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Using Low-cost Sensors to Quantify the Effects of Air Filtration on Indoor and Personal Exposure Relevant $PM_{2.5}$ Concentrations in Beijing, China

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ABSTRACT

Residents of polluted cities frequently use indoor air purifiers in an attempt to improve their health by reducing their exposure to air pollutants, despite the fact that few studies have assessed these devices under relevant field conditions. Low-cost air monitors are increasingly popular for monitoring air pollution exposure; however, they must be calibrated and evaluated in their deployment location first to ensure measurement accuracy and precision. In this study, we developed a 2-step calibration method in which a low-cost monitor is calibrated against a reference analyzer and is then used to calibrate other monitors, shortening the required calibration time and reducing measurement error. The monitors in our experiment measured indoor, outdoor, and personal exposure $PM_{2.5}$ concentrations during 1 week each of true and sham filtration in 7 homes in Beijing, China. On average, filtration reduced the indoor and personal exposure relevant concentrations by 72% (std. err. = 7%) and 28% (std. err. = 5%), respectively. This study indicates that minimizing personal exposure, however, also requires reducing the infiltration of outdoor air in homes or decreasing $PM_{2.5}$ pollution at the city or country level.

Keywords: Air filtration; Low-cost sensors; $PM_{2.5}$; Personal exposure; Plantower.

INTRODUCTION

Fine particulate matter ($PM_{2.5}$) is associated with multiple adverse health outcomes (Laden *et al.*, 2006; Miller *et al.*, 2007; Puett *et al.*, 2009). $PM_{2.5}$ concentrations are above the World Health Organization (WHO) annual guideline of 10 μg m^{-3} (World Health Organization, 2016) in many cities globally (Cheng *et al.*, 2016). Reducing exposure to $PM_{2.5}$ has the potential to significantly benefit health (Morishita *et al.*, 2015), especially in cities with elevated levels of air pollution, such as Beijing, China (Cheng *et al.*, 2019). Although $PM_{2.5}$ has improved over the past few years—from 90 μg m^{-3}, on average, in 2013 to 58 μg m^{-3} in 2017 (Cheng *et al.*, 2019)—it is still almost 6 times the WHO guideline.

Improving outdoor $PM_{2.5}$ in the short-term is largely out of the hands of individual citizens and depends on the actions of national and local governments. Improving indoor $PM_{2.5}$, however, is more easily achieved by the individual through measures to reduce indoor-generated $PM_{2.5}$ (e.g., not smoking or burning incense indoors, ventilating during cooking, reducing fuel combustion for heating and cooking), to reduce the penetration of outdoor $PM_{2.5}$ into the indoor environment (e.g., better-sealed rooms) and to remove $PM_{2.5}$ indoors (e.g., through the use of HEPA filters, indoor plants) (Li *et al.*, 2017; Pettit *et al.*, 2018). Indoor air can be highly polluted as it is a combination of outdoor pollutants that infiltrate indoors and pollutants from indoor sources (Mohammed *et al.*, 2015). Indoor air quality is especially important since adults living in urban areas of China spend roughly 82% of their time indoors (Wang *et al.*, 2008).

Portable air filtration devices are a common solution to poor air quality in China, especially in more affluent urban areas (Sun *et al.*, 2017). Indoor filtration is potentially an

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effective strategy to reduce particles (Cui *et al.*, 2018), but the performance of purifiers is variable depending on the device and the environment in which it is deployed (Zhang *et al.*, 2011).

To quantify the effectiveness of indoor interventions on reducing indoor $PM_{2.5}$ and personal exposure to $PM_{2.5}$, many indoor and personal exposure measurements must be taken. Air quality measurements taken in many locations are also important for health studies since assumptions of uniform exposure may mask health associations. Real-time $PM_{2.5}$ can be measured simultaneously in many locations using low-cost, optically-based PM monitors for a reasonable cost (< US$300 per monitor (Zheng *et al.*, 2018, Malings *et al.*, 2019)). Performance of these sensors varies and the importance of calibrating and evaluating these sensors in each environment where they will be deployed has been highlighted in previous studies (Snyder *et al.*, 2013; Jiao *et al.*, 2016; Borghi *et al.*, 2018; Feinberg *et al.*, 2018; Johnson *et al.*, 2018; Morawska *et al.*, 2018; Zheng *et al.*, 2018). Testing monitors in the environment where they will be deployed is important both because aerosol optical properties are variable and because sensor measurement ranges vary and are often not well reported by the manufacturer. Some studies use low-cost, optical monitors to evaluate personal exposure (Steinle *et al.*, 2015; Ozler *et al.*, 2018) or indoor air quality (Steinle *et al.*, 2015; Mazaheri *et al.*, 2018; Zuo *et al.*, 2018) or explore the performance of these monitors (Jiao *et al.*, 2016; Feinberg *et al.*, 2018; Jayaratne*et al.*, 2018; Johnson *et al.*, 2018; Zheng *et al.*, 2018) but very few authors have both calibrated and evaluated their monitor to ensure data validity in their deployment location and subsequently used the sensors to evaluate indoor air quality and personal exposure (Morawska *et al.*, 2018). The aims of this study were two-fold: 1) to determine the best strategy for calibrating the monitors and to better quantify monitor error and 2) to apply this calibration to assess the impact of air filtration on indoor air quality and personal exposure.

In this paper, we present field measurements conducted in Beijing. Low-cost monitors are deployed to assess the impacts of air purifiers on personal exposure and indoor air quality. To ensure the accuracy of these measurements a calibration method is first developed that reduces error and inter-monitor variability and may be useful for future studies.

METHODS

Study Overview

This intervention study took place in Beijing, China, over a 2-week period during July and August 2016. 7 participants received roughly 1 week of true filtration and 1 week of sham filtration. Low-cost $PM_{2.5}$ monitors were used to measure indoor, outdoor, and personal exposure. The low-cost monitors were calibrated by collocating them on a rooftop near a tapered element oscillating micro-balance (TEOM) before and after in-home sampling (Fig. 1). Two calibration methods were evaluated: 1) calibrating directly against the TEOM and 2) calibrating all monitors against a monitor that was calibrated against the TEOM for a longer period. Collocated gravimetric samples were collected in homes to verify this calibration method. Low-cost and comparison methods are described in detail in the following sections. Indoor to outdoor ratios, infiltration factors, and personal to outdoor ratios were calculated to determine purifier performance in these homes.

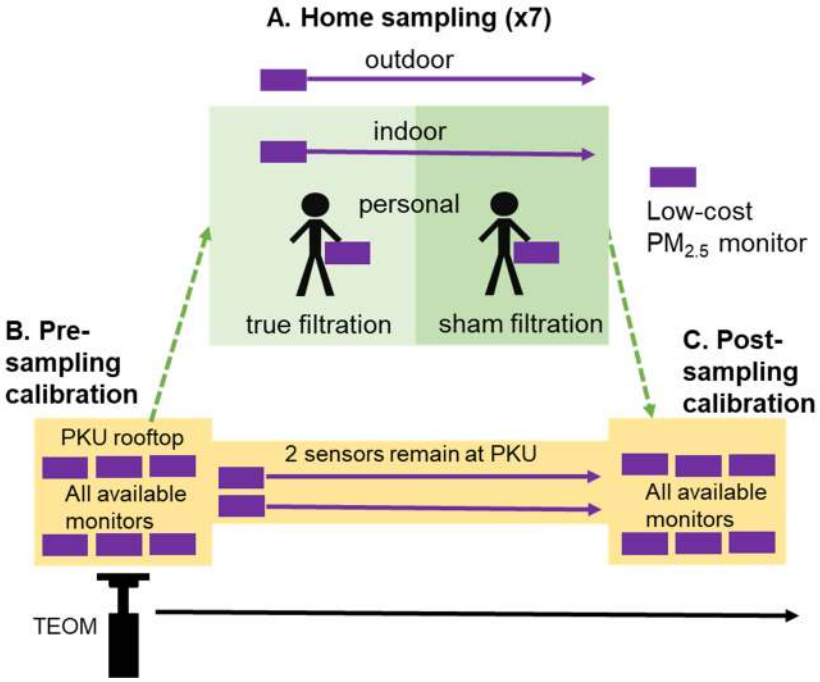

Fig. 1. Project overview: (a) Sampling occurred at 7 homes during both true and sham filtration. Low-cost $PM_{2.5}$ monitors were used to measure outdoor, indoor, and personal exposure at each home. The monitors were collocated on a rooftop at Peking University (PKU) near a TEOM for calibration (b) before and (b) after the deployments.

