Characterizing the Burden of Occupational Chemical Exposures by Sociodemographic Groups in the United States, 2021

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See also Public Health Workforce, pp. 38–67.

Objectives. To estimate the number and prevalence of workers in the United States exposed to chemical hazards available in the Canadian job-exposure matrix (CANJEM) database and examine exposure disparities across sociodemographic groups.

Methods. We merged US worker demographic data from the Current Population Survey with CANJEM to characterize the burden and sociodemographic distribution of 244 chemical exposures in the United States in 2021. An interactive version of the full data set is available online (https://deohs.washington.edu/us-exposure-burden).

Results. Of the chemical exposures examined, the most prevalent were cleaning and antimicrobial agents (14.7% of workforce estimated exposed), engine emissions (12.8%), organic solvents (12.1%), polycyclic aromatic hydrocarbons (10.1%), and diesel engine emissions (8.3%). Racial and ethnic minoritized groups, persons with lower educational attainment, foreign-born noncitizens, and males were generally overrepresented in exposure to work-related chemical hazards.

Conclusions. In the United States, marginalized sociodemographic groups are estimated to experience an inequitable burden to many chemical exposures because of occupational segregation. Data from this analysis can inform occupational and public health research, policy, and interventions aimed at reducing the burden of disease and health inequities in the United States. (*Am J Public Health*. 2024;114(1):57–67. https://doi.org/10.2105/AJPH.2023.307461)

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Each year, hazardous work-related exposures are responsible for thousands of deaths and millions of injuries and illnesses in the United States.[1] Yet, occupational health surveillance, a key component of public health prevention, remains limited in the United States.[2] Occupational health surveillance is the ongoing systematic collection, analysis, interpretation, and dissemination of data related to occupational hazards and health outcomes.[2–4] Current occupational health surveillance systems primarily focus on the collection of health outcome data[2] and are known to undercount injuries and illnesses,[2,5] especially latent and chronic diseases.[4,5] Surveillance of occupational exposures has historically been limited in the United States, but was identified as a top priority in the 2018 National Academies of Sciences, Engineering, and Medicine report, "Developing a Smarter National Surveillance System for Occupational Safety and Health in the 21st Century."[2] Exposure surveillance can address gaps in current health surveillance efforts, especially identifying opportunities for intervention before work-related injuries and illnesses occur.[2–4]

In addition to characterizing the burden of workplace exposures, it is also important to consider how they are distributed across working populations—another need highlighted in the report.[2] This is critical because the US workforce remains heavily segregated across sociodemographic strata,[6] resulting in the uneven distribution of work-related exposures, which may influence health and contribute to health disparities.[2,7–10] Although previous research has documented occupational health disparities in the United States, with workers from marginalized groups generally experiencing worse health outcomes,[7,11,12] a lack of empirical information on the social distribution of work-related exposures remains.

Identification of at-risk working populations is particularly important considering that many groups have been underrepresented or excluded from public health policies, research, and interventions. The primary governmental agency responsible for worker health and safety in the United States is the Occupational Safety and Health Administration (OSHA), which was shaped largely by lobbying of labor unions that historically represented White male workers in goods-producing industries.[13] While OSHA has been successful in reducing exposures to certain widely recognized hazards, many working populations and hazards have long been excluded from OSHA protections, such as domestic workers who are predominantly female and from racial and ethnic minoritized (REM) groups.[14] Since its inception, OSHA has faced challenges in updating existing standards, as well as introducing new standards that may be more relevant to a more diverse American workforce that is largely employed in services-providing industries.[15] Exposure surveillance can help us understand who is most at risk, a critical step toward prevention and achieving occupational health equity.

Population-level exposure surveillance is considerably challenging, due largely to limited accurate exposure information for a wide variety of hazards and work settings. The last large-scale exposure surveillance effort in the United States was the National Occupational Exposure Survey, a nationwide observational survey conducted in the early 1980s.[2] While the survey addressed the need for general working population exposure surveillance, it was highly resource-intensive, and the data are now considered outdated and of limited use.[2] More recent exposure surveillance efforts, such as the Occupational Health Supplements in the National Health Interview Survey, have been more narrow in scope, focusing on a limited set of exposures or work settings.[2] One approach that can address the need for population-level exposure surveillance takes advantage of existing data in the form of a job-exposure matrix (JEM). JEMs are data sources that link individual job titles to exposure indices and have been used for decades in occupational epidemiology research.[16] Though JEMs are not without limitations, they are highly efficient and low cost to use,[16] making them an attractive and powerful source of exposure information when individual worker-level data are unavailable.

Few multihazard JEMs covering a wide span of work settings exist in the world, and fewer are applicable to a North American population. Arguably, the most comprehensive JEM available for developing population-level estimates of work-related chemical exposures in the US context is the Canadian job-exposure matrix (CANJEM).[17] CANJEM provides exposure prevalence, intensity, and frequency estimates for more than 250 occupational agents based on data from jobs held in the Montreal, Quebec, area between 1930 and 2005.[17,18] CANJEM's strengths lie in its wide coverage of work settings and chemical exposures, semiquantification of frequency and intensity of exposure, and expert assessment of exposures from worker interviews. CARcinogen EXposure (CAREX) Canada is another JEM providing exposure prevalence and level estimates for multiple occupational agents across a wide span of work settings in Canada in 2016; however, this database is limited to select carcinogens.[19]

Although not a JEM, other researchers have used the Occupational Information Network (O*NET) as a source of occupational exposure information.[20] O*NET is a public database providing detailed occupational characteristic information for hundreds of occupations, which can be used to estimate a variety of occupational exposures. However, O*NET lacks coverage of chemical exposures and is reliant on self-report. While obtaining exposure information represents a considerable challenge, CANJEM is one of the few exposure information systems in the world with data on multiple agents spanning a wide range of work settings.

Previous US studies have used JEMs to estimate the prevalence of occupational exposures at the population level.[21,22] However, these studies were limited in the scope of chemical exposures, geographical area, or working populations investigated and did not look comprehensively at sociodemographic differences in exposure burden. In this study, we combined US employment and workforce demographic data with exposure data from CANJEM to characterize the burden and sociodemographic distribution of 244 chemical exposures in US workplaces. Identifying prevalent exposures and at-risk working populations can inform future interventions to improve worker health and reduce health inequities.

