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Proxy methods for detection of inhalation exposure in simulated office environments

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BACKGROUND: Modern health concerns related to air pollutant exposure in buildings have been exacerbated owing to several factors. Methods for assessing inhalation exposures indoors have been restricted to stationary air pollution measurements, typically assuming steady-state conditions.

OBJECTIVE: We aimed to examine the feasibility of several proxy methods for estimating inhalation exposure to CO₂, PM_{2.5}, and PM₁₀ in simulated office environments.

METHODS: In a controlled climate chamber mimicking four different office setups, human participants performed a set of scripted *sitting* and *standing* office activities. Three proxy sensing techniques were examined: stationary indoor air quality (IAQ) monitoring, individual monitoring of physiological status by wearable wristband, human presence detection by Passive Infrared (PIR) sensors. A ground-truth of occupancy was obtained from video recordings of network cameras. The results were compared with the concurrent IAQ measurements in the breathing zone of a reference participant by means of multiple linear regression (MLR) analysis with a combination of different input parameters.

RESULTS: Segregating data onto *sitting* and *standing* activities could lead to improved accuracy of exposure estimation model for CO₂ and PM by 9–60% during *sitting* activities, relative to *combined* activities. Stationary PM_{2.5} and PM₁₀ monitors positioned at the ceiling-mounted ventilation exhaust in vicinity of the seated reference participant accurately estimated inhalation exposure (adjusted $R^2 = 0.91$ and $R^2 = 0.87$). Measurement at the front edge of the desk near abdomen showed a moderate accuracy (adjusted $R^2 = 0.58$) in estimating exposure to CO₂. Combining different sensing techniques improved the CO₂ exposure detection by twofold, whereas the improvement for PM exposure detection was small (~10%).

SIGNIFICANCE: This study contributes to broadening the knowledge of proxy methods for personal exposure estimation under dynamic occupancy profiles. The study recommendations on optimal monitor combination and placement could help stakeholders better understand spatial air pollutant gradients indoors which can ultimately improve control of IAQ.

Keywords: Personal exposure estimation; Environmental monitoring; Workplace exposures; Carbon dioxide; Particulate matter

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INTRODUCTION

Indoor air quality (IAQ) is shaped by myriad factors such as ventilation strategy, space type, and outdoor and indoor climatic conditions and air pollution sources [1]. In particular, human presence and activities have considerable impact on spatio-temporal variation of indoor air pollutants such as particulate matter (PM), carbon dioxide (CO₂), and total volatile organic compounds (TVOCs) [2, 3]. Exposure to elevated levels of metabolically-generated CO₂ could have implications for several health symptoms (e.g., sneezing, irritated eyes, dry or itchy skin), impaired cognitive functioning and decision making [4, 5]. Similarly, elevated exposure to PM_{2.5} and PM₁₀ can increase cumulative incidence of respiratory symptoms such as, throat irritation, coughing, asthma [6].

In office buildings, where occupants are often major contributors to air pollution burden [7], occupancy information could be utilized to characterize IAQ. Occupant activities (e.g., walking, cleaning, and sitting on furniture) cause resuspension of particles, particularly in the coarse (>2.5 μm) size range [8, 9]. Humans also generate bioeffluents including water vapor, CO₂, and VOCs [10–12]. Thus, occupancy-associated emissions are potent determinants of IAQ and as such, they play a fundamental role in exposure estimation and ventilation control [13, 14].

Inhalation exposure assessment studies performed in controlled chambers typically included steady-state conditions and a fixed occupancy [15–17]. Although steady-state studies can be useful, highly controlled environments give little resemblance with the actual exposures that are encountered in real buildings.

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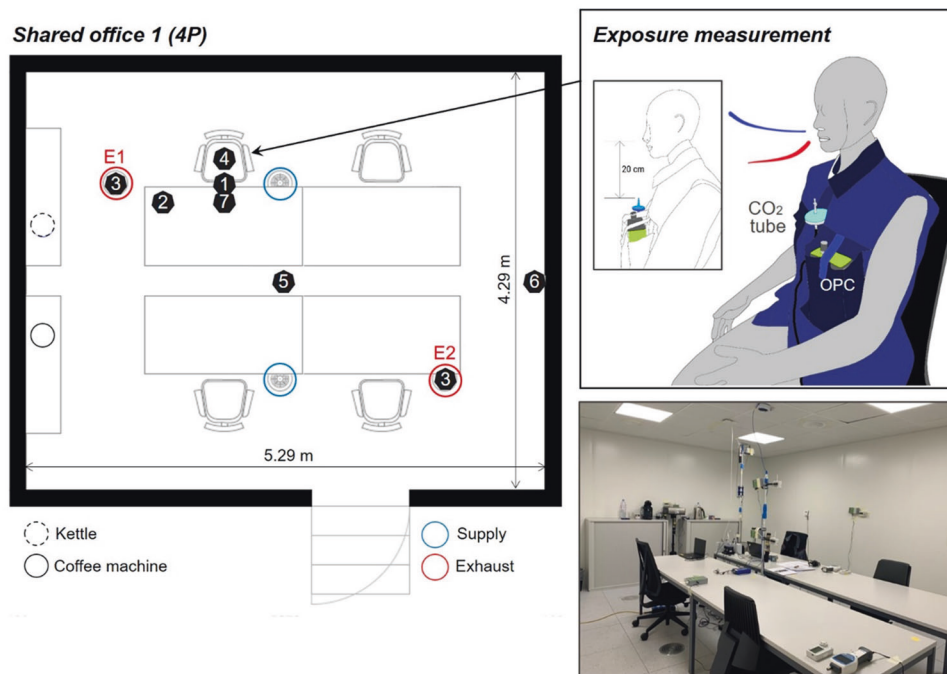


Fig. 1 Example of monitor placement in the Shared office 1 (4 participants) and exposure measurement (CO₂, PM) in the breathing zone of the reference participant. Each monitor location is marked with an ID number which is described in Table 1. Notes: E1 = Exhaust 1, E2 = Exhaust 2.

Furthermore, in spaces where indoor air is imperfectly mixed, spatial heterogeneity of air pollution represents a challenge for assessing inhalation exposures [18].

The common practice of positioning an IAQ monitor indoors is based on standard recommendations that consider the ergonomics of the thermal environment (e.g., EN ISO 7726:2001, EPA Air Sensor Guidebook) [19, 20]. Researchers typically position CO₂ monitors in the middle of an occupied zone with heights between 1.0–1.2 m, which falls into a breathing zone height [21]. Other frequently selected locations for examining indoor air pollution include supply/exhaust ventilation grills, walls and office desks [22, 23]; although substantial differences between concentrations recorded from stationary monitors and those recorded in the breathing zone of occupants have been reported [24, 25].