Seven volunteer adult participants were recruited from around Beijing. They were recruited by word of mouth by staff at Tsinghua University, and indoor smokers, and residents of dormitory-style housing were excluded. Participants lived within 20 km of Peking University (PKU) and all homes were apartment-style dwellings. A brief survey about each home, its residents, and general behavior patterns was collected and is summarized in Table 1. Participants and home residents were all adults, and in many cases, multiple generations were present in the home (i.e., adult children and parents, adult grandchildren and grandparents, or adult children, parents, and grandparents). There were 1–4 residents per apartment with a resident defined as someone who spends at least 4 hours per day in the home.

A portable Amway Atmosphere™ air purifier (Ada, Michigan, USA; www.amway.com) was set up in each household. The purifiers contained 3 layers of filtration: 1) a coarse pre-filter for removing large particles, 2) an activated carbon filter, and 3) a high-efficiency particulate air (HEPA) filter. Purifiers were operated as a "true" purifier for 1 week and as a "sham" purifier (a device without the activated carbon or HEPA filters) for another week in each participant's home. Participants were instructed to leave the windows and doors in the room closed. A summer time frame in Beijing was selected to avoid the severe haze events that often occur during colder months and spring dust storms in Beijing (Zhao *et al.*, 2013; Yu *et al.*, 2016; Qiu *et al.*, 2019). The performance of air purifiers during severe winter pollution would be less transferable to other parts of the world and during other periods.

Two air monitors recorded 2 weeks of data at each home while the purifier was operating. 1 monitor was set up in the participant's bedroom with the purifier, about 1 meter above the ground (e.g., on a nightstand or a convenient shelf). The other monitor was set up outside the participant's home, usually hanging from a bar on the balcony. Participants carried a personal monitor for 48 hours during both the true and sham periods (roughly 96 hours total).

Purifier Operation

The purifiers were operated at a manufacturer reported clean air delivery rate (CADR) of 2.8 m^3 min^{-1} (fan speed: "level 2" on the purifier), and were run continuously. Level 2 was the highest setting deemed quiet enough to not disturb the participants. Since the purifier fans ran at 2.8 m^3 min^{-1} during both the true and sham filtration, we assume the room was relatively well mixed. Based on the purifier CADR of 2.8 m^3 min^{-1}, a removal efficiency of the HEPA filter of 99% and an estimated typical room size of 35 m^3, a first-order decay equation can be used to estimate the time it takes for the room to reach steady-state. 90% of the steady-state concentration could be reached in roughly 30 minutes. This means that the steady-state was likely achieved fairly quickly after each pollutant event, or after turning on the air purifier.

Monitor Design

Low-cost sensors are often sold as stand-alone components

Table 1. Home parameters and general home activity data from survey.

		Home 1	Home 2	Home 3	Home 4	Home 5	Home 6	Home 7
Home parameters	Number of residents	3	1	4	1	4	3	3
	On which floor is the apartment located?	3	ground	6	3	5	19	
	How often is air conditioning used while people are home?*	most	some	most	most	some	some	some
Cooking	Days stove or oven used (weekly)	7	4	0	0	0	1	0
	Main cooking fuel	Natural gas						
	Average hours stove or oven used on cooking days	2.5	0	0	0	0	3	2
	Exhaust fan used during cooking	yes	yes	yes	yes	yes	yes	yes
Other potential indoor PM sources	Frequency of burning candles or incense (weekly)	0	1–2	0	0	0	0	0
	Shoes worn inside the house	yes	yes	yes	yes	yes	yes	no
	Indoor pets	no	no	no	no	no	yes	yes

*"some": some of the time; "most": most of the time.

that need to be assembled into a larger monitoring device to log data. Although many low-cost monitors currently exist on the market, none met our needs with reliable data storage, portability for personal exposure, and well-defined sensor performance. This led us to design our own monitors. Low-cost air monitors used during this project were developed over multiple years by researchers at Duke University. The monitors contained a PM sensor (PMS 3003; Plantower), a custom printed circuit board, a Teensy microcontroller, an SD card for data logging, and a real-time clock to time-stamp the data. A Sensirion SHT15 sensor was used to collect supporting temperature and relative humidity (RH) data (Fig. 2). The Plantower PM sensor costs ~$30, and the entire monitor costs ~$200 in parts plus assembly. Additional gas-phase sensors (O_3, NO, NO_2, and CO_2) were included in many of our monitors (for an additional cost ~$400), although results are not discussed here. Monitors recorded 1-minute averaged data that were averaged to 1 hour or longer time intervals for analysis. Monitors were connected to wall power where available and convenient or with 20-ampere-hour lithium ion power bank batteries where wall power was not easily accessible (e.g., outdoor balconies). Additional details about the monitors can be found on our open-source webpage (dukearc.com). These monitors have been used to monitor personal exposure and trash burning emissions in previous publications (Ozler *et al.*, 2018; Vreeland *et al.*, 2018; Zhang *et al.*, 2019).

The electronics were enclosed either in a hard, electrical case (Fig. 2(a)) or in a modified eye-glass case for personal exposure monitoring (Figs. 2(b) and 2(c). 22 monitors were deployed in total with 5 personal exposure monitors and the remainder as indoor/outdoor monitors.

The key measurements discussed in this paper are made by the Plantower sensor, which is an optical particle sensor that provides a serial output of PM_1, $PM_{2.5}$, and PM_{10} mass. A fan draws air into the sensing chamber where light

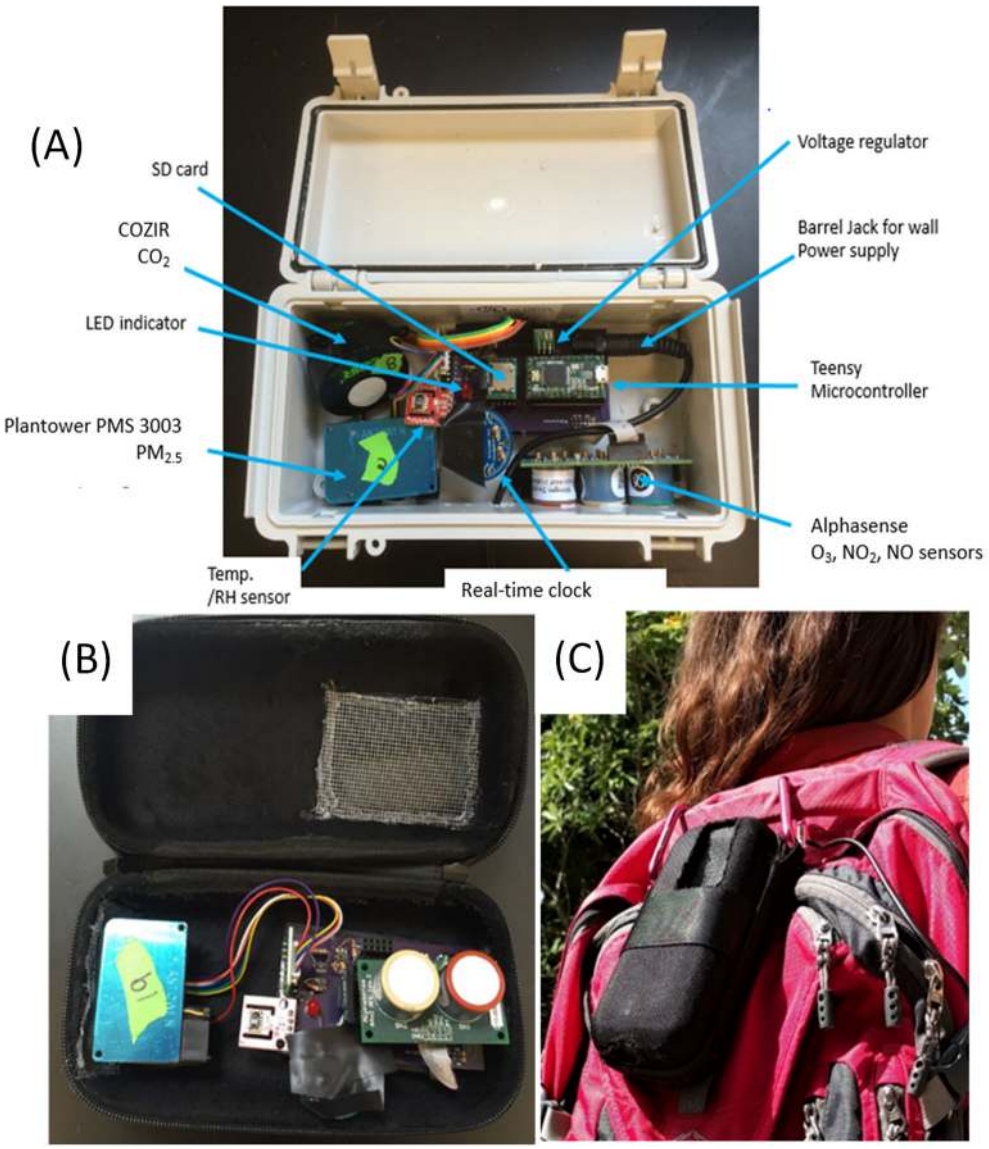

Fig. 2. (a) All sensor package components in indoor/outdoor sampling case, (b) personal monitoring case with internal components, and (c) personal monitor hanging on a backpack.

scattered perpendicular to the beam is measured by a photodiode detector. Previous work has been done to calibrate and evaluate this PMS 3003-based monitor in India and the U.S. (Zheng *et al.*, 2018) and other work has used and evaluated other Plantower monitors (Kelly *et al.*, 2017; Borghi *et al.*, 2018; Gupta *et al.*, 2018; Jayaratne *et al.*, 2018; Marques *et al.*, 2018; Sayahi *et al.*, 2019).