TABLE 1— Average Employment Estimates in the United States by Sociodemographic Group: 2021 Current Population Survey

Sociodemographic Group	Employee Count (% of Workforce)
Race/ethnicity[a]	
AI/AN	1 674 000 (1.1)
Asian	10 017 000 (6.6)
Black or African American	18 726 000 (12.3)
Multiracial	3 203 000 (2.1)
NH/PI	670 000 (0.4)
White	118 291 000 (77.5)
Non-Hispanic White	93 983 000 (61.6)
Hispanic White	24 308 000 (15.9)
Hispanic or Latino, any race	27 429 000 (18.0)
Not Hispanic or Latino, any race	125 152 000 (82.0)
Racial and ethnic minoritized groups[b]	58 597 000 (38.4)
Sex	
Female	71 752 000 (47.0)
Male	80 829 000 (53.0)
Education level	
< High-school diploma	11 438 000 (7.5)
High-school diploma or equivalent	39 006 000 (25.6)
Some college or associate degree	40 278 000 (26.4)
≥ Bachelor's degree	61 858 000 (40.5)
Nativity and citizenship status	
Native-born	126 177 000 (82.7)
Foreign-born, citizen	13 354 000 (8.8)
Foreign-born, noncitizen	13 049 000 (8.6)
Total	152 581 000 (100)

Note. AI/AN = American Indian/Alaska Native; NH/PI = Native Hawaiian/Pacific Islander. Employee counts are rounded to the nearest thousand.
[a]Persons of Hispanic or Latino ethnicity are of any race and are also counted in their preferred race category.
[b]Racial and ethnic minoritized groups include persons identifying as AI/AN, Asian, Black/African American, multiracial, NH/PI, or Hispanic/Latino.

METHODS

We used two sources of data in this analysis, which are described in more detail here.

Data Sources

Current Population Survey. We obtained 2021 employment and worker demographic data using the Employed Labor Force query system developed by the National Institute for Occupational Safety and Health, which generates workforce estimates based on the US Census Bureau and US Bureau of Labor Statistics Current Population Survey (CPS).[23] We obtained employment counts by 2018 Census occupation codes and sociodemographic groups describing race and ethnicity, sex, education, and nativity and citizenship (Table 1). These categories represent axes of social and health inequity and allow us to examine how occupational segregation across sociodemographic characteristics may contribute to unequal occupational exposure burdens.

For race and ethnicity categories, persons within each race category are of any ethnicity, except for persons who identify as non-Hispanic White, and persons of Hispanic/Latino ethnicity are also counted in their preferred race category. American Indian/Alaska Native, Asian, Black/African American, multiracial, Native Hawaiian/Pacific Islander, and Hispanic/Latino persons were aggregated into an additional category of all REM groups. Employment estimates less than 1000 are considered unstable within the Employed Labor Force query system. Although their contribution to the overall burden estimates is minor, we have purposefully included these estimates to maximize our representation of small populations often left out of occupational health research.

Canadian Job-Exposure Matrix. CANJEM is a general-population JEM providing semiquantitative exposure information for 258 occupational agents—mainly chemical—by industry or occupation.[17,18] CANJEM was built from the accumulation of more than 40 person-years of expert assessment of occupational exposures from detailed worker interviews completed in 4 case–control cancer studies conducted between 1979 and 2004 in Canada. Collectively, more than 30 000 jobs from 1930 to 2005 held by nearly 9000 participants comprising a largely urban population in the greater Montreal region were evaluated. Details regarding the development and validity of CANJEM have been previously described.[17,18] CANJEM represents a uniquely large and extensive database of exposure information collected from a North American population into the early 21st century.

To develop the JEM data, a team of experts assessed each job for potential exposure to approximately 300 occupational agents. The experts considered a job to be exposed to an agent if it was present in the workplace above background levels found in the general population. For each job thought to be exposed, the experts assigned exposure characteristics of intensity (low, medium, high), frequency (hours per week), and degree of confidence that the exposure occurred (possible, probable, definite). For each coded occupation, CANJEM provides a probability of exposure for each occupational agent. An additional exposure metric, frequency-weighted intensity (FWI) is also provided, which is a continuous measure of intensity of exposure averaged over a 40-hour workweek (FWI = exposure intensity*frequency of exposure in hours worked per week/40 hours).

As informed by Sauvé et al.,[18] we calculated probability of exposure as the proportion of jobs exposed to an agent with a frequency of exposure of at least 30 minutes per week, a “possible” or higher degree of confidence that the exposure occurred, and an FWI of at least 0.05 (corresponding to low exposure for 2 hours/week). We used versions of CANJEM coded into 3-, 5-, and 6-digit 2010 Standard Occupational Classification codes that summarized data collected from jobs held between 1985 and 2005 (closest to present day) and included occupations with a sample size of 5 or more jobs from 5 or more participants. We included 244 chemical agents from CANJEM, including specific chemicals, mixtures, families, or groups based on use. While the chemical agents vary in toxicity and health effects, all the evaluated exposures have some health risk to workers, and we did not conduct any risk assessment or weigh the exposures by toxicity in reporting our results.

Analytic Approach

We used R statistical software version 4.3.0 to merge and analyze the data.[24] We merged the data sets by 2018 Census codes at the specific (most granular) occupation level using crosswalks provided by the Bureau of Labor Statistics.[25] The final matrix included exposure information on 229 Census occupation codes based on 6220 jobs from CANJEM.

Exposure burden estimates. We estimated the number of US workers exposed for each occupational agent by multiplying the number of workers in each occupation by the agent–occupation specific probability of exposure and summing the estimated numbers across all occupations. We calculated the prevalence of exposed workers by dividing the estimated number of workers exposed by the total number of workers in the United States. We assumed workers employed in occupations without exposure information to have no exposure and included them in the denominator for the prevalence calculations. We calculated count and prevalence estimates for all workers and separately by sociodemographic group.

Exposure disproportionality estimates. Estimates of exposure disproportionality reflect the extent to which sociodemographic groups are over- or underrepresented in exposure burden. We calculated these estimates by finding the absolute and relative differences between the estimated number of exposed workers in a sociodemographic group and the number of workers expected to be exposed based on their overall proportion in the total workforce. We considered a group to be overrepresented if the estimated number of exposed workers in a particular sociodemographic group was in excess of the expected value.

