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Assessment of $PM_{2.5}$ concentrations, transport, and mitigation in indoor environments using low-cost air quality monitors and a portable air cleaner†

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In this study, we deployed multiple low-cost air quality monitors (AQMs) to investigate the transport of kitchen-generated fine particulate matter ($PM_{2.5}$) into the bedrooms of four homes of different sizes over a period of more than nine weeks at each home. We also estimated the human exposure to $PM_{2.5}$ associated with each microenvironment and evaluated the effects of using a portable air cleaner (PAC) to reduce those exposures. To select the best AQM for these analyses, we compared the field response of five commercially available models with that of a research-grade optical particle spectrometer. The AirVisual AQM showed the best correlation during collocation phases with R^2 values in the range of 0.5–0.9 during cooking and background periods for all locations. The bedroom monitors picked up cooking emissions from the kitchen area within 1–45 min depending on the layout of each home, and median $PM_{2.5}$ concentrations in the bedroom were up to 30% lower than those in the kitchen. Results from the exposure analysis suggest that PAC use is an important intervention strategy for reducing personal $PM_{2.5}$ exposure, especially in indoor environments where cooking is the main source of $PM_{2.5}$ concentrations. In three of the four homes using PAC consistently in the kitchen or bedroom area during intensive cooking periods reduced overall exposure values by 30–90%. Moreover, during nighttime periods, PAC usage in the bedroom area yielded the lowest levels of $PM_{2.5}$ exposure for all the homes.

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Environmental significance

This article describes a comprehensive study of the $PM_{2.5}$ response from a low-cost air quality monitor to study the transport between the kitchen and bedroom areas of four different houses and the resulting exposures at these fixed locations. We also quantified the benefits of using a portable air cleaner (PAC) in the kitchen and bedroom areas to reduce the resulting exposures due to indoor cooking and outdoor penetration. This study brings forth multiple results of interest to the science community as well as the general public, such as the effect of different control strategies such as window opening, extracting range hood use over the stove, and PAC use to reduce the overall PM exposure values in built environments.

1 Introduction

In recent years, significant attention has been placed on improving indoor air quality (IAQ) in built environments primarily by reducing the indoor concentrations of fine particulate matter ($PM_{2.5}$) attributed mainly to indoor sources or infiltration from outdoors.[1–4] This is because $PM_{2.5}$ exposure has been linked to several adverse health outcomes, such as increased cancer risk and premature mortality,[5–9] added to the fact that people spend approximately 90% of their time indoors.[10] Due to increased awareness of the health effects of $PM_{2.5}$ exposure, the general public is being encouraged to use low-cost air quality monitors (AQMs) to monitor indoor pollutant levels.[11–13] AQMs offer a low-cost alternative to research-grade instruments for monitoring air quality enabling users to easily deploy them in home environments.[14–17] They can be integrated with different interfaces (website, mobile applications, computer software) so the data collected can be easily accessed by the user. Some AQMs also employ color scales or display windows for ease of viewing and understanding the air quality index data.[18]

For indoor environments, basic strategies adopted for improving IAQ (mainly by reducing $PM_{2.5}$ concentrations) include source control, increased ventilation, and pollutant removal.[19,20] Source control measures include using improved

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cookstoves for lower emissions, switching to cleaner fuels for residential heating and cooking purposes.[21,22] $PM_{2.5}$ levels indoors can also be managed by using a mechanical ventilation system or opening the windows to increase the ventilation rates. However, the latter is only applicable in areas with low levels of ambient pollutants.[23,24] In cases where source control and natural ventilation are not effective control strategies, using range hoods over the stove and portable air cleaners near the receptor can be a good alternative to reduce $PM_{2.5}$ exposure.[25–30] In terms of control strategies, AQMs provide an opportunity to alert consumers about degrading levels of air quality in their homes and enable them to perform some of these mitigation strategies. AQMs can also be deployed in different areas of a household, and their real-time data can be used to decide on the best placement of air cleaners for effective particle removal in multizone indoor environments.[31] In terms of occupant exposure, people spend about 70% of their time in a residence.[10] Of the time spent at home, people are estimated to spend about 10% of it in the kitchen microenvironment and 53% in the bedroom microenvironment.[32] Although the time spent in the kitchen is significantly smaller than that in the bedroom, higher total $PM_{2.5}$ exposures may take place in the kitchen depending on cooking habits, control strategies used, and outdoor penetration of ambient $PM_{2.5}$.

Most AQMs measure particulate matter (PM) concentrations using a low-cost PM sensor which either uses an optical particle counter (OPC) to count particles in various size bins based on assumptions about particle shape and refractive index or use a nephelometer to measure the amount of light scattered by each particle which is in turn converted into a mass concentration using a conversion factor based on laboratory calibration.[33] Previous studies, focusing on determining correction factors for different types of aerosols and ambient locations, have reported that the sensors used in AQMs need to be calibrated according to the local conditions for better correlation with data reported by federal equivalent methods of measurement.[34–36] In recent studies, the hygroscopic growth of sampling aerosols in humid conditions (relative humidity >50%) has also been shown to affect the PM response of AQMs.[37,38] There are also concerns about their performance during periods of low concentrations or very high concentrations, especially in ambient environments where they tend to deviate from linear correlation with reference instruments.[39–41] Even with these challenges, the data reported by low-cost air quality monitors can provide reliable results for quantifying personal exposure, especially compared to exposure values estimated from outdoor fixed monitoring stations.[42] For consumers, low-cost AQMs can be especially informative in educating occupants in real-time about their own activities that generate large amounts of $PM_{2.5}$ and, conversely, actions that are effective in lowering concentrations.

