Health Impacts of Acute Wildfire Smoke Exposure on the Active-Duty Military Population at Joint Base Lewis-McChord, Washington, USA

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Abstract

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Wildfire smoke is an increasingly recognized health risk worldwide. This study investigates the short-term health impacts of acute wildfire smoke exposure among active-duty military personnel stationed at Joint Base Lewis-McChord (JBLM), Washington, USA, from 2018 to 2024. Using two $PM_{2.5}$ thresholds ($\geq$35.4 µg/m³, corresponding to the EPA's "Unhealthy for Sensitive Groups," and $\geq$20.4 µg/m³, based on previous studies), we assessed emergency department (ED) visits for respiratory, cardiovascular, and behavioral health outcomes. We employed conditional logistic regression models adjusting for daily average temperature and examined lag effects from 0 to 7 days prior to ED visits.

Our findings reveal that even moderate $PM_{2.5}$ levels were associated with increased odds of respiratory and behavioral health ED visits. For respiratory visits adverse effects emerged after a lag period (e.g., lag 4). Behavioral health outcomes including anxiety, mood disorders, and depression, were significantly

elevated several days post-exposure. This outcome underscores the potential mental health burden of wildfire smoke. While asthma and angina visits showed no consistent patterns, these analyses were limited by smaller sample sizes.

The results highlight the vulnerability of even a relatively healthy military population to wildfire smoke, with implications for broader public health. Future research should examine the role of preexisting conditions, additional pollutants, and exposures at other military installations. Mitigation strategies, such as an “air category” system, may help safeguard both military readiness and civilian well-being in an era of increasing wildfire frequency and intensity.

1. Background:

Globally, air pollution continues to be one of the biggest risk factors for disease and premature death. The World Health Organization estimates that in 2019 ambient (outdoor) air pollution caused 4.2 million premature deaths worldwide.[1] Ambient air pollution is known to increase the risk of many different health concerns such as exacerbations of current medical diagnosis, respiratory infections, heart disease, cancers, and other health effects.[2] However, more studies are also showing poor air quality, with higher levels of particulate matter 2.5 ($PM_{2.5}$), is associated with an increased risk of psychological distress and worsening mental health.[3] Health risks from air pollution can vary widely depending on the degree of air pollution, age of an individual, location, current health status, and many other factors.

Wildfires are a growing concern and contributing factor for increased air pollution. Because of the increased prevalence of wildfires, understanding the health impacts of exposure is becoming more important.[4,6,10,11] These wildfire trends in the U.S. are expected to increase in frequency and intensity.[4,12,13] The estimated area of burned land in the western U.S. by forest fire almost doubled between 1984-2015.[4,5] This estimated area of burned land is expected to continue worsening, with climate projections indicating wildfires in the western U.S. will continue increasing in frequency and intensity.[4,12,13] The Intergovernmental Panel on Climate Change (IPCC) estimates that due to climate change the length of wildfire season in North America will increase by 10–30%.[4,14] As a result, worsening air quality in the future during wildfire seasons is expected.[4,15]

Wildfire smoke is harmful to human health as it contains a large variety of compounds, including $PM_{2.5}$, acrolein, benzene, carbon monoxide, and polycyclic aromatic hydrocarbons.[4,16,17] It is concerning when individuals are exposed to these toxic compounds near the source. However, the concern remains and extends hundreds to thousands of kilometers away from the source.[4,18-20] Toxic compounds from wildfire smoke migrate long distances and can still potentially expose people thousands of miles downstream from the source.[4,21] However, the health effects of being exposed to wildfire smoke are just beginning to be understood.[4,21]

A recent study showed that in Washington State, when comparing wildfire smoke days to non-wildfire smoke days, there is an increase of odds for mortality of all ages with same-day and previous-day wildfire smoke exposure.[4] Another recent study demonstrates that in Washington State there is an increased odds of asthma visits in the emergency department (ED) immediately after and in all five days following initial wildfire smoke exposure days versus non-wildfire smoke days. There is also an increased odds of all-cause respiratory visits in all five days following initial exposure.[6] For cardiovascular visits, observations showed a small increased odds after several days following the initial exposure of wildfire smoke versus a non-wildfire smoke day. They also showed increased odds across all visit categories for a 10 $\mu g*m^{-3}$ increase in smoke-impacted $PM_{2.5}$.[6] This study highlights concerning evidence that wildfire smoke increases the risk of respiratory emergency department visits immediately following initial exposure and increased risk of cardiovascular emergency department visits several days following initial exposure.[6]

In addition to respiratory and cardiovascular effects, there is a growing body of studies now showing how wildfire smoke exposure, and higher levels of $PM_{2.5}$ exposure negatively impacts mental health. A recent study looked at mental health trends near 25 large wildfires in California over an eight-year span. This study demonstrated a statistically significant increase in psychoactive drug prescriptions in the six weeks after the fires. The increase of psychoactive drug prescriptions included new and renewed prescriptions for depression, anxiety, and bipolar disorder.[22]

For active-duty military personnel, numerous studies have been conducted on exposures of poor air quality in deployed settings to include exposure to burn pits, sandstorms, and other fume inhalations.[23] Hundreds of thousands of U.S. military personnel deployed to the Middle East between 2001 to 2013 were exposed to burn pits, sandstorms, exhaust fumes, and other toxic exposures that increased the risk for long term health conditions to include asthma.[23] Analysis of 75,770 military personal showed that up to 5% developed new onset of asthma on deployment during this period.[23]

Very few military health studies conduct research on the health impacts of the military population in non-deployed settings within the United States, and the impacts of their medical readiness due to episodes of poor air quality and increased exposure to $PM_{2.5}$. Over the past 12 years we have found only two studies. One 2023 study showed that $PM_{2.5}$ is a major independent contributor to the development of chronic rhinosinusitis.[24] The second study was a 2015 ecological study highlighting that short-term changes in ambient concentrations of particulate matter are associated with short-term changes in acute respiratory-related health outcomes in a healthy, active-duty subgroup.[25] Moreover, we have not found any studies that specifically examine the health effects of active-duty military personnel due to wildfire smoke exposure on a military installation within the United States.