To improve the accuracy of personal air pollution exposure assessment, several studies have combined other methods with IAQ monitoring [26–28]. These studies collected occupancy information through self-reported diaries, staff monitoring or Passive Infrared (PIR) sensors, and correlated them with personal CO₂ [26, 27] or PM [26, 28] exposures. However, previous studies have not investigated occupancy characteristics (e.g., occupant activities) in order to better characterize inhalation exposure to indoor air pollutants.

As previously noted, methods for detecting personal exposures to CO₂ and PM under dynamic indoor environments are largely unexplored. To bridge this knowledge gap, our study examined a combination of physical parameters (environmental, contextual, and physiological) which best represents inhalation exposures to CO₂, PM_{2.5}, and PM₁₀ in a simulated office environment with dynamic occupancy profiles. Specifically, we performed continuous air quality measurements in the breathing zone of a reference participant with the concurrent IAQ measurement by stationary monitors, occupancy presence by PIR sensors, physiological characteristics of the participant by wearable wristband. A ground-truth occupancy was collected from the network cameras installed in the chamber. A multiple linear regression (MLR) analysis was applied to identify the best proxy methods to detect inhalation exposure to CO₂, PM_{2.5}, and PM₁₀. Finally, we proposed

the best proxy method(s) for characterizing inhalation exposure for investigated scenarios, which includes information about what parameters to monitor and where.

METHODS

Chamber description and space layouts

The experiments were conducted in a controlled climate chamber (floor area: 24.8 m², volume: 60 m³), where air temperature and relative humidity were controlled within narrow ranges, 24.9 ± 0.4°C and 54.3 ± 4%, respectively. To simulate typical mechanically-conditioned office spaces, we selected the mixing ventilation strategy, which is the most common air distribution method applied in commercial office buildings [29]. Here, the conditioned air was supplied and exhausted through the two swirl-type diffusers at the ceiling of the chamber (Fig. 1). The air change rate was constant (2.4–2.6 h⁻¹), which was confirmed by the CO₂ tracer gas decay method [30]. The corresponding air change rate matched the recommendation value (ventilation rate of 144–156 m³/h for four persons and a floor area of 24.8 m²) from the European standard of EN16798-1 (Non-residential building; Category 1) [31]. The supply air was 100% outdoor air filtered by two-stage media filter (F6 and F9) and additional HEPA filter, so that background particle level was close to zero.

We studied four typical workplace layouts: Shared office 1 and 2 (without and with a common space), Meeting room, and Cafeteria. For instance, the Shared office 1 consisted of two or four office desks/chairs depending on the number of participants (two and four), and kettle and coffee machine on two cabinets (Fig. 1). The details of each floor plan with furniture organization are presented in Figure S1.

Human participants

A total of six human participants were recruited (three males and females). The number of the participants was two and four for the two shared offices, and six for the Meeting room and Cafeteria. The selected occupancy number was based on occupancy density in office building specified by the Standard EN16798-1 [31]. The age of participants was between 26–31 and the average BMI ranged within 20.3–23.8 kg/m² for females and 25.1–31.8 kg/m² for males. We distributed the number of males and females equally in each experiment to minimize the impact of gender on human CO₂ emission [11, 15] and maintained the same participants throughout the experiments. The participants wore typical office summer clothing (average 0.4 *clo*). One female participant (28 years

Table 1. Monitor ID, measurement parameters, and placements.

| ID | Parameters measured | Measurement placement (No. of monitors) | Measurement method |
|----|---|---|------------------------------|
| 1 | CO ₂ , Size-resolved particle number concentration | Front edge of participant desk (1) <i>Front edge of desk near an abdomen of the reference participant</i> | CO ₂ monitor, OPC |
| 2 | | Desk (1) <i>On each participant's desk</i> | CO ₂ monitor, OPC |
| 3 | | Exhaust (2) <i>Ceiling-mounted exhaust diffusers, 2.4 m</i> • Exhaust 1 (E1, Fig. 1): near the reference participant • Exhaust 2 (E2, Fig. 1): additional placement | CO ₂ monitor, OPC |
| 4 | | Breathing zone (1) <i>20 cm below from the reference participant's nose</i> | CO ₂ monitor, OPC |
| 5 | Participant presence, number, body posture, and type of office activity | Ceiling (2) <i>Ceiling in the center of the chamber, 2.4 m</i> | PIR, Network camera |
| 6 | | Wall (2) <i>Side wall, 1.4 m and 2.0 m</i> | PIR, Network camera |
| 7 | Participant presence | Below the desk (1) <i>Below the participant desk</i> | PIR |

old, BMI = 22.4 kg/m²) was designated as a reference participant for inhalation exposure measurements.

Experimental design

We conducted a total of 11 chamber experiments during the summer period (13.07.2020–11.08.2020, Table S1). Each experiment was replicated two times except the cafeteria scenario. The measurements included the following three categories: air quality parameters (CO₂, PM_{2.5}, and PM₁₀), contextual parameters (participants' presence, number, body posture, and type of office activity) detected by PIRs and network cameras, and physiological parameters (skin temperature, heart rate and 3-axis acceleration) recorded by wearable wristbands. We determined seven sensor placements (IDs 1–7, Table 1) based on the literature and current best practices [24, 32, 33]. One example of monitor placement for the Shared office 1 is shown in Fig. 1, whereas the others are shown in Fig. S1. For breathing zone measurements, the reference participant wore one CO₂ and one optical particle counter (OPC) at the sampling point located 20 cm below the nose (Fig. 1). The sampling tube connected to the CO₂ monitor was fixed near the reference participant's chest, whereas the OPC was placed in the pocket of an experimental vest. Two network cameras were installed at the ceiling and wall to provide ground-truth occupancy information.

The reference participant received wearable wristband before entering the chamber. Upon entering the chamber, the participants filled out the questionnaire about the seat number and their personal information (age, height, weight and clothing). During the experiment, the participants followed a set of scripted activities that were executed simultaneously by all. Seven activities were executed in two shared office spaces and six in the Meeting room and Cafeteria to simulate realistic occupancy interactions. All activities excluding entering and leaving the chamber were divided into two activity conditions: *sitting* activities and *standing* activities. *Standing* activities included standing or walking. A detailed description of scripted activities is provided in Fig. S2. Duration of each activity spanned from 5 to 25 min. All the participants exited the chamber after 60 min of the experiment and the chamber was sealed for 30 min to permit monitoring air pollutant concentration decay. The ethical and safety considerations of the experiments were approved by the Human Research Ethics Committee of EPFL.

