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Optimal sensor placement for personal inhalation exposure detection in static and dynamic office environments

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ABSTRACT

Modern health and productivity concerns related to air pollutant exposure in buildings have sparked the need for occupant-centric monitoring and ventilation control. The existing personal exposure monitoring is often restricted to stationary air quality sensors and static occupancy. This study aims to identify optimal stationary sensor placement that best represents exposure to CO_2, $PM_{2.5}$, and PM_{10} under static and dynamic office occupancies. A total of 48 controlled chamber experiments were executed in four office layouts with variation of occupant numbers (2, 4, 6 or 8), activities (sitting/standing and static/dynamic), ventilation strategies (mixing/displacement) and air change rates (0.5–0.7 h^{-1}, 2.4–2.6 h^{-1}, and 3.8–4.2 h^{-1}). The breathing zone concentration of a reference occupant was monitored with concurrent measurements at seven stationary locations: front edge of the desk, sides of two desks, two sidewalls, and two exhaust vents. The proximity of sensors to the reference occupant and ventilation rate/strategy were important determinants of personal exposure detection. Regression analyses showed that the wall- and desk-mounted CO_2 sensors near the occupant (<1 m) best captured CO_2 exposure under dynamic–standing activities (R^2~0.4). The wall immediately behind the seated occupant and the ceiling-mounted exhaust near the standing occupant (<1–1.5 m) were the best sensor placements for capturing exposure to particles (R^2=0.8–0.9). Separating static from dynamic occupancy activities resulted in improved exposure prediction by 1.4-6.1× . This study is a step towards provision of practical guidelines on stationary air quality sensor placement indoors with the consideration of dynamic occupancy profiles.

1. Introduction

Building HVAC (Heating, ventilation and air conditioning) systems are important determinants of occupants' health, comfort, and productivity [1,2]. Poorly ventilated workplaces have been linked to sick building syndrome (SBS) symptoms, reduced employee productivity, and increased absenteeism [3,4]. Knowledge on how to properly monitor indoor air quality and occupant inhalation exposures can improve control of indoor environments and prevent unnecessary energy consumption of building HVAC. Both personal inhalation exposures and ventilation effectiveness are influenced by the space type, ventilation strategy and occupancy dynamics (occupant number and activities). In imperfectly mixed environments with substantial air pollutant concentration gradients, personal air pollution exposure can be considerably underestimated or overestimated, which could lead to inaccurate health risk assessment. Hence, understanding the spatial relationships among sensor location, air pollutant sources, and the occupant breathing zone is required for accurate assessment of inhalation exposures [5,6].

The current practices for indoor air quality (IAQ) sensor positioning are often based on industry best practices or limited standards (e.g., EN ISO 7726:2001, EPA Air Sensor Guidebook). The existing standards recommend locations for indoor environmental monitoring by considering ergonomics of the thermal environment [7,8]. The emerging green building certification schemes are one of the key drivers for continuous monitoring of indoor air quality [9]. The WELL v2 [10] specifies that one sensor should be installed in every 325 m^2 or minimum one sensor per each floor of a building at the height of 1.1–1.7 m above the floor while avoiding operable windows or air diffusers [10]. The RESET v2 [11] specifies that sensors should be installed at the wall and centrally-located in monitored spaces within the breathing zone height (0.9–1.8 m above the floor) and 5 m away from operable windows and air filters or diffusers. These guidelines for continuous monitoring have recently become the focus of research [12–14]. Nevertheless, the

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existing guidelines for continuous monitoring of IAQ are typically based on industry best practices and ease of installation, which may not accurately represent true inhalation exposures of occupants.

Among the research studies that sought to understand the optimal air quality sensor placement indoors, several research groups placed CO_2 sensor at the height between 0.9 and 1.3 m in the middle of an occupied zone [15–17]. This sensor height partially overlaps with the breathing zone height (0.8–1.8 m above the floor) defined by ANSI/ASHRAE standard 62.1 [18]. Pei et al. investigated different sensor positions (in room exhaust vent, wall-mounted at breathing zone height, and on office desk) for estimating breathing zone CO_2 by simulating two different ventilation strategies (mixing and displacement ventilation) in a controlled chamber [19]. They concluded that CO_2 sensors located at the room exhaust performed the best for detecting the breathing zone CO_2 concentration under mixing ventilation. However, when displacement ventilation was used, the CO_2 sensor near the room exhaust overestimated the CO_2 concentration in the breathing zone while consuming more energy. Another simulation-based study [20] that investigated the impact of number of sensors on capturing spatial distribution of CO_2 and sum of volatile organic compounds (ΣVOC) and sensor accuracy in office settings reported that the best solution would be to upgrade the quality of a single sensor in the return duct in case of small offices with fixed airflows. In the search for an optimal stationary IAQ sensor location for accurate personal exposure detection in occupied spaces, there has been no discrete analysis on dynamics of building occupancy. Most studies on estimating personal exposure by stationary IAQ sensors have been constrained to static or steady-state conditions with a few selections of sensor location inside restricted types of space, which may not represent the real-life dynamic occupancy scenarios [21–25]. Other studies [9,26,27] also mentioned that ideal IAQ management by using low-cost or IoT sensors needs to tackle the ambiguity of sensor placement/number/-accuracy, data resolution and repeatability.