Joint Base Lewis-McChord (JBLM), WA is a large military installation located in western Washington along the Seattle-Olympia corridor. It has a population of approximately 300,000 people.[26] JBLM experiences intermittent times of poor air quality due to wildfire smoke. Despite these episodes of poor air quality, military day-to-day activities, operations, and training typically continues during these times. No matter the weather or circumstances, military units are continuously training for future missions. Training is critical for military preparation. However, at the same time soldiers must also be medically ready. Medical readiness is the state of health that allows soldiers to conduct military operations when needed. Soldiers that are sick or have certain medical conditions are unable to deploy or may not perform optimally. This then inhibits military units from successfully accomplishing their respective missions. Therefore, in this study we aim to investigate the health effects of acute exposure to wildfire smoke on active-duty military personnel stationed at JBLM and how that may impact military health readiness.

2. Design and Methods:

2.1 Time period and study location

The study period spanned June-September,[4,6] 2018-2024. We include October in the year 2022 as there was a known large wildfire in Washington State at that time.[27] The June-September time interval, including October 2022, all host major wildfire smoke events.[4,6,27] However, we excluded the days of 4 & 5 July of each year due to the celebration of Independence Day and the possible confounding of firework smoke.

The study location included the ED at Madigan Army Medical Center located on JBLM. The population on JBLM is approximately 300,000 thousand people that includes over 30,000 active-duty soldiers stationed at JBLM at any given time (Table 1).[26]

Table 1. Demographic Characteristics and Diagnoses by Year (All years, 2018–2024)

		All years	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
Total Encounters[a]		10882	1376	1457	1617	1610	1854	1440	1528
Demographics									
Age Group (%)	17-25	5459 (50.2)	758 (55.1)	774 (53.1)	837 (51.8)	830 (51.6)	904 (48.8)	645 (44.8)	711 (46.6)
	26-35	3721 (34.2)	429 (31.2)	455 (31.2)	534 (33.0)	531 (33.0)	661 (35.7)	568 (39.4)	543 (35.6)
	36-45	1383 (12.7)	156 (11.3)	179 (12.3)	188 (11.6)	200 (12.4)	233 (12.6)	193 (13.4)	234 (15.3)
	46-55	282 (2.6)	31 (2.3)	44 (3.0)	53 (3.3)	40 (2.5)	51 (2.8)	31 (2.2)	32 (2.1)
	>=56	33 (0.3)	2 (0.1)	5 (0.3)	4 (0.2)	7 (0.4)	5 (0.3)	3 (0.2)	7 (0.5)
Sex (%)	Male	7683 (70.6)	1011 (73.5)	1048 (71.9)	1150 (71.1)	1102 (68.4)	1302 (70.2)	1027 (71.3)	1043 (68.3)
	Female	3199 (29.4)	365 (26.5)	409 (28.1)	467 (28.9)	508 (31.6)	552 (29.8)	413 (28.7)	485 (31.7)
Branch of Service (%)	Army	9266 (85.1)	1197 (87.0)	1224 (84.0)	1425 (88.1)	1355 (84.2)	1554 (83.8)	1206 (83.8)	1305 (85.4)
	Air Force	1223 (11.2)	131 (9.5)	193 (13.2)	153 (9.5)	199 (12.4)	212 (11.4)	177 (12.3)	158 (10.3)
	Navy	305 (2.8)	36 (2.6)	33 (2.3)	27 (1.7)	38 (2.4)	67 (3.6)	48 (3.3)	56 (3.7)
	Marine	52 (0.5)	7 (0.5)	4 (0.3)	6 (0.4)	13 (0.8)	11 (0.6)	7 (0.5)	4 (0.3)
	Other[b]	36 (0.3)	5 (0.4)	3 (0.2)	6 (0.4)	5 (0.3)	10 (0.5)	2 (0.1)	5 (0.3)
Rank Group (%)	E1-E4	6074 (55.8)	852 (61.9)	846 (58.1)	928 (57.4)	902 (56.0)	1031 (55.6)	732 (50.8)	783 (51.2)
	E5-E6	2917 (26.8)	323 (23.5)	369 (25.3)	440 (27.2)	442 (27.5)	477 (25.7)	444 (30.8)	422 (27.6)
	E7-E9	865 (7.9)	97 (7.0)	125 (8.6)	109 (6.7)	125 (7.8)	166 (9.0)	116 (8.1)	127 (8.3)
	O1-O2	265 (2.4)	24 (1.7)	32 (2.2)	29 (1.8)	36 (2.2)	62 (3.3)	37 (2.6)	45 (2.9)
	O3-O5	562 (5.2)	54 (3.9)	63 (4.3)	80 (4.9)	85 (5.3)	87 (4.7)	88 (6.1)	105 (6.9)

