced in the 2020s. In the 1960s and 70s, for example, the US economy was dominated by goods-producing jobs, as opposed to services-providing jobs. Unionization was more common, there were fewer women in the workforce, and the standard employment relationship (a full-time, permanent contract between a single employer and employee, often with benefits including a pension) was more common.[40] As such, even validated, the JCQ may not accurately reflect the experiences of workers in the US workforce in the 2020s. While our aggregate measures were informed by previous researchers who had used O*NET to operationalize these constructs, the aggregate exposure measures included in our analysis have been not been tested against the gold standard measures and cannot be considered to be generalizable or valid, making their utility for population surveillance unknown. However, despite limitations in how the aggregate measures were operationalized in this analysis, job demand, job control, job strain, emotional labor, and substantive complexity are all considered to be important metrics for assessing the psychosocial work environment and, in our view, warrant inclusion in this study. As research continues into these factors, as well as the use of O*NET data to proxy occupational exposure, our approach to characterizing the burden and distribution of these exposures can be amended.

This work represents the largest comprehensive assessment of the US burden of psychosocial exposures by sociodemographic characteristics to date. While Hawkins and Alenó Hernández[7] characterized a smaller subset of psychosocial hazards by race and ethnicity, our study expands that effort by focusing on a larger number of hazards and sociodemographic factors. There are several other strengths to this study, including that our exposure surveillance approach is highly efficient and low cost. Additionally, our exposure information sources are frequently updated, unlike most job-exposure matrices, which limits potential misclassification associated with changes in exposures over time. Lastly, with availability of exposure information at the specific-occupation level, we were able to capture more variability in exposures than if we only had information at the detailed- or major-occupation level. Future work should consider expanding coverage of the working population and psychosocial exposures investigated, utilizing an intersectional approach, finding ways to minimize misclassification, and continuing to study the use and validity of O*NET for exposure surveillance purposes.

4.1 | Use in public health practice, policy, and research

Characterizing the burden and distribution of work-related psychosocial exposures is an important and pressing need given the high societal cost of work-related stress, the changing nature of work which has resulted in an increase in psychosocial exposures, and the high burden of cardiovascular disease and depression partially attributable to work-related psychosocial exposures.[41] Until a national comprehensive exposure surveillance system can be established, analyses such as the one detailed here can help our understanding of the contribution of work to population health and health inequities, as well as inform equitable occupational and public health research, policy, and interventions to reduce the burden of disease and health inequities in the United States. In particular, the database developed by this project will have utility to practitioners, researchers, and policymakers in occupational health. For practitioners, this database could be used by occupational health nurses or physicians to understand different occupations and the potential stressors and hazards faced by workers in those occupations, allowing them to better link physical and mental health ailments to workplace factors. For those working in industrial hygiene or safety roles, understanding the psychosocial hazards present in given occupations can help to provide a more well-rounded approach to health and safety programs. More generally, this database can be used to educate practitioners about the reality of occupational segregation, its potential role in contributing to inequities in occupational exposures across working populations, and therefore provide a rationale for incorporating equity considerations into occupational health and safety practice. For researchers, this database could inform exposure assessments for occupational epidemiological studies (and allow the inclusion of multiple psychosocial exposures, and investigation of differences by sociodemographic factors), or help researchers to identify understudied occupational populations for more targeted research. This database will also have utility for policymakers, who can use the findings to prioritize populations or outcomes for additional investigation and potential policy efforts, while ensuring that policy efforts are not contributing to occupational injustices. Understanding which hazards are shared across many occupations, and which occupations or groups of workers tend to experience the highest burden of exposure will also enable targeted outreach and educational efforts to equitably protect workers.

AUTHOR CONTRIBUTIONS

All authors participated in the conception and design of the work. Shelley C. Stephan-Recaido, Trevor K. Peckham, and Marissa G. Baker acquired the data, and Shelley C. Stephan-Recaido analyzed the data and built the online data application. All authors contributed to the interpretation of the data. Shelley C. Stephan-Recaido drafted the manuscript, tables, and figures, and all authors revised the work critically for important intellectual content. All authors provided final approval of the version to be published and are in agreement to be helped accountable for all aspects of the work and ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

ACKNOWLEDGMENTS

Grant Sponsors: National Institute for Occupational Safety and Health (NIOSH), federal training grant T42OH008433; National Institute of Environmental Health Sciences (NIEHS), award P30ES00703. Additional funding provided by the Hazardous Waste Fund, administered by the Hazardous Waste Management Program in King County, Washington. The content is solely the responsibility of the authors and does not necessarily represent the official views of NIOSH, NIEHS, or King County.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DISCLOSURE BY AJIM EDITOR OF RECORD

Jian Li declares that he has no conflict of interest in the review and publication decision regarding this article.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available at https://shiny.deohs.washington.edu/app_direct_i/us-exposures-onet-app/_/

ETHICS STATEMENT

As this was an analysis of existing, unidentified, population-level data, no ethics review was necessary.