The main goal of this study was to assess the indoor transport of $PM_{2.5}$ and its mitigation in four households of different sizes and configurations for a total duration of nine months. Specific research objectives were to: (1) compare the $PM_{2.5}$ concentration measurements from four different AQMs with a research-grade instrument to select the best AQM for subsequent research objectives. (2) Study the transport of $PM_{2.5}$ between the kitchen and a bedroom for each home during cooking activities by placing identical and inter-corrected AQMs in these two areas of the household. (3) Determine the effectiveness of deploying a filtering portable air cleaner (PAC) to reduce $PM_{2.5}$ exposure primarily due to indoor cooking. (4) Investigate the effects of PAC placement—in the kitchen or a bedroom—in reducing personal $PM_{2.5}$ exposure during different periods of the day.

2 Methods

2.1 Instrumentation

For this study, we used an Optical Particle Sizer (TSI OPS 3330, St Paul, MN) as a relatively portable comparison instrument for studying $PM_{2.5}$ concentrations in different indoor environments. $PM_{2.5}$ concentrations were calculated from mass distribution data assuming particle density of 1 g cm^{-3} which has been used in previous studies measuring indoor PM concentrations.[43–45] The OPS instrument had been recently purchased when deployed at the start of the study, so it had been recently factory calibrated. Additionally, flow calibration checks were conducted, and new filters were also installed at the start of the study.

We chose the OPS as a comparison instrument for this study because it also operates on the principle of single particle counting using a laser and photodetector assembly.[46] It can measure particles in the size range of 0.3–10 μm (16 bins) with an inlet flow rate of 1 liter per minute. Its compact size and low pump noise make it suitable for indoor environments. Although the OPS is not a regulatory reference instrument, it has been widely used in previous studies and has shown good agreement with other research-grade instruments.[46,47] The four AQM models used in this study are also listed in Table 1. Two identical units were deployed for each AQM model.

Because all particle instruments used in this study are limited to particles > ~0.3 μm in diameter, their measurements are likely to underestimate actual $PM_{2.5}$ concentrations because they miss potential PM mass contributions from particles < 300 nm, which may be important indoors, especially during some indoor cooking activities. As such, all $PM_{2.5}$ concentrations reported in this work should be interpreted as $PM_{0.3–2.5}$.

The different AQMs chosen for this study had been extensively tested in previous studies and were readily available in the market. PM sensors used in the PurpleAir AQMs (Plantower) have been deployed on large scales in different studies for various applications, primarily in ambient environments.[41,57–59] Foobot AQMs have been used to quantify personal exposures in different indoor settings.[51–53] In recent studies, the AirVisual Pro has been shown to be a reliable AQM with ease of access and better accuracy in indoor environments.[48,55]

The PAC used in this study (EJ120, Oransi, Raleigh, US) uses a combination of an activated carbon filter and a MERV 17 (Minimum Efficiency Reporting Value) filter to provide a maximum air flow of 330 cubic feet per min (0.16 m^3 s^{-1}). It is recommended for rooms sizes up to 116 m^2 with 2 air changes per hour.[63] The manufacturer recommends changing the filter

Table 1 The four AQMs used for this study and their properties

Product	Foobot, home	IQAir, AirVisual Pro	PurpleAir, PA-II-SD	PurpleAir, PA-I-Indoor
Air quality measurements	$PM_{2.5}$, total volatile organic compounds (TVOCs)	$PM_{2.5}$, carbon dioxide	PM_1, $PM_{2.5}$, PM_{10}	PM_1, $PM_{2.5}$, PM_{10}
Time resolution	~300 s	10 s	80 s	80 s
PM sensor	Sharp GP2Y1010AU0F	AVPM25b	Plantower PMS5003	Plantower PMS1003
PM detection technique	Light scattering (0.3–2.5 μm)	Light scattering (0.3–2.5 μm)	OPC (6 size bins 0.3–2.5 μm)	OPC (6 size bins 0.3–2.5 μm)
Cost estimate	$240	$270	$230	$180
Example studies that used or evaluated these AQMs	48–54	18, 48, 49, 55 and 56	38, 41 and 57–61	33 and 62

every 12 months, so we used the same filter for all the homes during the entire study period of nine months. Filter loading effects were not quantified for this study and were assumed to be negligible due to the generally low background PM concentrations found in all four homes.

2.2 Data acquisition and processing

For this study, we used only the $PM_{2.5}$ sensor data from each AQM and compared those values with the corresponding OPS data. All AQMs were connected to local Wi-Fi networks for data acquisition. Foobot data were recorded using an IFTTT ("If This, Then That" automation tool) recipe and was exported in ~5 min time resolution to a Google Sheet output. The AirVisual data were exported to a computer using the local Wi-Fi network, at 10 s time resolution. PurpleAir data were exported through the PurpleAir website at 80 s time resolution. While the PurpleAir PA-II-SD monitors include two Plantower $PM_{2.5}$ sensors providing two sets of mass concentration readings, we only used data corresponding to the 'CF = 1' channel, recommended for indoor monitoring.[38,61] For the PurpleAir Indoor monitors, data from the same channel (CF = 1) were also used for intercomparison. The $PM_{2.5}$ data from all AQMs were synchronized in 60 s time resolution with the OPS data using the MATLAB

Fig. 1 Layouts for all the locations used for this study. Note all the layouts are approximate to scale (1″:16′ for a printed page). The OPS and AQMs were placed on a wire shelf rack, at either 0.3 m or 0.6 m above the floor.