Air pollutant emission from occupants themselves is an important determinant of spatio-temporal variation of indoor air pollution and personal exposure [23,28,29]. Specifically, a significant factor influencing the spatial-temporal indoor air pollution and exposures in buildings is the occupancy dynamics, namely the number of occupants and their activities [30–32]. Occupant activities strongly contribute to air pollution burden associated with CO_2 [33–35], particulate matter (PM) [36–38] and VOCs [39–41]. According to one study that examined the proximity effect for indoor air pollutants [6], the concentrations of coarse particles (particle diameter <10 μm) were more affected by human activity than by the combustion source, while the concentrations of fine particles (<2.5 μm) appeared to be more strongly affected by the combustion than by human activity. Particularly in office settings, some studies reported that the occupant activities significantly contribute to bioaerosol burden [42,43]. Saraga et al. showed that indoor office activities and ventilation type were the main causes of the spatio-temporal variation of indoor pollution in office buildings [44].

As noted above, there is a lack of studies on optimal stationary sensor placement while considering dynamic occupancy profiles in office settings. To elucidate stationary sensing strategies that capture inhalation exposures under dynamic occupancy, our study proposes the following two research questions: 1) What are the adequate locations for stationary sensor placement that best approximate personal exposures under two different occupancy conditions (dynamic and static)? and 2) How categorical variables (occupancies, office layout, ventilation type, ventilation rate) influence personal exposure detection? We hypothesize that the optimal sensor placement for personal exposure detection may differ according to the given building ventilation and occupancy (number and activities). We addressed the research questions by developing a regression model that detects personal air pollution exposures while evaluating contributions of studied input variables – occupancies (occupant number/activities), office layouts, and ventilation strategies/rates. The study compared breathing zone (BZ) and stationary air pollution levels by placing seven stationary sensors for CO_2, $PM_{2.5}$ and PM_{10} detection throughout the space. Further, the study developed linear regression models to identify key indicators for personal exposure detection and proposed optimal IAQ sensor placements. The findings from this study could be beneficial for improving accuracy of exposure assessment, and for advancing the existing guidelines for continuous monitoring and occupant-centric building HVAC controls.

2. Materials and methods

2.1. Chamber description and office layouts

We conducted experiments in a controlled climate chamber with a floor area of 24.8 m^2 and a volume of 60 m^3. The HVAC system controlled the room air temperature and relative humidity within narrow ranges, 24.9±0.4 °C and 54.3±4% respectively, measured across seven stationary sensors in a climate chamber. This temperature condition was higher than usual comfortable values; however, it is relatively common in offices with high internal heat loads and relatively low ventilation rates. We studied two ventilation strategies, Mixing and Displacement ventilation, each operating with a single-pass ventilation (100% outdoor air). Under mixing ventilation, which is the most common air distribution method applied in commercial office buildings [45], the air was supplied and exhausted through the two swirl type diffusers at the ceiling of the chamber. Under displacement ventilation, the air was supplied from the two diffusers at the floor and exhausted through two diffusers at the ceiling of the chamber. The study examined three air change rates (ACH): 0.5–0.7 h^{-1}, 2.4–2.6 h^{-1}, and 3.8–4.2 h^{-1}, and the values were confirmed by the CO_2 tracer gas decay method [46]. The ACH of 2.4–2.6 h^{-1} matched the recommendation value for office buildings (ventilation rate of 144–156 m^3/h for four persons and a floor area of 24.8 m^2) from the European standard (EN16798-1, Office buildings; Category 1) [47]. The background particle level in the chamber was kept close to zero (<limit of detection) by filtering the supply air first by a two-stage media filter (F6 and F9) and then by an additional HEPA filter.

The chamber was configured into four distinct office layouts: Shared office 1 (without a common space), Shared office 2 (with a common space), Meeting room, and Cafeteria. The floor plans and furniture organization of simulated office layouts are shown in Fig. S1 in the Supplementary Information (SI). The Shared office 1 was equipped with two or four office desks/chairs according to the number of occupants (two and four) with two cabinets. Shared office 2 had a similar workstation setup as Shared office 1 but also had a resting area with fabric sofa and coffee table. The Meeting room was equipped with two desks with six office chairs with a TV screen placed on one sidewall. The Cafeteria was composed of two lounge tables with six lounge chairs with two cabinets where a coffee machine, kettle, and microwave were placed.