Monitor Calibration

During this project, monitors were calibrated by collocating them on the rooftop of an academic building on PKU's campus near a TEOM, and generating a calibration based on the 1-hour-averaged data. The TEOM measures $PM_{2.5}$ by collecting particles on an element that oscillates. As the inertia of the element increases the frequency of oscillation decreases as a function of mass (Gilliam and Hall, 2017). The monitors and TEOM were located away from major roads and localized pollution sources. Most monitors (n = 13) were collocated for 2 days prior to field deployment in the homes, and 1 day after field deployment in the homes (79–82 hours per monitor in total) but some monitors (n = 7) did not have both pre- and post-data due to issues related to retrieving monitors from homes after sampling, user error, or power supply. The remaining 2 monitors stayed on the rooftop near the TEOM for the duration of the project for an extended comparison (315 and 485 hours).

There are some limitations to calibrating low-cost sensors in a single outdoor location when monitors will also be used for indoor and personal exposure monitoring since the aerosol optical properties may vary. However, it is infeasible to do calibrations with real-time reference monitors in these locations. To check whether an outdoor calibration is reasonable for indoor and personal exposure aerosol, filter-based measurements were also taken alongside a subset of indoor and personal exposure monitors. These are discussed in greater detail below.

Selecting a Calibration Method: Direct or 2-step

Two possible methods of calibration were considered in this work: 1) calibrate each monitor directly against the TEOM and 2) calibrate 1 monitor against the TEOM and subsequently calibrate all other monitors against this calibrated monitor. For the second method, we chose the monitor that collected the most $PM_{2.5}$ data during this prolonged collocation. The second calibration method may be useful for future work where it is impossible or impractical to collocate all monitors with a reference analyzer. Root mean square error (RMSE) and the normalized root mean square error (NRMSE), calculated as the RMSE divided by the average $PM_{2.5}$ concentration, have been used to summarize the inter-monitor variability and the variability between the monitors and the TEOM.

In addition, 95% confidence intervals (CI) have been compared to suggest how much bias the calibration may be adding to our low-cost measurements. The 95% CI on the direct TEOM calibrations were calculated using 2 times the standard error of the slope. The standard error is the square root of the variance of the variable and was calculated using the linear regression function in R (R core team, 2015). The 95% CI of the direct calibration between the reference low-cost monitor ("b2") and the TEOM ("CI_{b2}") is used in the calculation of the 2-step calibration 95% confidence interval. The 95% CI on the 2-step calibration was calculated by combining the 95% CI between the individual monitor, and b2 and CI_{b2} using the rule for error propagation when multiplying (Caldwell and Vahidsafa, 2018).

After calibration, a limit of detection (LOD) was calculated. Using the monitoring data that corresponds to the lowest concentrations measured by the TEOM (5–6 μg m^{-3}), the LOD was calculated as 2 times the standard deviation of this low-concentration monitoring data. All data below the LOD were replaced by the LOD.

Calibration Considerations: Influences of RH

Previous work has shown that both low-cost and research-grade, optically-based methods overestimate $PM_{2.5}$ at high humidity as compared to dried methods (i.e., TEOM, other Federal Reference Methods, and filter-based measurements). Previous work has shown this relationship is non-linear at high RH (> 80%) and can be represented by the equation (Zhang *et al.*, 1994; Day *et al.*, 2001; Chakrabarti *et al.*, 2004; Soneja *et al.*, 2014; Zheng *et al.*, 2018):

$$\frac{\text{raw optical } PM_{2.5}}{\text{reference } PM_{2.5}} = a + b \times \frac{RH^2}{(1 - RH)} \quad (1)$$

where a and b are empirical coefficient, and a represents the constant ratio between the optical and reference PM at low RH and b represents the non-linear increase in light scattering with increasing RH. This equation has been used in previous work with these low-cost monitors (Zheng *et al.*, 2018). This equation was considered for calibration in this study as well.

Comparisons with Collocated Gravimetric Samples

In addition to the in-home low-cost monitor measurements, 48-hour 37-mm quartz and Teflon $PM_{2.5}$ filter samples were collected indoors and outdoors in a subset of the homes. Only Teflon filters were collected for personal exposure to limit the burden on the participants. All filter measurements occurred at the same time as the real-time personal exposure monitoring (Zhan *et al.*, 2018). Filter samplers were placed in the bedroom near the low-cost monitor, outdoors near the low-cost monitor and on the personal monitoring bag with the low-cost monitor. SKC Personal Environmental Monitors (PEMs) were used with SKC AirChek pumps to sample indoor and outdoor $PM_{2.5}$ at 4 L min^{-1} and personal exposure at 2 L min^{-1}. $PM_{2.5}$ mass was determined by weighing Teflon filters before and after sampling after equilibrating under controlled temperature (22–24°C) and RH (40–50%) using a microbalance (0.001 mg) (Shirmohammadi *et al.*, 2015). 5 trip blanks and 5 loading blanks were collected for quality assurance during the study. The results of these

filter-based measurements are discussed in detail elsewhere (Zhan *et al.*, 2018). 48-hour-averaged low-cost monitor measurements have been compared to these filter-based measurements. Filter-based measurements were excluded if flow rates changed by more than 15% during sampling. The bias, calculated as the average of the error between the methods, was used along with the NRMSE to compare the filter and low-cost monitor measurements.

Indoor to Outdoor Ratios

Since indoor $PM_{2.5}$ is typically dependent on outdoor $PM_{2.5}$, a simple way to evaluate an indoor intervention, such as an air purifier, is by calculating the indoor to outdoor pollutant ratio (I/O) (Chen and Zhao, 2011) and comparing I/O during the true and sham periods. This allows the indoor and outdoor concentrations to be normalized by taking into account the differences in outdoor concentrations during different times and locations across the city.

Estimating Indoor Infiltration Factors

$PM_{2.5}$ indoors may come from indoor sources or may be due to infiltration from outdoor $PM_{2.5}$. Identifying the contribution of indoor and outdoor sources may help to determine the most effective mitigation strategy for improving indoor air quality. Infiltration factors can be calculated to estimate the fraction of outdoor PM that enters the indoor environment while taking into account indoor sources as shown by Eq. (2) (Chen and Zhao, 2011). Under steady-state conditions, the indoor concentration (C_{in}) can be represented as a function of the outdoor concentration (C_{out}), the effective infiltration factor (F_{in}) and the effective indoor source (s) as follows:

$$C_{in} = F_{in} \times C_{out} + s \quad (2)$$

The effective infiltration factor is a function of the air exchange rate, the particle penetration factor, and the particle removal (which includes deposition and purifier use). The effective indoor source strength is a function of the indoor source, the room volume, and removal rate (Chen and Zhao, 2011). The infiltration factor and the effective indoor source can be estimated by determining the slope and intercept, respectively, of the indoor vs. the outdoor $PM_{2.5}$ data.

Although there is often a time lag between indoor $PM_{2.5}$ approaching equilibrium with outdoor $PM_{2.5}$, this time lag is typically assumed to be negligible for measurement time periods of 24 hours or more (Diapouli *et al.*, 2013). In this case, we have generated 24-hour averages of the indoor and outdoor data for comparison. Both sham and true periods had 4–8 24-hour data points depending on how many complete 24-hour periods were sampled in the homes. Although indoor sources are likely to vary over the course of a day due to household activities (cooking, use of personal care products, cleaning, etc.), we assume they stay relatively constant from day to day.