Table 2 Data collection process repeated for each of the four households

Phase	0A	1	2	3	0B
Activity	Collocation (no PAC)	No PAC	PAC in kitchen	PAC in bedroom	Collocation (no PAC)
AQM location	Kitchen	Kitchen + bedroom	Kitchen + bedroom	Kitchen + bedroom	Kitchen
Duration	2 days (min)	3 weeks	3 weeks	3 weeks	2 days (min)

synchronize function incorporating a linear interpolation method to obtain time series as shown in Fig. S1 and S2.† Both Foobot AQMs consistently reported constant values for $PM_{2.5}$ concentrations without showing any response during cooking events in later stages of deployment in Home 2 and Home 3. Therefore, Foobot $PM_{2.5}$ data were not used for further analysis.

2.3 Description of the homes

This study was carried out in four different non-smoking households within Boulder County. The layout for each home is shown in Fig. 1. Home 1 and Home 4 were located near the University of Colorado Campus. Home 2 was located in the suburbs with the nearest state highway around 500 m from home. Home 3 was located on the city's outskirts, with no significant highways within a 500 m radius. Homes 1, 3, and 4 were apartments while Home 2 was a single-family detached home. Homes 3 and 4 were located on the first floor whereas Home 1 was located on the ground floor.

The study spanned nine months in 2019 and 2020, comprising fall, winter, spring, and summer seasons in Boulder, CO. The ambient daily average $PM_{2.5}$ data provided by United States Environmental and Protection Agency (US EPA) for Boulder County location during these nine months is also shown in Fig. S3.† All the four homes used for this study were within a 10 km radius from the monitoring station. In Homes 1–3, the windows and doors were kept shut to maintain comfortable living conditions ($T = \sim$21–25 °C, RH = 30–50%) inside the homes through mechanical HVAC systems. Home 4 did not have a cooling system, so the windows were kept open continuously throughout the deployment because that coincided with the peak summer season.

Homes 1 and 3 had recirculated microwave range hoods over the stove, whereas Home 2 had an extracting wall mounted range hood (Vent-a-hood dual blower 600 CFM). Extracting range hood usually have a higher capture performance.[64] Home 4 did not have a range hood over the stove. The bedroom areas in Homes 2 and 3 were mostly unoccupied throughout the day whereas in the case of other two homes, the bedroom areas were inhabited. The occupants also maintained a time log with information about the start and end times of all cooking activities. This study was exempted from Institutional Review Board review for lacking participant information or risk. Additional details regarding each location are also given in Table S1.†

2.4 Phases of AQM deployment

Deployment in each home took place sequentially from Home 1 through Home 4. The data collection for each home was divided into three different phases (Table 2). Phase 0 was a two-day minimum collocation period at the start and at the end of the deployment period for each home (Phases 0A and 0B, respectively). During Phase 0, all eight AQM units (two of each model) and an OPS were collocated in the kitchen area. In Phase 1 (2–4 weeks), one set of AQMs, including the four different models, were kept in the bedroom area, while the other set with matching models (and the OPS) were maintained in the kitchen area. This was followed by Phase 2 of a similar duration, during which a PAC was used in the kitchen area. The same PAC was moved from the kitchen area to the bedroom area for Phase 3. The PAC was operated at the lowest fan setting of 1 at all the times; however, the occupants were advised to increase the fan setting during cooking periods. The exact deployment dates for each phase of this study are also given in Table S2.†

3 Results and discussion

3.1 Intercomparison with OPS $PM_{2.5}$ measurements during collocation phases

An intercomparison of $PM_{2.5}$ measurements between AQMs and the OPS was first performed by taking the ratio of time-averaged concentrations for a given cooking period to calculate a C_{AQM}/C_{OPS} factor. These datasets were 90 min in duration and also included the decay period post cooking activities. 2–4 cooking activities and background periods (also 90 min in duration) were selected for each collocation period, and the resulting values were plotted in Fig. S4† to observe the overall trend of this factor between different homes. The resulting C_{AQM}/C_{OPS} values were in the range of 1–4 for most of the AQMs during both cooking and background periods for different collocation phases in all the homes and did not change over time. Therefore, we did not observe any significant sensor measurement drift within the timeframe of this study.

Next, we combined the collocation data from all the homes into two distinct periods—cooking and background. The resulting distributions of C_{AQM}/C_{OPS} values (in 1 min time resolution) are shown in Fig. 2. All AQMs presented $PM_{2.5}$ concentrations that were higher—sometimes >10× higher—than that of the OPS. Both AirVisual AQMs had the highest coefficient of determination (R^2) values with the OPS $PM_{2.5}$ data as shown in Tables S3 and S4.†

During cooking periods, the median C_{AQM}/C_{OPS} values for the two AirVisual sensors (AV1 and AV2) were 2.2 and 1.7. The corresponding values for the PurpleAir and PurpleAir (I) AQMs ranged from 1.6–1.9. These results agree well with previous studies that also reported overestimation of $PM_{2.5}$ concentrations within a factor of 2 by different low-cost AQMs compared