	O6-O10	33 (0.3)	8 (0.6)	7 (0.5)	5 (0.3)	1 (0.1)	5 (0.3)	4 (0.3)	3 (0.2)
	Warrant Officer	166 (1.5)	18 (1.3)	15 (1.0)	26 (1.6)	19 (1.2)	26 (1.4)	19 (1.3)	43 (2.8)
DOD Occupation Code Group (%)	Infantry	1032 (9.5)	135 (9.8)	147 (10.1)	160 (9.9)	166 (10.3)	186 (10.0)	113 (7.8)	125 (8.2)
	Supply Administration	781 (7.2)	80 (5.8)	110 (7.5)	114 (7.1)	128 (8.0)	137 (7.4)	93 (6.5)	119 (7.8)
	Automotive	516 (4.7)	69 (5.0)	58 (4.0)	86 (5.3)	63 (3.9)	97 (5.2)	63 (4.4)	80 (5.2)
	Aircraft	428 (3.9)	54 (3.9)	51 (3.5)	55 (3.4)	74 (4.6)	80 (4.3)	63 (4.4)	51 (3.3)
	Motor Vehicle Operator	424 (3.9)	52 (3.8)	56 (3.8)	62 (3.8)	71 (4.4)	69 (3.7)	57 (4.0)	57 (3.7)
	Combat Operations Control	423 (3.9)	61 (4.4)	58 (4.0)	58 (3.6)	49 (3.0)	73 (3.9)	62 (4.3)	62 (4.1)
	Food Service	414 (3.8)	56 (4.1)	58 (4.0)	62 (3.8)	64 (4.0)	80 (4.3)	49 (3.4)	45 (2.9)
	Medical Care and Treatment	400 (3.7)	58 (4.2)	59 (4.0)	73 (4.5)	55 (3.4)	57 (3.1)	41 (2.8)	57 (3.7)
	Law Enforcement	330 (3.0)	34 (2.5)	43 (3.0)	59 (3.6)	47 (2.9)	65 (3.5)	38 (2.6)	44 (2.9)
	Other[c]	6134 (56.4)	777 (56.5)	817 (56.1)	888 (54.9)	893 (55.5)	1010 (54.5)	861 (59.8)	888 (58.1)
Diagnoses[a,d]									
	All Respiratory	2803 (25.8%)	432 (31.4%)	490 (33.6%)	291 (18%)	352 (21.9%)	437 (23.6%)	391 (27.2%)	410 (26.8%)
	All Cardiac	710 (6.5%)	81 (5.9%)	137 (9.4%)	96 (5.9%)	95 (5.9%)	114 (6.1%)	89 (6.2%)	98 (6.4%)
	All Mental Health	2455 (22.6%)	393 (28.6%)	292 (20%)	383 (23.7%)	413 (25.7%)	459 (24.8%)	282 (19.6%)	233 (15.2%)

	Cardio and Respiratory Signs and Symptoms	4510 (41.4%)	464 (33.7%)	545 (37.4%)	723 (44.7%)	647 (40.2%)	736 (39.7%)	657 (45.6%)	738 (48.3%)
	Asthma	64 (0.6%)	13 (0.9%)	10 (0.7%)	13 (0.8%)	6 (0.4%)	12 (0.6%)	7 (0.5%)	3 (0.2%)
	MI/Angina	28 (0.3%)	7 (0.5%)	3 (0.2%)	6 (0.4%)	3 (0.2%)	2 (0.1%)	2 (0.1%)	5 (0.3%)
	Anxiety	357 (3.3%)	48 (3.5%)	54 (3.7%)	72 (4.5%)	42 (2.6%)	57 (3.1%)	54 (3.8%)	30 (2%)
	Depression	334 (3.1%)	60 (4.4%)	36 (2.5%)	55 (3.4%)	63 (3.9%)	58 (3.1%)	42 (2.9%)	20 (1.3%)
	Mood Disorders	382 (3.5%)	68 (4.9%)	43 (3%)	58 (3.6%)	73 (4.5%)	66 (3.6%)	47 (3.3%)	27 (1.8%)
	Wheezing	706 (6.5%)	55 (4%)	86 (5.9%)	125 (7.7%)	83 (5.2%)	94 (5.1%)	120 (8.3%)	143 (9.4%)
	Cough	876 (8%)	63 (4.6%)	97 (6.7%)	82 (5.1%)	101 (6.3%)	155 (8.4%)	160 (11.1%)	218 (14.3%)

[a] This includes all encounters total, and total encounters in each respective diagnosis category, regardless of availability of air quality data at any given lag day. When the models were fit, any encounter missing air quality data was excluded.

[b] Other includes members of the Coast Guard, Public Health Corps, and National Oceanic and Atmospheric Administration.

[c] All Department of Defense Occupational code groups.

[d] An encounter can be counted in multiple outcome categories as all listed diagnosis codes are used to identify the outcome.

2.2 Exposure assessment

We identified two separate thresholds of $PM_{2.5}$, a high and low threshold, to define a wildfire smoke day within the area nearest Madigan Army Medical Center. First, for the high threshold we used the daily average $PM_{2.5}$ of ≥ 35.4 µg m^{-3} as this is the Air Quality Index breakpoint, defined by the EPA, as going from Moderate and Unhealthy for Sensitive Groups.[28] Secondly, for the low threshold we used the daily average $PM_{2.5}$ of ≥ 20.4 µg m^{-3} as used by Doubleday et al. in a 2023 publication about wildfire smoke exposure and emergency department visits in Washington State. A $PM_{2.5}$ of 20.4 µg m^{-3} was based on the cut point between Moderate and Unhealthy for Sensitive Groups in the previously used

Washington Air Quality Advisory.[6] All regression models are adjusted for daily average temperature to account for its potential confounding effects on both $PM_{2.5}$ levels and health outcomes (Table 2).

Table 2. Summary of Daily Average $PM_{2.5}$ (High and Low Thresholds) and Temperature by Year

	All years	2018	2019	2020	2021	2022	2023	2024
High Threshold Days								
Number of Days	28	7	0	10	0	7	3	1
PM25- Mean (SD)	79.575 (42.317)	62.757 (20.088)	NaN (NA)	106.68 (55.53)	NaN (NA)	55.614 (22.041)	85.267 (30.093)	76.9 (NA)
Temperature (F)- Mean (SD)	64.893 (6.356)	68.714 (4.03)	NaN (NA)	64.8 (5.095)	NaN (NA)	57.857 (4.811)	70.333 (4.041)	72 (NA)
Low Threshold Days								
Number of Days	45	8	0	12	3	16	4	2
PM25- Mean (SD)	59.818 (41.973)	58.037 (22.892)	NaN (NA)	93.383 (59.057)	24.4 (5.546)	40.131 (20.033)	71.3 (37.202)	53.2 (33.517)
Temperature (F)- Mean (SD)	65.333 (7.271)	67.375 (5.317)	NaN (NA)	65.917 (5.334)	80.667 (3.786)	59.188 (4.151)	70.25 (3.304)	70 (2.828)
Non-Wildfire Days								
Number of Days	805	114	120	110	98	132	117	114
PM25- Mean (SD)	4.594 (3.218)	4.199 (3.689)	4.296 (2.055)	4.195 (2.7)	4.636 (2.814)	5.755 (4.129)	5.138 (3.229)	3.753 (2.887)
Temperature (F)- Mean (SD)	64.297 (5.582)	64.053 (5.921)	64.817 (4.793)	65.055 (5.117)	63.969 (5.383)	64.356 (6.573)	63.784 (5.475)	64 (5.484)