Ratios of Personal Exposure to Outdoor Concentrations

The personal to outdoor ratio (P/O) has been used to assess how well the interventions worked since personal exposure is typically a function of outdoor concentration. The difference in actual personal exposure (in μg m^{-3}) would be more important for health effects while the ratio can allow for comparisons of true and sham personal exposure even if outdoor concentrations were significantly different.

RESULTS AND DISCUSSION

Plantower Output

The Plantower sensors provide both "raw" PM concentrations (PM_1, $PM_{2.5}$, and PM_{10}) and the same 3 concentration values with a proprietary ambient correction. To generate the ambient corrected data, the manufacturer has applied a non-linear calibration to the "raw" $PM_{2.5}$ concentration data. This is apparent when plotting the raw output vs. the ambient corrected output where a non-linearity in the response is seen between 50 and 100 of the raw Plantower output (20–40 μg m^{-3} as measured by the TEOM) (Fig. 3). The first step of calibrating our low-cost monitors was to determine which of the two manufacturer-supplied $PM_{2.5}$ values to use throughout this project. The ambient corrected data better took into account non-linearity in the sensor output at low concentrations since a

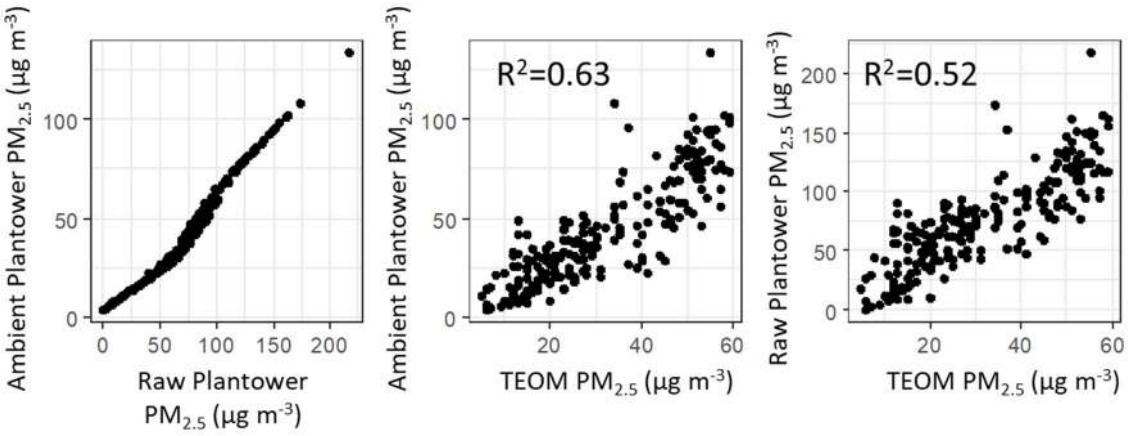

Fig. 3. The non-linear relationship between the 2 outputs from the Plantower as provided by the manufacturer. At low concentration (< 60 μg m^{-3}) better agreement is seen between the ambient corrected output than the raw output.

different equation is applied to the data below and above ~30 μg m^{-3} (< 60 μg m^{-3}: "raw" R^2 = 0.52, ambient R^2 = 0.63). The ambient corrected $PM_{2.5}$ concentrations have been used throughout this paper. Previous work with this monitor has used the "raw" output so a limited comparison can be made (Zheng *et al.*, 2018).

Conditions during Calibration

Details of the calibrations are presented in Table 2. During the pre-calibration period, the average $PM_{2.5}$ concentration as measured by the TEOM was 65 ± 40 μg m^{-3} (mean ± standard deviation) while during post-calibration the concentration was lower with less variability (16 ± 6 μg m^{-3}). 1-hour $PM_{2.5}$ concentrations as measured by the TEOM were as high as 225 μg m^{-3} but rarely exceeded 150 μg m^{-3}.

Calibration Considerations: Calibration Intercept, and Drift over Time

During calibration, $PM_{2.5}$ concentrations were seldom < 10 μg m^{-3} (4% of the time). Due to the small amount of low concentration PM data, there is uncertainty in the calibration intercept. A calibration using linear regression with a non-zero intercept resulted in underestimates of low concentrations of $PM_{2.5}$, and led to many negative $PM_{2.5}$ values during the low concentration periods (< 10 μg m^{-3}). Negative $PM_{2.5}$ values were especially noticeable once the calibrations were applied to the indoor data, given the lower concentrations experienced indoors during this study. Since the intercepts were typically not significantly different from zero (linear regression intercept: $p < 0.05$) the intercepts for all monitors have been set to 0. Non-linear calibrations including quadratic regression were also considered but they did not significantly improve the R^2 or the RMSE of the $PM_{2.5}$ monitor estimates.

In order to assess whether or not sensor performance deteriorated over time, separate linear calibrations were generated for the pre- and post-calibration periods when data were available. Pre- and post-calibration slopes were stable over the 2-week project (pre- and post-slopes within 1%); therefore, all available data were aggregated to generate a single calibration for each monitor.

Comparison of Two Possible Calibration Strategies

Without calibrations, the monitor values were highly correlated with the TEOM (R^2 = 0.95) but overestimated the $PM_{2.5}$ concentrations by roughly 40% on average (Fig. 4). This highlights the importance of calibrating these monitors instead of using the raw values of $PM_{2.5}$ reported by the sensor at the concentration range experienced during this project. The monitors were even more highly correlated amongst each other even at a 1-minute time interval (R^2 > 0.97), underscoring the high precision of the monitors.

The high correlation of each monitor with both the reference TEOM and all other monitors (N = 21) suggests that either directly calibrating the low-cost monitors against the TEOM or calibrating them against a calibrated monitor may be a valid solution to ensure data accuracy. The results of these two calibration methods (including NRMSE and 95% CI of the slope) are summarized in Table 1. The TEOM columns show the results for a direct calibration. The 2-step columns show the results for a 2-step calibration where first a monitor is calibrated against the TEOM and then all other monitors are calibrated against that calibrated monitor.

Using the direct TEOM calibration the average calibration slope is 1.32 ± 0.13 (average slope ± standard deviation for all monitors). 2 times the standard deviation will give the 95% CI on the slopes across the different monitors. The 95% CI across the monitors' slopes is 0.26 or 20%. This suggests that using a single calibration for a monitoring network could bias measurements from different sensors by ±20% and stresses the importance of generating a calibration for each individual sensor.

For the 2-step calibration method, Monitor b2 has been used as the calibrated monitor since during this project, b2 was collocated with the TEOM for the longest period of time. The average calibration slope is 1.36 ± 0.11 similar to the direct TEOM calibration but significantly different using a paired t-test. This distribution of monitor calibrations again highlights the importance of generating a calibration for each individual monitor especially for applications that require high-accuracy measurements, such as this project.

The slopes generated by the direct calibration and the 2-step method vary by 3% on average, with a maximum difference of 19%. The slopes with the most change are from the sensors that ran during only post-calibration, where the $PM_{2.5}$ was low and had limited variability.

Difference between Monitors and TEOM

The difference between the TEOM and the monitor measurements is summarized as the NRMSE calculated between each individual low-cost monitor and the TEOM. The average NRMSE between the calibrated monitor data and the TEOM is 28% using either method. These discrepancies in measured values are due to differences in measurement methods and noise in the 1-hour TEOM measurements. The NRMSE would be much lower for most of the results reported in this paper since they are reported at averaging times longer than 1 hour (Zheng *et al.*, 2018). The 1-hour 28% error is consistent with past results and may be driven primarily by the precision of the reference monitor (Zheng *et al.*, 2018).

Inter-monitor Variability

The 1-hour NRMSE between the monitors and Monitor b2 is low on average using either method (TEOM = 7%, 2-step = 2%). However, 3 monitors have an NRMSE with b2 of 14–22% using the direct TEOM calibration method. This higher inter-monitor variability is undesirable in applications like ours since many comparisons are made between monitors in different locations (i.e., indoor and outdoor or outdoor across different locations)—for our application we want the difference between data from monitors to be due to real differences in localized pollutants, not monitor variability. Using the 2-step calibration the maximum NRMSE for any monitor with b2 is only 4%. By reducing the inter-monitor variability, we make it easier to

Table 2. Calibration results for each monitor. The TEOM section summarizes the results for a linear calibration with 0 intercept between each monitor and the TEOM directly including the 95% confidence interval (CI) of the slope and the NRMSE between the individual calibrated monitor measurement and both the TEOM and the calibrated reference monitor (b2). The 2-step column shows the same parameters for calibration against Monitor b2. The difference between the two calibration slope estimates is shown in the final column.