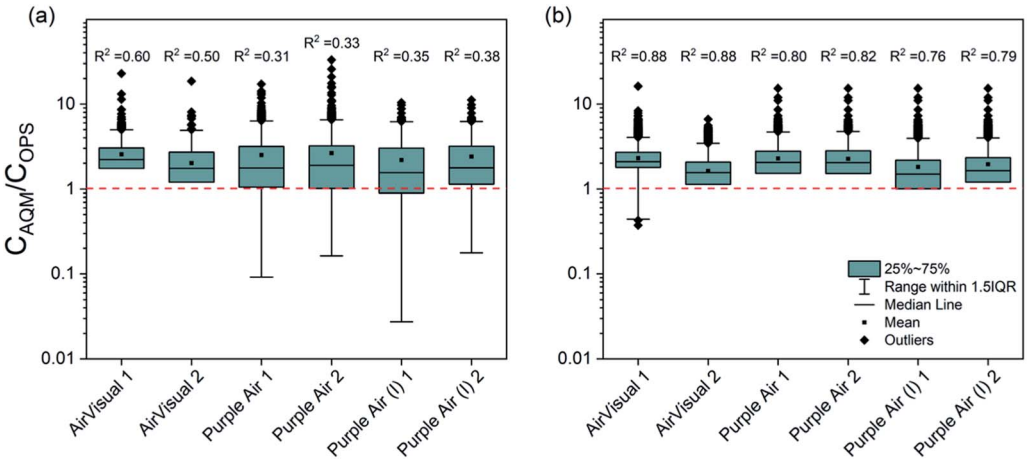

Fig. 2 Boxplots showing the distribution of C_{AQM}/C_{OPS} values for different AQMs during two time periods: (a) cooking periods ($n = 1365$ min) and (b) background periods ($n = 2618$ min). The corresponding R^2 values for each AQM with OPS $PM_{2.5}$ concentrations are also shown above each box. Note that the y-axis is in log scale.

to mass-based measurements from different reference instruments.[33,49,51,58,65] Moreover, low-cost OPCs and nephelometers have been shown to exhibit greater amounts of error in mass loading values compared to the high end OPCs in these conditions.[66] The R^2 values for all AQMs were higher during background periods than cooking periods. During background periods, particles are likely to have penetrated from outdoors and are more likely to match low-cost sensor calibration inputs. Infiltrated particles are also less unlikely to suffer strong temporal and spatial gradients. During cooking periods, particle concentration, size distribution, optical properties, and chemical composition are likely to change quickly, creating strong temporal and spatial gradients. Sudden changes in these parameters may have led to deviation of response linearity.

$PM_{2.5}$ measurements from the AirVisual units presented the highest values of R^2 in the range of 0.5–0.9 for both units, and the corresponding slope values ranged between 1.3–2.2. Moreover, the mean normalized bias (MNB) and the root mean squared error (RMSE) values were lowest for the AirVisual 2 unit as compared to other AQMs during both background and cooking periods (Tables S3 and S4†). Based on these results, the $PM_{2.5}$ concentrations reported by AirVisual had the best agreement with OPS among the AQMs tested in this study. For this reason, we used AirVisual results for all subsequent analyses in this work. In order to get the results of the two AirVisual units in the kitchen and bedroom areas to agree, we applied a correction factor to the AV1 $PM_{2.5}$ values which was derived from a linear regression analysis obtained from Phase 0 (collocation) data as shown in Fig. S5.†

3.2 Indoor $PM_{2.5}$ transport between kitchen and bedroom among different homes

We studied the indoor $PM_{2.5}$ transport between the kitchen and bedroom areas using the $PM_{2.5}$ time series reported by the AirVisual AQMs located in the kitchen and the bedroom areas for each home during Phase 1 (no PAC use). A characteristic

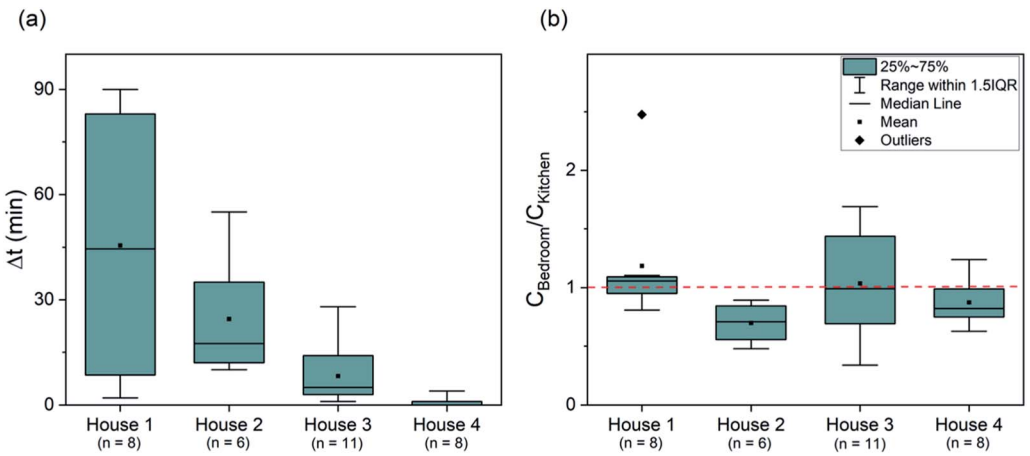

Fig. 3 Panel (a) represents the distribution of the time elapsed between the kitchen and bedroom peak $PM_{2.5}$ concentrations for a given cooking period during Phase 1. Panel (b) represents the distribution of $C_{Bedroom}/C_{Kitchen}$ factors for different homes.

time series for a given cooking period during Phase 1 for each home is also shown in Fig. S6.† We also calculated the first-order decay rate associated with each cooking event to compare the effective particle loss rates (including deposition losses) in the kitchen areas for different homes, as shown in Fig. S7.† The median values for the first three homes were close to 1 h^{-1} whereas Home 4 had a higher median value ($\sim$2 h^{-1}), likely due to open windows.

A $C_{Bedrrom}/C_{Kitchen}$ factor was used to compare the concentrations in the kitchen and bedroom area for each home. This factor was calculated by taking the time-averaged concentrations over 90 min for both kitchen and bedroom $PM_{2.5}$ concentrations, considering a starting time ($t = 0$) the concentration peak as reported by the bedroom monitor. Similar factor mentioned as L/K ratio in Wan *et al.*[67] has been used to compare PM levels due to indoor cooking in the living rooms and kitchens of 12 different homes. We also calculated the time difference (Δt) between the peak as it occurred in the kitchen and in the bedroom for a given cooking activity during Phase 1. A boxplot showing the distributions of Δt and $C_{Bedroom}/C_{Kitchen}$ factors for all four homes is shown in Fig. 3.

