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Fine particulate matter infiltration at Western Montana residences during wildfire season

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Abstract

Background/Aims: Wildfire air pollution is a growing public health concern as wildfires increase in size, intensity, and duration in the United States. The public is often encouraged to stay indoors during wildfire smoke events to reduce exposure. However, there is limited information on how much wildfire smoke infiltrates indoors at residences and what household/behavioral characteristics contribute to higher infiltration. We assessed fine particulate matter ($PM_{2.5}$) infiltration into Western Montana residences during wildfire season.

Methods: We measured continuous outdoor and indoor $PM_{2.5}$ concentrations from July-October 2022 at 20 residences in Western Montana during wildfire season using low-cost $PM_{2.5}$ sensors. We used paired outdoor/indoor $PM_{2.5}$ data from each household to calculate infiltration efficiency (F_{inf}; range 0–1; higher values indicate more outdoor $PM_{2.5}$ infiltration to the indoor environment) using previously validated methods. Analyses were conducted for all households combined and for various household subgroups.

Results: Median (25th percentile, 75th percentile) daily outdoor $PM_{2.5}$ at the households was 3.7 μg/m^3 (2.1, 7.1) during the entire study period and 29.0 μg/m^3 (19.0, 49.4) during a 2-week period in September impacted by wildfire smoke. Median daily indoor $PM_{2.5}$ at the households was 2.5 μg/m^3 (1.3, 5.5) overall and 10.4 μg/m^3 (5.6, 21.0) during the wildfire period. Overall F_{inf}

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Conflict of interest statement:

The authors declare they have no conflicts of interest.

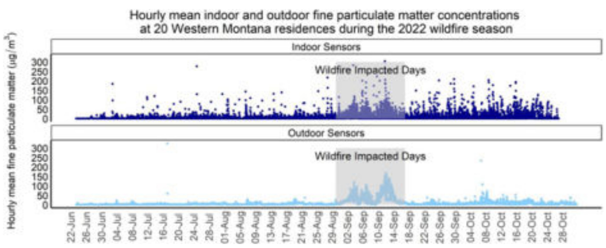
Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

was 0.34 (95% Confidence Interval [95%CI]: 0.33, 0.35) with lower values during the wildfire period (0.32; 95%CI: 0.28, 0.36) versus non-wildfire period (0.39; 95%CI: 0.37, 0.42). Indoor $PM_{2.5}$ concentrations and F_{inf} varied substantially across household subgroups such as household income, age of the home, presence of air conditioning units, and use of portable air cleaners.

Conclusions: Indoor $PM_{2.5}$ was substantially higher during wildfire-impacted periods versus the rest of the study. Indoor $PM_{2.5}$ and F_{inf} were highly variable across households. Our results highlight potentially modifiable behaviors and characteristics that can be used in targeted intervention strategies.

Graphical Abstract:



Keywords

$PM_{2.5}$; indoor air quality; infiltration efficiency; smoke; wildfires

1. Introduction

Wildfire season has lengthened and wildfire events have increased in intensity and duration in recent decades in the United States (US)[1,2]. As a result, the burned area from wildfires in the US has nearly quadrupled over the past 40 years and the contribution of wildfires to overall fine particulate matter ($PM_{2.5}$) in the US has increased, with up to 50% of ambient $PM_{2.5}$ in some Western regions attributed to wildfires[2]. Similar trends of increasing wildfire activity have been observed across the globe, creating a substantial public health and economic burden for many countries that is predicted to worsen with climate change[3,4].

There is substantial evidence that wildfire air pollution is associated with all-cause and cardiovascular and respiratory mortality, as well as cardiovascular and respiratory disease including exacerbation of asthma, chronic obstructive pulmonary disease, myocardial infarction, stroke, and heart failure[3–8]. Evidence from recent studies also suggests that wildfires adversely impact mental health and well-being[9,10], birth outcomes including pre-term birth and low birth weight[11–13], and can worsen respiratory infection such as influenza[14] and coronavirus[15]. However, the overall public health burden of wildfires, particularly the impact on subclinical health outcomes and underlying disease processes, is difficult to assess due to the unpredictable, transient nature of wildfire events[5,6]. Many previous studies have classified wildfire air pollution exposures using stationary monitors or models that incorporate satellite and meteorological data[6,7]. Such methods allow for wildfires to be studied over wide geographic areas and timeframes, but spatial resolution is typically low using these methods and household-level exposures can be misclassified due to widely variable household- and individual-level characteristics and behavioral patterns.

Another important consideration when estimating the public health burden of wildfire air pollution is that individuals in the US spend nearly 90% of their time indoors[16]. Consequently, ambient exposure estimates may not accurately represent what individuals are exposed to during wildfires. Understanding how wildfires impact indoor air quality will help improve public health messaging and risk reduction efforts during wildfire events. More accurate exposure characterization that includes both indoor and outdoor measurements will also allow researchers to better assess how wildfires impact health outcomes.

In an effort to understand indoor air pollution exposures during wildfires, some studies have calculated outdoor particle infiltration to the indoor environment during wildfire events[17–22]. Infiltration efficiency, or F_{inf}, is the fraction of outdoor particles that penetrate indoors and remain suspended[23]. F_{inf} can be estimated by measuring infiltration of surrogate particles such as sulfate or by using mass balance equations that incorporate particle penetration efficiency, particle deposition rate, and air exchange rate of the indoor environment[23]. By calculating F_{inf}, we can better understand how sources of ambient $PM_{2.5}$, such as wildfires, impact the indoor environment where we spend the majority of our lives.

In a 2021 study, Liang et al. used publicly-available $PM_{2.5}$ data from low-cost sensors in California to assess indoor vs outdoor air quality and particle infiltration during wildfires[17]. The authors reported that mean indoor $PM_{2.5}$ concentrations were nearly 3 times higher during wildfire events vs non-wildfire periods, yet ambient particle infiltration inside the buildings was lower during wildfire events, potentially due to behavior changes of building residents during wildfires[17]. Indoor $PM_{2.5}$ concentrations and particle infiltration also varied across geographic location and building characteristics such as age of the residence[17]. This study highlights the importance of indoor and outdoor exposure characterization at the household-level. Moreover, the need for further investigating the impact of household/sociodemographic characteristics and behavioral changes during wildfires and the subsequent impact on indoor air quality is evident.

In a 2022 study, Burke et al. used data from smart phones, social media posts, and internet search activity to assess behavioral responses during wildfire events[18]. The authors found that behavioral responses to wildfire smoke varied depending on neighborhood-level income status, with wealthier locations more likely to search for information on health protection than lowerincome neighborhoods[18]. They also reported that particle infiltration and indoor smoke exposures were less correlated with income status and suggest that individual-level behaviors such as opening windows may have stronger associations with indoor smoke exposures during wildfire events than type or quality of residential building materials[18].

The studies by Liang and Burke were innovative in their use of publicly-available data and have contributed substantially to our understanding of indoor exposures during wildfire events[17,18]. These studies also highlight the need for further research that measures individual-level data to better understand what household and behavioral characteristics impact particle infiltration and indoor exposures during wildfire events. We aimed to inform these gaps in the literature by implementing a novel study framework to measure continuous indoor and outdoor $PM_{2.5}$ concentrations at individual households over the course of the 2022 wildfire season in Western Montana. In a pilot study among 20 households, we utilized an entirely distance-based approach in which we mailed air pollution sensors to participant households and remotely collected real-time indoor and outdoor $PM_{2.5}$ data over a 4-month period during wildfire season. We also collected baseline sociodemographic and household characteristics as well as weekly health and activity surveys from each participant. Here we present results that demonstrate the feasibility of a novel study framework as well as how household characteristics and individual behaviors impact indoor air quality and wildfire smoke infiltration to the indoor environment.