Research instrumentation

Two types of monitors were deployed to measure stationary indoor and breathing zone CO₂ concentrations. Three HOBO MX CO₂ Loggers (MX1102, Onset Computer Corporation, USA, measurement range: 0 to 5000 ppm, accuracy: ±50 ppm) were used for stationary indoor CO₂ measurements. Additional two high-accuracy gas analyzers (LI-850, LI-COR Biosciences GmbH, Germany, measurement range: 0 to 20,000 ppm, accuracy: ±1.5%) with an air pump were deployed at the Exhaust 1 and at the Breathing zone of the reference participant. To capture size-resolved

particle number concentration, we used four stationary and one wearable OPCs. Stationary monitors included: Met One 804 (Metone instruments, USA, 4 channels, size range: 0.3–10 µm, accuracy: ±10% to traceable standard) at the Exhaust 1 and the Front edge of participant desk; Met One HHPG 6+ (Beckman Coulter, USA, 6 channels, size range: 0.3–10 µm, counting efficiency: 50% at 0.3 µm (100% for particles >0.45 µm)) at the Exhaust 2; Mini-WRAS 1371 (GRIMM Aerosol Technik Ainring GmbH & Co., Germany, size range: 10 nm to 35 µm, >95% accuracy for single particle counting) on the Desk near the reference participant. One OPC (Met One 804) was worn by the reference participant.

Three PIR sensors (HOBO Occupancy/Light Data Logger, UX90-006x, Onset Computer Corporation, USA, Detection range: 12 m) were installed in the chamber. We also introduced one wearable wristband (E4, Empatica Inc., USA, frequency range: 32 Hz) that measured physiological state of the reference participant. Lastly, we installed two network cameras (M1065-LW and M3057-PLVE, Axis communications, Sweden, frequency range: 64 Hz) inside the chamber. All IAQ data were obtained at 1-min time intervals except for the CO₂ measurements at breathing zone, which was measured at 0.5-s interval. The PIRs recorded occupancy information as binary code at 1-min time interval. Skin temperature was measured at 4 Hz frequency (0.25 s), heart rate at 1 Hz frequency (1 s) and acceleration at 32 Hz frequency (0.03125 s).

Data analysis

Kierat et al. [16] proposed that accurate CO₂ exposure assessment requires breathing zone measurements to be performed during the inhalation period only. To eliminate the effect of human exhalation, we selected only a single minimum value (Fig. S3) out of one respiratory cycle, where each cycle typically had six measurement points. Then the average breathing zone concentration was calculated as the average of the minimum concentrations recorded in each respiratory cycle. The possible lag between respiratory phase air sampling moment and the actual instrumental measurement time was removed. For breathing zone PM measurement, the full duration of the respiratory cycle was considered. The PM mass concentration (µg/m³) was estimated from measured number concentration by assuming that particles are spherical with density of 2.5 g/cm³, and by supposing that the mass-weighted size distribution, $dM/d(\log d_p)$, is constant within each particle size group [34]. As density of indoor particles is typically in the range 1–2.5 g/cm³, the reported particle mass concentrations are likely to be upper-bound estimates [35].

We removed the contribution of the former activity to the CO₂ and PM concentrations due to multiple participant activities conducted in a relatively short time period. We firstly estimated CO₂ concentration by removing preceding 5-min average CO₂ concentration from each time stamp (Fig. S4). For PM, we followed data processing approach described in [9] where the evolution of PM level from the former activity was calculated and removed (Fig. S5).

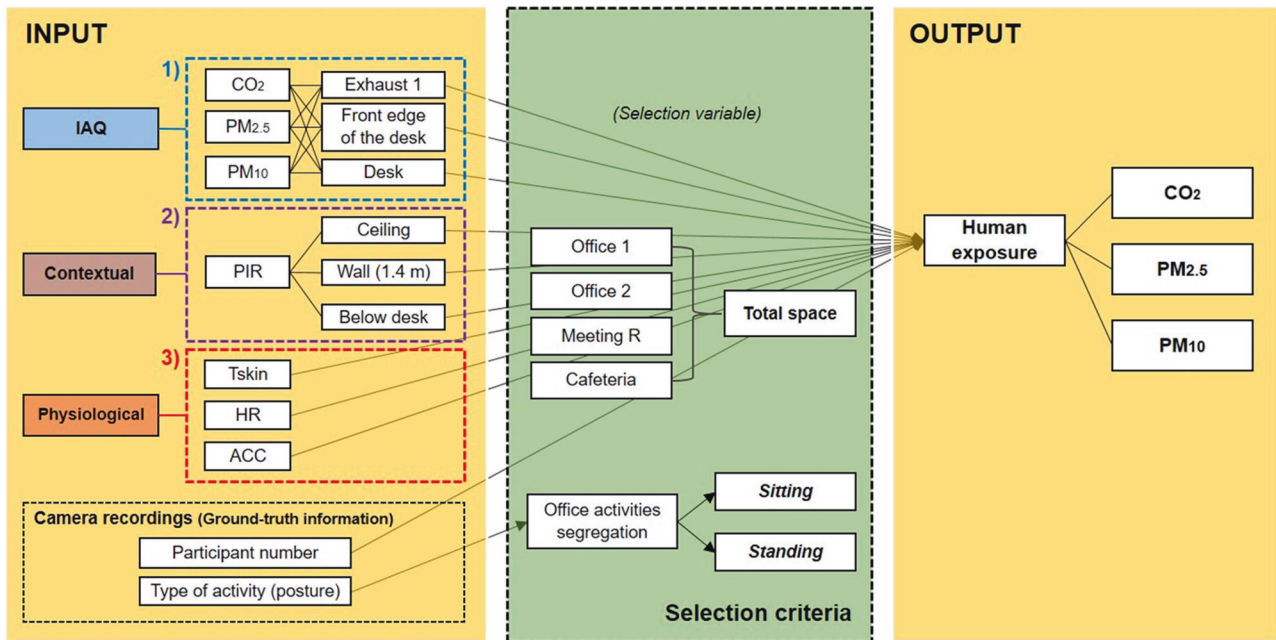


Fig. 2 Input and output variables in composing MLR models. Selection criteria were applied while separating the collected data into *sitting* and *standing* activities. Notes: Exhaust 2 was not included as input in MLR analysis. Tskin stands for skin temperature, HR for heart rate, and ACC for resultant acceleration ($ACC = \sqrt{ACC.x^2 + ACC.y^2 + ACC.z^2}$). Description of *sitting* and *standing* activities is shown in Figure S2.