For Home 1, the median values of Δt were highest among all the homes (45 min). This could be because the bedroom door was usually kept closed. The corresponding median value of $C_{Bedroom}/C_{Kitchen}$ value was close to 1 since the kitchen area was adjacent to the bedroom area in this home, so $PM_{2.5}$ concentrations equalized between the two spaces whenever the bedroom door was opened. A similar median value of $C_{Bedroom}/C_{Kitchen}$ factor was also calculated for Home 3. In this home, the bedroom was located directly across the hallway from the kitchen area. For this home, the median value of Δt was $\sim$5 min, which is much lower than in Home 1, probably because in Home 3 the bedroom door was always open.

The distance between the stove and bedroom AQMs was largest for Home 2 ($\sim$10 m around two corners) and, therefore, the median value of $C_{Bedroom}/C_{Kitchen}$ (0.7) was lowest among all the homes studied. The corresponding median value of Δt for this home was 17.5 min and the bedroom door was always open. In Home 4, due to open windows in the bedroom and kitchen area, and due to the absence of interior walls between the two units (Home 4 being a studio apartment), the bedroom AQMs picked up the concentrations from the kitchen area within a minute for each cooking activity and the median $C_{Bedroom}/C_{Kitchen}$ was 0.8.

Overall, the most important factors governing $PM_{2.5}$ transport from the kitchen to the bedroom of these four homes were the presence of physical barriers between these spaces (*e.g.*, interior walls and whether doors were kept open or shut), different layouts of kitchen and bedroom areas in each home, distance from the stove to the kitchen and bedroom AQMs in

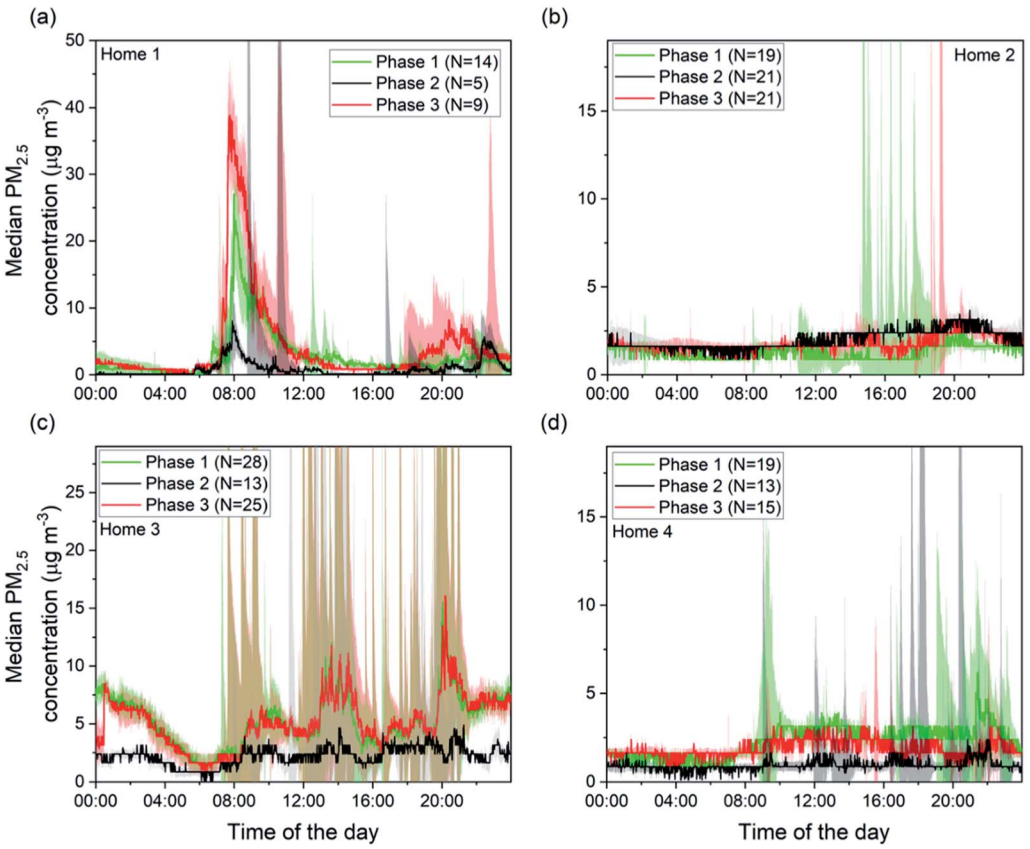

Fig. 4 Median $PM_{2.5}$ concentrations in the kitchen area during the day for different phases in Homes 1–4 are shown in panels (a), (b), (c), and (d), respectively. The shaded region represents standard error. The brown shaded region represents the overlap between Phase 1 and Phase 3. Note that the *y* axis is different for each panel.

addition to the ventilation conditions (*e.g.*, open windows). It is also interesting to note that the median values of $C_{Bedroom}/C_{Kitchen}$ for homes which had an extracting fume hood (Home 2) and open windows in the kitchen area during cooking periods (Home 4) were lower than that value for the other homes. This could be due to the fact that these control measures prevented the majority of the kitchen concentrations from reaching the bedroom area, thereby lowering the time-averaged concentrations (calculated for 90 min post peak). These results indicate the effectiveness of such control measures in reducing PM exposure due to indoor cooking in both the kitchen and bedroom areas. This is expanded in greater detail in the next section.