2. Methods

2.1 Study overview

Our study took place among 20 households in and around the city of Missoula in the US state of Montana. The Missoula area commonly experiences waves of wildfire air pollution between July and October each year from local wildfires as well as regional fires from across the Western US and Canada. We recruited participants through the help of a local climate advocacy organization. Interested individuals filled out an eligibility survey and were contacted to discuss study details if all criteria were met. To be eligible, participants had to be a consenting adult (≥ 18 years of age), non-smoking and live in a non-smoking household, have access to an electronic device to submit online surveys, and live within range of a cellular data tower so a Wi-Fi hotspot could be used in their home. Participants signed a written informed consent form prior to engaging in any study activities. The study was approved by the University of Montana Institutional Review Board.

Following the consent process, packages with study equipment were mailed to each participant's household during June and July of 2022. Packages contained 2 low-cost air pollution sensors (PAII-SD, PurpleAir, Inc, USA) that were paired with a Wi-Fi hotspot (Solis Lite, Skyroam, Inc, USA). Pairing the PurpleAir sensors with Wi-Fi hotspots helped simplify the in-home setup by participants while also allowing the research team to monitor and retrieve the PurpleAir data in real time from the PurpleAir online database. Our research staff scheduled a phone call with each participant to talk through in-home equipment setup, study procedures, and to ensure the PurpleAir sensors were online and collecting data. After the initial setup call, participants completed a baseline household and demographic survey followed by weekly activity surveys. Participation lasted through October 2022, after which participants mailed the equipment back to the University of Montana using pre-paid postage. Participants were compensated for time spent completing study procedures.

2.2 Exposure assessment

The PurpleAir PAII-SD instruments use dual optical sensors (PMS5003, Plantower, China) to measure particle numbers every 2 minutes. The PurpleAir sensors also measure temperature and humidity and are weather resistant, allowing them to be used indoors and outdoors through varying weather conditions. Prior to being mailed to participant households, we collocated the PurpleAir sensors with both indoor and outdoor continuous particulate monitors (BAM 1020, Met One Instruments, Inc., USA) designated as $PM_{2.5}$ equivalent methods by the US Environmental Protection Agency (EPA). Using methods previously employed and published by our research group[19], we compared hourly mean

$PM_{2.5}$ concentrations from each PurpleAir with hourly mean $PM_{2.5}$ concentrations from the BAM to ensure all sensors had similar readings prior to being shipped to participant households.

Once delivered to the study households, participants set up 1 indoor and 1 outdoor sensor with guidance from study personnel. The indoor sensor was placed 1 to 2 meters above the floor in a common room away from indoor pollution sources (e.g., kitchen), windows, doorways, and areas with potential drafts that could impact measurements. Outdoor sensors were placed 1 to 2 meters above the ground and away from potential air pollution sources (e.g., vehicle exhaust or air vents) and other obstacles that could impact measurements. Once the sensors were placed at the study households, participants only had to plug them into a power source and turn on the Wi-Fi hotspot to begin the real-time, continuous, cloud-based data collection. PurpleAir data were also stored on internal SD cards and downloaded at the end of the wildfire season as a backup data collection method.

Once set up at participant households and online, PurpleAir data were downloaded in real time and stored in a local database at the University of Montana. From the local database, we set up daily, automated data checks to assess data quality and completeness. The data checks helped us ensure that sensors functioned properly and remained plugged in and online through the duration of the study. Our study team received automated email alerts for a variety of situations: 1) if a sensor went offline, 2) if less than half the expected $PM_{2.5}$ datapoints were received for a given hour, 3) if less than 80% of hourly datapoints were received for a given day (i.e., <19 hours), 4) if $PM_{2.5}$ data were negative, or 5) if $PM_{2.5}$ data were consistently recording very high concentrations (>250 μg/m^3 for >12 hours in a day). We also set up daily email reports with data summaries and time-series plots of $PM_{2.5}$ data for each sensor to visually inspect trends in the data for further quality control throughout the study. If a sensor went offline during the study, we contacted the participants to perform basic troubleshooting to ensure both the sensors and Wi-Fi hotspot were online. There were 2 instances in which a sensor issue could not be resolved remotely and a replacement set of PurpleAir sensors paired with a new Wi-Fi hotspot were mailed to the participant.

2.2.1 PurpleAir data and correction equation—$PM_{2.5}$ mass concentrations are reported by PurpleAir in 2 primary data series designated ATM and CF1. These data series are calculated using proprietary algorithms developed by the sensor manufacturer[24]. Wallace et al. also describe an alternative (ALT) method for calculating $PM_{2.5}$ concentrations from PurpleAir particle counts using reproducible and transparent methods[24]. The ALT method aligns more closely with reference monitors than the ATM or CF1 methods[24] and is now available on the PurpleAir website and database. Previous studies have found that PurpleAir ATM and CF1 data overestimate $PM_{2.5}$ concentrations in field settings[19,24–27]. Barkjohn et al. developed a nationwide correction equation for PurpleAirs using collocated PurpleAir sensors and Federal Reference Method/Federal Equivalent Method instruments from across the US[26].

We used similar methods to develop a location- and time-appropriate correction equation for the PurpleAir sensors used in our study. We analyzed PurpleAir $PM_{2.5}$ data from two sensors that were collocated with an outdoor BAM instrument in Missoula during the entire study period from late June through October of 2022. The BAM we used for outdoor collocation is a Federal Equivalent Method instrument that is maintained by local and state air quality experts in Montana. We used hourly mean $PM_{2.5}$ data from the BAM and the PurpleAir sensors to develop a correction equation for the PurpleAir sensors used in our study:

$$PM_{2.5\_corrected} = (0.387 \times PA_{cf1}) - (0.008 \times PA_{RH}) + 1.047 \quad \text{Equation 1}$$

where $PM_{2.5\_corrected}$ = corrected hourly mean PurpleAir $PM_{2.5}$,

PA_{cf1} = hourly mean PurpleAir CF1 $PM_{2.5}$, and PA_{RH} = hourly mean relative humidity measured by the PurpleAir.

Based on our collocation data, correction equations using PurpleAir's ATM and CF1 $PM_{2.5}$ methods, as well as the ALT $PM_{2.5}$ method by Wallace et al., all performed similarly in comparison to the BAM reference monitor. We chose to use the corrected CF1 $PM_{2.5}$ to be consistent with previous studies by our group and others[19,26]. We used the same correction equation for both indoor and outdoor $PM_{2.5}$ in our study. Our rationale for this decision is that we are assuming one of the dominant sources of indoor $PM_{2.5}$ in the households is from ambient $PM_{2.5}$ infiltration. While the households may have other indoor sources of $PM_{2.5}$, we censor the indoor sources for the calculation of F_{inf} (see analysis section below). Additionally, to our knowledge, there are no indoor-specific correction equations for PurpleAir sensors due to the widely varying indoor environmental conditions and indoor air pollution sources. Thus, in order to make comparisons between indoor and outdoor $PM_{2.5}$ in our study, it seemed more appropriate to correct both indoor and outdoor $PM_{2.5}$ concentrations in the same manner rather than to leave the indoor concentrations uncorrected.

2.3 Survey administration and covariates

2.3.1 Survey design and workflow—Study surveys were administered electronically using a platform called Research Electronic Data Capture (REDCap; Vanderbilt University and NIH, USA). REDCap is a secure, HIPAAcompliant, web-based software platform designed to support data capture for research studies. Private links were sent to each participant via email to complete surveys and submit them to the REDCap database. We used a private dashboard at the University of Montana to track survey submission status and send reminder emails if surveys were not completed within 24 hours. If surveys were not completed after another 24 hours, reminder emails and further participant follow-up was conducted at the discretion of study personnel.

2.3.2 Baseline survey—After the initial phone call to guide participants through equipment setup, study personnel sent participants an email link to complete a one-time baseline survey on demographics and household characteristics. Demographic variables included age, sex, and race/ethnicity of the participants, household income, occupation, participant education, and number of residents in the home. Household characteristics included type of residence (e.g., house, mobile, apartment), size (e.g., square meters, levels, bedrooms), year the home was built, and number of windows and doors in the home. Other factors that could influence $PM_{2.5}$ exposures within the home were assessed, such as primary heating and cooling methods, cooking stove type (e.g., gas or electric), presence of wood stove or fireplace, and use of portable air cleaners (PACs). Survey questions were modified from surveys used in previous field studies conducted by our team[28–30].