JBLM does not have its own air quality sensors. Therefore, we used the "nearest monitor" approach.[6] The air quality data, to include the daily $PM_{2.5}$ and daily temperature, was obtained from publicly available data from the Puget Sound Clean Air Agency and the U.S. Environmental Protection Agency.[29,30] The sensor used for air quality data is a Met One Bam sensor, and is the closest sensor to

Madigan Army Medical Center, which is located approximately 7 miles from Madigan Army Medical Center on Tacoma South L Street.[29,30]

2.3 Data Acquisition

As this study is focused on comparing the occurrence of certain diagnoses of interest, the natural focus of the first phase of data acquisition was on encounter data. MDR (Military Health System Data Repository)'s Genesis BDE (Bulk Data Extract) 3.0 tables were filtered for encounters at Madigan Army Medical Center that contained (in the first 10 diagnosis positions) any member codes of the ICD10 code groupings given in Table 3. Patient ID, patient age, patient sex, visit date, encounter type (clinic, ER, etc.), race, and beneficiary category (active duty, retiree, etc.) were collected. The collection was limited to individuals under 90 years of age. The encounter data were then further filtered to include only ER visits by active-duty patients during each year's wildfire season, as discussed in section 2.1, time period and study location. The remaining demographic information was acquired by merging the relevant variables for each patient from the MDR VM6BEN DEERS (Defense Enrollment Eligibility Reporting System) table corresponding to the fiscal month and year of each visit. Patient IDs and visit dates were removed and replaced with SHA256 hashes (with randomly generated 256-bit salt) before any data were downloaded from MDR.

After all the encounter and demographic data were acquired, the MDR data were then merged with air quality data (sourced from the Puget Sound Clean Air Agency and the U.S. Environmental Protection Agency).[29,30] This merge was performed in such a way that each row of the MDR data was repeated (with different air quality data, including for lag days up to 7) for each referent day. An indicator variable which was set to 1 for rows containing air quality data for an encounter day and 0 otherwise was established to delineate which rows were encounter days and which were referent days. If overlap occurred such that another same-patient-same-diagnosis-group encounter occurred on what would have otherwise been a referent day for any encounter, the overlapping days were considered encounters in all same-patient-same-diagnosis encounter/referent strata in which they appeared. Finally, the data were filtered by diagnosis code grouping (removing any same-patient-same-day-same-diagnosis-group encounters) and fed to the model fitting functions.

Table 3. Diagnoses and ICD-10 Codes

Diagnosis	ICD-10 Codes
All-Cause Respiratory	J00-J99, Diseases of the respiratory system
All-Cause Cardiac	I00-I99, Diseases of the circulatory system
All-Cause Behavioral Health	F01-F99, Mental, behavioral and neurodevelopmental disorders
All-Cause Cardio & Resp Signs/Symptoms	R00-R09, Symptoms and signs involving the circulatory and respiratory systems
Asthma	J45, asthma
Angina/Myocardial Infarction	I20-25, Ischemic heart disease
Anxiety	F40-41, Phobic anxiety disorders/Other anxiety disorders
Mood Disorders	F30-39, Mood [affective] disorders
Depression	F32-33, Depressive episodes/Major depression disorder
Wheezing	R06, Abnormalities of breathing
Coughing	R05, Cough

2.4 Outcome assessment

We selected ED encounters at Madigan Army Medical Center from all active-duty service members enrolled in the Madigan Army Medical Center Military Health System (MHS) throughout our study period. The health data was pulled from the MHS Data Repository (MDR) using the SAS Enterprise Guide. The MHS contains patient demographic information, data about each patient ED encounter, and clinic information pertinent to each patient. We examined the following groups of diagnoses as our outcomes of interest: all-cause respiratory (ICD-10-CM Codes: J00-J99, Diseases of the respiratory system), all-cause cardiovascular (ICD-10-CM Codes: I00-I99, Diseases of the circulatory system), all-cause cardiovascular and pulmonary symptoms (ICD-10-CM Codes: R00-R09, Symptoms and signs involving the circulatory and respiratory systems), all-cause behavioral health (ICD-10-CM Codes: F01-F99, Mental, behavioral and neurodevelopmental disorders), asthma (ICD-10-CM Codes: J45, asthma), Angina/Myocardial Infarction (MI) (ICD-10-CM Codes: I20-25, Ischemic heart disease), Anxiety (ICD-10-CM Codes: F40-41, Phobic anxiety disorders/Other anxiety disorders), Mood disorders (ICD-10-CM Codes: F30-39, Mood [affective] disorders), Depression (ICD-10-CM Codes: F32-33, Depressive episodes/Major depression disorder), wheezing (ICD-10-CM Codes: R06, Abnormalities of breathing), and cough (ICD-10-CM Codes: R05, Cough) (Table 3). We excluded all active-duty encounters from the study under the following conditions: 1) visits not seen in the ED, 2) visits not within the study time period, 3) patients who had multiple same-day encounters that were given the same diagnosis, 4) encounters that administratively did not match an active-duty military member, 5) all encounters that include a COVID-19 diagnosis, and 6) days for which the corresponding lag did not have air quality data.