3.3 Understanding the role of PAC location in reducing indoor $PM_{2.5}$ exposure

Time-averaged $PM_{2.5}$ concentrations were used to estimate an occupant's exposure with the assumption that the individual was present in the kitchen or bedroom area for the entire duration of the analysis. Although this approach is limited due to the monitor's fixed location, this has been applied in previous studies to quantify black carbon and PM exposure due to indoor cooking in controlled indoor environments.[68,69] A time series showing the median $PM_{2.5}$ concentrations in the kitchen area of each home is shown in Fig. 4. As observed by median peaks, each home showed consistent daily cooking trends in the kitchen area, especially for Home 1 and Home 3.

For Homes 1 and 3, median concentrations during Phase 2 (PAC in kitchen) were significantly lower than that of the other two phases indicating the effectiveness of PAC use for reducing $PM_{2.5}$ exposure. The median concentrations for Phase 1 and Phase 3 in all the homes also exhibit the same diurnal pattern and an overlap to a certain extent. This shows that PAC deployment in the bedroom (Phase 3) did not affect concentrations in the kitchen in a significant manner. Homes 2 and 4 had significantly lower $PM_{2.5}$ concentrations in the kitchen area, due to an efficient extracting range hood in Home 2 and open windows in Home 4, as explained in the previous section. According to the inhabitants of Home 3, the high $PM_{2.5}$ concentrations observed overnight in kitchen of Home 3 during could be attributed to the infiltration of tobacco and marijuana smoke from the downstairs unit. Smoke transported into the apartment through the kitchen sink drainpipes.

Next, we present the $PM_{2.5}$ exposure analysis in the kitchen and bedroom areas for two distinct periods: a daytime analysis using time intervals between 6:00 am to 10:00 pm and a nighttime analysis using the remainder of the day (10:00 pm to 6:00 am).

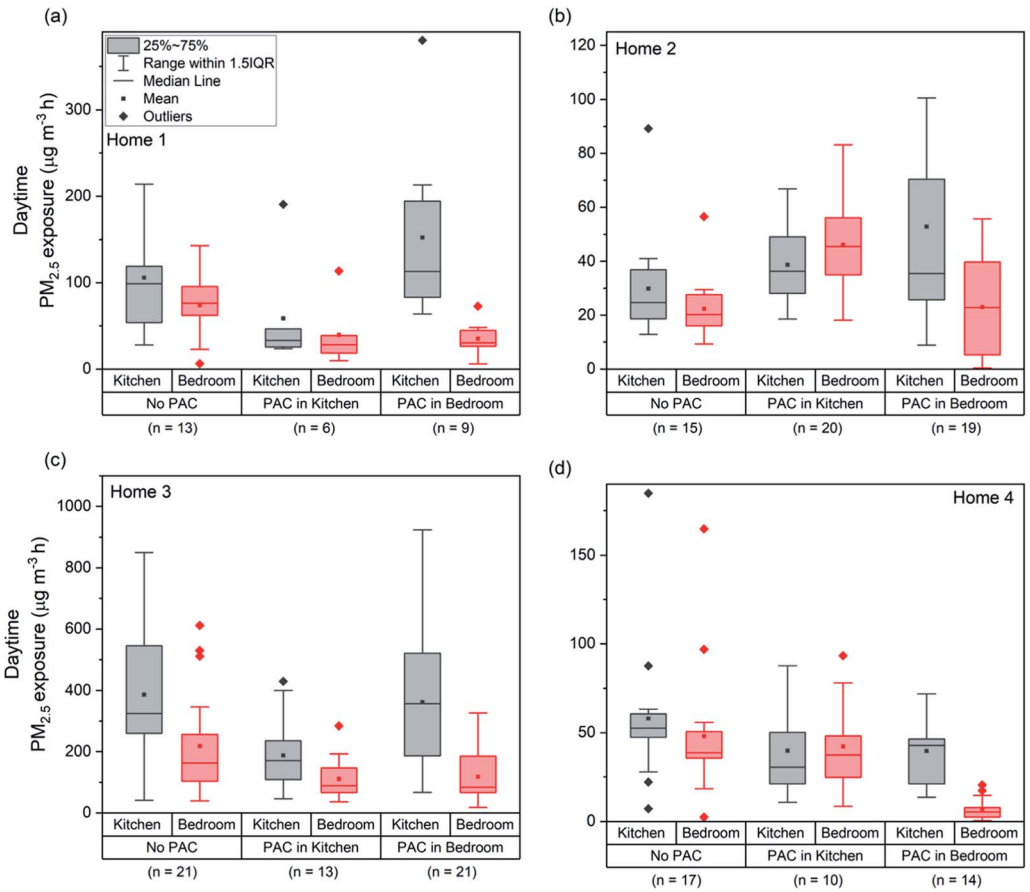

Fig. 5 Boxplot of daily $PM_{2.5}$ exposure values during time periods between 6:00 am to 10:00 pm for Homes 1–4 is shown in panels (a), (b), (c), and (d), respectively. The number of datasets for each phase is also represented by *n*. Note that the *y*-axis in each panel has a different scale.

3.3.1 Daytime exposure analysis. Daytime exposure values for different phases in all four homes are shown below in Fig. 5. When no PAC was used, the average (± standard error) daytime $PM_{2.5}$ concentration in all four homes was 10.3 ± 0.2 μg m^{-3} in the kitchen and 6.3 ± 0.1 μg m^{-3} in the bedroom. During nighttime, concentrations were ~3–4× lower. The average $PM_{2.5}$ concentrations were 2.8 ± 0.1 μg m^{-3} in the kitchen and 2.5 ± 0.1 μg m^{-3} in the bedroom.