2.3.3 Weekly survey—

In addition to the baseline survey, participants also completed weekly surveys that included an activity assessment and a study equipment checkup. Each participant had the opportunity to complete up to 16 of the weekly surveys. An email link for the survey was sent out each Tuesday afternoon with instructions to complete it at 7pm on Tuesday evening. The survey asked questions about frequency and duration of activities over the previous week: out-of-town travel, leaving the home to go to work, time spent outdoors, moderate to vigorous physical activity outdoors (activities that lasted at least 10 minutes and caused large increases in breathing, heart rate, or leg fatigue, or caused them to perspire), time spent indoors at home, moderate to vigorous physical activity indoors at home, number of days with self-reported poor outdoor air quality (haze, limited visibility), number of days in which they left windows and/or doors open for extended periods of time at their home, and number of days they encountered other air pollution sources indoors or outdoors. Wording for the activity questions was modified from the Yale Physical Activity Survey[31]. We included an open-ended question for participants to describe other details about their weekly activity they saw as important. The survey also prompted participants to check and document that the PurpleAir sensors and Wi-Fi hotspot were plugged in and turned on. The weekly survey also included a health assessment with participant-reported blood pressure and health symptoms. Results from the health assessment, including associations between in-home $PM_{2.5}$ and blood pressure, are reported separately.

2.4 Statistical analysis

2.4.1 Data cleaning—

The data cleaning and analyses for the study were performed using R software version 4.2.1[32]. We calculated hourly mean $PM_{2.5}$ concentrations for each PurpleAir sensor by averaging the real-time (2-minute) CF1 $PM_{2.5}$ concentrations across the dual sensors within each PurpleAir. Equation 1 was applied to the hourly mean $PM_{2.5}$, and the hourly corrected $PM_{2.5}$ was used for all subsequent analyses. We removed 603 hourly $PM_{2.5}$ concentrations (0.6%) in which there were fewer than half the expected hourly datapoints (<15 of 30 expected datapoints). We also removed 1070 hours (1.1%) from a single sensor in which the humidity sensor malfunctioned and Equation 1 could not be applied to the $PM_{2.5}$ data. For instances when we used 24-hour mean $PM_{2.5}$ concentrations in the analysis, we removed days with less than 19 hours of data in a given day. This resulted in an additional 2329 hours (2.5%) being removed from the dataset.

2.4.2 Wildfire Period and Day definitions—

During the 2022 wildfire season, the Missoula area was largely unimpacted by wildfire smoke until September. During the first half of September 2022 there was consistent wildfire smoke from local and regional fires in the study area as documented by local Air Quality Specialists[33]. In the following analyses and results, Wildfire Period is defined as September 1st −16th, 2022 when the study area was impacted by wildfire smoke. Similarly, we define a Wildfire Day as a single 24-hour day during this Wildfire Period.

2.4.3 Summary statistics—We calculated descriptive statistics for numeric variables (n, mean, standard deviation [sd], minimum [min], 25th percentile [P25], median, 75th percentile [P75], maximum [max]) and categorical variables (n, percent of total [%]). Descriptive statistics are presented for overall study data and by subgroups of self-reported demographic characteristics, household characteristics, and activities.

Table 2 summarizes the percentage of days a self-reported activity or observation was recorded by a participant since the previous survey was submitted. Although surveys were sent out electronically at a consistent day and time each week, they occasionally were not taken on the intended/scheduled day. For the self-reported activities/observations in Table 2, participants were told the number of days since their previous survey and asked to report the number of days each activity or observation occurred during that specific timeframe. Table 2 is reporting statistics on the percentage of days each activity or observation occurred out of the total number of days since the previous survey was taken.

2.4.4 Linear regression—In Table 2 and Table 3, we report estimates from simple linear regression models to demonstrate crude associations between $PM_{2.5}$ concentrations and various subgroups of the study population. $PM_{2.5}$ concentrations were natural log transformed for the regression analyses. In Table 2, estimates are from simple linear regression models with mean $PM_{2.5}$ since the previous survey as the outcome and self-reported activities/observations as predictor variables. Estimates are presented as percent change in geometric mean indoor $PM_{2.5}$ per 10% increase in days with the self-reported activity/observation. In Table 3, estimates are from simple linear regression models with 24-hour mean $PM_{2.5}$ as the outcome and household/demographic characteristics as predictor variables. Estimates are presented as percent difference in geometric mean $PM_{2.5}$ compared to the reference group.

2.4.5 Infiltration efficiency—We used the paired indoor/outdoor hourly $PM_{2.5}$ concentrations at each household to calculate F_{inf}, which is defined as the fraction of the outdoor $PM_{2.5}$ concentration that penetrates to the indoor environment and remains suspended[34,35]. We used methods that have been previously validated by others[35,36] and implemented by our group at the University of Montana[19,34]. Specifically, we used paired indoor and outdoor 1-hour mean $PM_{2.5}$ concentrations in a recursive mass balance model. Indoor air pollution sources were censored from model data by identifying periods during which indoor $PM_{2.5}$ concentrations increased without corresponding increases in the paired outdoor $PM_{2.5}$ concentrations[35,36]. After censoring indoor $PM_{2.5}$ sources, we analyzed the data in a model which states that indoor $PM_{2.5}$ is equal to a fraction of outdoor $PM_{2.5}$ from the current hour, a fraction of indoor $PM_{2.5}$ from the previous hour, and indoor $PM_{2.5}$ from the current hour[35,36]. Results are presented as F_{inf}, a unitless number between 0 and 1 where higher values indicate more ambient particle infiltration to the indoor environment.

3. Results

3.1 Participant and household characteristics

Demographic and household characteristics for the 20 participants and households are reported in Table 1. The participants had a mean age of 49 years (sd=16). Seventeen of the participants (85%) reported their sex as female, with the other 3 participants reporting their sex as male (15%). All 20 participants reported their race as White, and all 19 participants who reported their ethnicity described themselves as non-Hispanic. All participants had at least some college education, with 50% having advanced degrees. Over half of the participants (n=11, 55%) reported a household income of at least $50,000 United States Dollars (USD), and 50% of the participants worked at least 40 hours per week at the time of the study. Two of the participants (10%) lived in an apartment or condominium with multiple levels and the rest of the participants (n=18, 90%) lived in single-family homes. The mean age of the study homes was 51 years (sd=37). Twelve of the homes (60%) had two levels (including basement) and the other 8 homes were single-level (40%). Twelve of the homes (60%) had air conditioning of any kind (central, window, or portable), 3 of the homes (15%) had a wood heating stove or fireplace, 6 of the homes (30%) had a gas stovetop, and 14 of the participants (70%) reported that they used a PAC in their home.

3.2 Self-reported activities and participant observations

Table 2 describes self-reported activities and observations made by the participants during the weekly electronic surveys throughout the study. In total, participants submitted 316 weekly surveys over 2091 days of follow-up. Windows and doors were left open more often during non-wildfire days compared to wildfire days (62.0% vs 43.3%). The action of leaving windows/doors open had stronger associations with indoor $PM_{2.5}$ on wildfire days compared to non-wildfire days (Table 2). For example, on wildfire days, geometric mean indoor $PM_{2.5}$ was 11.4% higher per 10% increase in days with windows/doors open (95% Confidence Interval [95% CI]: 6.4, 16.7); on non-wildfire days, geometric mean indoor $PM_{2.5}$ was 2.6% higher per 10% increase in days with windows/door open (95% CI: 0.2, 5.1). Participants reported observing ambient air pollution or haze near their home on 72.1% of wildfire days compared to 23.8% of non-wildfire days. Self-reported observation of ambient air pollution also had stronger associations with indoor $PM_{2.5}$ on wildfire days (estimate: 7.7, 95% CI: 0.7, 15.3) compared to non-wildfire days (estimate: 3.0, 95% CI: −0.4, 6.5). Other common activities reported by participants were cleaning in the home, smoke in the home from cooking activities, gas stovetop used for cooking in the home, and mowing outside the home; the frequency of these activities/observations did not substantially vary across wildfire vs non-wildfire days (Table 2). Cooking with a gas stovetop indoors, as well as outdoor cooking activities using charcoal and gas grills, did not have meaningful associations with indoor $PM_{2.5}$ concentrations (Table 2).