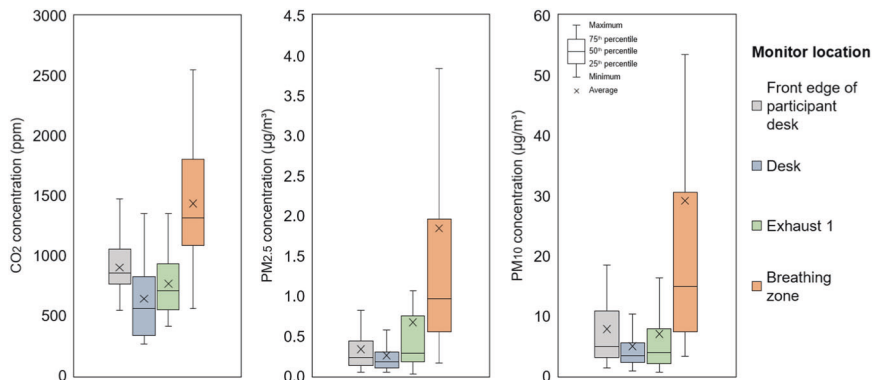


Fig. 3 The CO_2 , $PM_{2.5}$ and PM_{10} concentration at different stationary monitors across all activities and experiments.

Pearson correlation r value indicates existence of association between the measured variables, where stronger linear relationship appears as the r value approaches ± 1 [36]. Our study examined r value between the measured IAQ parameters in order to identify the strength of the correlation between them. Through MLR analyses, we composed regression models by investigating the appropriateness of various physical parameters (presented as input variables) to estimate human exposure (presented as output variable) to CO_2 , $PM_{2.5}$, and PM_{10} (Fig. 2). Firstly, we composed a regression model by using input variable from each data category: 1) air quality; 2) contextual; 3) physiological. We also included participant number as input variable to build a model that is not restricted to one specific office scenario. Data from all office layouts were integrated in analysis to create sufficient datasets to derive validate models. The ground-truth data (type of activity and body posture of the participants) acquired from network cameras allowed us to separate office activities into *sitting* and *standing*. Occupancy data obtained from PIR at Wall (2.0 m) and IAQ data of Exhaust 2 were excluded because of their limited datasets. Then, we composed regression models with input variables from all three different data categories and evaluated their accuracies compared to a model built with the air quality data only. The adjusted R^2 values of each model were identified and compared to assess model accuracy, where the value of 0.75, 0.50, or 0.25 was deemed as strong, moderate or weak fit of

the model as rule of thumb [37, 38]. Further, we examined β (standardized regression coefficients) to identify the positive or negative relationship between the input and output variables, and the magnitude of contribution of the input for estimation accuracy.

Quality assurance

All the CO_2 monitors and OPCs were calibrated ahead of the experiments with side-by-side test to eliminate the gap of measurement discrepancies among the monitors. The HOBO MX CO_2 Loggers were inter-calibrated based on the linear correlation with the high-accuracy gas analyzer (LI-850) in a controlled chamber. The OPCs (two Met One 804 and one Met One HHP6+) were compared against the high-accuracy OPC (Mini-WRAS 1371). Adjustment factors of the side-by-side instrument performance tests are shown in Table S2.

RESULTS AND DISCUSSIONS

Summary of descriptive statistics and correlations of IAQ measurements

In order to understand spatial IAQ variations in the chamber, we examined variations of studied air pollutant concentrations in

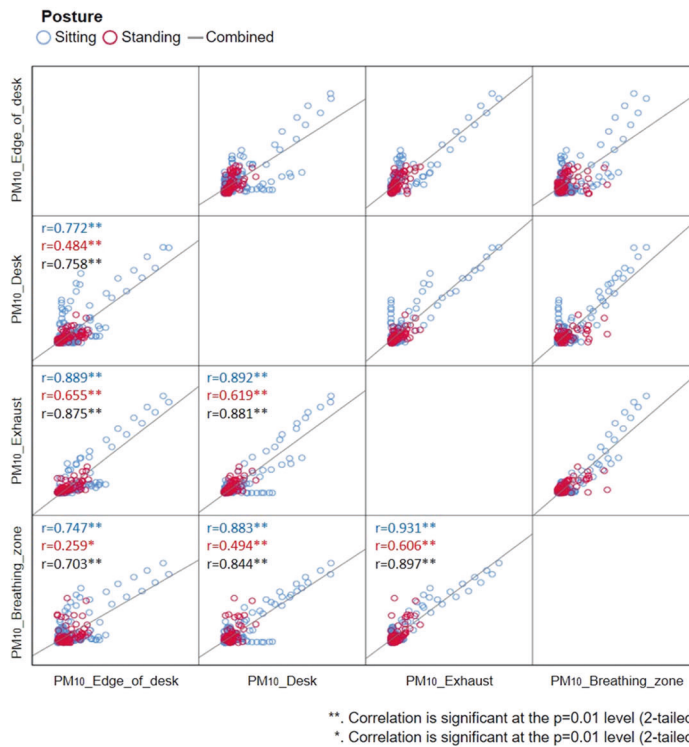
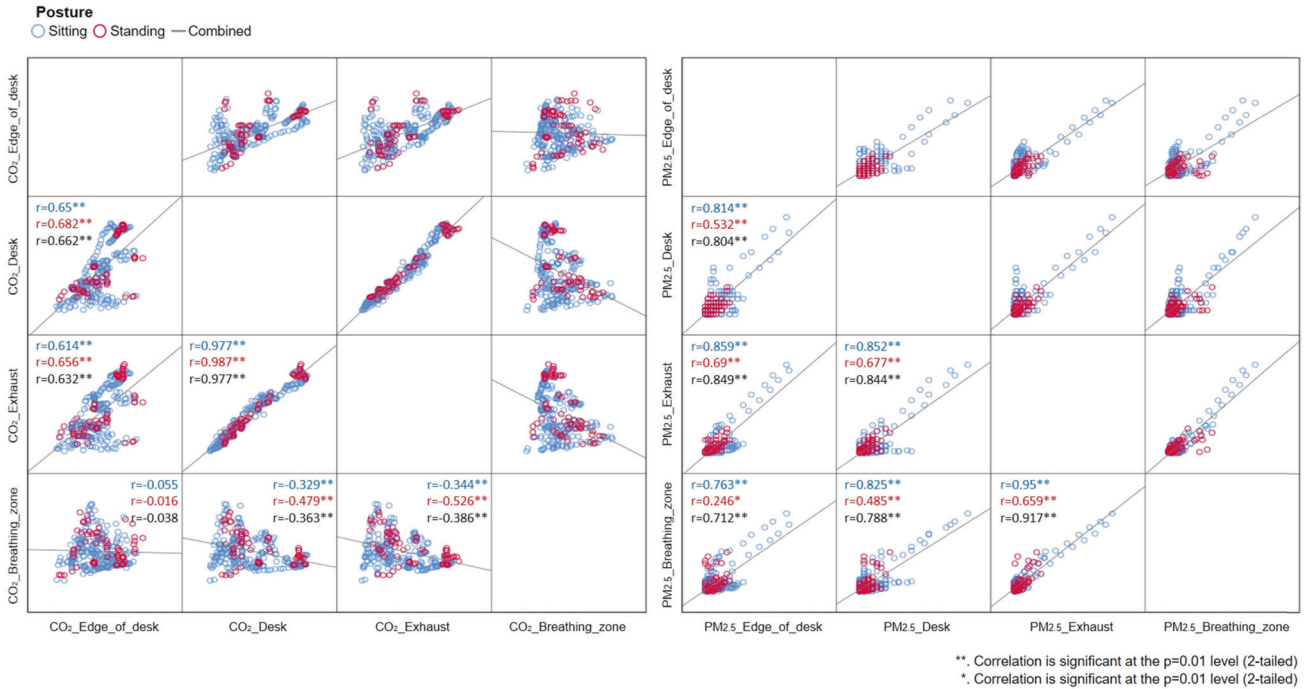