Sensitivity analyses. We conducted 3 sensitivity analyses to examine the robustness of our results to alternative methodological decisions: (1) using a more stringent level of experts’ confidence of exposure when developing the JEM data, (2) excluding workers employed in specific Census occupation codes without exposure information from our calculations, and (3) using JEM data based on broader occupational categories, which improved coverage of workers with exposure information. Detailed methods are presented in Appendix A (available as a supplement to the online version of this article at https://ajph.org).

RESULTS

In 2021, the US workforce comprised approximately 152.6 million workers per CPS estimates. Average employment estimates by sociodemographic group are presented in Table 1. CANJEM exposure information meeting temporal and sample size selection criteria covered 229 of 525 (43.6%) 2018 US Census codes with employment data in the CPS, representing approximately 116.8 million of the 152.6 million (76.5%) workers counted in the 2021 US workforce (Appendix B Table A). Workers for whom exposure information was available were somewhat more likely to be male or from historically marginalized sociodemographic groups (Appendix B Table B). These workers were also more

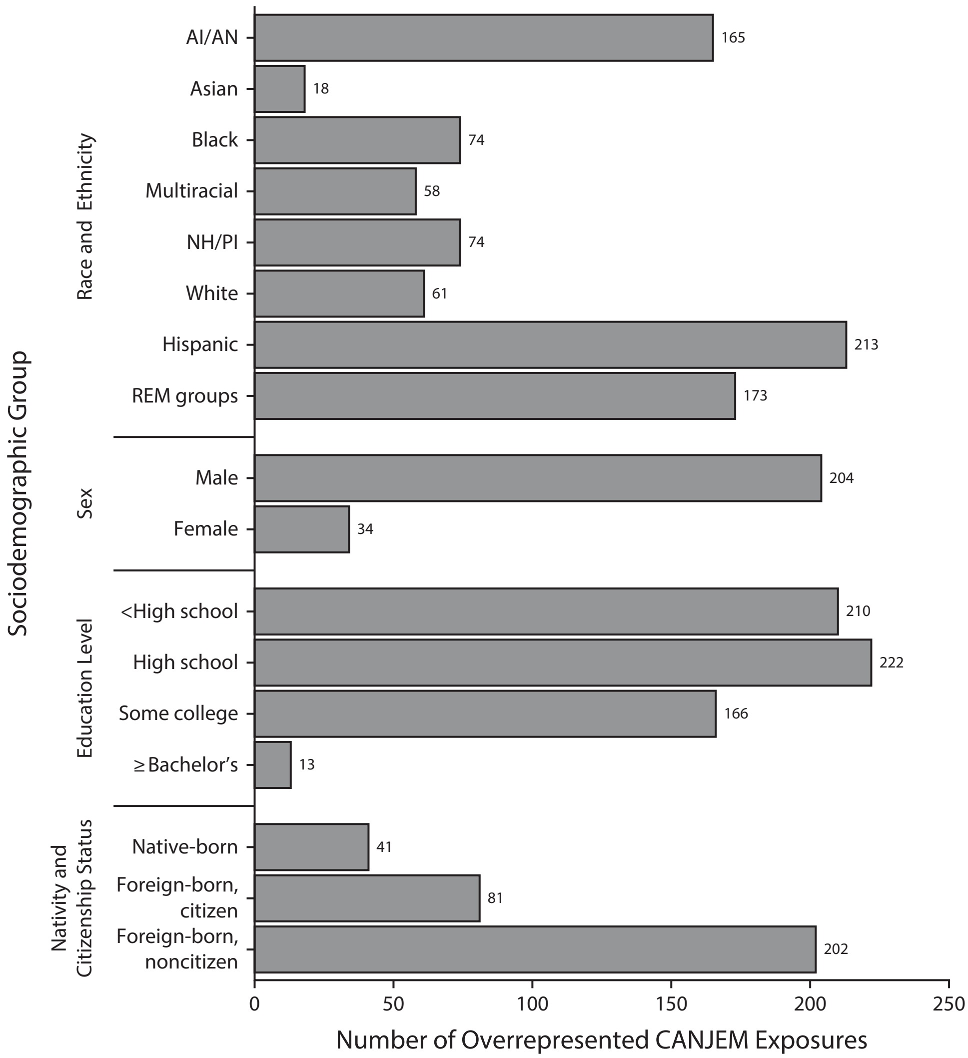

FIGURE 1— Total Number of Overrepresented Chemical CANJEM Exposures by Sociodemographic Group in the United States, 2021

Note. AI/AN = American Indian/Alaska Native; Black = Black/African American; CANJEM = Canadian job-exposure matrix; Hispanic = Hispanic/Latino; NH/PI = Native Hawaiian/Pacific Islander; REM groups = racial and ethnic minoritized groups; some college = some college or associate degree; White = non-Hispanic White. Persons within each race category are of any ethnicity, except for persons who identify as non-Hispanic White, and persons of Hispanic/Latino ethnicity are also counted in their preferred race category. REM groups include persons identifying as American Indian/Alaska Native, Asian, Black/African American, multiracial, Native Hawaiian/Pacific Islander, or Hispanic/Latino.

likely to be employed in blue-collar occupations (Appendix B Table C).

Table 2 shows the estimated number and percentage of US workers exposed to the 10 most-prevalent chemical agents, stratified by sociodemographic group. Among all workers, the most-prevalent exposures were cleaning and antimicrobial agents (22.5 million US workers exposed; 14.7% of total workforce), engine emissions (19.5 million; 12.8%), organic solvents (18.5 million; 12.1%), polycyclic aromatic hydrocarbons (15.4 million; 10.1%), and diesel engine emissions (12.7 million; 8.3%). The prevalence of exposures varied across sociodemographic groups.