3.3 Indoor and outdoor $PM_{2.5}$ and infiltration efficiency

Figure 1 displays daily mean indoor and outdoor $PM_{2.5}$ concentrations over the course of the study. The figure suggests trends for indoor $PM_{2.5}$ closely mirrors trends for outdoor $PM_{2.5}$ over the course of the study. Table 3 and Figure 2 describe 24-hour indoor $PM_{2.5}$ concentrations, associations with various demographic and household characteristics, and particle infiltration from the outdoor to indoor environment. After data cleaning procedures were applied, there were 1914 outdoor $PM_{2.5}$ sampling days and 1860 indoor $PM_{2.5}$ sampling days across all study households. Shown in Table S1, the mean 24-hour outdoor $PM_{2.5}$ concentration across all study households was 9.1 μg/m^3 (sd=16.1; median=3.7; P25=2.1; P75=7.1). The mean 24-hour indoor $PM_{2.5}$ concentration across all study households was 5.6 μg/m^3 (sd=8.7; median=2.5; P25=1.3; P75=5.5). F_{inf} for all study households combined was 0.34 (95% CI: 0.33, 0.35) and ranged from 0.04 to 0.84 across individual households. Both outdoor and indoor $PM_{2.5}$ were substantially higher during the wildfire-impacted period in September 2022 compared to the rest of the study (Tables 3 and S1). During the wildfire period, the mean outdoor $PM_{2.5}$ concentration was 36.8 μg/m^3 (sd=26.4; median=29.0; P25=19.0; P75=49.4) and the mean indoor $PM_{2.5}$ concentration was 15.9 μg/m^3 (sd=14.7; median=10.4; P25=5.6; P75=21.0). F_{inf} during the wildfire period (0.32; 95% CI: 0.28, 0.36) was slightly lower than during the non-wildfire periods (0.39, 95% CI: 0.37, 0.42). These findings indicate that even though indoor $PM_{2.5}$ was higher during the wildfire period, a smaller proportion of outdoor particles actually infiltrated indoors during the wildfire period compared to the rest of the study, an important finding that will be discussed further below.

Other results from Table 3 suggest that indoor $PM_{2.5}$ was associated with various participant demographic and household characteristics such as household income, age of the home, pets in the home, presence of air conditioning (AC), and presence of a wood heating stove or fireplace. For example, households with income greater than $75,000 USD had 24-hour geometric mean indoor $PM_{2.5}$ concentrations that were 27% lower (estimate: −26.8; 95% CI: - 33.6, −19.2) than households with self-reported income less than $75,000 USD. In contrast, indoor $PM_{2.5}$ was not associated with presence of a gas stovetop in the home or participant education (Table 3). We also found that higher mean daily outdoor temperatures (>24 degrees Celsius [C], the median value across all study days/participants) were associated with 30.1% lower indoor $PM_{2.5}$ concentrations compared to days with mean temperature <24 C (estimate: −30.1; 95% CI: −36.3, −23.3).

When comparing particle infiltration across subgroups of the study households, the largest differences in F_{inf} were observed across subgroups of household income, participant education, age and size of the household, and use of a PAC in the household (Table 3). For example, households in which the participant reported use of a PAC had F_{inf} of 0.25 (95% CI: 0.24, 0.26) compared to F_{inf} of 0.57 (95% CI: 0.54, 0.60) among households without a PAC. F_{inf} did not vary substantially across household subgroups of participant age or presence of central AC (Table 3).

4. Discussion

We measured continuous, real-time $PM_{2.5}$ concentrations indoors and outdoors at 20 households across Western Montana over a 4-month period that spanned the 2022 wildfire season. Outdoor $PM_{2.5}$ concentrations over the entire study period (mean=9.1 μg/m^3; median=3.7) were higher than indoor $PM_{2.5}$ concentrations (mean=5.6 μg/m^3; median=2.5), and both indoor and outdoor $PM_{2.5}$ concentrations were substantially higher during a wildfir-eimpacted period in September (Table 3). We have also reported results among subgroups of the study population that highlight participant demographics, household characteristics, and selfreported activities that are associated with indoor $PM_{2.5}$ concentrations and particle infiltration to the indoor environment. Our results demonstrate important characteristics and activities that may impact indoor $PM_{2.5}$ at the household level and lead to future strategies for improving indoor air quality through education and behavioral interventions.

Although there is growing literature on the impacts of wildfires on indoor air quality and public health, few studies have focused on exposure assessment and health outcomes at the household level. Due to the unpredictable, transient nature of wildfires, research studies typically use fixed-site regulatory monitors or spatial models to characterize wildfire exposures. Xiang et al. assessed indoor $PM_{2.5}$, $PM_{2.5}$ infiltration factor, and the impact of PACs on indoor $PM_{2.5}$ among 7 households in Seattle, Washington during a wildfire episode in 2020[37]. The authors reported that mean particle infiltration was 0.56 (range 0.33 to 0.76 across the households) and suggested that staying indoors during wildfire events may be an insufficient protective measure on its own[37]. Another study by May et al reported F_{inf} among 26 residences, 6 schools, and 10 commercial buildings in the Western US during a 2020 wildfire-impacted period[20]. They reported that while overall F_{inf} was lower in residences than in schools or commercial buildings, the F_{inf} across residences had a wide range of 0.01 to 0.87; this range of F_{inf} across households matched our findings very closely (0.04 to 0.84)[20]. These findings help corroborate the results we have reported, which suggest that while indoor $PM_{2.5}$ does substantially increase during wildfire events, there may be modifiable household or behavioral factors that can lead to lower particle infiltration to the indoor environment.

Larger-scale studies have also reported indoor vs outdoor $PM_{2.5}$ and/or $PM_{2.5}$ infiltration during wildfire events using publicly available data. Liang et al. used publicly-available $PM_{2.5}$ sensors to assess indoor air pollution during wildfire season among 1400 buildings across metropolitan California[17]. Similar to our study, they reported that particle infiltration was lower during wildfire days (0.27) vs non-wildfire days (0.45) and that indoor $PM_{2.5}$ concentrations were substantially higher during wildfire days (mean=11.1 $\mu g/m^3$) vs non-wildfire days (mean=4.1 $\mu g/m^3$)[17]. While not calculating $PM_{2.5}$ infiltration specifically, O'Dell et al. reported 82% higher indoor $PM_{2.5}$ concentrations on wildfire-impacted days vs non-wildfire days across more than 1200 locations in the Western US during the 2020 wildfire season[38]. Similar to other recent studies, their message is that indoor air quality declines substantially during wildfire events across a wide spectrum of indoor environments[38].

Although the focus of this current study is residential buildings, $PM_{2.5}$ infiltration during wildfire events have also been reported by our group and others at healthcare facilities[19,21]. In contrast to infiltration results at residences that were lower during wildfire events compared to non-wildfire events, infiltration rates at the healthcare facilities were higher during wildfire periods, potentially due to differences in building characteristics and behavioral responses of the building occupants[19,21]. These results further suggest that wildfire smoke infiltration to the indoor environment varies depending on complex behavioral factors and building characteristics.

Although a common message during wildfire events is to stay indoors, our work adds to the growing body of literature which shows that simply remaining indoors is not sufficient to avoid the harmful effects of wildfire smoke[39,40]. Due to the complexity of indoor environments and the high variability in indoor air quality from building to building, it is difficult to make blanket statements on recommendations for reducing indoor exposures during wildfires and other similar events involving poor ambient air quality. A strength of our study was the focus on household-level characteristics and participant-reported activities that provide insight into what factors may impact indoor air quality. Understanding such factors will help us identify households that are more at-risk and develop strategic and targeted public health messaging during wildfire events.