Fig. 4 Pearson correlations of CO₂, PM_{2.5}, and PM₁₀ measurements during *sitting*, *standing*, and *combined* participant activities.

relation to monitor placement. Figure 3 shows minimum, first quartile, median, third quartile, maximum and average CO₂, PM_{2.5}, and PM₁₀ concentrations for each monitor placement (ID 1–4) averaged across all activities and experiments. Regardless of the air pollutant type, the breathing zone concentrations were substantially higher relative to stationary concentrations. The average of breathing zone CO₂ concentrations of the reference participant were approximately two times higher than the ones from stationary monitors. This finding showed a notable increase in breathing zone CO₂ concentration compared to a study by

Melikov et al. [39], where CO₂ concentration inhaled by a breathing thermal manikin was only 16% higher than in the room exhaust. The average PM_{2.5} and PM₁₀ showed 6.7× and 6.8× higher concentrations at the breathing zone than the ones at stationary monitors, respectively.

The highest average CO₂ and PM₁₀ concentration among stationary IAQ monitors were recorded at the Front edge of participant desk which was the closest stationary monitor to the reference participant. This can be a result of exhaled CO₂ jet that propagates downwards during *sitting* activities, as well as

Table 2. Adjusted R^2 value of MLR models for IAQ exposure estimation by using different numbers and combinations of stationary CO₂ and PM measurements during *combined* and separated activities (*sitting* and *standing*).

| Number of variables | IAQ stationary monitor placement | Combined activities ^a | | | Sitting ^a | | | Standing ^a | | |
|---------------------|---|----------------------------------|-------------------|------------------|----------------------|-------------------|------------------|-----------------------|-------------------|------------------|
| | | CO ₂ | PM _{2.5} | PM ₁₀ | CO ₂ | PM _{2.5} | PM ₁₀ | CO ₂ | PM _{2.5} | PM ₁₀ |
| 1 | Front edge of participant desk | 0.326 | 0.516 | 0.495 | 0.26 | 0.61 | 0.58 | 0.579 | 0.068 | 0.073 |
| | Desk | 0.292 | 0.671 | 0.731 | 0.24 | 0.77 | 0.82 | 0.517 | 0.215 | 0.224 |
| | Exhaust 1 | 0.291 | 0.841 | 0.803 | 0.24 | 0.91 | 0.87 | 0.514 | 0.442 | 0.363 |
| 2 | Front edge of participant desk + Desk | 0.328 | 0.68 | 0.738 | 0.26 | 0.78 | 0.83 | 0.581 | 0.202 | 0.214 |
| | Front edge of participant desk + Exhaust 1 | 0.328 | 0.855 | 0.831 | 0.26 | 0.92 | 0.90 | 0.584 | 0.501 | 0.376 |
| | Desk + Exhaust 1 | 0.29 | 0.843 | 0.819 | 0.23 | 0.91 | 0.89 | 0.512 | 0.433 | 0.371 |
| 3 | Front edge of participant desk + Desk + Exhaust 1 | 0.326 | 0.861 | 0.842 | 0.26 | 0.93 | 0.91 | 0.578 | 0.498 | 0.396 |

Bolded values have moderate or strong correlation ($R^2 > 0.5$).

^aAll models included participant number as one input variable

human thermal plume that transports locally generated airborne particles to the breathing zone [40]. This was not the case of PM_{2.5}, where the highest average concentration among stationary monitors was detected at the Exhaust 1, likely because of vigorous activities (e.g., stuffing the cabinet with paper boxes) that occurred nearby. Further, we compared the absolute mean CO₂ and PM₁₀ concentration between the Exhaust 1 and Exhaust 2 (Fig. S6), where difference and variation of mean concentration were trivial in case of CO₂, while it was significant in case of PM₁₀.

Figure 4 shows the Pearson correlation r values between stationary indoor and breathing zone CO₂ and PM concentrations during *sitting*, *standing*, and *combined* (*sitting* and *standing*) activities. Relative to *combined* activities, r values for CO₂ were often higher when we segregated participant activity into *sitting* and *standing* activities. The correlation r between the CO₂ in the breathing zone and at the Front edge of participant desk was 45% higher during *sitting* activities relative to *combined* activities. For *standing* activities, the relative increase was 36% and 32% at the Exhaust 1 and Desk locations compared to *combined* activities. CO₂ measurements at the Exhaust 1 had a moderate correlation ($r = 0.526$) with the breathing zone measurements during *standing* activities. This finding agrees in part with a study by Pei et al. [24] who reported CO₂ measured at the room exhaust well correlates with the inhalation exposure to CO₂ under mixing ventilation. The two highest correlations between breathing and stationary CO₂ measurement were at Exhaust 1 and Desk during *standing* activities. This is due to the contribution of spatial air pollution gradients and the proximity between the reference participant and the sensor locations during the *standing* activities. During the *sitting* activities, a relatively weak correlation (-0.3) between CO₂ at the Exhaust 1 and in the Breathing zone may be attributed to spatial non-uniformity of air pollution concentration and greater distance between Exhaust 1 and seated reference participant. Lu et al. [41] also recognized that inconsistent patterns of CO₂ concentrations in breathing zone of occupants may contribute to discrepancies of correlations between room exhaust and breathing zone CO₂ level.