During Phase 1 (no PAC use), daytime $PM_{2.5}$ exposure values were on average 17–43% lower in the bedroom compared to the kitchen of the four homes. This is likely due to $PM_{2.5}$ emissions during cooking activities increasing concentrations in the kitchen, which are then diluted and lost to surface deposition and exfiltration during transport to the bedroom.[70,71] During the nighttime (Fig. 6), this difference dropped to 0–23%, which further confirms the hypothesis that the differential is driven by cooking activities.

Using a PAC in the kitchen (Phase 2) or bedroom (Phase 3) reduced the mean exposure values by 30–90% in that respective area when compared to the corresponding values from Phase 1 (no PAC use) in three of the four homes. When the PAC was used in the kitchen (Phase 2), the average mean exposure values in the kitchen area dropped by 30–70% for all homes except Home 2. For Home 2, an increase in exposure was observed during PAC use compared to Phase 1. However, this phase also coincided with the holiday season, with additional guests and significantly more cooking being performed in the home. A similar comparison between the mean exposure values of the bedroom area during Phase 3 (PAC in bedroom) with Phase 1 values also yielded similar reductions in mean values: 53% for Home 1, 46% for Home 3, and 85% for Home 4.

Also noteworthy is that for both Homes 2 and 4, the mean exposure values were slightly higher in the bedroom area compared to the kitchen area during Phase 2. This could be because Home 2 had an extracting range hood and Home 4 occupants opened windows during cooking periods. These strategies may have played larger roles in governing $PM_{2.5}$ exposures than the use of a PAC in the kitchen. Therefore, the exposure values calculated for the bedroom areas may be from other sources, such as outdoor infiltration.

The use of a PAC in the bedroom (Phase 3) was also very effective in reducing daytime $PM_{2.5}$ exposure in that room. The mean values in the bedroom area were 53–85% lower than in the kitchen area for all four homes. This difference is much more pronounced than during Phase 1 (no PAC use), when bedroom exposures were 17–43% lower than in the kitchen. Between Phase 2 and Phase 3, the bedroom exposure values were either in the same range (Home 1 and Home 2) or slightly

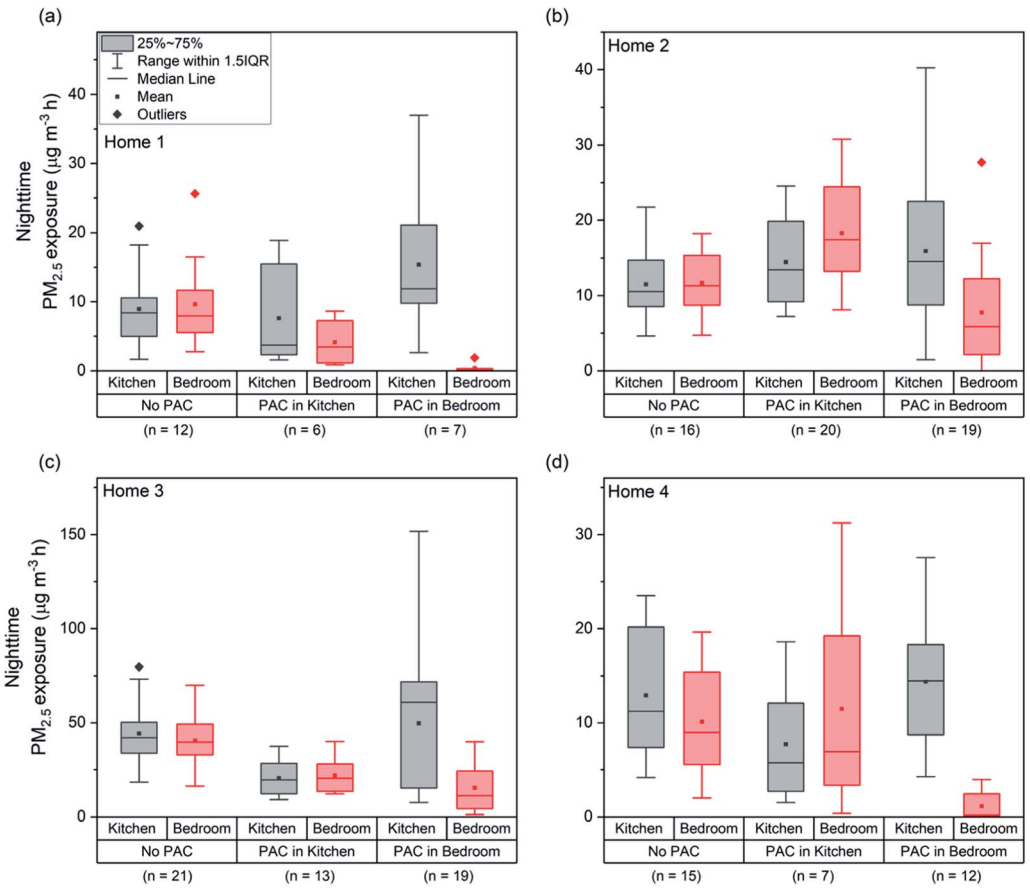

Fig. 6 Boxplot of $PM_{2.5}$ exposure values for time periods between 10:00 pm to 6:00 am the following day for Homes 1–4 is shown in panels (a), (b), (c), and (d) respectively. Note that the *y*-axis in each panel has a different scale.

lower for the latter phase in the case of remaining homes. Therefore, PAC use in the kitchen area during the daytime can be an effective option for reducing personal $PM_{2.5}$ exposure levels due to indoor cooking for occupants who will be spending majority of their time indoors in the kitchen and bedroom areas combined during that period. Moreover, after the period of active cooking when the occupant moves out of the kitchen to other areas, pollutants could homogenize spatially over the entire home, therefore, maximizing personal exposure which again supports this intervention strategy of reducing emissions at the source.