We found that indoor $PM_{2.5}$ was lower among older participants and participants with higher household income (Table 3). Compared to homes built before 1975 (median home age), homes built after 1975 had substantially lower indoor $PM_{2.5}$ (Table 3). Specifically, geometric mean indoor $PM_{2.5}$ was 37% lower (estimate: −36.9; 95% CI: −42.4, −30.9) among the newer homes compared to the older homes. While some of these household and demographic factors may not be easily modifiable for targeted educational interventions, they do provide insight into what types of households may be more at risk for higher indoor $PM_{2.5}$ during wildfire events.

Another important factor was presence of an AC unit within the study households. Homes with no AC (n=8) had geometric mean indoor $PM_{2.5}$ that was 41.9% higher (95% CI: 29.0, 56.0) than homes with any (portable, window, mini-split, or central) AC (n=12). F_{inf} was also higher among homes with no AC (0.42 vs 0.30), which could be due to participants opening windows to cool their homes. A 10% increase in participant-reported days with windows/doors left open for ventilation was associated with an 11.4% increase in indoor $PM_{2.5}$ during wildfire days (Table 2). These findings about AC are an important part of the discussion on coping with wildfire smoke as the climate warms and summer temperatures increase in regions that traditionally do not have central AC systems. Similar to other Northern US states, less than half of homes in Montana (40%) have central AC, although 65% of homes reported having some form of AC[41]. Many individuals are left with the choice of opening windows at night to cool their homes or keeping windows shut to prevent smoke from getting indoors. F_{inf} among homes with any AC (0.30) was similar to F_{inf} among homes with central AC (0.32), suggesting that even portable, window, or mini-split AC units may help reduce particle infiltration to the indoor environment.

Our findings further suggest that outdoor temperature impacts behavior and $PM_{2.5}$ infiltration inside study households. Participants reported opening windows/doors for ventilation on 65% of study days with outdoor daily mean temperature greater than 24 C vs 49% of study days with outdoor daily mean temperature less than 24 C (24 C was the median for daily mean outdoor temperature across all study days/households recorded on the outdoor PurpleAir sensors). Opening windows and doors for increased ventilation will impact air exchange rates in the home and consequently particle infiltration, as observed in our F_{inf} results (Table 3). Specifically, we saw higher F_{inf} on days with outdoor temperature above 24 C (0.40) vs days below 24 C (0.32). While our study took place only during warmer months, other studies have reported seasonal differences in particle infiltration and suggest outdoor temperature impacts particle infiltration across longer timeframes[42,43]. Although indoor $PM_{2.5}$ in our study was 30% lower on days with outdoor temperature above 24 C (Table 3), we believe this is primarily because outdoor $PM_{2.5}$ was 29% lower on days with outdoor temperature above 24 C (Table S1). To summarize, although higher outdoor temperatures were not associated with higher indoor or outdoor $PM_{2.5}$ concentrations, higher outdoor temperatures did result in more $PM_{2.5}$ infiltrating to the indoor environment.

We also found that presence of a PAC in the home is associated with lower indoor $PM_{2.5}$ (Table 3), and that F_{inf} among homes without a PAC was over twice as high as households with a PAC (0.25 vs 0.57). While using PACs will not reduce how much $PM_{2.5}$ infiltrates indoors, they will reduce the amount of $PM_{2.5}$ that remains suspended in the indoor environment by filtering out the particles that infiltrate indoors. Our results, along with other studies on PAC use and indoor air quality[37,44], demonstrate the utility of these devices at reducing indoor $PM_{2.5}$. We also observed differences in PAC ownership across categories of participant education level. Of the 20 participants in the study, 10 had a graduate degree and 14 reported that they owned a PAC. Of those with a graduate degree, 9 (90%) participants had a PAC; of the 10 participants with less than a graduate education, 5 (50%) reported owning a PAC. We observed similar trends between PAC ownership and household income. Of the participants who reported household income less than $75,000 USD, 3 (38%) reported owning a PAC. In contrast, 10 (91%) of the participants with household income greater than $75,000 USD reported owning a PAC. Although our sample size of participants was small, these findings giver further insight into the results from Table 3 that show differences in indoor $PM_{2.5}$ and F_{inf} across categories of education and household income. From a community perspective, educational approaches or reimbursement programs could be strategies to increase PAC use and improve indoor air quality.

Although the focus of this study was on measuring and assessing wildfire-related air pollution, the Graphical Abstract highlights another important finding: even during periods with low ambient $PM_{2.5}$ concentrations, there are still short-term spikes in indoor $PM_{2.5}$ that likely come from indoor sources. We also found that some participant-reported behaviors, such as opening doors and windows, incense burning, and construction activities near the home, were associated with higher indoor $PM_{2.5}$ concentrations (Table 2). While not related to wildfires specifically, these activities demonstrate potential areas for education and other intervention strategies that can help individuals further improve their indoor air quality. These findings add to a growing body of literature focused on monitoring and improving indoor air quality, particularly among households with vulnerable individuals who have pre-existing conditions that make them more susceptible to the adverse effects of air pollution exposures[45–47].

Indoor environments and air pollution sources vary substantially from household to household, but our results help highlight potentially modifiable characteristics and behaviors that can be incorporated into future educational intervention strategies. Given the complexity of indoor environments and behaviors across different households, we believe there is a benefit to using PACs continuously rather than just during extreme events such as wildfires. Although cost may be a barrier for some, our results suggest that use of a portable AC unit may be an effective solution to improve indoor air quality in homes without a central AC system. We also found that participants reported observing ambient air pollution or haze near their home on 72% of wildfire days, and that this observation was associated with higher indoor $PM_{2.5}$ concentrations (Table 2). Even without access to quantitative air pollution data, visual observation of ambient air pollution may be a useful que for individuals to stay indoors and implement practices such as PAC use.

Somewhat counterintuitively, presence and use of a gas stovetop was not associated with indoor $PM_{2.5}$ (Tables 2 and 3). However, only 6 homes in our study had gas stovetops. We also encouraged participants to set up their sensors away from potential pollution sources, so it is likely that sensors were not located near the gas stoves. In general, measuring air pollution from gas stovetops was not the focus of our study and these findings should be interpreted with caution.

There are limitations in our study, including the small sample size (n=20). However, this smallscale pilot study demonstrates the feasibility of an entirely remote field study using low-cost sensors that require minimal setup by participants. Our study methods also resulted in minimal missing data and a robust dataset of continuously monitored $PM_{2.5}$. We have demonstrated a method in which the impacts of wildfires can be studied in a field setting at a household level with minimal personnel. Another limitation in this study is the source we recruited participants from (a local climate advocacy organization). The participants who enrolled in our study generally had high education and household income and were predominantly White and female. It should be acknowledged that our results may not be generalizable to the entire Western Montana population. However, one of our primary aims was to collect high-quality $PM_{2.5}$ data and participant-reported outcomes over the course of an entire wildfire season to help inform larger-scale studies among more vulnerable populations. While the methods we implemented may be less feasible in populations with different demographics, we have successfully demonstrated the feasibility of using low-cost $PM_{2.5}$ sensors in participant households during wildfire season. The framework we have described could also be modified to enhance equipment setup and participant engagement among different study populations. For example, rather than setting up a Wi-Fi hotspot and real-time data retrieval, study personnel could use more passive data collection by relying on the SD card data in the PurpleAir sensors. Potential recall bias is also a limitation in our study, as we had participants report number of days between weekly surveys in which they did certain activities. Daily activity logs can help improve recall in such surveys, but they also add substantial participant time involvement. It may be unrealistic for participants to complete daily activity logs over the course of a long-term research study.