The correlation r between stationary and Breathing zone PM_{2.5} and PM₁₀ measurement improved marginally during *sitting* activities (4–7%) and did not improve during *standing* activities compared to *combined* activities (Fig. 4). *Sitting* activities had better correlation for PM_{2.5} and PM₁₀ than *standing* activities by threefold. Specifically, the correlation r between Exhaust 1 and Breathing zone during sitting condition showed over 0.9 for both PM_{2.5} and PM₁₀. Low correlation between stationary and breathing zone PM levels during *standing* activities is attributed to irregular

and high-intensity activities that resulted in highly episodic particle emissions. This result confirms that human inhalation exposure can be highly dependent on human activity and its intensity [17, 42]. Further, we compared correlation r between the two exhausts with the Breathing zone measurement (Table S3). In case of PM₁₀, r value at Exhaust 2 decreased by 41–83% compared to the one at Exhaust 1 due to the distance between the reference participant and the deployed OPCs.

Multiple linear regression models for estimating human exposure

MLR models based on stationary IAQ measurements. We investigated the accuracy of human exposure estimation to CO₂, PM_{2.5}, and PM₁₀ by using the input variables from the stationary IAQ monitors. Regression model for each studied air pollutant was proposed while considering a different number (1, 2, or 3) and combination of IAQ input variables. Table 2 shows adjusted R^2 values of each model under *combined* and separated *sitting* and *standing* activities. Segregated human activities can improve inhalation exposure estimation for all studied air pollutants. During *standing* activities, accuracy for estimating CO₂ inhalation exposure was 77% higher compared to one under *combined* activities. This result agrees with the previous report (Fig. 4) of significant improvement of correlation between stationary and breathing zone CO₂ measurements when participants' activities were separated. Accuracy of PM_{2.5} and PM₁₀ exposure estimation was 8% higher during *sitting* activities (adjusted R^2 0.93 and 0.91 respectively) compared to the ones during *combined* activities. In case of PM, *sitting* activities had better estimation accuracy relative to *combined* activities owing to a closer distance between seated participants and the OPCs with a fewer episodic particle emission relative to *standing* activities. Licina et al. [42] also identified personal cloud effect with elevated PM concentration in breathing zone of seated occupants while reporting that well-mixed representation of indoor space might underestimate human exposure to coarse particles. During *sitting* activities, the best single input variable for PM_{2.5} and PM₁₀ exposure detection was PM measurement at the Exhaust 1 (R^2 of 0.91 and 0.87), which was located near the head of the reference participant.

The CO₂ exposure estimation by using a single stationary IAQ monitor during *sitting* activities was not accurate (average adjusted $R^2 = 0.25$ across all single monitors, Table 2). Furthermore, the PM_{2.5} and PM₁₀ exposure estimations by using a single OPC during *standing* activities were also not accurate (average adjusted R^2 of 0.24 and 0.22 across all single OPCs, Table 2). The results indicate that the single stationary IAQ monitoring location recommended by standards and guidelines

Table 3. Adjusted R^2 value of MLR models for IAQ exposure estimation by using different combinations of PIRs measurements during *combined*, *sitting*, and *standing* activities.

| Number of variables | PIR measurement placements | Combined activities | | | Sitting | | | Standing | | |
|---------------------|-----------------------------|---------------------|-------------------|------------------|-----------------|-------------------|------------------|-----------------|-------------------|------------------|
| | | CO ₂ | PM _{2.5} | PM ₁₀ | CO ₂ | PM _{2.5} | PM ₁₀ | CO ₂ | PM _{2.5} | PM ₁₀ |
| 1 | Ceiling | 0.294 | 0.004 | 0.003 | 0.241 | 0.008 | 0.007 | 0.505 | -0.006 | -0.004 |
| | Wall | 0.288 | -0.006 | -0.006 | 0.247 | 0.002 | 0.002 | 0.568 | 0.002 | -0.01 |
| | Below desk | 0.296 | 0.011 | 0.017 | 0.247 | 0.019 | 0.026 | 0.526 | -0.012 | -0.016 |
| 2 | Ceiling + Wall | 0.292 | 0.000 | 0.000 | 0.25 | 0.005 | 0.005 | 0.561 | -0.005 | -0.01 |
| | Ceiling + Below desk | 0.299 | 0.017 | 0.022 | 0.25 | 0.023 | 0.03 | 0.518 | -0.022 | -0.02 |
| | Wall + Below desk | 0.297 | 0.01 | 0.015 | 0.277 | 0.015 | 0.023 | 0.57 | -0.009 | -0.021 |
| 3 | Ceiling + Wall + Below desk | 0.301 | 0.016 | 0.021 | 0.279 | 0.02 | 0.026 | 0.563 | -0.018 | -0.024 |

Bolded values have moderate correlation ($R^2 > 0.5$).

Table 4. Adjusted R^2 value of MLR models for IAQ exposure estimation by using different combinations of wearable wristband measurements during *combined*, *sitting*, and *standing* activities.

| Number of variables | Wearable wristband parameters ^a | Combined activities | | | Sitting | | | Standing | | |
|---------------------|--|---------------------|-------------------|------------------|-----------------|-------------------|------------------|-----------------|-------------------|------------------|
| | | CO ₂ | PM _{2.5} | PM ₁₀ | CO ₂ | PM _{2.5} | PM ₁₀ | CO ₂ | PM _{2.5} | PM ₁₀ |
| 1 | Tskin | 0.407 | 0.039 | 0.016 | 0.477 | 0.121 | 0.067 | 0.528 | -0.015 | -0.017 |
| | HR | 0.3 | -0.006 | -0.006 | 0.237 | 0.001 | 0.000 | 0.54 | -0.007 | -0.003 |
| | ACC | 0.288 | -0.003 | -0.002 | 0.235 | 0.005 | 0.005 | 0.506 | -0.014 | -0.017 |
| 2 | Tskin + HR | 0.459 | 0.04 | 0.014 | 0.475 | 0.118 | 0.062 | 0.594 | -0.022 | -0.019 |
| | Tskin + ACC | 0.405 | 0.043 | 0.021 | 0.476 | 0.13 | 0.074 | 0.521 | -0.031 | -0.031 |
| | HR + ACC | 0.3 | -0.006 | -0.004 | 0.234 | 0.001 | 0.002 | 0.537 | -0.022 | -0.016 |
| 3 | Tskin + HR + ACC | 0.457 | 0.043 | 0.018 | 0.474 | 0.127 | 0.07 | 0.589 | -0.038 | -0.032 |

Bolded values have moderate correlation ($R^2 > 0.5$).

^aTskin skin temperature, HR heart rate, ACC resultant acceleration ($\sqrt{ACC.x^2 + ACC.y^2 + ACC.z^2}$)

19, 20, 43] does not capture exposure well and the measurements may not be reliable particularly when complex airflow interactions exist in the space.