Monitor	Hours	Active calibration periods	$PM_{2.5}$		TEOM					2-step					Slope difference
			Mean	SD	R^2	Slope	95%	NRMSE		R^2	Slope	95%	NRMSE		
			($\mu g\ m^{-3}$)				CI	TEOM	b2			CI	TEOM	b2	
b2	485	pre, post, base	59	40	0.96	1.4	2%	24%	0%	1.00	1.4	2%	24%	0%	NA
b10	315	pre, post, base	63	42	0.96	1.49	2%	26%	3%	1.00	1.51	2%	25%	2%	–1%
b24	82	pre, post	47	39	0.94	1.24	5%	32%	7%	1.00	1.28	3%	31%	2%	–3%
b19	82	pre, post	47	39	0.95	1.27	5%	29%	7%	1.00	1.3	3%	28%	2%	–3%
b27	82	pre, post	47	39	0.95	1.22	5%	31%	6%	1.00	1.26	3%	31%	2%	–3%
b16	82	pre, post	47	39	0.95	1.36	5%	29%	5%	1.00	1.4	2%	28%	2%	–3%
b15	82	pre, post	47	39	0.95	1.24	5%	30%	6%	1.00	1.28	3%	30%	2%	–3%
b23	82	pre, post	47	39	0.95	1.35	5%	30%	5%	1.00	1.39	3%	29%	2%	–3%
b9	81	pre, post	46	38	0.96	1.25	5%	27%	7%	1.00	1.26	3%	27%	2%	–1%
b5	81	pre, post	46	38	0.96	1.45	5%	26%	6%	1.00	1.46	3%	26%	2%	–1%
b8	81	pre, post	46	38	0.95	1.17	5%	30%	4%	1.00	1.19	3%	29%	2%	–2%
b7	81	pre, post	46	38	0.96	1.49	5%	26%	8%	1.00	1.51	3%	26%	2%	–1%
b6	80	pre, post	45	36	0.96	1.48	4%	25%	6%	1.00	1.47	3%	24%	2%	1%
b28	80	pre, post	45	36	0.95	1.29	5%	29%	4%	1.00	1.29	3%	28%	2%	0%
b13	79	pre, post	45	36	0.91	1.39	7%	39%	22%	0.97	1.4	5%	38%	4%	0%
b22	52	pre	65	40	0.95	1.26	7%	27%	5%	1.00	1.29	3%	27%	2%	–3%
b1	52	pre	65	40	0.95	1.41	7%	27%	5%	1.00	1.45	3%	27%	2%	–3%
b17	52	pre	65	40	0.96	1.39	6%	25%	5%	1.00	1.42	3%	25%	2%	–2%
b18	51	pre	63	38	0.96	1.39	6%	24%	5%	1.00	1.4	3%	24%	2%	–1%
b12	48	pre	64	39	0.96	1.43	6%	22%	3%	1.00	1.51	3%	22%	2%	–6%
b14	30	post	16	6	0.93	1.13	10%	28%	14%	1.00	1.3	3%	30%	2%	–14%
b25	17	post	13	5	0.89	0.95	17%	37%	19%	1.00	1.13	3%	36%	3%	–19%
Mean			49	36	0.95	1.32	6%	28%	7%	1.00	1.36	3%	28%	2%	–3%

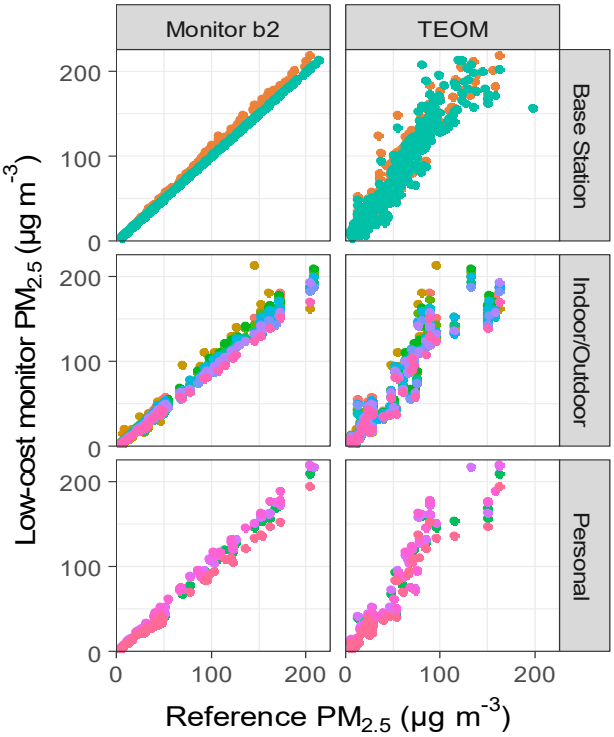

Fig. 4. Better agreement is seen between the low-cost reference monitor (b2) and all the low-cost monitors than the TEOM and all the low-cost monitors. Base stations have the most comparison data but relationships are similar between different monitor types.

distinguish whether Home A indoor is different than Home A outdoor or whether Home A outdoor is different than Home B outdoor. The reason for this difference in inter-monitor variability will be discussed in the following section.

Calibration Error: Slope Confidence

When comparing the 95% CI on each individual calibration slope, the 95% CI on the 2-step Plantower calibration is 2–5% while the 95% CI on the direct TEOM calibration is 2–17%. The direct calibration with the TEOM is limited in that only a few days (roughly 2 days prior to home deployment and 1 day after home deployment) of data are being used for the calibration. In contrast, when the 2-step calibration is applied, the initial relationship (calibration of b2 against the TEOM) is estimated using more than 2 weeks of data. Based on the central limit theory, gathering a large enough sample will give us a normal distribution around the true mean value or in this case the true mean relationship between the low-cost monitors and the TEOM. Some monitors do not have enough data points to generate a confident mean relationship directly between the monitor and the TEOM. However, since the inter-monitor correlation is relatively high ($R^2 > 0.97$), the accuracy generated with the 2-step calibration seems to be independent of hours sampled.

The Selected 2-step Calibration Method

The 2-step calibration has been selected since it gives a more confident estimate of the slope than calibrating directly against the TEOM. The 2-step method reduces the error more for the monitors that ran for the shortest time. These results suggest that roughly 24 hours of calibration against a calibrated reference monitor of the same type (e.g., Duke Plantower-based monitor) could be sufficient to generate a calibration. In addition, the 2-step method does not require as dynamic a range of $PM_{2.5}$ to generate a calibration estimate (95% CI < 10%) as demonstrated by the monitors with only post-calibration data ($PM_{2.5}$ = 16 ± 6 µg m^{-3}). It should be noted that during the time drift analysis the 2-step calibration was used to determine that there was no change in calibration from the pre-calibration to the post-calibration periods.

This 2-step calibration strategy is an important result for future field projects. This method can provide a lower-budget way to calibrate optical monitors where less collocation time is required and may provide a way to quickly check calibrations periodically over the course of longer projects. In addition, if all monitors cannot be brought to a single collocation site a reference monitor could be rotated to different sites to calibrate each monitor over short time periods after undergoing its own calibration with a true reference analyzer (i.e., Federal Reference, Federal Equivalent, other non-optical methods).

Limit of Detection

The minimum TEOM concentration measured outdoors at the base station was 5 µg m^{-3} during this project. This may lead to challenges for indoor monitoring where the concentrations may be below this level. Therefore, an LOD was calculated. There were 30 hours of matching TEOM and monitor measurements where the TEOM measured 5–6 µg m^{-3} of $PM_{2.5}$, which is roughly 2% of the total hours of calibration data (1312 hours). Using this data, the LOD is calculated by using 2 times the standard deviation (3 µg m^{-3}); therefore, the LOD is 6 µg m^{-3}. Hence, any measurements below 6 µg m^{-3} have been replaced with 6 µg m^{-3}. As expected, indoor locations had the most data below the LOD (26%). Only 1% of the outdoor data and 8% of the personal exposure data was below the LOD. Overall, 10% of the total data was below the LOD.