Figure 1 shows the total number of exposures in which each sociodemographic group was disproportionately exposed. For both the 10 most prevalent agents and all agents combined, American Indian/Alaska Native, Hispanic/Latino, male, and foreign-born noncitizen workers; workers from REM groups as a whole; and workers with lower educational attainment were routinely overrepresented in exposure. Workers from other REM groups were estimated to experience disproportionate exposure to many of the 10 most-prevalent exposures, including Native Hawaiian/Pacific Islander (10 of 10),

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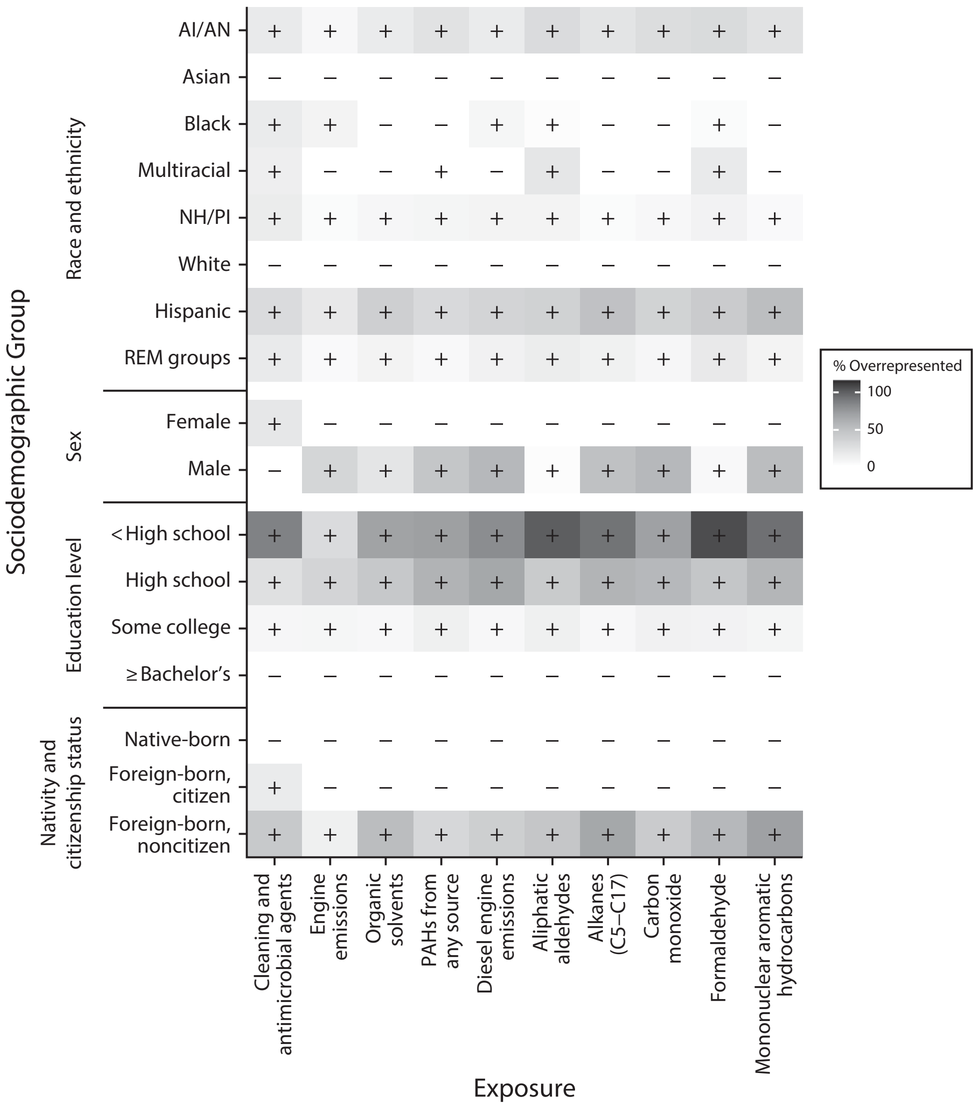

FIGURE 2— Magnitude of US Workers by Sociodemographic Group Overrepresented in Exposure to the 10 Most Prevalent Chemical Agents in CANJEM, 2021

Note. AI/AN = American Indian/Alaska Native; Black = Black/African American; CANJEM = Canadian job-exposure matrix; Hispanic = Hispanic/Latino; NH/PI = Native Hawaiian/Pacific Islander; PAHs = polycyclic aromatic hydrocarbons; REM groups = racial and ethnic minoritized groups; White = non-Hispanic White. A positive sign indicates overrepresentation of exposure (i.e., the number of workers exposed is in excess of the expected exposed based on the group's share of the total workforce). Darker shades of gray indicate higher percentages of overrepresentation. A negative sign indicates underrepresentation of exposure (i.e., the number of workers exposed is under the expected exposed based on the group's share of the total workforce). Persons within each race category are of any ethnicity, except for persons who identify as non-Hispanic White, and persons of Hispanic/Latino ethnicity are also counted in their preferred race category. REM groups include persons identifying as AI/AN, Asian, Black/African American, multiracial, Native Hawaiian/Pacific Islander, or Hispanic/Latino.

Black/African American (5 of 10), and multiracial (4 of 10) groups. Figure 2 shows the magnitude of overrepresentation of exposure to the 10 most-prevalent agents by sociodemographic group. Workers with lower educational attainment generally experienced increasingly greater magnitudes of disproportionate exposure, and Hispanic workers experienced the greatest magnitude of disproportionate exposure among all racial and ethnic groups.

A full interactive version of the data set is available for use by occupational and public health researchers, policymakers, practitioners, and others at https://deohs.washington.edu/us-exposure-burden. The online application allows users to generate tables and figures of the estimates for all agents and sociodemographic groups considered. Users can additionally explore estimates based on high-level

TABLE 2— Number, in Thousands, and Percentage of US Workers by Sociodemographic Group Exposed to the 10 Most Prevalent Chemical CANJEM Exposures, 2021