2.5 Data analysis

We conducted a time-stratified case-crossover design to evaluate the effect of wildfire smoke presence versus absence on active-duty military personnel receiving a certain medical diagnosis during ED visits.[6] This design uses conditional logistic regression to find the odds of getting a medical diagnosis when comparing exposures within individuals during a time-stratified referent window.[6] For both exposure definitions, a high and low threshold of daily average $PM_{2.5}$, we examined lag effects from the same day of the ED visit (index day or lag 0) and up to 7 lag days prior, while adjusting for daily average temperature. In all models, the analysis was stratified by the individual ED identifier and the date of the visit. The exposure on the index date (lag 0), or a prior day for lagged exposures, is compared to the exposure on referent days. Referent days are defined as 1) the same days of the weeks that are not on the same week as the index day, and 2) within the same month of the index day.[6] We report the odds ratio (OR) and confidence intervals (CI) for a given ED diagnosis outcome on wildfire smoke days compared to non-wildfire smoke days. We report the OR separately for lag days 0–7 for all outcomes to give time for symptoms to develop and the patients deciding to go to the ED.[6] Lag 0 represents initial exposure on the day of the ED visit. Lag 1 represents initial exposure on the day prior to the ED visit, etc. Thus, the strata for the conditional logistic regressions were formed by each unique combination of patient ID and encounter date. Every stratum was comprised of an encounter day and its attendant referent days. If any strata contained referent days (as defined above) on which a same-patient same-diagnosis-group encounter occurred, those days were considered additional encounter days in all strata for that patient. Thus, some strata include multiple encounters.

We ran a binary conditional logistic regression model for the combined years (2018-2024) to yield an overall OR for the study period, adjusting for temperature by including the average daily temperature on the corresponding lag day as a numerical covariate. All analyses were performed using R version 4.0.2 and the R package survival version 3.1-12.

The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines were followed.[31] The study's reporting adhered to a checklist of items to ensure a clear and transparent presentation of our study's methodology, results, and conclusions (Table S4 (Supplemental Digital Content)).

3. Results:

Below, we report the findings for the following outcomes of interest for both high and low thresholds using OR's and CI's: All-cause respiratory, all-cause cardiovascular, all-cause cardiovascular and pulmonary symptoms, all-cause behavioral health, asthma, myocardial infarction/angina, anxiety, mood disorders, depression, wheezing, and cough. For all results, the OR describes the odds of the diagnosis given in the ED when exposed to a wildfire smoke day versus a non-wildfire smoke day at the corresponding lag day, adjusting for daily average temperature. A summary of the odds of receiving a diagnosis in the ED when exposed to a wildfire smoke day versus a non-wildfire smoke day with each lag day is summarized in Figure 1 and Tables S5.

All-Cause Respiratory ED Visits

High Threshold: For the high threshold exposure models of all-cause respiratory ED visits, the OR differed by lag day. Lag 0 showed a protective association with a statistically significant 26% reduction in odds of an all-cause respiratory ED diagnosis (OR = 0.74,95% confidence interval [CI]: 0.56–0.98, $p = 0.036$). Lag 4 showed 34% increased odds of diagnosis (OR = 1.34, 95% CI: 1.04–1.73, $p = 0.023$). The estimates for the other lag days were not statistically significant.

Low Threshold: In the low threshold models, a similar pattern was observed. Lag 0 showed a protective association when exposed to a wildfire smoke day with 29% lower odds of diagnosis (OR = 0.71, 95% CI: 0.56–0.90, p = 0.004). Lag 4 and lag 7 showed 33% and 25% increased odds diagnosis in the ED (OR = 1.33, 95% CI: 1.06-1.65, p = 0.012 and OR = 1.25, 95% CI: 1.01-1.56, p = 0.043 respectively) (Figure 1, Table S5).

All-Cause Cardiac ED Visits

High Threshold: We found that none of the lag-specific associations reached statistical significance (ORs ranging from approximately 0.85 to 1.11; all p > 0.1).

Low Threshold: Exposure on lag 0 showed a protective association with a statistically significant 39% reduction in the odds of a cardiac ED visit (OR = 0.61, 95% CI: 0.50–1.18, p = 0.038). The associations at other lags were not statistically significant (Figure 1, Table S5).

All-Cause Behavioral Health ED Visits

High Threshold: For outcomes related to all-cause behavioral health, we found the pattern of association with a high threshold $PM_{2.5}$ exposure to be more consistent. There were no significant associations observed for lag 0–1; At lag 2 there was a trend toward increased odds that reached either borderline or statistical significance at several lags (e.g., at lag 4 OR = 1.60, 95% CI: 1.24–2.06, p < 0.001; at lag 5 OR = 1.38, 95% CI: 1.06-1.81, p = 0.019).

Low Threshold: Significant positive associations of an ED diagnosis were again observed at lag 3 (OR = 1.27, 95% CI: 1.01-1.60, p = 0.040), lag 4 (OR = 1.44, 95% CI: 1.16-1.80, p = 0.001) and at lag 5 (OR = 1.39, 95% CI: 1.10-1.75, p = 0.005) (Figure 1, Table S5).

All-Cause Cardiac and Respiratory Signs and Symptoms ED Visits

High Threshold: High threshold models yielded null associations except for lag 4, which was associated with a 26% increase in odds (OR = 1.26, 95% CI: 1.02–1.57, p = 0.034).

Low Threshold: In low threshold models, significant positive associations were observed at lag 3 (OR = 1.23, 95% CI: 1.03–1.46, p = 0.022) and at lag 4 (OR = 1.26, 95% CI: 1.05–1.51, p = 0.012), with similar patterns noted at lag 7 (Figure 1, Table S5).

Asthma ED Visits

High / Low Threshold: Models for asthma exacerbation were estimated on a smaller subset of encounters. In both high and low threshold analyses, no statistically significant associations between $PM_{2.5}$ exposure and asthma were observed at any lag, with wide confidence intervals, likely reflecting the limited sample size (Figure 1, Table S5).