Using all three IAQ inputs (Front edge of participant desk + Desk + Exhaust 1) for estimating PM_{2.5} and PM₁₀ exposure showed 2% and 5% higher adjusted R^2 for *sitting* activities, and 13% and 9% higher adjusted R^2 for *standing* activities relative to using single IAQ input. This was not the case for CO₂ exposure estimation, where there was no difference between using single and multiple variables. Further, we reported regression coefficients of the models (Table S4) consisted of a single stationary IAQ measurement and participant number as input variables with the best estimation accuracy. The regression equations (Eqs. 1–3) are listed based on the models (Table S4) composed with one stationary IAQ measurement and participant number ($part_{num}$) as inputs. A negative correlation between participant number and CO₂ inhalation exposure was observed, while a positive correlation between CO₂ level at the Front edge of participant desk and CO₂ inhalation exposure was detected during *standing* activities (Eq. 1). As indicated in Eq. (2) and Eq. (3), two inputs ($part_{num}$, $part_{exhaust}$) had a positive correlation with output (inhalation exposure to PM_{2.5} and PM₁₀) during *sitting* activities. Interestingly, inhalation exposure to PM₁₀ was more dependent on the participant number than the stationary PM₁₀ measurement at the ventilation exhaust, while the opposite aspect was shown for inhalation exposure to PM_{2.5}.

$$CO_{2, exposure} = -281.51part_{num} + 0.829CO_{2, front\ edge\ of\ participant\ desk} + 1983.328 \tag{1}$$

$$PM_{2.5, exposure} = 0.172part_{num} + 1.795PM_{2.5, exhaust} - 0.007 \tag{2}$$

$$PM_{10, exposure} = 2.497part_{num} + 1.652PM_{10, exhaust} + 1.098 \tag{3}$$

MLR models based on contextual measurements. We derived the MLR models by using input variables obtained from PIRs installed at three different placements; ceiling, wall, and below the participant desk. Table 3 summarizes adjusted R^2 values of each model with different combination of inputs under *combined* and separated *sitting* and *standing* activities. The estimation accuracy did not show any significant R^2 values throughout all proposed models, meaning that the human presence/absence data is generally not effective in detecting personal exposures. However, data obtained by all three PIRs was moderately effective ($R^2 > 0.5$) in estimating inhalation exposure to CO₂ during *standing* activities. Our results point towards conclusion that the PIR alone is able to detect human presence in the space (see $\beta = 0.26$, Table S5), but none of the three PIRs showed a sufficient ability to estimate inhalation exposure solely.

MLR models based on physiological measurements. We also examined MLR models composed of physiological measurements from wearable wristband (E4), which included the skin temperature (T_{skin}), heart rate (HR), and resultant three-axis acceleration (ACC) of the reference participant. Adjusted R^2 values of each model under *combined*, *sitting* and *standing* activities are presented in Table 4. In general, physiological measurements gave poor estimate of inhalation exposures for the investigated scenarios except the CO₂ exposure in *standing* activities that had a moderate accuracy ($R^2 > 0.5$). A discrepancy of estimation accuracy between *sitting* and *standing* activities is aligned with the findings of two experimental studies [44, 45] that indicated a complex relationship of human physiological status and indoor CO₂ concentration. Having more than one physiological parameter could improve the estimation accuracy relative to single measurement in some cases. For example, the model accuracy for detecting PM_{2.5} and PM₁₀ exposure by multiple inputs showed 5 and 10% increase in sitting activities and showed 10% increase in standing activities in case of CO₂ compared to the model with a

Table 5. Adjusted R^2 value (relevant input variables) of MLR models with combined input parameters for IAQ exposure estimation during sitting and standing activities.

| Combinations of parameters ^a (used as input variables) | Adjusted R^2 of composed MLR model (relevant input variables ^b) | | | |
|--|--|---|---|---|
| | Sitting | Standing | | |
| Single IAQ | CO₂ estimation 0.26 (Part_num, CO ₂ , Front edge of participant desk) | PM_{2.5} estimation 0.91 (Part_num, PM _{2.5} , Exhaust 1) | PM₁₀ estimation 0.87 (Part_num, PM ₁₀ , Exhaust 1) | CO₂ estimation 0.579 (Part_num, CO ₂ , Front edge of participant desk) |
| IAQ + E4 | 0.492 (Part_num, CO ₂ , Desk, Exhaust 1, Tskin) | 0.931 (Part_num, PM _{2.5} , Front edge of participant desk, Desk, Exhaust 1, HR) | 0.925 (Part_num, PM ₁₀ , Front edge of participant desk, Desk, Exhaust 1, Tskin, HR) | 0.594 (Part_num, Tskin, HR) |
| IAQ + PIRs | 0.292 (Part_num, CO ₂ , Front edge of participant desk, PIR_Wall, Desk) | 0.933 (Part_num, PM _{2.5} , Front edge of participant desk, Desk, Exhaust 1, PIR_Wall, Desk) | 0.912 (Part_num, PM ₁₀ , Front edge of participant desk, Desk, Exhaust 1, PIR_ceiling) | 0.615 (Part_num, CO ₂ , Front edge of participant desk, PIR_Wall) |
| IAQ + E4 + PIRs | 0.524 (Part_num, CO ₂ , Desk, Exhaust 1, Tskin, PIR_Wall, Desk) | 0.939 (Part_num, PM _{2.5} , Front edge of participant desk, Desk, Exhaust 1, HR, PIR_Wall, Desk) | 0.925 (Part_num, PM ₁₀ , Front edge of participant desk, Desk, Exhaust 1, Tskin, HR) | 0.594 (Part_num, Tskin, HR) |
| Improvement of estimation accuracy (Single IAQ vs combination of parameters, percent increase %) | 101 | 3.2 | 6.3 | 6.2 |
| | | | | 13.8 |
| | | | | 0 |

Bolded characters in parentheses indicate the best parameter or a combination of parameters to estimate inhalation exposure. The last row of the table indicates how much percent increase (%) was obtained in terms of estimation accuracy when using combined parameters compare to using a single IAQ parameter.

^aIAQ: IAQ measurement from stationary IAQ monitors, E4: Physiological measurement from wearable sensor, and PIRs: Contextual measurement from PIR sensor

^bPart_num number of participants, Tskin skin temperature, HR heart rate

single input. However, overall model accuracy by physiological inputs was still insufficient to estimate inhalation exposures. Further, we reported regression coefficients of a model that best estimated CO₂ exposure (adjusted $R^2 = 0.594$) by physiological inputs, where large β coefficient was shown in order of participant number, T_{skin} , and HR (Table S6).