2.2. Human occupants

In each experiment, we had the equivalent number of healthy male (50%) and female (50%) occupants to avoid a possible influence of sex variation on human CO_2 emission [34]. We kept the same occupant composition for the scenarios with the same number of occupants. The average age of the occupants was between 26 and 34, with BMI ranging between 20.3 and 23.8 kg/m^2 for female occupants, and 24.8–31.8 kg/m^2 for male occupants. During the experiments, the occupants wore typical office summer clothing (average 0.4 Clo) and this factor was not controlled. We selected one female occupant (28 years old, BMI = 22.4 kg/m^2) as a reference occupant who participated in all experimental scenarios consistently for monitoring air pollutant concentrations in the BZ.

2.3. Experimental design

A total of 48 experiments excluding the replicates were conducted

during two time periods (2020.07.13–2020.08.11; and 2021.09.20–2021.09.29), as shown in Table 1. These experiments consisted of 32 runs with dynamic occupancy and 16 runs under static occupancy. In the experiments, we varied occupancy number by 2, 4, 6 and 8 occupants depending on the office layouts. The number of human occupants was selected as 2 and 4 for two shared office spaces and 6 and 8 for meeting room and cafeteria based on occupancy density in the office building of Standard EN15251 [48]. Dynamic occupancy included frequent alteration between sitting and standing activities, whereas static occupancy consisted of one sitting or one standing activity extended over a longer time period.

Fig. 1 illustrates the design of the two occupancy conditions, including occupancy activities and durations. As an example of dynamic occupancy in the Meeting room, occupants performed the following sequence of activities: entering the chamber, sitting and working on laptops, presentation by one person, sitting and discussing as a group, standing and talking, and leaving the chamber. All activities, excluding entering and leaving the chamber, were categorized into two activity conditions: sitting activities and standing activities. Standing activities included standing or walking. Furthermore, two activity intensities were examined: half and full, where half intensity means half of the occupants including the reference occupant executed standing activities, whereas others remained seated. The full activity intensity means that all occupants carried out all the sitting and standing activities together. Duration of each activity spanned from 5 to 25 min under dynamic occupancies, 30 min for static-standing and 60 min for static-sitting occupancies.

One day before each experiment, occupants received a general instruction about the experiments. Upon their arrival, the occupants entered the chamber and were asked to fill out the questionnaire form about their seat number and personal information (age, height, weight and clothing). During the experiments, the occupants simultaneously executed a sequence of scripted activities. The total duration of experiment for dynamic occupancy scenarios lasted 60 min, whereas it lasted 30 or 60 min for static occupancy. After each case of the experiment, all occupants exited the chamber. The chamber was sealed for 30 min after the experiments to monitor a decay of air pollutant concentrations for the purpose of 1) ensuring that the background air pollution concentration prior to the subsequent experiments remained sufficiently low; and 2) evaluating the air change rate of each experiment based on CO_2 decay method.

2.4. Measurement protocol

Concurrent measurements of CO_2 and size-resolved particle number concentrations were conducted at seven stationary locations in the climate chamber. The locations of the sensors were largely determined based on current best practices [19,49–53]. Seven stationary (IDs 1–4) and one breathing zone monitoring location (ID 5) for IAQ sensors are described in Table 2. The sampling interval for monitoring CO_2, $PM_{2.5}$ and PM_{10} was 1-min except the case of breathing zone CO_2 monitoring which was kept at 0.5 s.

An example of sensor placement in the Shared office 1 and Meeting room and the exposure measurement in the BZ of the reference occupant are shown in Fig. 2. To characterize BZ concentrations, the reference occupant wore an experimental jacket to which one CO_2 sampling tube and one OPC were attached. Compliance with the experimental design was monitored and confirmed by the reference occupant.

2.5. Research instrumentation

Two types of instruments monitored stationary indoor and BZ CO_2 concentrations. Six HOBO® MX CO_2 Loggers (MX1102, Onset Computer Corporation, USA, measurement range: 0 to 5′000 ppm, accuracy: ±50 ppm) were used for stationary indoor CO_2 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 monitored CO_2 levels at the Exhaust 1 and at the BZ of the reference occupant. Seven stationary and one wearable OPCs were deployed to capture size-resolved particle number concentration. Stationary sensors included: Met One 804 (Met One instruments, USA, 4 channels, size range: 0.3–10 μm, accuracy: ±10% to traceable standard) at the Front edge of occupant desk, Desk 2, Wall 1/2, and Exhaust 1; Met One HHPC 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 (10–193 nm: electrical mobility analyzer, 0.253–35 μm: optical light scattering sensor), >95% accuracy for single particle counting) on the Desk 1. The reference occupant wore the Met One 804.