Sociodemographic Group	No. of Workers Exposed (% of Group Exposed)									
	Cleaning and Antimicrobial Agents	Engine Emissions	Organic Solvents	PAHs From Any Source	Diesel Engine Emissions	Aliphatic Aldehydes	Alkanes (C5–C17)	Carbon Monoxide	Formaldehyde	Mononuclear Aromatic Hydrocarbons
All	22 474 (14.7)	19 479 (12.8)	18 465 (12.1)	15 437 (10.1)	12 706 (8.3)	11 882 (7.8)	11 787 (7.7)	9 862 (6.5)	9 530 (6.2)	9 328 (6.1)
Race/ethnicity[a]										
AI/AN	292 (17.4)[b]	229 (13.7)[b]	238 (14.2)[b]	213 (12.7)[b]	164 (9.8)[b]	170 (10.1)[b]	159 (9.5)[b]	139 (8.3)[b]	137 (8.2)[b]	128 (7.7)[b]
Asian	1 347 (13.4)	800 (8.0)	805 (8.0)	599 (6.0)	453 (4.5)	658 (6.6)	433 (4.3)	379 (3.8)	533 (5.3)	329 (3.3)
Black	3 252 (17.4)[b]	2 642 (14.1)[b]	2 129 (11.4)	1 779 (9.5)	1 699 (9.1)[b]	1 509 (8.1)[b]	1 333 (7.1)	1 154 (6.2)	1 223 (6.5)[b]	964 (5.1)
Multiracial	544 (17.0)[b]	391 (12.2)	381 (11.9)	326 (10.2)[b]	265 (8.3)	304 (9.5)[b]	240 (7.5)	188 (5.9)	238 (7.4)[b]	189 (5.9)
NH/PI	116 (17.2)[b]	90 (13.4)[b]	88 (13.1)[b]	74 (11.1)[b]	61 (9.2)[b]	58 (8.6)[b]	54 (8.1)[b]	47 (6.9)[b]	47 (6.9)[b]	43 (6.5)[b]
White	12 234 (13.0)	11 559 (12.3)	10 642 (11.3)	9 130 (9.7)	7 255 (7.7)	6 566 (7.0)	6 688 (7.1)	5 750 (6.1)	5 174 (5.5)	5 358 (5.7)
Hispanic	5 275 (19.2)[b]	4 188 (15.3)[b]	4 642 (16.9)[b]	3 673 (13.4)[b]	3 109 (11.3)[b]	2 940 (10.7)[b]	3 178 (11.6)[b]	2 436 (8.9)[b]	2 444 (8.9)[b]	2 554 (9.3)[b]
REM groups[c]	10 240 (17.5)[b]	7 920 (13.5)[b]	7 822 (13.3)[b]	6 306 (10.8)[b]	5 452 (9.3)[b]	5 316 (9.1)[b]	5 099 (8.7)[b]	4 112 (7.0)[b]	4 356 (7.4)[b]	3 970 (6.8)[b]
Sex										
Female	12 763 (17.8)[b]	5 573 (7.8)	6 495 (9.1)	3 381 (4.7)	2 230 (3.1)	5 370 (7.5)	2 349 (3.3)	1 693 (2.4)	4157 (5.8)	1 750 (2.4)
Male	9 710 (12.0)	13 906 (17.2)[b]	11 970 (14.8)[b]	12 055 (14.9)[b]	10 477 (13.0)[b]	6 512 (8.1)[b]	9 438 (11.7)[b]	8 168 (10.1)[b]	5 373 (6.6)[b]	7 578 (9.4)[b]
Education level										
< High-school diploma	3 140 (27.5)[b]	1 905 (16.7)[b]	2 361 (20.6)[b]	1 993 (17.4)[b]	1 729 (15.1)[b]	1 796 (15.7)[b]	1 705 (14.9)[b]	1 264 (11.1)[b]	1 542 (13.5)[b]	1 360 (11.9)[b]
High-school diploma or equivalent	7 278 (18.7)[b]	6 754 (17.3)[b]	6 864 (17.6)[b]	6 307 (16.2)[b]	5 427 (13.9)[b]	4 358 (11.2)[b]	4 796 (12.3)[b]	3 942 (10.1)[b]	3 580 (9.2)[b]	3 759 (9.6)[b]
Some college	6 412 (15.9)[b]	5 606 (13.9)[b]	5 229 (13.0)[b]	4 620 (11.5)[b]	3 621 (9.0)[b]	3 559 (8.8)[b]	3 360 (8.3)[b]	2 912 (7.2)[b]	2 802 (7.0)[b]	2 692 (6.7)[b]
≥ Bachelor's degree	5 644 (9.1)	5 214 (8.4)	4 011 (6.5)	2 517 (4.1)	1929 (3.1)	2 170 (3.5)	1 926 (3.1)	1 744 (2.8)	1 606 (2.6)	1 518 (2.5)
Nativity and citizenship status										
Native-born	17 377 (13.8)	15 932 (12.6)	14 452 (11.5)	12 479 (9.9)	10 098 (8.0)	9 380 (7.4)	9 113 (7.2)	7 851 (6.2)	7 432 (5.9)	7 213 (5.7)
Foreign-born, citizen	2 321 (17.4)[b]	1 650 (12.4)	1 591 (11.9)	1 201 (9.0)	1 086 (8.1)	1 014 (7.6)	989 (7.4)	805 (6.0)	828 (6.2)	750 (5.6)
Foreign-born, noncitizen	2 775 (21.3)[b]	1 898 (14.5)[b]	2 422 (18.6)[b]	1 757 (13.5)[b]	1 522 (11.7)[b]	1 488 (11.4)[b]	1 685 (12.9)[b]	1 206 (9.2)[b]	1 270 (9.7)[b]	1 366 (10.5)[b]

Note. AI/AN = American Indian/Alaska Native; ≥ Bachelor's = bachelor's or advanced degree; Black = Black/African American; CANJEM = Canadian job-exposure matrix; Hispanic = Hispanic/Latino, NH/PI = Native Hawaiian/Pacific Islander; PAHs = polycyclic aromatic hydrocarbons; REM groups = racial and ethnic minoritized groups; Some college = some college or associate degree; White = non-Hispanic White.

[a]Persons within each race category are of any ethnicity, except for persons who identify as non-Hispanic White, and persons of Hispanic/Latino ethnicity are also counted in their preferred race category.

[b]Overrepresentation in exposure.

[c]REM groups include persons identifying as American Indian/Alaska Native, Asian, Black/African American, multiracial, Native Hawaiian/Pacific Islander, or Hispanic/Latino.

exposures and different occupational classification levels.

Results from our 3 sensitivity analyses suggest our conclusions are robust to alternative analytic decisions. In each case, the rank order of the most common occupational exposures (i.e., number of workers exposed) and the pattern of exposure disparities across sociodemographic groups were generally similar, resulting in the same conclusions as our primary analysis. The overall prevalence of the occupational exposures did vary in expected ways, with prevalence of exposures generally decreasing in sensitivity analysis 1 and increasing in sensitivity analyses 2 and 3. The full results and discussion of the sensitivity analyses are presented in Appendix A.