Angina/Myocardial Infarction ED Visits

High / Low Threshold: Analyses for angina exacerbation/MI were based on relatively few events. For several lag days the estimates were unstable (evidence by extreme coefficient values and warnings about convergence), precluding reliable interpretation (Table 1, Table S5).

Anxiety, Mood Disorders, and Depression ED Visits

High Threshold: High threshold models for *anxiety* demonstrated statistically significant increases in odds at lag 2 (OR = 2.12, 95% CI: 1.09–4.13, p = 0.027) and borderline at lag 4 (OR = 1.91, 95% CI: 0.99–3.69, p = 0.055). For *mood disorders*, high threshold exposure at lag 4 and 7 were significantly associated with increased odds (OR = 1.97, 95% CI: 1.07–3.65, p = 0.030 and OR = 1.91, 95% CI: 1.03–3.56, p = 0.041 respectively). For *depression* the most pronounced association was observed with increased odds at lag 2, 4, and 7 (OR = 2.14, 95% CI: 1.09–4.22, p = 0.027; OR = 2.15, 95% CI: 1.15–4.02, p = 0.017; OR = 1.91, 95% CI: 1.00–3.63, p = 0.050 respectively).

Low Threshold: Low threshold exposure was significantly associated with increased odds of *mood disorders* at lags 3 and 4 (OR = 1.90, 95% CI: 1.12–3.19; p = 0.018; OR = 1.77, 95% CI: 1.05–2.97, p = 0.031) and *depression* at lags 2, 3, and 4 (OR = 1.95, 95% CI: 1.07–3.53, p = 0.028; OR = 2.13, 95% CI: 1.23–3.70, p = 0.007; OR = 1.93, 95% CI: 1.12–3.33, p = 0.018) (Figure 1, Table S5).

Wheezing and Coughing ED Visits

High Threshold: For wheezing high and low threshold models produced no significant associations. For coughing, high threshold analyses were null at all lags.

Low Threshold: Among the low threshold models, only the lag 4 exposure demonstrated a significant association with increased odds of an ED diagnosis of coughing (OR = 1.55, 95% CI: 1.02–2.37, p = 0.041) (Figure 1, Table S5).

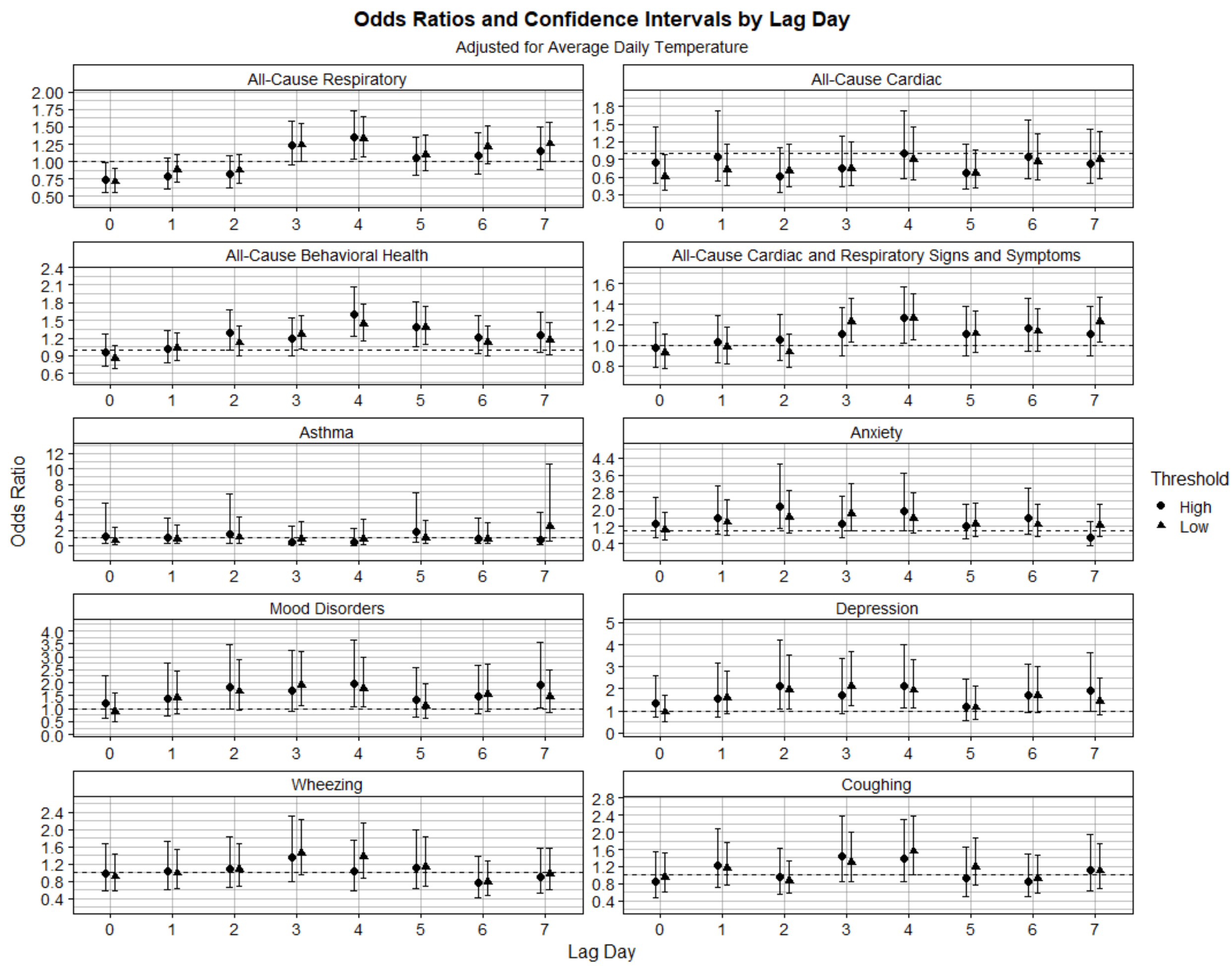

Figure 1. Lag-specific odds ratios of ED visits by outcome comparing wildfire smoke versus non-wildfire smoke days, controlling for daily average temperature. Note: y-axes vary by outcome to allow for visualization of results. Same ED encounter could be included in multiple outcomes.