2.6. Data analysis

Accurate assessments of CO_2 exposure requires sampling in the BZ during the inhalation period only [54,55]. Our study followed the same method of the study of Yun et al. [56], by selecting only a single minimum value within each respiratory cycle which allowed us to eliminate the effect of exhalation. Based on actual BZ CO_2 measurements, each respiratory cycle lasted for 2–4.0 s depending on the activities. By selecting only the minimum sampling point within one respiratory cycle, we could minimize the effect of human exhalation. We also eliminated the lags between the instrument's actual measurement time and the air sampling moment of the occupant's breathing phase. Finally, the average BZ CO_2 concentration was calculated as the average of the minimum CO_2 concentrations measured from each human respiration cycle. For the measurement of particle number concentration in the BZ, the full respiration periods were considered. The PM mass concentration ($\mu g/m^3$) was estimated from the measured number concentration by assuming that particles are in spherical shape with density of 1.0 g/cm^3, and the mass-weighted size distribution, $dM/d(\log d_p)$, is constant within each particle size group [57].

In case of dynamic occupancies, the air pollution contribution of a

Table 1
Experimental design associated different office layouts, occupancies and environmental conditions (total 48 experiments).

Occupancy condition	Office layout	No. of occupants	ACH	Activity intensity	Activity type	Ventilation type
Dynamic[a]	Shared office 1	2 vs. 4	2.4–2.6 h^{-1}	Half vs. Full	6-7 combined activities designed for each office layout (Fig. 1)	Mixing ventilation vs. Displacement ventilation
	Shared office 2	2 vs. 4	2.4–2.6 h^{-1}			
		4	3.8–4.2 h^{-1}			
	Meeting room	6 vs. 8	2.4–2.6 h^{-1}			
	Cafeteria			Full		
Static	Shared office 1	2	0.5–0.7 h^{-1}, 2.4–2.6 h^{-1}, 3.8–4.2 h^{-1}	Full	Sitting vs. Standing	
	Meeting room	6	2.4–2.6 h^{-1}			

[a] Experiments in two shared offices and meeting room were replicated (additional 24 experiments).

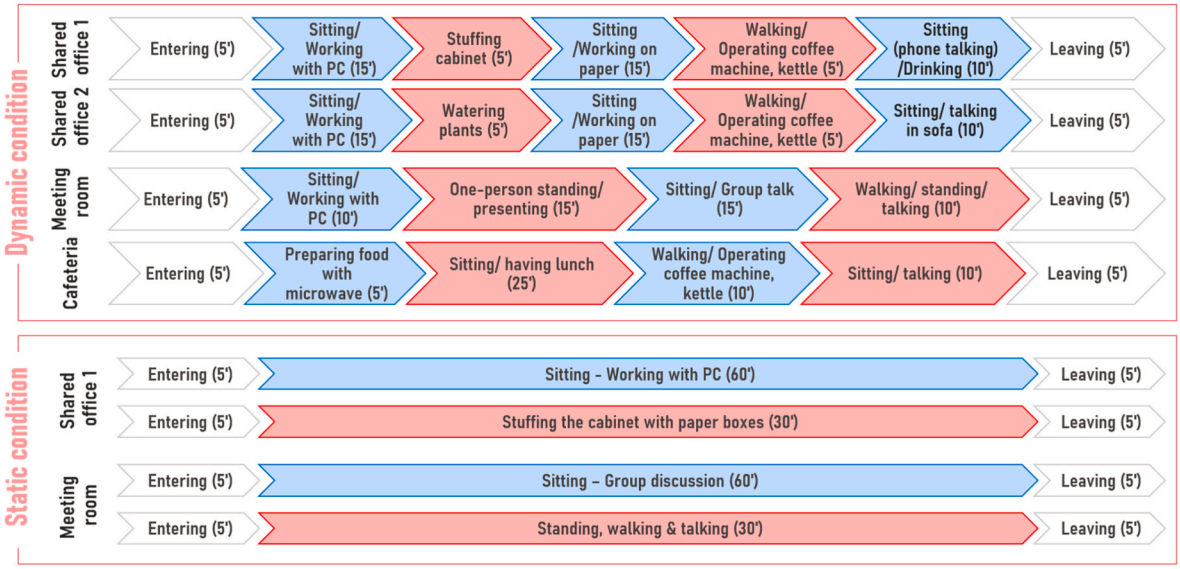

Fig. 1. Occupants' office activities (duration in minutes) in each simulated office layout and occupancy condition. Sitting activities are marked as blue shading while standing activities are marked as red shading. "Entering", "Leaving" and "One-person standing/presenting" activities were excluded in data analysis. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Sensor placements (Sensor IDs, measurement placements and parameters).