Low-cost sensors can be ideal for studying the localized effects of air pollution at the household level, although it is important to acknowledge that these sensors also have limitations. Low-cost, light-scattering sensors are typically not as accurate as reference monitors that are usually used at fixed sights and have a much higher up-front cost. However, our group and others have worked to develop correction factors that can be applied to $PM_{2.5}$ data from low-cost sensors to improve their accuracy. Many benefits also come with using low-cost sensors, such as much better spatial and temporal resolution due to the portability of the sensors, and ability to conduct real-time, continuous, cloud-based data collection methods. In combination with the Wi-Fi hotspots we deployed, our exposure assessment system required very little hands-on setup by study participants.

Although this study was implemented in Montana, the methodology is adaptable and applicable to other settings. Provided households have a signal from a cellular data tower, this method we have developed can be deployed to households that may otherwise be under-represented in research due to barriers such as Wi-Fi access or distance from study coordination sites. In areas without cellular or Wi-Fi access, the option to use offline data collection on internal sensor storage further increases flexibility of sensor placement. From a global perspective, low-cost sensors increase the feasibility of conducting air quality research not only during wildfires, but also for household air pollution studies aimed at assessing cookstove-related air pollution that is prevalent in many lower- and middle-income countries. One study of 7 sub-Saharan African countries found the implementation of low-cost air quality sensors to be feasible, with a median data recovery rate of 94%, despite electrical outages[48]. Low-cost sensors have also been used to identify strategies to improve building design, ventilation, and air filtration during bushfires in Australia[49].

Overall, we have reported several key findings from this study. We have demonstrated the feasibility of using low-cost sensors to measure indoor and outdoor $PM_{2.5}$ at individual households over the course of an entire wildfire season. When implemented in wildfire prone areas, these methods can help researchers study wildfire exposures and individual-level health outcomes prospectively by having sensors deployed and sampling before, during, and after wildfire smoke impacts the study area. We have also shown that wildfire-related $PM_{2.5}$ infiltrates into residences and that the amount of infiltration varies by demographic and household characteristics. Finally, we have reported on other participant characteristics and behaviors that adversely impact indoor air quality even during periods with minimal ambient air pollution. These findings will help inform future studies and intervention strategies aimed at improving indoor air quality and related health outcomes.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights

- Distance-based field study with low-cost sensors at residences during wildfire season
- Indoor and outdoor fine particulate matter increased markedly during wildfire events
- Indoor air quality and particle infiltration varied across household subsets
- Newer homes and those with air conditioners/cleaners had lower particle infiltration

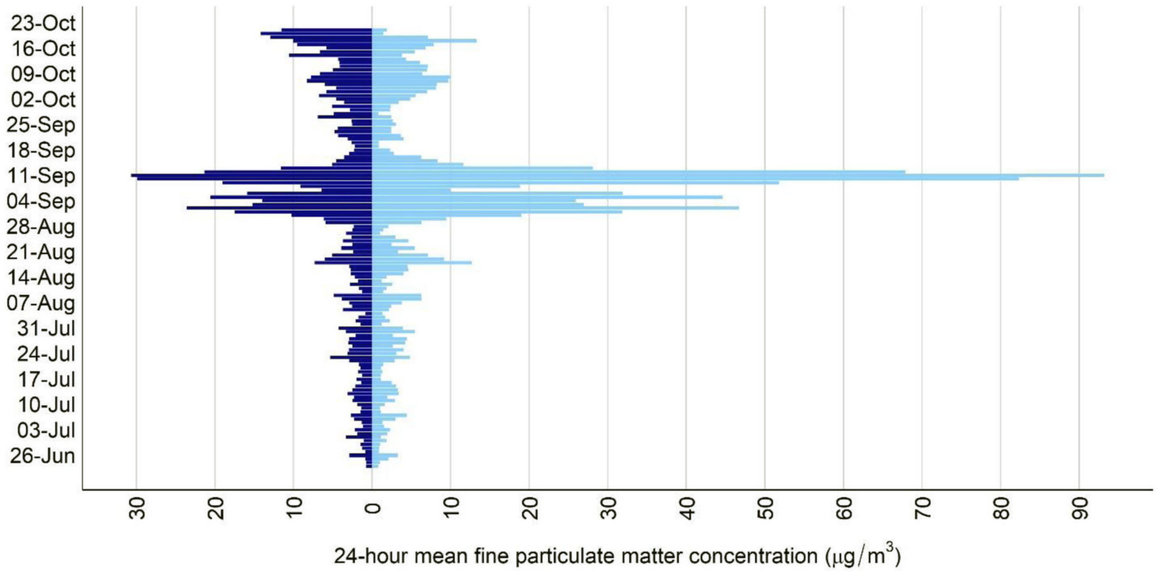

Figure 1:

24-hour mean indoor (dark blue, left columns) and outdoor (light blue, right columns) fine particulate matter concentrations at 20 Western Montana households during the 2022 wildfire season

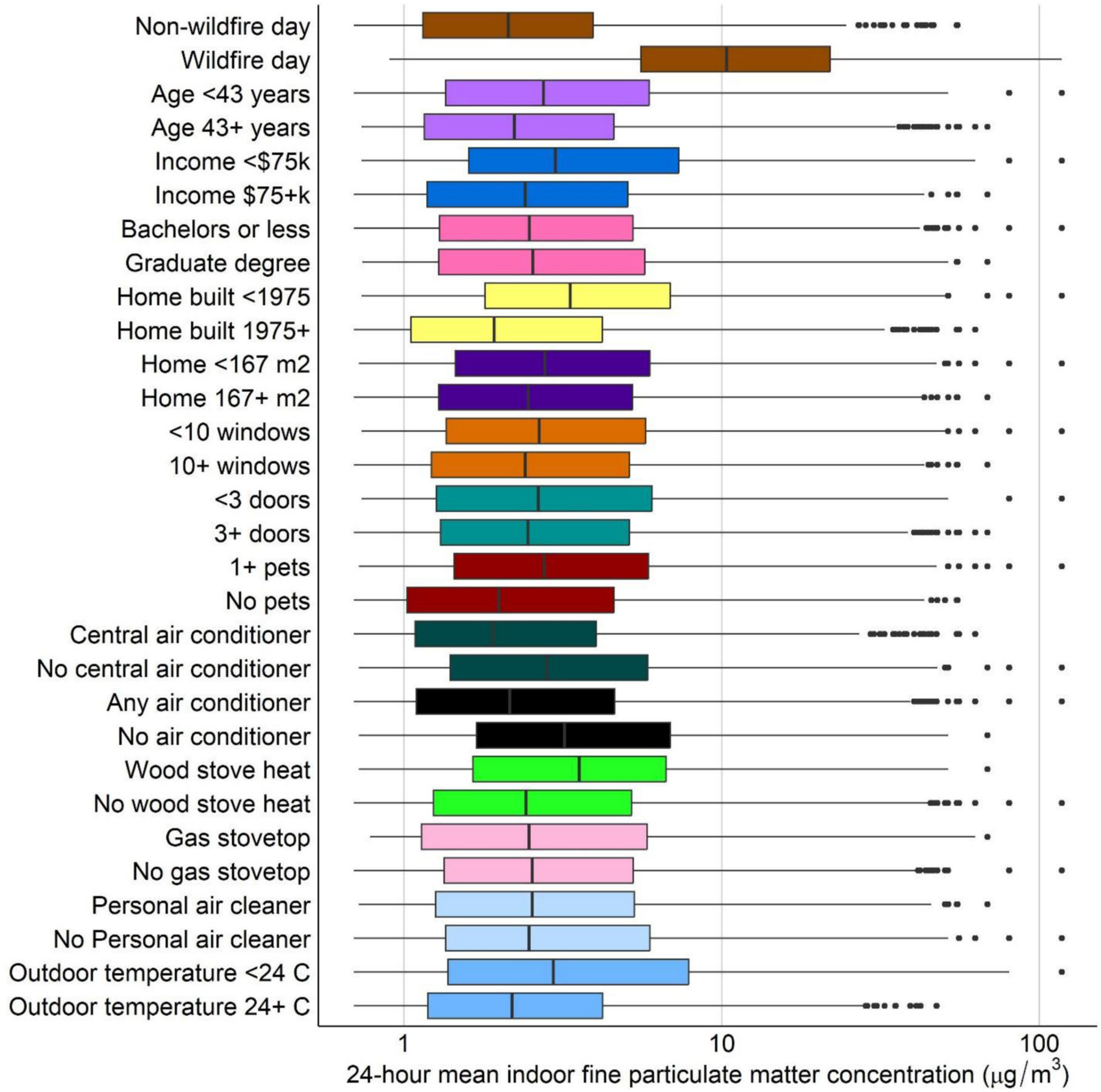

Figure 2:

24-hour mean indoor fine particulate matter concentrations across subcategories of 20 Western Montana residences during the 2022 wildfire season

m2 = square meters; C = degrees Celsius; $75k = 75 thousand United States Dollars

Outdoor temperature categorized by median daily outdoor temperature measured by PurpleAir sensors over the duration of the study (24 C).

The lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles). The upper whisker extends from the hinge to the largest value no further than 1.5 * IQR from the hinge (where IQR is the interquartile range, or distance between the first and third quartiles). The lower whisker extends from the hinge to the smallest value at most 1.5 * IQR of the hinge. Data beyond the end of the whiskers are called “outlying” points and are plotted individually.

Table 1:

Household and demographic characteristics among 20 study households in Western Montana

Participant or household characteristic	Summary statistic (N = 20)
Age in years, mean (sd)	49 (16)
Unknown, n (%)	3 (15)
Sex	
Female, n (%)	17 (85)
Male, n (%)	3 (15)
Race	
White, n (%)	20 (100)
Other, n (%)	0 (0)
Ethnicity	
Not Hispanic, n (%)	19 (95)
Unknown, n (%)	1 (5)
Household income, USD	
<$20,000, n (%)	0 (0)
$20,000 to $34,999, n (%)	2 (10)
$35,000 to $49,999, n (%)	2 (10)
$50,000 to $74,999, n (%)	4 (20)
$75,000 to $99,999, n (%)	4 (20)
$100,000+, n (%)	7 (35)
Unknown, n (%)	1 (5)
Education	
High school or less, n (%)	0 (0)
Some college, no degree, n (%)	1 (5)
Bachelor's degree, n (%)	9 (45)
Master's degree, n (%)	6 (30)
Doctorate or professional degree, n (%)	4 (20)
Employment	
Up to 39 hours per week, n (%)	2 (10)
40 or more hours per week, n (%)	10 (50)
Retired, n (%)	4 (20)
Self-employed, n (%)	3 (15)
Other, n (%)	1 (5)
Total residents living in household	
1, n (%)	2 (10)
2, n (%)	12 (60)
3, n (%)	3 (15)
4, n (%)	2 (10)
Unknown, n (%)	1 (5)
Type of home	
Multi-level apartment/condo, n (%)	2 (10)

Participant or household characteristic	**Summary statistic (N = 20)**
Single family home with basement, n (%)	10 (50)
Single family home without basement, n (%)	4 (20)
Other, n (%)	4 (20)
Home age in years, mean (sd)	51 (37)
Home area in square meters, mean (sd)	171 (93)
Unknown, n (%)	1 (5)
Home levels including basement	
1, n (%)	8 (40)
2, n (%)	12 (60)
Windows in home, mean (sd)	15 (10)
Doors in home	
1, n (%)	2 (10)
2, n (%)	6 (30)
3, n (%)	8 (40)
4, n (%)	3 (15)
7, n (%)	1 (5)
Bedrooms in home	
1, n (%)	3 (15)
2, n (%)	3 (15)
3, n (%)	8 (40)
4, n (%)	4 (15)
5, n (%)	3 (15)
Pets in home	
0, n (%)	7 (35)
1, n (%)	7 (35)
2, n (%)	3 (15)
3, n (%)	1 (5)
4, n (%)	2 (10)
Central air conditioning in home	
No, n (%)	15 (75)
Yes, n (%)	5 (25)
Air conditioning in home (any type - central, window, portable, or mini-split)	
No, n (%)	8 (40)
Yes, n (%)	12 (60)
Wood heating stove or fireplace in home	
No, n (%)	17 (85)
Yes, n (%)	3 (15)
Gas stovetop	
No, n (%)	14 (70)
Yes, n (%)	6 (30)
Portable air cleaner in home	

Participant or household characteristic	Summary statistic (N = 20)
No, n (%)	6 (30)
Yes, n (%)	14 (70)

sd = standard deviation; USD = United States Dollars;

Table 2:

Percentage of days with self-reported activities and observations among 20 participants in Western Montana, June through October 2022

Self-reported activity/observation	Wildfire vs non-Wildfire days	Total days activity/ observation was reported (n = 2091 days of follow-up)	Summary statistics[a]	Association with indoor $PM_{2.5}$[a]
			mean (sd) min, P25, median, P75, max	Estimate[b] (95% CI)
Windows and/or doors left open for ventilation	Non-wildfire days	993	62.0 (41.7) 0, 14.3, 76.9, 100, 100	2.6 (0.2, 5.1)
	Wildfire days	174	43.3 (36.2) 0, 12.5, 42.9, 66.7, 100	11.4 (6.4, 16.7)
Ambient air pollution or haze observed	Non-wildfire days	387	23.8 (29.7) 0, 0, 14.3, 37.5, 100	3.0 (−0.4, 6.5)
	Wildfire days	281	72.1 (28.3) 0, 50, 75, 100, 100	7.7 (0.7, 15.3)
Cleaning (dusting/sweeping) occurred in the home	Non-wildfire days	307	20.7 (18.0) 0, 0, 15.5, 28.6, 100	9.2 (3.4, 15.3)
	Wildfire days	52	15.0 (15.9) 0, 0, 14.3, 28.6, 71.4	17.0 (3.1, 32.7)
Incense burned in the home	Non-wildfire days	17	1.3 (6.6) 0, 0, 0, 0, 57.1	22.7 (5.1, 43.3)
	Wildfire days	8	3 (13.5) 0, 0, 0, 0, 66.7	9.5 (−8.4, 30.9)
Candle burned in the home	Non-wildfire days	25	1.9 (6.4) 0, 0, 0, 0, 42.9	14.1 (−2.9, 34.0)
	Wildfire days	1	0.4 (2.6) 0, 0, 0, 0, 16.7	25.3 (−50.4, 216.4)
Smoke from cooking in the home	Non-wildfire days	118	8.4 (14.9) 0, 0, 0, 14.3, 85.7	13.2 (5.9, 20.9)
	Wildfire days	24	7.3 (15.1) 0, 0, 0, 9.2, 71.4	3.4 (−10.7, 19.6)
Gas stove used inside the home	Non-wildfire days	307	22.5 (37.2) 0, 0, 0, 35.1, 100	2.2 (−0.6, 5.0)
	Wildfire days	74	22.6 (38.6) 0, 0, 0, 26.8, 100	−4.5 (−9.9, 1.3)
Charcoal grill used outside the home	Non-wildfire days	24	1.9 (6.5) 0, 0, 0, 0, 42.9	−2.1 (−16.4, 14.7)
	Wildfire days	10	2.9 (9.7) 0, 0, 0, 0, 42.9	5.2 (−17.8, 34.5)

Self-reported activity/observation	Wildfire vs non-Wildfire days	Total days activity/ observation was reported (n = 2091 days of follow-up)	Summary statistics[a]	Association with indoor $PM_{2.5}$[a]
			mean (sd) min, P25, median, P75, max	Estimate[b] (95% CI)
Gas grill used outside the home	Non-wildfire days	82	6.4 (12.7) 0, 0, 0, 14.3, 100	−4.0 (−11.3, 4.0)
	Wildfire days	20	5.9 (10.1) 0, 0, 0, 13.4, 33.3	−4.6 (−24.7, 20.7)
Mowing lawn/grass occurred outside the home	Non-wildfire days	149	11.0 (13.5) 0, 0, 11.1, 14.3, 66.7	1.3 (−5.9, 9.1)
	Wildfire days	34	10.6 (12.7) 0, 0, 12.5, 14.3, 42.9	25.4 (6.5, 47.7)
Construction occurred outside the home	Non-wildfire days	92	6.8 (20.4) 0, 0, 0, 0, 100	7.7 (2.5, 13.1)
	Wildfire days	27	8.2 (26.3) 0, 0, 0, 0, 100	10.0 (1.2, 19.5)

$PM_{2.5}$ = fine particulate matter; sd = standard deviation; min = minimum; P25 = 25th percentile; P75 = 75th percentile; max = maximum; CI = confidence interval

[a]Surveys were sent out electronically each week, but occasionally were not taken on the intended/scheduled day. For the self-reported activities/observations above, participants were told the number of days since their previous survey and asked to report the number of days each activity or observation occurred. Table 2 is reporting statistics on the percentage of days each activity or observation occurred out of the total number of days since the previous survey was taken.