ORCID

Shelley C. Stephan-Recaido http://orcid.org/0000-0003-3322-2585

Trevor K. Peckham http://orcid.org/0000-0001-8196-4298

Devan Hawkins http://orcid.org/0000-0002-7823-8153

Marissa G. Baker http://orcid.org/0000-0003-3136-0490

REFERENCES

1. Mokdad AH, Ballestros K, Echko M, et al. The state of US health, 1990-2016: burden of diseases, injuries, and risk factors among US states. *JAMA*. 2018;319(14):1444-1472.
2. Dwyer-Lindgren L, Kendrick P, Kelly YO, et al. Cause-specific mortality by county, race, and ethnicity in the USA, 2000–19: a systematic analysis of health disparities. *Lancet*. 2023;402(10407):1065-1082.
3. Thoits PA. Stress and health: major findings and policy implications. *J Health Soc Behav*. 2010;51(suppl):S41-S53.
4. Dobson M, Schnall P, Rosskam E, Landsbergis P. Work-related burden of absenteeism, presenteeism, and disability: an epidemiologic and economic perspective. In: Bültmann U, Siegrist J, eds. *Handbook of Disability, Work and Health*. Springer; 2020:251-272.
5. LaMontagne AD, Keegel T, Louie AM, Ostry A. Job stress as a preventable upstream determinant of common mental disorders: a review for practitioners and policy-makers. *Adv Mental Health*. 2010;9(1):17-35.
6. Landsbergis PA, Grzywacz JG, LaMontagne AD. Work organization, job insecurity, and occupational health disparities. *Am J Ind Med*. 2014;57(5):495-515.
7. Hawkins D, Alenó Hernández KM. Racial and ethnic differences in the prevalence of work organization and occupational psychosocial exposures. *Am J Ind Med*. 2022;65(7):567-575.