Summary of Temperature Effects

Across outcomes, the affect for daily average temperature when adjusted for a $PM_{2.5}$ threshold was included in each model. In several models—particularly those predicting behavioral health ED visits—temperature was associated with an increased odds of receiving a diagnosis in the ED, although its adjusted effect size was generally modest compared with that of $PM_{2.5}$ exposure (Table S5 and Table S6).

4. Discussion:

This study evaluated the acute effects of wildfire smoke exposure, using daily average $PM_{2.5}$ levels, on ED visits among active-duty military personnel at JBLM and enrolled in the Madigan Army Medical Center MHS between 2018 and 2024. Using two exposure thresholds (a high threshold of $\geq$35.4 $\mu g/m^3$, corresponding to the EPA's breakpoint for "Unhealthy for Sensitive Groups," and a lower threshold of $\geq$20.4 $\mu g/m^3$), and examining lag effects from 0 to 7 days, our analyses revealed that wildfire smoke is significantly associated with a range of adverse health outcomes, including respiratory, cardiac, and behavioral health events. Even exposures in the lower threshold, defined by the EPA as a "moderate" category in the Air Quality Index, were linked to significant changes in ED visit risk. This suggests that health effects may occur at levels below those traditionally used for public health warnings. Taken together, these results suggest that acute exposure to wildfire smoke–related $PM_{2.5}$ is associated with short-term alterations in the risk of ED visits among military personnel. These temporal patterns may reflect the complex interplay between acute exposure, symptom development, and health-seeking behavior. The consistency of some associations across both the high and low threshold definitions of exposure supports the robustness of these findings.

Summary of Overall Results

For respiratory outcomes, the high threshold models sometimes indicated a protective association at lag 0 (e.g., OR $\approx$ 0.74) but revealed adverse effects at intermediate lags (e.g., OR $\approx$ 1.34 at lag 4). Similar trends were observed with the low threshold models where exposures, even within the moderate air quality range, were associated with increased odds at specific lag days. In analyses of behavioral health outcomes—including anxiety, mood disorders, and depression—the models demonstrated significant associations at various lag periods, underscoring the sensitivity of mental health to acute wildfire smoke exposure. Outcomes for wheezing and coughing were generally null under the high threshold but indicated significant positive associations at certain lags in the low threshold analyses. Overall, these findings suggest that acute exposure to wildfire smoke may negatively impact physical and mental health Figure 1, Table S5).

The widened confidence intervals observed for the diagnosis of anxiety, mood disorders, and depression suggest that our estimates are less precise. This may be due to relatively fewer ED visits for these specific conditions compared to other outcomes, as well as increased variability in how these conditions are reported and diagnosed. As a result, while our point estimates indicate an association between wildfire smoke exposure and these mental health outcomes, the true effect could be smaller or larger. Further research with larger samples and more detailed mental health assessments is needed to clarify these estimates Figure 1, Table S5).

Thresholds of $PM_{2.5}$ Exposure and Public Health Implications

The high threshold of $PM_{2.5}$ ($\geq$35.4 μg/m³) we used was established by the EPA as the point at which air quality transitions from "Moderate" to "Unhealthy for Sensitive Groups." Traditionally, this breakpoint is used to issue health advisories. However, our finding is that significant health impacts also occur at the lower threshold, where air quality is considered moderate. This indicates that even lower concentrations of wildfire smoke may be harmful. Such an observation underscores the need for additional research to pinpoint the dose–response relationship at these lower $PM_{2.5}$ levels and to reexamine existing air quality guidelines.

Healthy Worker Effect and Application

Military personnel are typically considered to be a healthier segment of the population due to rigorous accession standards, physical fitness standards, and regular health monitoring. The observation that wildfire smoke exposure is associated with statistically significant changes in ED visits—across respiratory, cardiac, and behavioral health outcomes—suggests that the toxic components of wildfire smoke (e.g., $PM_{2.5}$) may overwhelm even a robust baseline of health. In other words, if a healthy military workforce is adversely affected by acute exposures, then populations with more variable or poorer baseline health (e.g., civilians, the elderly, children, pregnant women, and those with chronic conditions) could be at even greater risk. This finding supports previous evidence from civilian wildfire smoke studies and highlights the need for broader public health interventions during wildfire events.

Implications for Military Health Readiness

Beyond individual health, wildfire smoke exposure may have broader military readiness implications. Our findings indicate that acute exposures are associated with increased ED visits, which may result in temporary medical absences and missing personnel from training and operational duties. Given that military readiness depends on the sustained availability and performance of its personnel, even short-term disruptions can undermine unit cohesion and mission capability. As training schedules are already demanding, the need for affected soldiers to seek medical care could further compromise military preparedness during periods of environmental stress such as poor air quality from wildfire smoke exposure.

Mental Health Considerations

The analysis of behavioral health outcomes suggests that wildfire smoke exposure is linked to acute episodes of anxiety, mood disorders, and depression. Importantly, these episodes may represent exacerbations of existing conditions rather than the onset of new mental health issues. In the military where chronic stress and psychological burden are not uncommon, such acute exacerbations could compound long-term mental health challenges. This psychological burden affects overall quality of life and performance. The observation that both high and low threshold $PM_{2.5}$ exposures are associated with these acute behavioral health events underscores the need for further awareness and mental health monitoring during wildfire events. However, given the widened confidence intervals for anxiety, mood disorders, and depression, additional research with larger samples and more detailed mental health assessments are needed to confirm these estimates.