DISCUSSION

Our goal was to quantify the number of US workers exposed to a large set of chemical hazards and characterize patterns of exposure by sociodemographic strata. Our estimates suggest that a substantial number of US workers experience exposure to chemical hazards at work. Of the chemical exposures examined, the most common were cleaning and antimicrobial agents, engine emissions, organic solvents, polycyclic aromatic hydrocarbons, and diesel engine emissions. Our results are largely consistent with Doubleday et al.,[22] who applied a subset of the CANJEM data to workers in Federal Region 10 (Alaska, Idaho, Oregon, and Washington State) in 2019. Using a qualitative JEM to estimate cancer-related occupational exposures among California working women, Beckman et al.[21] similarly found cleaning and antimicrobial agents were among the most common exposures. However, there were also some differences in findings—for example, Beckman et al.[21] finding phthalates among the most common exposures, which were not as common in our study. This is likely attributable to the different goals and methods of the studies, the time period in which the exposure data were obtained, and increasing knowledge on the ubiquity of phthalates in occupational settings.

Exposures were found to be unevenly distributed by sociodemographic groups, driven by the occupational segregation of workers. This pattern was observed whether examining the sociodemographic distribution of the 10 most-prevalent exposures or the total number of overrepresented exposures. Particularly stark disparities in occupational exposures were observed across education and nativity, as workers with lower educational attainment and foreign-born (especially noncitizen) workers were disproportionately exposed to a larger number of agents compared with workers with higher educational attainment and native-born workers, respectively. Compared with non-Hispanic White workers, workers from REM groups as a whole, Hispanic/Latino workers, and American Indian/Alaskan Native workers were notably more likely to be disproportionately exposed to the agents examined in this analysis, while Asian workers were less likely to be disproportionately exposed. Though women were largely underrepresented in exposures in this analysis, they were disproportionately exposed to cleaning and antimicrobial agents, which is generally associated with service-providing occupations. In contrast, men were disproportionately exposed to the remaining top exposures, generally associated with goods-producing occupations. When looking at the magnitude of overrepresentation of exposure to the 10 most-prevalent exposures, a stark gradient was found across educational groups in which, generally, the lower the educational attainment level, the greater the degree of overrepresentation. Among all racial and ethnic groups, Hispanic/Latino workers experienced the greatest degree of overrepresentation of exposures.

Although Asian and female workers generally experienced a lower burden of the chemical exposures considered, this should not be interpreted as these populations needing less attention from occupational health practice and policy. There are work settings in which these populations have been documented to experience substantial chemical exposures (e.g., nail salons).[26] Our analysis may also somewhat underestimate their level of exposure because these workers have historically been underrepresented in occupational health research,[27] which may contribute to less knowledge of chemical hazards in jobs in which they are overrepresented. These gaps in historical occupational health knowledge may have affected the types of hazards evaluated and ascertainment of exposure within CANJEM, possibly leading to less or inaccurate information on exposures within occupations that women and Asian workers are overrepresented.

Overall, the sociodemographic groups found to carry the greatest burden of exposures in our analysis are consistent with Krieger's inverse hazard law, which postulates that the "accumulation of health hazards tends to vary inversely with the power and resources of the populations affected."[28(p1971)] Our findings are also generally consistent with earlier research on disparities in occupational health outcomes, in which workers from historically marginalized sociodemographic groups were observed to suffer more work-related injuries and illnesses.[7,11,12] While our study focused upstream on exposures rather than health outcomes, the consistency of findings provides some external validation to our study's results.

The results from our analysis call particular attention to cleaning and antimicrobial agents, identified as the most common exposure based on number of US workers exposed and which disproportionately burden marginalized working populations. Occupational cleaners and some studied cleaning and antimicrobial agents have been associated with various adverse respiratory effects, though specific causal agents and mechanisms of this broad category are still not well understood.[29] Many also do not have specific OSHA regulations, implying less knowledge, awareness, and control in the workplace. Attention to cleaning and antimicrobial agents is especially imperative and timely given enhanced cleaning and disinfecting measures in workplaces because of the COVID-19 pandemic.[30] Overall, our findings suggest that public health research and control efforts for cleaning and antimicrobial agents could be impactful for reducing occupational exposure and health inequities.

Limitations

First, it is important to acknowledge occupational hazards and populations that are not covered in this analysis. Military and institutionalized workers are excluded from the CPS, so these populations were not covered.[23] Approximately a quarter of the counted workforce did not have exposure information because of employment in occupations either missing from CANJEM or excluded on the basis of our selection criteria. The portion of the workforce without CANJEM-provided exposure information was disproportionately employed in white-collar and service occupations (88% employed within white-collar and service occupations; see Appendix B Table C) in which chemical exposures are less likely,[31] and would thus be expected to contribute minimally to the overall burden estimates.

In assuming workers without exposure information had no occupational exposure, we therefore expect that our results may slightly underestimate true exposure prevalence. Furthermore, the portion of the workforce with CANJEM-provided exposure information was slightly more likely to be from historically marginalized groups, including REM groups as a whole; Hispanic/Latino, Black/African American, and foreign-born noncitizen persons; and persons with lower educational attainment (see Appendix B Table B). We therefore expect that our results may slightly overestimate exposure disparities for those groups overrepresented in the sample with CANJEM-provided information. We tested the implications of our methodological decisions for handling workers without exposure information and found that our results and overall conclusions are robust to alternative analytic approaches (see sensitivity analyses 2 and 3 in Appendix A).

Overall, we feel our primary estimates balance adequate coverage of the workforce with valid estimates of exposure and reduced misclassification, while being specific enough to inform future research, practice, and policy. It is still important to consider that workers in some of the excluded occupations likely do experience relevant chemical exposures (e.g., home health aides) and are amenable to intervention efforts. Furthermore, while our analysis includes many chemicals, it does not cover other important occupational hazards, including psychosocial, biological, physical, and other chemical hazards.

In addition, the probabilities of exposures of the CANJEM data are static and based on jobs held by an urban Canadian population between 1985 and 2005, which is geographically and temporally different than the US population in 2021 and may not account for differences in industries, occupations, and regulations between the 2 populations or changes in exposures over time. These limitations could potentially lead to an over- or underestimation of exposures for some agents attributable to, for example, changes in federal and state regulations (e.g., crystalline silica), increased knowledge and awareness of certain occupational hazards (e.g., phthalates), changes in protective technologies (e.g., carbon monoxide), and changes in work practices (e.g., cleaning and antimicrobial agents because of the COVID-19 pandemic[30]). It is therefore important to consider the historical context of these agents when interpreting the study's findings. Despite these limitations, CANJEM is the most comprehensive JEM available for a wide range of occupations and chemical exposures in North America.