8. Vanroelen C, Levecque K, Louckx F. Differential exposure and differential vulnerability as counteracting forces linking the psychosocial work environment to socioeconomic health differences. *J Epidemiol Commun Health*. 2010;64(10):866-873.
9. International Organization for Standardization. ISO 45003: 2021. 2021.
10. Landsbergis PA, Dobson M, LaMontagne AD, Choi B, Schnall P, Baker DB. *Occupational Stress*. Oxford University Press; 2017.
11. Niedhammer I, Chastang JF. Overall fraction of disease attributable to multiple dependent risk factors: a new formula. *Lancet Neurol*. 2021;20(12):979-980.
12. Goh J, Pfeffer J, Zenios SA. The relationship between workplace stressors and mortality and health costs in the United States. *Manage Sci*. 2016;62(2):608-628.
13. Peckham TK, Baker MG, Camp JE, Kaufman JD, Seixas NS. Creating a future for occupational health. *Ann Work Expo Health*. 2017;61(1):3-15.
14. Landsbergis P, García-Rivas J, Juárez-García A, et al. Occupational psychosocial factors and cardiovascular disease. In: Tetrick LE, Fisher GG, Ford MT, Quick JC, eds., *Handbook of Occupational Health Psychology*. American Psychological Association; 2024.
15. National Academies of Sciences, Engineering, and Medicine. *A Smarter National Surveillance System for Occupational Safety and Health in the 21st Century*. The National Academies Press; 2018. doi:10.17226/24835
16. Azaroff LS, Levenstein C, Wegman DH. Occupational injury and illness surveillance: conceptual filters explain underreporting. *Am J Public Health*. 2002;92(9):1421-1429.
17. Wegman DH. Hazard surveillance. In: Halperin W, Baker Jr. EL, Monson RR, eds. *Public Health Surveillance*. Vol 67. Van Nostrand Reinhold; 1992:62-75.
18. Stephan-Recaido SC, Peckham TK, Lavoué J, Baker MG. Characterizing the burden of occupational chemical exposures by sociodemographic groups in the United States, 2021. *Am J Public Health*. 2024;114(1):57-67.
19. National Center for O*NET Development. About O*NET. O*NET Resource Center. Accessed September 21, 2023. September 5, 2023. https://www.onetcenter.org/overview.html
20. The National Institute for Occupational Safety and Health. Worker Health Information from the National Health Interview Survey: about the questions used in the occupational health supplements. Centers for Disease Control and Prevention. Accessed November 15, 2022. March 31, 2022. https://www.cdc.gov/niosh/topics/nhis/questions.html
21. Doubleday A, Baker MG, Lavoué J, Siemiatycki J, Seixas NS. Estimating the population prevalence of traditional and novel occupational exposures in Federal Region X. *Am J Ind Med*. 2019;62(2):111-122.
22. Alterman T, Luckhaupt SE, Dahlhamer JM, Ward BW, Calvert GM. Prevalence rates of work organization characteristics among workers in the U.S.: data from the 2010 National Health Interview Survey. *Am J Ind Med*. 2013;56(6):647-659.
23. Alterman T, Luckhaupt SE, Dahlhamer JM, Ward BW, Calvert GM. Job insecurity, work-family imbalance, and hostile work environment: prevalence data from the 2010 National Health Interview Survey. *Am J Ind Med*. 2013;56(6):660-669.
24. National Institute for Occupational Safety and Health Division of Safety Research. The Employed Labor Force (ELF) query system. Centers for Disease Control and Prevention. Accessed May 13, 2021. December 9, 2021. https://wwwn.cdc.gov/wisards/cps/
25. National Center for O*NET Development. Office of management and budget clearance. O*NET Resource Center. Accessed August 22, 2023. October 24, 2023. https://www.onetcenter.org/ombclearance.html
26. National Center for O*NET Development. O*NET® database releases archive. O*NET Resource Center. Accessed April 11, 2023. 2023. https://www.onetcenter.org/db_releases.html
27. Handel MJ. The O*NET content model: strengths and limitations. *J Labour Mark Res*. 2016;49(2):157-176.
28. Fujishiro K, Koessler F. Comparing self-reported and O*NET-based assessments of job control as predictors of self-rated health for non-Hispanic whites and racial/ethnic minorities. *PLoS One*. 2020; 15(8):e0237026.
29. Cifuentes M, Boyer J, Gore R, et al. Inter-method agreement between O*NET and survey measures of psychosocial exposure among healthcare industry employees. *Am J Ind Med*. 2007;50(7):545-553.
30. Meyer JD, Cifuentes M, Warren N. Association of self-rated physical health and incident hypertension with O*NET factors: validation using a representative national survey. *J Occup Environ Med*. 2011;53(2):139-145.
31. Fujishiro K, MacDonald LA, Crowe M, McClure LA, Howard VJ, Wadley VG. The role of occupation in explaining cognitive functioning in later life: education and occupational complexity in a US national sample of black and white men and women. *J Gerontol Series B*. 2019;74(7):1189-1199.
32. Occupational Employment and Wage Statistics: OEWS Documentation. U.S. Bureau of Labor Statistics. Accessed February 8, 2024. April 25, 2023. https://www.bls.gov/oes/oes_doc.htm
33. R Core Team. R: a Language and Environment for Statistical Computing. Accessed April 26, 2023. 2023. https://www.R-project.org/
34. Hopson A. Mapping Employment Projections and O*NET data: a methodological overview. Monthly Labor Review, U.S. Bureau of Labor Statistics. Accessed March 13, 2023. August 2021. https://www.bls.gov/opub/mlr/2021/article/mapping-employment-projections-and-onet-data.htm
35. National Center for O*NET Development. Crosswalk files. O*NET Resource Center. Accessed December 1, 2023. https://www.onetcenter.org/crosswalks.html
36. US Census Bureau. Industry and occupation code lists & crosswalks. United States Census Bureau. Accessed February 16, 2023. November 30, 2022. https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html
37. Doza S, Bovbjerg VE, Vaughan A, Nahorniak JS, Case S, Kincl LD. Health-related exposures and conditions among US fishermen. *J Agromedicine*. 2022;27(3):284-291.
38. Cifuentes M, Boyer J, Lombardi DA, Punnett L. Use of O* NET as a job exposure matrix: a literature review. *Am J Ind Med*. 2010;53(9): 898-914.
39. Karasek RA. Job demands, job decision latitude, and mental strain: implications for job redesign. *Adm Sci Q*. 1979;24(2):285-308.
40. Kalleberg AL. Nonstandard employment relations: part-time, temporary and contract work. *Annu Rev Sociol*. 2000;26(26):341-365.
41. Schulte PA, Sauter SL, Pandalai SP, et al. An urgent call to address work-related psychosocial hazards and improve worker well-being. *Am J Ind Med* 2024;67(6):499-514.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Stephan-Recaido SC, Peckham TK, Hawkins D, Baker MG. Burden and social distribution of occupational psychosocial exposures in the United States workforce, 2022. *Am J Ind Med*. 2024;67:888-900. doi:10.1002/ajim.23641