Calibration Considerations: Influences of RH

Our objective was to find a standardized calibration method for all monitors that reduces error and inter-monitor variability. We first examined the potential application of an RH calibration (Eq. (1)) using the same method as described previously where first a calibration was generated between the TEOM and b2 and then a calibration was generated between b2 and each low-cost monitor. The ratio between monitor b2 and the TEOM had a moderate relationship with the RH (R^2 = 0.4). Previous work has used an $R^2 \leq 0.4$ as a cut off where an RH correction is not necessary (Zheng *et al.*, 2018). 91% was the highest RH experienced during calibration with only 4 monitors measuring at least 1 hour of RH above 90%. Some of the monitors (N = 6) had no data above 80% RH and more than one third (N = 9) had fewer than 2 calibration points

above 80% RH. This led to 2 monitors having poor correlations with b2 (R^2 < 0.4) and led to significant uncertainties in the other 7 monitors above their maximum RH during calibration. Since RH calibrations could not be applied uniformly across monitors and since the relationship between b2 and the TEOM had an R^2 = 0.4 no RH correction was applied.

Comparison of Collocated Gravimetric Samples

Collocated filter and low-cost monitor measurements showed similar relationships between indoor, outdoor, and personal exposure pairs. The NRMSE between the filter and low-cost monitor measurements was similar across measurement types with an NRMSE of 27% outdoors (N = 12), 26% indoors (N = 6), and 24% for personal exposure (N = 5). Although this is a small sample size for comparison, it highlights that monitor measurements are similarly able to capture indoor, outdoor, and personal exposure concentrations. On average, the bias of the low-cost monitor measurements is +1 μg m^{-3}, with a bias of –1 μg m^{-3} indoors, a bias of +2 μg m^{-3} outdoors, and a bias of +0.5 μg m^{-3} for personal exposure, as determined based on comparisons with the filter-based measurements. Future work should be undertaken on a larger sample of filter-monitor pairs in order to draw more robust conclusions; however, in the current study, the similar NRMSE and low bias in the locations suggests the outdoor calibration was appropriate for the indoor and personal exposure monitors.

Environmental Conditions

Temperature and RH were measured in every low-cost monitor except the indoor monitor in Home 4, in which the sensor did not work (Fig. 5). The range of temperature and RH measured during the calibration covered the full range of temperature and RH experienced in the different environments during sampling at the homes. There were few hours with high RH (> 80%) data (N = 22 hr, 0.7% of total data; comprises data outdoors at 3 homes and for 1 personal exposure sampling event). Many of the outdoor monitors were in the direct sun for at least part of the day and the warmth of the electronics may also have increased the temperature measured in the cases as is suggested by the hours > 40°C. All homes reported using air conditioning for at least some of the time while people were home and this is reflected in the lower indoor temperatures experienced in all homes except 1 and 3, where air conditioning was likely used less frequently.

Data Completeness

Some data were lost throughout the deployment due to equipment malfunction, researcher error, and study subjects disturbing the equipment. In total, we successfully collected > 99% of the indoor data, 91% of the outdoor data, and 97% of the personal exposure data that we set out to collect. Slightly more outdoor data was missing due to the use of batteries in the outdoor locations that sometimes ran out of power.

Influence of Indoor Filtration on Indoor $PM_{2.5}$ Concentrations

Indoor and outdoor $PM_{2.5}$ concentrations at each home from roughly July 30 until August 16 are shown in Fig. 6 and Table 3. 1-hour outdoor concentrations range from roughly 25 to > 200 μg m^{-3} while indoor concentrations range from < LOD to > 200 μg m^{-3} (Fig. 6). Although the participants' homes were spread across Beijing, many similar events are recorded by PM monitors across the city (i.e., steep decreases in PM levels of roughly 100 μg m^{-3} in $PM_{2.5}$ seen on August 7 and 12 (Fig. 6)).

During true filtration, significantly larger differences

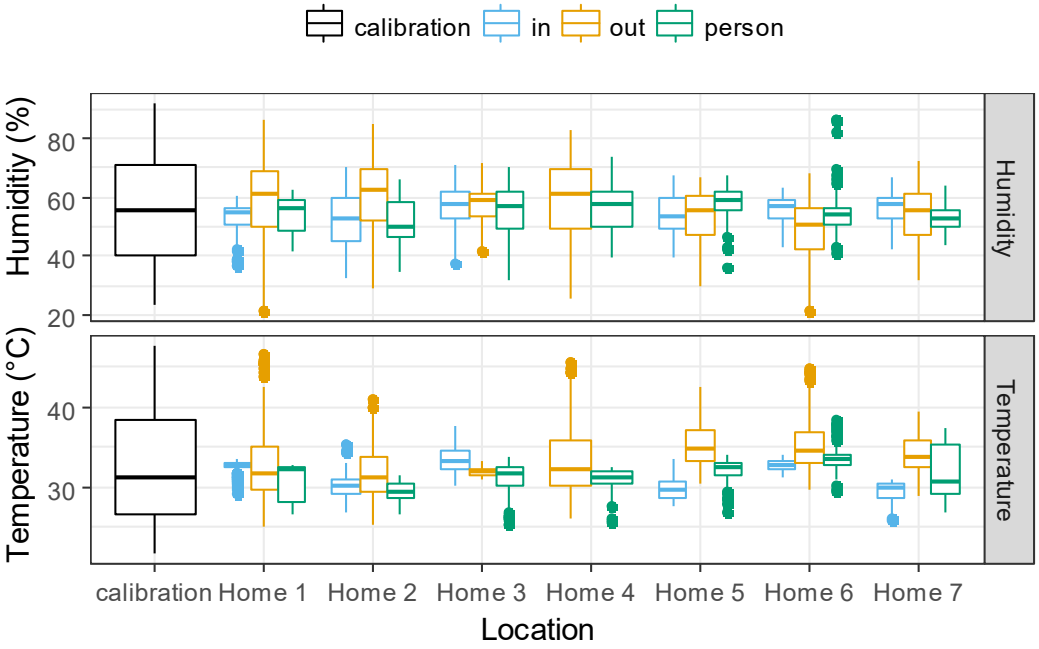

Fig. 5. Temperature and relative humidity during calibration and across homes.

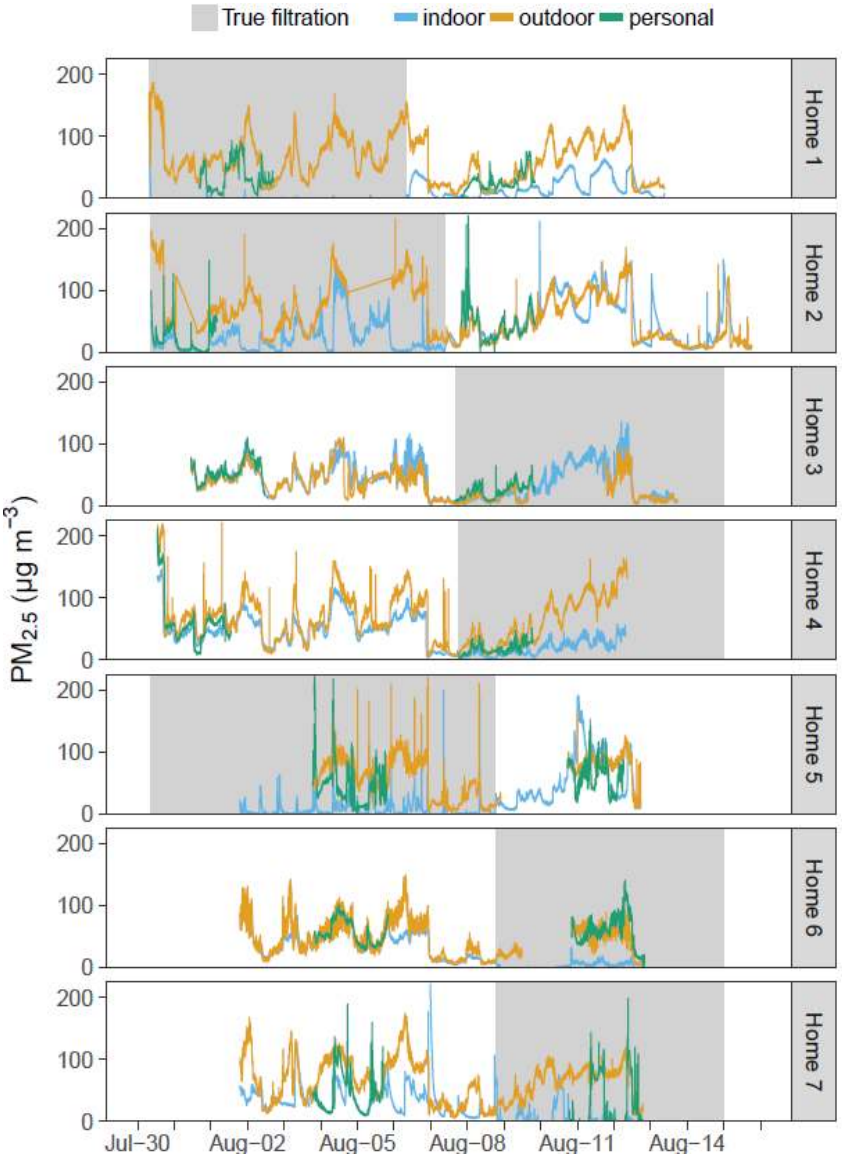

Fig. 6. $PM_{2.5}$ concentration time-series plot for monitors used in Homes 1–7. The plots present all data collected by the monitors in the homes during the study. Indoor and outdoor data were collected for the 2-week period during both true and sham filtration periods. Personal data were collected for two 48-hour periods, once during true filtration and once during sham filtration.