MLR models based on multiple parameter measurements. We finally derived MLR models by combining stationary IAQ, physiological (E4) and contextual (PIR) parameters and compared the results with the models composed of a single parameter. We examined the models under segregated activities (*sitting* and *standing*), which was more advantageous in terms of model accuracy relative to *combined* activities as previously noted in “MLR models based on stationary IAQ measurements”. Adjusted R^2 values of each model were reported with relevant input variables listed in parentheses (Table 5). In case of *sitting* activities, the estimation accuracy showed twofold (101%) increase by using multiple parameters (IAQ+E4+PIR) compared to the model with a single stationary CO₂ measurement. When participants were moving around, CO₂ exposure estimation was better by integrating stationary CO₂ measurements with wearable (T_{skin} , HR) and PIR (PIR_{Wall}) measurement, however, the improvement was small (4–6% increase).

The relevant inputs for PM_{2.5} and PM₁₀ estimation during *standing* activities were stationary PM measurements but did not include any contextual or physiological indicators. During *sitting* activities, however, physiological state (T_{skin} , HR) of the participant was included as relevant input for PM exposure detection. Particularly, the skin temperature (T_{skin}) was advantageous in estimating PM₁₀ exposure while heart rate (HR) was useful in estimating both PM_{2.5} and PM₁₀ exposures. By combining IAQ with wearable and PIR measurements, adjusted R^2 for PM_{2.5} and PM₁₀ exposure estimation models slightly improved (3–6% increase in *sitting* activities). During *standing* activities, having two stationary monitors increased the estimation accuracy by 14% compared to having a single OPC monitor. This increase, however, has little relevance as the single IAQ input was sufficient to accurately estimate the exposure.

Except a notable improvement (twofold increase) of using combined parameters in CO₂ exposure estimation, the increase of model accuracy by combining the parameters was trivial. The regression equations of the best models with combined input parameters are reported as Eqs. (S1–S5). We also included normality test of the final regression models (Fig. S7) in order to make valid future inferences of the models. Lastly, we presented additional regression models that used single and combined parameters during *combined* (*sitting* + *standing*) activities (Table S7). As expected, the best model accuracy for estimating personal exposure to CO₂, PM_{2.5} and PM₁₀ was not apparent when participants’ activities were mixed. This finding confirms the importance of having contextual information, particularly occupant activities, for evaluating personal exposures.

Study limitations

Our study has several limitations. Firstly, our findings are limited to a handful of selections of office setups, activities, single air change rate, and single room air distribution strategy, which means our propositions may not be applicable to completely different circumstances. Our models might have been different if the exhaust vent was not positioned near the seated reference participant, as evidenced by analyzing indoor air pollution and correlation with breathing zone concentration between two different placements of exhaust (Exhaust 1 and 2). Furthermore, being limited to measuring personal exposure of one participant, we cannot generalize expiratory characteristics (e.g., the geometry of a person’s nose, lung capacity, the position of a head) to all population. Physical intrusiveness of measurements to the

participants remains a weakness because it could have influenced their movements. Lastly, experimental instruments were worn by the reference participant with a real-time camera recording, which would not be possible in a real-life scenario due to intrusiveness and privacy issues [46, 47]. To tackle these limitations, one promising technology is a novel camera-based human activity detector algorithm named PifPaf [48] that gives information about total number of participants and estimates the posture of participants containing 17 joints, without violating privacy issues.

CONCLUSION

Considering the challenges of direct measurements of human inhalation exposures, it is useful to explore the effectiveness of alternative methods for approximating exposure to typical indoor air pollutants. In a ventilated chamber with dynamic occupancy, we deployed three different sensing techniques (stationary IAQ, contextual and physiological measurements) to detect breathing zone CO₂, PM_{2.5}, and PM₁₀ concentrations.

The accuracy of estimating inhalation exposures was contingent upon occupant number, activities, and positioning of sensors. Firstly, occupant number was relevant in estimating exposures to investigated air pollutants except the case of PM_{2.5} in *standing* activities. A clear improvement of estimation accuracy was observed by segregating data into *sitting* and *standing* activities; the relative improvement was 9–60% during *sitting* compared to *combined* activities. Vigorous *standing* activities had higher correlation between stationary and breathing zone CO₂ measurement, attributed to reduced spatial air pollution gradients in the chamber. On the contrary, dynamic activities resulted in reduced correlation between stationary and breathing zone PM measurements due to the highly episodic and localized emissions. The CO₂ and PM measurement at ceiling-mounted ventilation exhaust above the reference participant showed the highest correlation with the breathing zone measurement regardless of activities.

Through regression analyses, the best IAQ sensor placement for personal exposure estimation was the Front edge of participant desk for CO₂ and the ventilation exhaust for PM. Specifically, the Front edge of the desk showed a moderate accuracy (adjusted $R^2 = 0.58$) for CO₂ inhalation exposure estimation of a standing participant. The PM measurements at the exhaust showed the substantial potential (adjusted $R^2 > 0.8$) as a proxy to detect personal exposure to PM_{2.5} and PM₁₀ of a seated participant. By combining multiple inputs (environmental, physiological, and contextual parameters), the model estimation on inhalation exposure to CO₂ improved by twofold during *sitting* activities, while the improvement was limited in case of PM (~10%). Our findings indicate that the personal exposure estimation could be enhanced by possessing contextual information (e.g., body posture and type of activity), although the improvement can be trivial in specific cases.

This study contributes to broadening the knowledge of proxy methods for detecting personal air pollution exposures under dynamic occupancies, which goes beyond the existing investigations typically performed under the static conditions [15, 16, 42]. Our findings are novel since it involves contextual and physiological parameters in the actual exposure estimation compared to the previous studies that only investigated the correlation between room occupancy information and exposures [26–28].

The practical recommendations on optimal monitor placement indoors could help stakeholders better understand a real human exposure to air pollutants and secure good IAQ in buildings. Placing a single IAQ monitor at a proper location can be a practical solution while minimizing the initial cost of monitor purchase and its maintenance fee. However, combined monitoring strategies (environmental, physiological, and contextual) could reduce potential errors resulting from having one monitor installed at suboptimal location. Further investigations should generalize the

regression models under different space contexts. Future developments of automatic occupancy detections are needed to develop a more robust and cost-effective approach for human exposure detection and management.

DATA AVAILABILITY

All data generated or analyzed during this study are included in this published article and its supplementary information files.

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AUTHOR CONTRIBUTIONS

Seoyeon Yun: Conceptualization (equal); Data analysis (lead); Investigation (lead); Methodology (lead); Writing-original draft (lead). Sailin Zhong: Data analysis (supporting), Writing-review & editing (supporting). Hamed S. Alavi: Data analysis (supporting), Writing-review & editing (supporting). Alexandre Alahi: Funding Acquisition (supporting); Data analysis (supporting), Writing-review & editing (supporting). Dusan Licina: Conceptualization (lead); Funding Acquisition (lead); Investigation (supporting); Methodology (equal); Resources (supporting); Writing-original draft (supporting).

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COMPETING INTERESTS

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

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