[b]Estimates are presented as percent change in geometric mean indoor $PM_{2.5}$ (since the previous survey) per 10% increase in days with self-reported activity/observation.

Table 3:

Summary of 24-hour indoor fine particulate matter concentrations and infiltration efficiency across subcategories of 20 households in Western Montana, June through October 2022

	Indoor $PM_{2.5}$ (μg/m^3)			Infiltration efficiency (95% CI)
	Sampling Days	mean (sd) min, P25, median, P75, max	Estimate[a] (95% CI)	
All study days/households	1860	5.6 (8.7) 1.0, 1.3, 2.5, 5.5, 117.7		0.34 (0.33, 0.35)
Non-Wildfire period	1567	3.6 (5.2) 1.0, 1.1, 2.1, 3.9, 55.3	Reference	0.39 (0.37, 0.42)
Wildfire period	293	15.9 (14.7) 1.0, 5.6, 10.4, 21.0, 117.7	358.3 (311.4, 410.6)	0.32 (0.28, 0.36)
Participant age <43 years (median)	707	5.7 (8.9) 1.0, 1.4, 2.7, 5.9, 117.7	Reference	0.33 (0.31, 0.35)
Participant age 43+ years (median)	867	5.6 (9.3) 1.0, 1.2, 2.2, 4.8, 68.7	−11.2 (−20.0, −1.5)	0.36 (0.34, 0.38)
Household income <$75,000 / year	715	7.2 (11.0) 1.0, 1.6, 3.0, 7.3, 117.7	Reference	0.52 (0.49, 0.54)
Household income $75,000+ / year	1040	4.8 (7.1) 1.0, 1.2, 2.4, 5.1, 68.7	−26.8 (−33.6, −19.2)	0.24 (0.23, 0.26)
Education bachelor's or less	989	5.5 (9.1) 1.0, 1.3, 2.5, 5.3, 117.7	Reference	0.41 (0.39, 0.43)
Education advanced degree	871	5.7 (8.3) 1.0, 1.3, 2.5, 5.7, 68.7	4.4 (−4.9, 14.7)	0.27 (0.25, 0.29)
Home built before 1975 (median)	902	6.8 (9.8) 1.0, 1.8, 3.3, 6.9, 117.7	Reference	0.41 (0.39, 0.43)
Home built 1975 (median) or later	958	4.4 (7.4) 1.0, 1.1, 1.9, 4.2, 62.9	−36.9 (−42.4, −30.9)	0.27 (0.26, 0.29)
Home area <167 sqm (median)	941	6.2 (9.6) 1.0, 1.5, 2.8, 5.9, 117.7	Reference	0.43 (0.41, 0.45)
Home area 167+ sqm (median)	824	5.3 (8.0) 1.0, 1.3, 2.5, 5.2, 68.7	−12.3 (−20.3, −3.5)	0.26 (0.24, 0.29)
Home <10 windows (median)	854	6.1 (9.6) 1.0, 1.4, 2.7, 5.8, 117.7	Reference	0.39 (0.37, 0.41)
Home 10+ windows (median)	1006	5.2 (7.9) 1.0, 1.2, 2.4, 5.1, 68.7	−12.7 (−20.5, −4.1)	0.29 (0.27, 0.31)
Home <3 doors	696	6.0 (9.4) 1.0, 1.3, 2.6, 6.0, 117.7	Reference	0.36 (0.33, 0.38)
Home 3+ doors	1164	5.3 (8.3) 1.0, 1.3, 2.5, 5.1, 68.7	−8.0 (−16.5, 1.3)	0.33 (0.31, 0.35)
No pets in home	631	5.0 (8.1) 1.0, 1.0, 2.0, 4.6, 55.3	Reference	0.24 (0.22, 0.27)
1+ pets in home	1229	5.9 (9.1) 1.0, 1.4, 2.8, 5.9, 117.7	27.6 (15.7, 40.7)	0.39 (0.37, 0.40)
Central AC in home	504	5.2 (9.3) 1.0, 1.1, 1.9, 4.0, 62.9	Reference	0.32 (0.29, 0.35)
No Central AC in home	1356	5.7 (8.5) 1.0, 1.4, 2.8, 5.9, 117.7	27.8 (15.1, 41.9)	0.35 (0.34, 0.37)
Any type of AC unit	1155	5.1 (8.9) 1.0, 1.1, 2.2, 4.6, 117.7	Reference	0.30 (0.28, 0.32)

	Indoor $PM_{2.5}$ (μg/m^3)			**Infiltration efficiency (95% CI)**
	Sampling Days	**mean (sd) min, P25, median, P75, max**	**Estimate[a] (95% CI)**	
No AC unit of any kind	705	6.4 (8.5) 1.0, 1.7, 3.2, 6.9, 68.7	41.9 (29.0, 56.0)	0.42 (0.40, 0.45)
No wood stove or fireplace in home	1593	5.5 (8.8) 1.0, 1.2, 2.4, 5.2, 117.7	Reference	0.33 (0.31, 0.34)
Wood stove or fireplace in home	267	6.1 (8.3) 1.0, 1.7, 3.6, 6.7, 68.7	25.1 (9.5, 42.9)	0.43 (0.40, 0.46)
No gas stovetop in home	1331	5.2 (8.1) 1.0, 1.3, 2.5, 5.3, 117.7	Reference	0.33 (0.31, 0.34)
Gas stovetop in home	529	6.4 (10.2) 1.0, 1.1, 2.5, 5.8, 68.7	3.1 (−7.1, 14.3)	0.37 (0.34, 0.40)
Portable air cleaner in home	1312	5.1 (7.4) 1.0, 1.3, 2.5, 5.3, 68.7	Reference	0.25 (0.24, 0.26)
No portable air cleaner in home	548	6.7 (11.3) 1.0, 1.4, 2.5, 5.9, 117.7	9.8 (−0.9, 21.6)	0.57 (0.54, 0.60)
Outdoor mean daily temperature[b] <24 C	932	7.1 (10.8) 1.0, 1.4, 3.0, 7.9, 117.7	Reference	0.32 (0.30, 0.33)
Outdoor mean daily temperature[b] 24+ C	910	4.0 (5.6) 1.0, 1.2, 2.2, 4.2, 47.5	−30.1 (−36.3, −23.3)	0.40 (0.37, 0.42)

$PM_{2.5}$ = fine particulate matter; sqm = square meters; sd = standard deviation; min = minimum; P25 = 25th percentile; P75 = 75th percentile; max = maximum; CI = confidence interval; C = degrees Celsius

[a]Estimates are from simple linear regression analyses with 24-hour mean $PM_{2.5}$ as the outcome and household/demographic characteristics as predictor variables. Estimates are presented as percent difference in geometric mean $PM_{2.5}$.

[b]Outdoor temperature categorized by median daily outdoor temperature measured by PurpleAir sensors over the duration of the study (24 C).