Table 3. Summary of indoor and outdoor $PM_{2.5}$ concentrations and indoor to outdoor ratios (I/O) by home during true and sham filtration (~1-week each), and the percentage reduction experienced with true filtration.

Home	Sham			True			I/O reduction
	Out	In	I/O	Out	In	I/O	
	($\mu g\ m^{-3}$)			($\mu g\ m^{-3}$)			
1	56	19	0.41	73	6	0.11	73%
2	44	51	1.36	72	22	0.36	74%
3	44	48	1.15	20	23	1.13	2%
4	71	62	0.93	66	23	0.36	61%
5	75	83	1.15	57	12	0.31	73%
6	49	40	0.87	45	7	0.23	73%
7	68	38	0.78	66	10	0.19	76%
Mean*	60	49	0.92	63	13	0.26	72%
StdErr*	4	6	0.09	5	2	0.09	7%

* Home 3 excluded.

(*t*-test: $p < 0.05$) were observed between indoor and outdoor concentrations than during sham filtration in most homes (Table 3). Home 3 is an exception where even during true filtration indoor and outdoor concentrations are similar. The similarity in indoor and outdoor concentrations suggests participant non-compliance, with this confirmed during home visits during which windows were often open. Since the windows were open for the majority of the sampling period, Home 3 was omitted from the analyses in this section.

Average indoor concentrations for the week across all homes were significantly lower during true filtration (13 μg m^{-3}) than during sham filtration (49 μg m^{-3}). The average indoor concentration during sham filtration is similar to the indoor concentration during the non-heating season (i.e., warm months where indoor heating is not required) during a larger-scale indoor study in Beijing (46 μg m^{-3}) (Zuo *et al.*, 2018). Our indoor concentrations were likely somewhat lower than they would be naturally because we requested that participants keep their windows closed and some participants would have opened the windows more often for cooling if we had not requested that they keep the windows closed. It is likely that participants may still have periodically opened the doors and windows to their homes; however, we do not have a record of these events. In addition, periodic window and door opening would be expected in a real-world best usage case of bedroom air purifiers.

Indoor to Outdoor Ratios

For both true and sham filtration, Home 1 has the lowest I/O (sham = 0.41, true = 0.11), and Home 2 the highest I/O (sham = 1.36, true = 0.36; "true" same as Home 4) (Table 3). Homes 2 and 5 have I/O greater than 1 during sham filtration, which suggests significant contributions from indoor sources. Indoor sources may have included cooking, wearing shoes in the home, or smoking on the balcony of the home, in the case of Home 5. Participant 2 was the only one who reported burning incense or candles. All compliant homes saw significant I/O reductions of at least 61%, ranging from 76% in Home 7 to 61% in Home 4 (average = 72%). This is an important result since for most homes, true filtration allows their home to meet the WHO daily ambient health guideline of 25 μg m^{-3} (World Health Organization, 2016) indoors. Since ambient concentrations in Beijing usually peak in the fall months with average concentrations of 90 μg m^{-3} typically (this study: average = 62 μg m^{-3}) (Zhang and Cao, 2015), the reduction in indoor concentrations due to air purifiers could be even more important during the fall and high air pollution episodes.

A previous study in Beijing showed I/O of 0.27 during true filtration, and an average ratio of 0.67 during sham filtration (Shao *et al.*, 2017). We observed similar results in our study during true filtration (0.26) and a higher average ratio during sham filtration (0.92).

Estimating Indoor Infiltration Factors

During sham filtration, 5 (of 6) compliant homes have coefficients of determination above 0.5 suggesting somewhat consistent 24-hour-average relationships between outdoor and indoor $PM_{2.5}$ concentrations (Table 4). During the sham period, the contribution from indoor sources is insignificant for all homes except Home 2. Home 2 also had the only I/O greater than 1. In Home 2 the indoor source of 16.1 μg m^{-3} and the F_{in} of 0.81 suggest that at an outdoor $PM_{2.5}$ concentration of 62 μg m^{-3} (this project's outdoor average), 75% of indoor $PM_{2.5}$ is attributable to outdoor sources. The average F_{in} and s for all homes during sham filtration suggests that 85% of $PM_{2.5}$, on average, is coming from outdoor sources. Previous work by Ji and Zhao (2015) found a lower contribution of outdoor air to indoor $PM_{2.5}$ (54–63%) when windows are closed and a 92% contribution from outdoor air when windows are open. While our results reflect conditions in a small subset of homes—those with windows closed and who do not have functional indoor air purifiers—this type of analysis highlights that most indoor pollution is primarily derived from infiltration from outdoor PM, even with the windows closed.

The addition of a household air purifier influences the effective infiltration factor and the effective indoor source. During true filtration, the effective indoor sources were lower on average, suggesting that most of the indoor-generated particles had been removed. The effective infiltration factor was reduced in all homes. The average reduction in the effective infiltration factor is 81%. This reduction is very similar to the reduction in I/O (80%). Although this work is with a small number of homes, this type of analysis can give us an idea of the potential utility of these air purifiers in homes around Beijing.

Table 4. Effective infiltration factors (F_{in}: unit-less fraction) and effective indoor sources (s: μg m^{-3}) by home as generated by regressing the 24-hour-averaged indoor concentration by the outdoor concentration using the following equation: $C_{in} = F_{in} \times C_{out} + s$.

Home	Sham			True			F_{in} reduction
	F_{in}	s	R^2	F_{in}	s	R^2	
1	0.34	*	0.96	0.01	5.7	0.14	98%
2	0.81	16.1	0.93	0.25	*	0.83	69%
4	0.87	*	0.99	0.30	2.5	0.97	65%
5	1.12	*	0.84	0.10	6.1	0.90	91%
6	0.80	*	0.97	0.14	0.5	1.00	83%
7	0.13	29.6	0.11	0.50	*	0.79	81%
Average	0.68	7.6	0.80	0.22	2.5	0.77	81%

* Intercept not significant ($p > 0.05$) so set to 0.

Influence of Indoor Air Filtration on Personal Exposure to $PM_{2.5}$

Personal exposure data were collected during 48 hours of each intervention period. All 7 homes have high data completion with almost 48 hours of $PM_{2.5}$ data collected during both true and sham filtration. For the most part, the personal exposure data follows indoor or outdoor concentration levels depending on where the participant is located at different times of the day (Fig. 6). Table 5 shows the indoor and outdoor averages from the two 48-hour monitoring sessions. The 48-hour indoor and outdoor averages in Table 5 are more variable than the 1-week indoor or 2-week outdoor averages shown in Table 3.

The lowest average 48-hour personal exposure during sham filtration was 28 μg m^{-3} in Home 1. The highest personal exposure during sham filtration was seen in Home 5 with a 48-hour average of 62 μg m^{-3}. Homes 1 and 5 also had the lowest and highest indoor and outdoor concentrations respectively during these periods.

During true filtration, personal exposure ranged from 19 μg m^{-3} in Home 4 to 60 μg m^{-3} in Home 6. Personal exposure was lower, on average, during true filtration (35 μg m^{-3}) than sham filtration (50 μg m^{-3}). Participants 1 and 6, had lower personal exposure during true filtration. Participant 1's higher personal exposure during true filtration is likely due to the higher outdoor concentrations during this period. Participant 6 did not appear to spend any time in the bedroom leading to no reduction in personal exposure (Fig 5).

Ratios of Personal Exposure to Outdoor Concentrations

Personal to outdoor ratios (P/O) and personal to indoor ratios (P/I) are listed in Table 5. Average outdoor concentrations for individual homes varied by up to 40 μg m^{-3} between the true and sham periods.