3.3.2 Overnight exposure analysis. In order to examine the role of ambient PM penetration into the homes, we performed an analysis of overnight periods, when cooking activities are less likely to occur. Overnight $PM_{2.5}$ exposure trends for different phases among the four homes are shown in Fig. 6. The mean exposure values in the bedroom area for all the homes were lowest for Phase 3 when the PAC was used in the bedroom area.

The overnight $PM_{2.5}$ exposure values during Phase 1 were one order of magnitude lower compared to daytime periods, thereby suggesting the role of outdoor infiltration in $PM_{2.5}$ on exposure levels indoors, even though its contribution is much lower than indoor cooking. This is likely due to low ambient $PM_{2.5}$ levels during this study. However, it is important to mention that the time period for daytime exposure was twice that of nighttime periods (16 h *vs.* 8 h). During Phase 2, the mean overnight exposure values for the kitchen area of Home 3 were ~50% lower than those of the corresponding mean values for Phase 1 (21 μg m^{-3} h). A moderate reduction in mean exposure (~35%) was also observed for Home 4, where the average exposure value during nighttime periods was calculated to be 8 μg m^{-3} h. Similarly, when the PAC was placed in the bedroom area (Phase 3), the mean exposure values in the bedroom area were 30–90% lower than the corresponding Phase 1 values for all the homes combined. Overall, the mean bedroom exposure values during Phase 3 were lowest among all the phases for all homes. The corresponding mean exposure values were calculated to be: Home 1 (1 μg m^{-3} h), Home 2 (8 μg m^{-3} h), Home 3 (15 μg m^{-3} h), and Home 4 (1 μg m^{-3} h).

In summary, using a PAC in the kitchen and bedroom areas reduced $PM_{2.5}$ exposure between 10–90% during daytime and overnight periods in most of the homes, with only a few exceptions as shown in Tables S5 and S6.† For homes that did not have an effective control strategy (Home 3 and Home 1), the reductions in mean exposure values were usually greater as compared to the other two homes with extracting range hood and open windows for higher air exchange rates, especially during Phase 2 of deployment. Moreover, the absolute values for the reduction in mean exposure compared to no PAC phase were greater in the kitchen area than the bedroom area during the daytime periods in both Homes 1 and 3, suggesting PAC placement in the kitchen areas during daytime periods. For overnight periods when people usually spend majority of the time in the bedroom area, the $PM_{2.5}$ exposure values in the bedroom area during Phase 3 were lowest as compared to the other phases in all the homes.

4 Conclusion

During Phase 1, when no PAC was employed, the overall mean (± standard error) daytime $PM_{2.5}$ concentration for all four homes was 10.2 ± 0.2 μg m^{-3} in the kitchen and 6.3 ± 0.1 μg m^{-3} in the bedroom. During the nighttime period, $PM_{2.5}$ concentrations were ~3× lower, with overall means of 2.8 ± 0.1 μg m^{-3} in the kitchen and 2.5 ± 0.1 μg m^{-3} in the bedroom. These concentration ranges are relatively low, likely due to low ambient $PM_{2.5}$ concentrations during the study period. The highest concentrations observed in all four homes occurred due to indoor cooking activities in the kitchen.

In terms of indoor $PM_{2.5}$ transport between the kitchen and bedroom areas of different homes, concentrations in the bedroom were 70–100% of those in the kitchen. The kitchen emissions peaked in the bedrooms after 1–45 minutes were elapsed from the start of a cooking event. The fastest transport was observed in Home 4 (no internal walls) and the slowest in Home 1, where the bedroom door was kept closed. Overall, both parameters varied depending upon the layout and relative location of the AQMs in the kitchen and bedroom area with regards to the stove. Baseline conditions were investigated during Phase 1, when no PAC was employed.

The exposure analysis performed in this study suggests that PAC use is an important intervention strategy for reducing personal $PM_{2.5}$ exposure, especially in indoor environments where cooking is the main source of $PM_{2.5}$. The bedroom exposure values were also comparable to the exposure at the kitchen location in all the homes. During daytime (6:00 am to 10:00 pm), PAC use in the bedroom or kitchen area yielded 30–90% reductions in $PM_{2.5}$ exposure in three of the four homes. Daytime exposure results also suggest that using a PAC in the kitchen results in lower exposure values in both the bedroom and kitchen areas. During overnight periods, PAC use resulted in the lowest exposure values in all homes, with a reduction in mean exposure values by 30–90% or 4–25 μg m^{-3} h as compared to not using a PAC in the bedroom.

This study is limited to four homes located in one city during a 9 month period when ambient $PM_{2.5}$ concentrations were relatively low. As such, our exposure analysis showed greater importance of cooking activities compared to outdoor $PM_{2.5}$ infiltration in driving the $PM_{2.5}$ exposure values indoors. Another important caveat of this study is the fact that people on average spend much less time in their kitchen areas as compared to the bedroom areas during an entire day. However, the concentrations in the kitchen are usually higher during active cooking periods, so the resulting exposure values in the kitchen area could still be comparable to the bedroom area values especially in areas where outdoor infiltration doesn't play a major role in driving the indoor $PM_{2.5}$ exposure. A study like this should be performed in a more polluted period or city and in homes with varying air-tightness levels to study the importance of outdoor infiltration that might become a greater contributor to indoor $PM_{2.5}$ exposure than cooking emissions.

Finally, we did not observe any drift in $PM_{2.5}$ concentrations as reported by various AQMs as they were moved from one

home to the other. Overall, $PM_{2.5}$ data reported by AirVisual AQM showed the best correlation with the corresponding OPS data during colocation phases with R^2 values in the range of 0.5–0.9 for cooking and background periods.

Conflicts of interest

There are no conflicts to declare.

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