ID	Parameters monitored	Measurement placements (No. of sensors; height)	Measurement methods
1	CO_2, Size-resolved particle number concentration	**Front edge of occupant desk (1; 0.7 m)** • 0.1 m from an abdomen of the reference occupant	Non-dispersive infrared technique (CO_2), Size-resolved particle number concentration detection by light scattering of individual particles
2		**Desks (2; 0.75 m)** • Desk 1: at the reference occupant's desk, 0.3 m from the reference occupant • Desk 2: at the desk across the reference occupant, 1 m from the reference occupant	
3		**Wall (2; 1.4 m)** • Wall 1: Side wall, 3 m from the reference occupant • Wall 2: Side wall, 1 m immediately behind the reference occupant	
4		**Exhaust (2; 2.4 m)** Ceiling-mounted exhaust diffusers: • Exhaust 1: Near the reference occupant's head, 1.5 m from the reference occupant • Exhaust 2: Exhaust across the reference occupant, 3.3 m from the reference occupant	
5		**Breathing zone, BZ (1; height range 0.95–1.3 m)** 20 cm below from the reference occupant's nose	

single preceding activity to the CO_2 was removed from the target activity by eliminating the preceding 5-min average CO_2 concentration. For CO_2 and PM under dynamic condition, where various human activities were mixed during 1 h experiment, we introduced the data processing approach described in Refs. [36,56]. We firstly predicted PM values of residual decay concentrations after the activity has finished. The predicted concentrations were then subtracted from the actual concentrations to remove the impact of the former activity. For CO_2, we calculated the CO_2 concentration by subtracting the 5-min average CO_2 concentration from each time stamp.

After data processing, we used two sample *t*-test [58] to examine the difference between room average and breathing zone concentration of CO_2, $PM_{2.5}$ and PM_{10} in each experimented occupancy condition. Here, the null hypothesis was that the population mean of dataset 1 is equal to the one of dataset 2. Further, the study investigated Pearson correlation (r) among measured locations, where r value close to ±1 indicates strong linear relationship among the measured variables [59]. The study investigated the impact of categorical variables (occupancies, office layouts, ventilation types/rates) on personal exposures to CO_2 and PM. To define an optimal sensor placement that best represents personal exposures to investigated air pollutants, we executed a multiple linear regression analysis [60] by using Python 3.10.7 with scikit-learn library [61] as a programming language. In the regression model presented in Fig. 3, the independent variables included CO_2, $PM_{2.5}$ and PM_{10} measured at six different stationary locations and categorical variables (occupancies, office layouts, ventilation types/rates). The dependent variable included CO_2, $PM_{2.5}$ and PM_{10} measured at the breathing zone of the reference occupant. Prior to composing a regression model, we categorized occupant posture into two categories (sitting and standing). We then examined the hierarchy of appropriateness of various physical and categorical variables (given as input variables) to estimate personal exposures to CO_2, $PM_{2.5}$ and PM_{10} (presented as output variable). We