During sham filtration, the average P/O was 0.93 for compliant homes but ranged from a minimum of 0.60 in Home 7 to a maximum of 1.44 in Home 2. In Home 2 the sham I/O was also well over 1 during personal exposure monitoring (sham I/O = 1.47) leading to a P/O greater than 1. A previous study by Du *et al.* (2010) in Beijing showed an average P/O of 0.80. This is similar to our P/O even though the average ambient concentration was much higher during the Du *et al.* (2010) study (128.5 μg m^{-3}) than this study (–62 μg m^{-3}). The similarity in P/O ratios may suggest that P/O is independent of outdoor concentration over a moderate outdoor $PM_{2.5}$ concentration (55–130 μg m^{-3}) but a larger study over a longer duration would be needed to confirm this.

During true filtration, P/O were significantly lower on average (0.72) than during sham filtration (0.93). P/O ranged from 1.31 in Home 6, also the home with the highest personal exposure, to 0.38 in Home 2 which had the lowest personal exposure. The P/O decreased in all compliant homes by 28% on average (min–max = 5–74%) when comparing sham with true filtration with the largest reduction in Home 2 (74%). Participants visit many micro-environments over the course of a day and high P/O ratios suggest locations with localized sources where the concentration is often higher than their local outdoor monitor.

Relationship between Personal Exposure and Outdoor $PM_{2.5}$

The 1-hour paired personal and outdoor concentrations are plotted in Fig. 7. On the plot, the 1:1 line highlights that true filtration is able to reduce the number of hours where personal exposure exceeds outdoor ambient concentrations (points above the 1:1 line: sham = 38%, true = 27%). The colors indicate the time of day where evening and night is 5 p.m.–5 a.m., and morning and afternoon is 5 a.m.–5 p.m. The filtration drops the number of hours with higher personal exposure during the evening (5 p.m.–10 p.m.: sham = 45%, true = 18%) and night (10 p.m.–5 a.m.: sham = 19%, true = 9%) hours when the participants are spending more of their time at home and in their bedroom. Filtration has less impact on the concentrations during the afternoon (12 p.m.–5 p.m.: sham = 54%, true = 41%) and morning hours (5 a.m.–12 p.m.: sham = 40%, true = 41%). The hours during which participants experience concentrations above outdoor values suggests local sources. These hours

Table 5. Average 48-hour $PM_{2.5}$ personal exposure (P) compared to the average indoor (I) and outdoor (O) concentrations for the same period. Personal to outdoor (P/O) and personal to indoor (P/I) unit-less ratios are included along with a percentage reduction in personal to outdoor ratios from sham to true filtration. The average values with the standard error (SE) are provided at the bottom of the table.

Home	Sham					True					P/O reduction
	O	I	P	P/O	P/I	O	I	P	P/O	P/I	
	(μg m^{-3})					(μg m^{-3})					
1	32	9	28	1	3.11	64	6	36	0.73	5.98	27%
2	32	47	45	1.44	0.92	71	12	22	0.38	1.63	74%
3	51	53	58	1.14	1.1	14	15	25	2.03	1.82	–78%
4	77	61	62	0.79	0.99	32	11	19	0.64	1.73	20%
5	84	98	61	0.73	0.77	70	13	46	0.69	4.8	5%
6	57	53	58	1.03	1.11	52	8	60	1.31	8.22	–27%
7	81	38	46	0.6	1.18	76	6	29	0.51	4.72	15%
Mean*	61	51	50	0.93	1.35	61	9	35	0.71	4.51	28%
SE*	4	5	2	0.05	0.15	3	1	3	0.05	0.42	5%

* Homes 3 and 6 excluded.

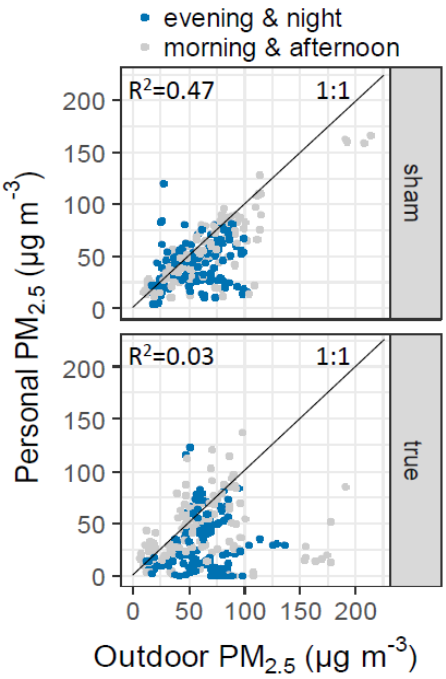

Fig. 7. The relationship between the hourly personal exposure concentrations as compared to the hourly outdoor $PM_{2.5}$ concentration at each home during true and sham filtration. Points above the 1:1 line indicate that personal exposure is higher than the ambient outdoor $PM_{2.5}$ concentration.

are of particular interest because they highlight time periods when participants have the opportunity to lower their exposure through a simple personal action by avoiding a local source.

Currently, there is no 1-hour standard for exposure to ambient $PM_{2.5}$ and there is uncertainty in the health impacts of shorter exposure periods like the 1-hour exposures shown in Fig. 7. The WHO 24-hour guideline for ambient $PM_{2.5}$ is 25 µg m^{-3} (World Health Organization, 2016). During the project, the 24-hour average outdoor $PM_{2.5}$ and personal exposure to $PM_{2.5}$ are often above 25 µg m^{-3}. Even with filtration, most of the 1-hour personal exposure measurements are greater than 25 µg m^{-3} leading to 24-hour averages above 25 µg m^{-3} in some cases.

During sham filtration, the linear relationship between 1-hour personal exposure and the outdoor ambient concentration is: personal = 0.60 × outdoor + 14. The relationship of both the slope and intercept are significant ($p < 0.05$) but they are moderately correlated ($R^2 = 0.47$) suggesting the outdoor $PM_{2.5}$ concentration explains only about half of the variation in the personal exposure experienced by the participants. During true filtration the linear relationship between personal exposure and outdoor $PM_{2.5}$ is: personal = 0.15 × outdoor + 27. Although both the slope and intercept are again significant, outdoor $PM_{2.5}$ is not a good predictor of personal exposure ($R^2 = 0.03$). The 48-hour personal exposure was slightly more correlated with outdoor $PM_{2.5}$ concentrations than the 1-hour measurements during sham filtration ($R^2 = 0.58$) and true filtration ($R^2 = 0.14$), but this does not change the findings of the analyses. These low correlations suggest that outdoor $PM_{2.5}$ is not a good indicator of personal exposure, and highlights the utility of these additional indoor and personal exposure measurements.

CONCLUSIONS

This work demonstrates an efficient 2-step approach to calibrating low-cost monitors against a single unit that has already been calibrated as opposed to calibrating them directly against a reference monitor (viz., a TEOM), thus reducing the collocation time required for calibrating numerous monitors, as only one monitor must be collocated with a reference analyzer for an extended period of time. After applying this method, the low-cost monitors displayed low inter-monitor variability (1-hour average NRMSE = 2%).

In homes where the windows remained closed, purifiers reduced the average indoor to outdoor ratios by 72% (the sham and the true filtration period exhibited an I/O of 0.92 and 0.26, respectively). The indoor and outdoor concentrations were significantly correlated ($R^2 > 0.8$) in all but one of the compliant homes during every filtration period, with minimal contributions from indoor sources, indicating that $PM_{2.5}$ in the bedroom was primarily generated by outdoor sources rather than activities inside the home. One issue with filtration intervention is that, not surprisingly, purifiers are less effective in rooms with open windows. However, during hot summers, sleeping with the windows closed in homes without air conditioning can be uncomfortable, forcing residents to prioritize their health or their personal comfort. In cases of extreme heat, this choice may lie between two unsafe situations: high air pollution or dangerous indoor temperatures.

The average 48-hour personal exposure concentration was 50 µg m^{-3} during sham filtration and 35 µg m^{-3} during true filtration. Additionally, the personal to outdoor concentration ratios were reduced in all compliant homes by an average of 28% (min–max = 5–74%). This study indicates that minimizing personal exposure, however, also requires reducing the infiltration of outdoor air in homes or decreasing $PM_{2.5}$ pollution at the city or country level.

Our results prove the feasibility of deploying low-cost monitors for indoor, outdoor, and personal exposure monitoring. The low correlations between the personal exposure and outdoor measurements suggest that these devices should monitor conditions in addition to the ambient $PM_{2.5}$ concentration, which, in itself, cannot provide an accurate estimate of personal exposure.

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