Another important limitation is exposure misclassification associated with the use of a JEM.[16] All individuals within an occupation code were assigned the same probability of exposure, and we were therefore unable to account for intraoccupational exposure differences across individuals or groups that may exist because of differences in assigned tasks or other occupational inequities, which have been previously documented.[7] Investigation of sex differences in the underlying CANJEM data by Lacourt et al.[32] found exposures were generally similar between men and women within the same occupation when employed in sufficient number. However, some notable differences in exposures between sexes were found, which could mostly be explained by different suboccupations, industries, or tasks performed within the same occupation. A subsequent investigation by Xu et al.[33] found that CANJEM's applicability to women may vary by agent. These studies suggest that there could be important intraoccupational exposure disparities that we are not able to account for in this analysis. Exposure disparities identified in our analysis can only be attributed to the differential distribution of workers across occupations (i.e., occupational segregation). Misclassification may have also been introduced from the use of crosswalks needed to merge the data sets by a common occupational classification system.[16]

The CPS also has important limitations to consider as our source of employment and demographic information. While we used the most recent year of employment data available, it is important to acknowledge that the US labor market in 2021 was in process of recovering from an economic recession caused by the COVID-19 pandemic in 2020.[34] Accordingly, our estimates are expected to be slightly different than current and future levels. We were also limited by the sociodemographic variables captured in the CPS, as more detailed demographic data would be useful in better identifying exposure disparities in specific populations. Lastly, while we did not investigate intersecting identities, an intersectional approach has been demonstrated to be useful in highlighting important social inequities and could be considered in future studies.[35]

Public Health Implications

To our knowledge, this is the first study to combine a population-based JEM with employment and demographic data to estimate the burden of occupational exposures and characterize exposure disparities by sociodemographic groups in the United States. JEM-based research approaches can help address the pressing need for occupational health surveillance to move upstream and characterize the burden of exposures rather than only health outcomes. Data from this analysis can inform occupational and public health research, policy, and interventions aimed at reducing the burden of disease in the United States. Our incorporation of sociodemographic information can additionally help inform equitable approaches to reduce health inequities and ensure health justice. Continual improvement to occupational exposure surveillance should be made a top priority in the United States as it is vital to the primary prevention of occupational injuries and illnesses and the broader understanding of work as a social determinant of health and health disparities. AJPH

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CONTRIBUTORS

S. C. Stephan-Recaido led the drafting of the article and led the data management, analysis, and interpretation. M. G. Baker and T. K. Peckham contributed to the conceptualization and design of the work, helped with interpretation of the data, and helped with drafting and reviewing the article for critically important intellectual content. J. Lavoué originated and designed the Canadian job-exposure matrix, contributed to the interpretation and analysis of the data, and reviewed the article for important intellectual content. All authors approved the final version of the article and agree to be held accountable for all aspects of the work and for ensuring questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

HUMAN PARTICIPANT PROTECTION

As this article was an analysis of de-identified existing secondary data, no human participant review was required.

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POSTPUBLICATION UPDATE

March 28, 2024: When originally published, the Figure and Table callouts in the first full paragraph beginning on p. 61 were reported incorrectly. The callouts were updated to the following order: Table 2, Figure 1, Figure 2.

Figure 1 and Figure 2 were swapped. Figure 1 is:

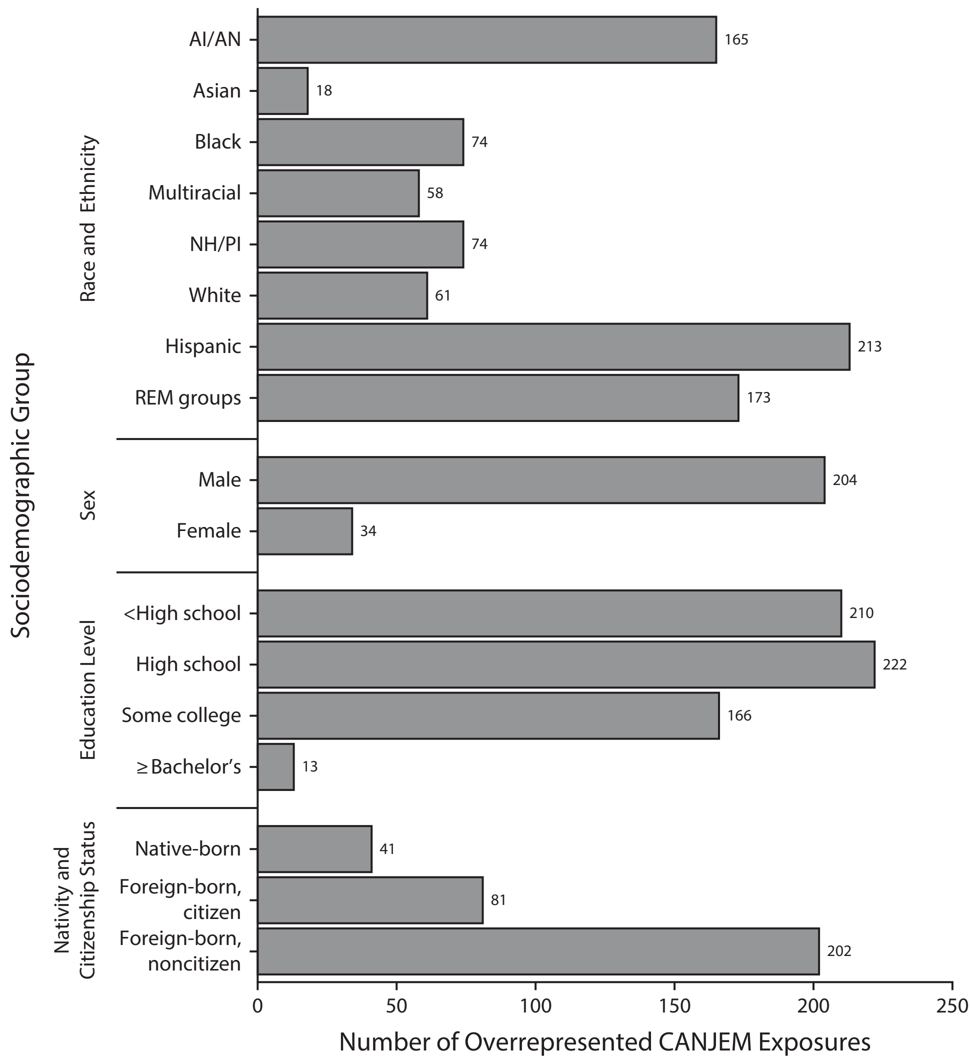

FIGURE 1— Total Number of Overrepresented Chemical CANJEM Exposures by Sociodemographic Group in the United States, 2021