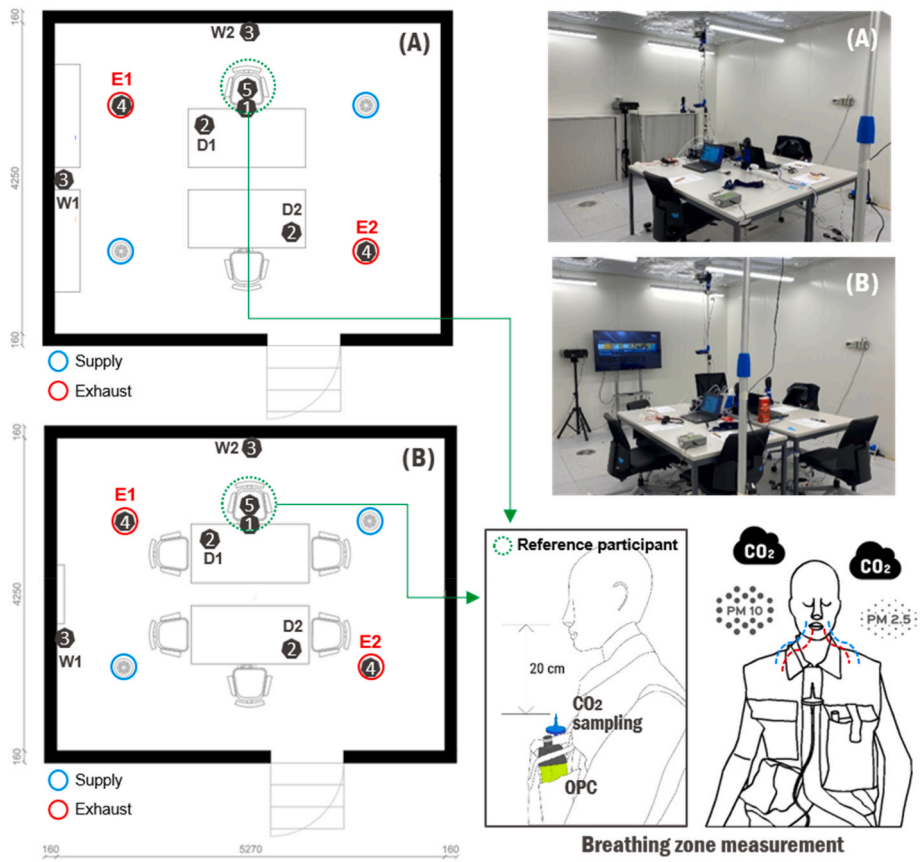

Fig. 2. Example of sensor placement (A) in the Shared office 1 with two occupants and (B) in the Meeting room with six occupants. The lower right part of the figure illustrates exposure measurement (CO_2, PM) in the BZ of the reference occupant. Each sensor placement is marked with an ID that is described in Table 2. Notes: E1 = Exhaust 1, E2 = Exhaust 2. W1 = Wall 1, W2 = Wall 2. D1 = Desk 1, D2 = Desk 2. OPC stands for optical particle counter.

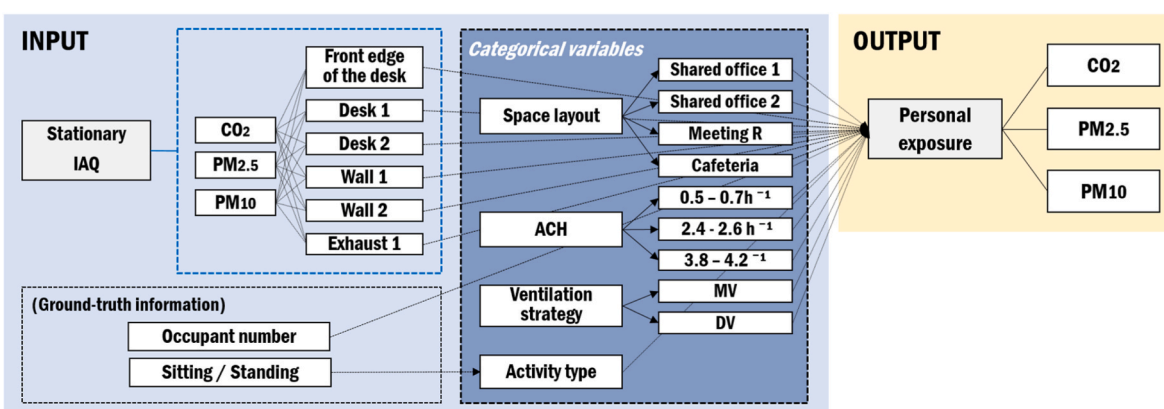

Fig. 3. Input and output variables used to compose the linear regression models for detecting personal exposures to CO_2, $PM_{2.5}$, and PM_{10}. Categorical variables were introduced using dummy variables. Note: Exhaust 2 was excluded from the regression analysis because of its limited dataset.

created dummy variables for categorical variables (occupancies, office layouts, ventilation types/rates) and used them as inputs along with the physical variables in every regression model. Each regression model was trained using 80% of the acquired datasets and tested using the remaining 20%. To avoid any biases on the created models, all datasets are chosen at random. Then, to assess the goodness of fit (accuracy of the model), we presented the R^2 value of the produced regression models. We listed mean absolute error (MAE) and root mean square error (RMSE) to evaluate the model performance, where a lower value of MAE and RMSE of a model indicates better performance of the model in terms of its ability to predict the target variable. Moreover, we applied a Decision Tree Classifier, a data mining method for developing classification based on multiple covariates [62,63], which allowed us to evaluate the contribution of each input variable that enhances the exposure detection.

2.7. Quality assurance

All the sensors (CO_2 and OPCs) were calibrated ahead of the experiments. In a controlled climate chamber, six HOBO® MX CO_2 Loggers were inter-calibrated based on the linear correlation with the high-accuracy gas analyzer (LI-COR Biosciences, Model LI-850). Similarly,

seven stationary OPCs (six Met One 804 and one Met One HHPC 6+) were compared against the high-accuracy OPC (Grimm, Mini-WRAS 1371) based on the PM mass concentrations (μg/m^3). Correction factors obtained from the side-by-side instrument performance tests are shown in Table S1. To account for any possible changes in occupant behavior from day to day, and to improve the robustness of data analyses, the scenarios related to the Shared office 1, Shared office 2 and Meeting room with dynamic occupancies were replicated (24 out of 48 runs). The repeatability between the duplicated runs was high; the variance on measured IAQ parameters stayed within the range of ±5%.

3. Results and discussions

3.1. Descriptive IAQ statistics under different categorical variables

We first examined spatial concentration variations of the studied air pollutant in the chamber. Fig. 4 shows the mean, minimum, first quartile, median, third quartile, maximum concentrations of CO_2, $PM_{2.5}$, and PM_{10} as the room average (across all seven stationary sensors) and in the BZ, categorized by dynamic and static (sitting/standing) occupancy. Across all occupancy activities, the average BZ CO_2 concentrations were 500–1500 ppm higher relative to the room average levels (averaged across all stationary locations). Interestingly, the average BZ CO_2 level during dynamic occupancy was 800–1000 ppm higher than the one during the static occupancies. This is because the combined (sitting + standing) activities during dynamic occupancy were likely associated with more intensive movements and increased metabolic CO_2 generation, which resulted in higher BZ CO_2 levels.