Establish Dedicated Air Quality Monitors on Department of Defense Installations

Military installations in areas at risk of wildfire smoke exposure should establish their own dedicated air quality monitoring system to safeguard the health of its active-duty personnel and maintain military readiness. Although publicly available and off-base sensors offer approximate air quality data, JBLM's unique geographic features, microclimates, and operational activities would benefit from on-site monitoring to accurately capture the exposure levels experienced by service members and their families. A dedicated monitor would enhance data precision, enabling rapid and tailored responses, such as modifying training schedules or deploying protective measures, when air quality deteriorates. Moreover, localized air quality data would better support epidemiological research, helping to clarify the relationship between wildfire smoke, $PM_{2.5}$ exposure, and adverse health outcomes. This evidence could help inform targeted interventions and prompt the development of site-specific health advisories, ensuring that military units and individuals receive timely warnings. As there is increasing frequency and intensity of wildfires, on-base monitoring is a practical, evidence-based strategy to mitigate health risks and maintain operational effectiveness, ultimately strengthening overall mission readiness.

Risk Mitigation Strategies: From Heatcat to Aircat

Military organizations have long implemented "heat categories" (Heatcat) to mitigate the risks of heat illnesses due to ambient temperatures, humidity, sunlight exposure, and wind speed during training and operations. The current study's findings suggest that similar risk management strategies might be beneficial for an air quality system. An analogous "air category" (Aircat) system could be developed, whereby real-time monitoring of $PM_{2.5}$ and possibly other pollutants, combined with temperature, would trigger predetermined mitigation measures. For example, if air quality degrades beyond a specified threshold, commanders could adjust training schedules, limit outdoor exposure, or provide additional protective equipment. Such proactive measures could help preserve both individual health and overall mission readiness during wildfire seasons and episodes of poor overall air quality.

Economic and Operational Impacts

The direct and indirect costs associated with increased ED visits during wildfire events can be substantial. Direct costs include the medical expenditures related to ED care, while indirect costs arise from lost training time, reduced operational capacity, and potential long-term impacts on soldier health. In a military setting, these costs can translate into decreased readiness and a potential strain on the military healthcare system. Extrapolated to the civilian sector, similar exposures could impose significant economic burdens through increased healthcare utilization and reduced workforce productivity.

Study Limitations

There are several limitations that warrant consideration in this study. First, our outcome measures were based on ED visit data, and we could not ascertain whether the patients had preexisting conditions. This limitation prevents us from distinguishing between incident cases and exacerbations of chronic diseases—a question that could be addressed in future studies with more detailed clinical data. Second, JBLM does not operate its own air quality monitoring station; we relied on the nearest available monitor, which may not perfectly reflect the local conditions experienced by military personnel. Third, while $PM_{2.5}$ is a major component of wildfire smoke, other pollutants (e.g., volatile organic compounds, carbon monoxide, and ozone) were not measured and may also contribute to adverse health outcomes. Fourth, our exposure assessment was based on area-level data only. We were unable to account for variations in individual behaviors that could influence personal exposure levels, such as the amount of time spent indoors versus outdoors or differences in physical activity. Fifth, we selected a 7-day lag period based on prior literature on acute effects; however, it is possible that longer-term health effects exist that were not captured by our models. Finally, many military personnel reside off-base, and our exposure estimates may not reflect their true individual-level exposures.

Future Research Directions

Future studies with larger sample sizes should build on the current work by differentiating between new-onset conditions and exacerbations of existing conditions by comparing active-duty personnel with preexisting pulmonary, cardiovascular, or mental health diagnoses to those without such conditions. This stratified approach would clarify whether individuals with preexisting health issues are at higher risk of adverse outcomes following wildfire smoke exposure. Moreover, continued research is needed to further explore the effects of air pollution on mental health and if these findings can be replicated, better understand the pathophysiology causing the adverse mental health outcomes, and how to better measure the mental health outcomes other than ED visits. Additionally, expanding the range of pollutants examined, such as acrolein, benzene, carbon monoxide, and polycyclic aromatic hydrocarbons,[5,17,18] and potentially incorporating individual-level exposure assessments (e.g., personal air monitors) could be valuable. This study also underscores the need for additional research to pinpoint the dose–response relationship at these lower $PM_{2.5}$ levels and to reexamine existing air quality guidelines. In addition, expanding the study population beyond active-duty personnel to include the entire cohort enrolled in the Madigan MHS would provide a broader understanding of wildfire smoke's impact across various demographic and health status groups. For example, examining outcomes such as premature birth could shed light on the reproductive health effects of wildfire smoke exposure—an area of growing public health concern.

Furthermore, considering recent wildfire events in regions such as Southern California, future investigations should assess wildfire smoke exposures at other military installations (e.g., bases in Southern California) and across different geographic regions in the United States. Such multicenter studies would help determine whether the associations observed at JBLM are generalizable to other populations and environments where wildfire smoke is prevalent.

By addressing these additional questions—such as the differential impacts on those with preexisting conditions, $PM_{2.5}$ levels of exposure, a larger and broader study population, reproductive health outcomes, and geographic variability—future research will refine our understanding of the acute and potentially long-term effects of wildfire smoke exposure. It will also inform targeted prevention and mitigation strategies.

5. **Conclusion**

This study suggests that wildfire smoke exposure, as measured by elevated $PM_{2.5}$ levels, adversely affects the health of a population known for its high baseline fitness and health, and hence the potential need for military installations to have their own air quality sensors. The acute impacts on respiratory, cardiac, and behavioral health have direct implications for military readiness and may also inform public health strategies in the broader community. In particular, the observation that adverse health effects occur even at $PM_{2.5}$ levels below the EPA's established breakpoint for "Unhealthy for Sensitive Groups" suggests that existing air quality guidelines may need to be revisited. The potential development of an "air category" system, analogous to existing heat management protocols, could represent an innovative step toward mitigating the adverse effects of poor air quality on both military and civilian populations.

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Figure Legend:

Figure 1: Odds Ratios and Confidence Intervals by Lag Day, Adjusted for Average Daily Temperature