Note. AI/AN = American Indian/Alaska Native; Black = Black/African American; CANJEM = Canadian job-exposure matrix; Hispanic = Hispanic/Latino; NH/PI = Native Hawaiian/Pacific Islander; REM groups = racial and ethnic minoritized groups; some college = some college or associate degree; White = non-Hispanic White. Persons within each race category are of any ethnicity, except for persons who identify as non-Hispanic White, and persons of Hispanic/Latino ethnicity are also counted in their preferred race category. REM groups include persons identifying as American Indian/Alaska Native, Asian, Black/African American, multiracial, Native Hawaiian/Pacific Islander, or Hispanic/Latino.

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Figure 2 is:

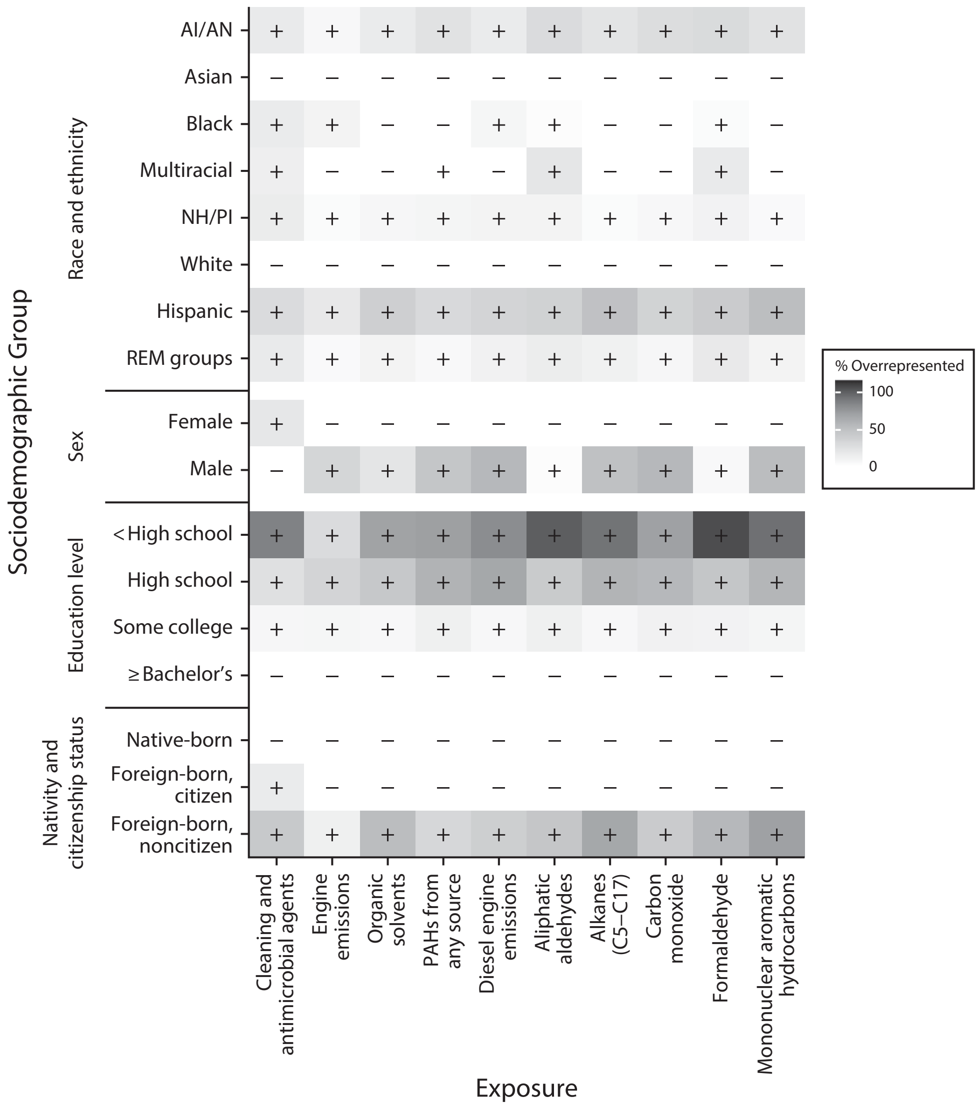

FIGURE 2— Magnitude of US Workers by Sociodemographic Group Overrepresented in Exposure to the 10 Most Prevalent Chemical Agents in CANJEM, 2021

Note. AI/AN = American Indian/Alaska Native; Black = Black/African American; CANJEM = Canadian job-exposure matrix; Hispanic = Hispanic/Latino; NH/PI = Native Hawaiian/Pacific Islander; PAHs = polycyclic aromatic hydrocarbons; REM groups = racial and ethnic minoritized groups; White = non-Hispanic White. A positive sign indicates overrepresentation of exposure (i.e., the number of workers exposed is in excess of the expected exposed based on the group's share of the total workforce). Darker shades of gray indicate higher percentages of overrepresentation. A negative sign indicates underrepresentation of exposure (i.e., the number of workers exposed is under the expected exposed based on the group's share of the total workforce). Persons within each race category are of any ethnicity, except for persons who identify as non-Hispanic White, and persons of Hispanic/Latino ethnicity are also counted in their preferred race category. REM groups include persons identifying as AI/AN, Asian, Black/African American, multiracial, Native Hawaiian/Pacific Islander, or Hispanic/Latino.

Jerome Lavoué's name appeared incorrectly in the full citation. On p. 63, in the Publication Information section, the correct author listing is "Lavoué J."

An erratum has since been issued, and this PDF has been updated to include the changes. AJPH

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