Across different occupancy and activity conditions, there were substantial differences in PM concentrations. The average BZ $PM_{2.5}$ and PM_{10} concentrations were 0.7–2.9 μg/m^3 and 13–16 μg/m^3, respectively, higher than the room average values (across all stationary locations) across all occupancy conditions. Through two sample *t*-test for each case of occupancy condition, the study found a significant difference between the room average and breathing zone concentration of CO_2, $PM_{2.5}$ and PM_{10} (p-value <0.001) except in two cases for $PM_{2.5}$ and PM_{10} under static-sitting condition as shown as Fig. 4. Particularly, static-standing activity resulted in greater room average and BZ PM levels compared to dynamic-combined or static-sitting activities. This is because the vigorous activity during static-standing condition such as stuffing the cabinets with paper boxes resulted in room average and BZ $PM_{2.5}$ and PM_{10} concentrations 2 to 75 times higher compared to other sitting activities. Unlike for dynamic and static-standing activities, there was no significant difference between room average and BZ $PM_{2.5}$ and PM_{10} concentrations during the static-sitting activity due to very slight movements of occupants as proven from the *t*-test ($p > 0.05$).

Fig. 5 shows the room average CO_2 and PM_{10} concentrations as a function of occupant number and ACHs under dynamic and static occupancies. The results of $PM_{2.5}$ were proportional to those of PM_{10}. In both static and dynamic occupancy, the room average CO_2 concentrations increased as the occupant number increased. Six-occupant scenario had ~250 ppm higher room average CO_2 level compared to the two-

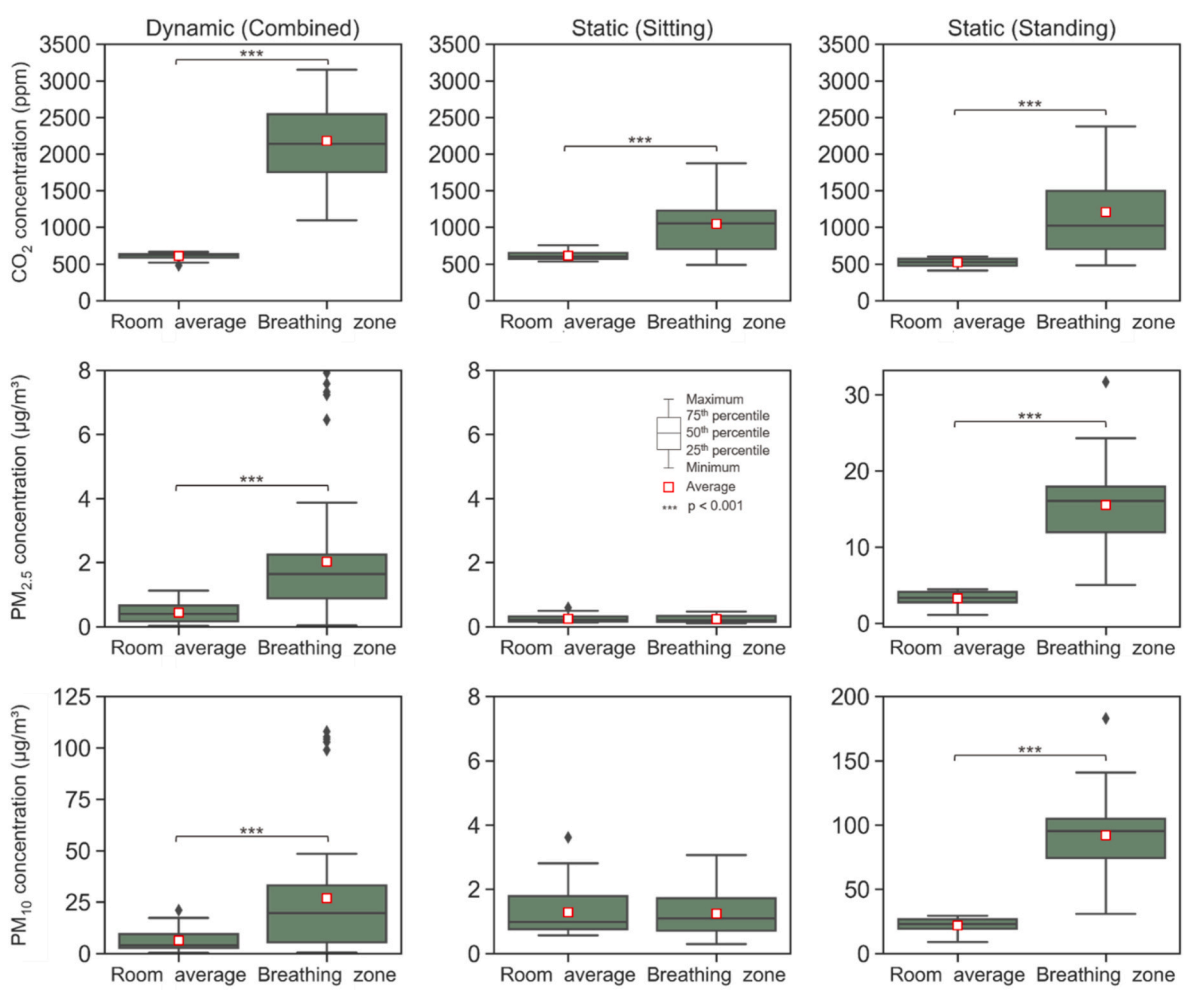

Fig. 4. Boxplot of room average and BZ CO_2, $PM_{2.5}$ and PM_{10} concentrations as a function of dynamic and static occupancy. The results are presented for the selected scenario of Shared office 1 (two people) under the mixing ventilation with a fixed ACH of 2.4–2.6 h^{-1}. The p-value from the *t*-test is star-marked.

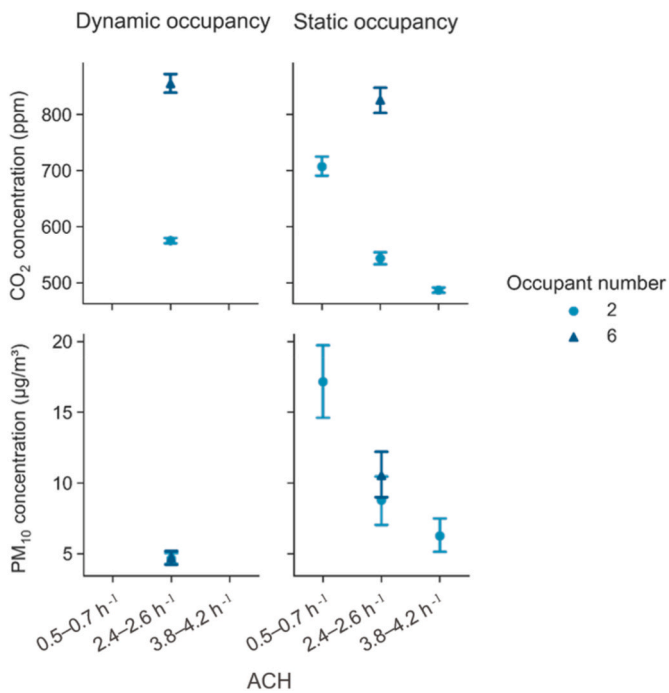

Fig. 5. Room average CO_2, $PM_{2.5}$, and PM_{10} concentration as a function of air change rate and occupant number in dynamic and static occupancies. Markers represent the average values while the vertical bars indicate standard deviation.

occupant scenario. Because of the vastly diverse occupant activities of varying intensities, there was no discernible variation in the room average PM levels under dynamic occupancy. We speculate that the effect of increased PM generation from more occupants was offset by increased air mixing and depositional losses of particles. During the static occupancy with reduced air mixing, however, a 1.25 × increase of PM level was shown in the six-occupant scenario compared to the two-occupant scenario. Correlation between ACH and room average concentration was expectedly negative and mostly linear regardless of the occupancy status.

Additionally, the study examined the impact of ventilation rates and strategies on room average and BZ concentrations of the investigated air pollutants under specific occupancy scenarios. Fig. S2 presents the room average and BZ CO_2 level as a function of three ACHs during occupant sitting or standing activities. Fig. S3 presents the impact of two different ventilation types (MV, DV) on room average and BZ CO_2, $PM_{2.5}$ and PM_{10} level at fixed ACH of 2.4–2.6 h^{-1} under the static occupancy.

3.2. Correlations between stationary and BZ sensors

Fig. 6 presents the correlations between stationary and BZ levels of the studied IAQ parameters during dynamic and static occupancies. As the study of Pei et al. [19] acknowledged the importance of developing quantitative relationships between BZ and the stationary CO_2 sensor according to different occupancy level to ensure a good ventilation performance, separating occupancy (dynamic vs. static) improved the average correlations by 4–31% compared to the combined occupancy (dynamic + static) in this study. The static occupancy had greater correlations, notably for PM, whereas there was little to no difference for CO_2. Under dynamic occupancy conditions, CO_2 showed higher correlation between stationary and BZ levels compared to the $PM_{2.5}$ and PM_{10}. Aerosol particles, especially coarse ones (PM_{10}), have several orders of magnitude lower diffusion coefficients than CO_2 molecules and are sensitive to gravitational settlement [38], which likely explains why correlations were lower for particles. A Similar result was reported in a study of González Serrano et al. [29], where 20% lower correlations were found between personal and stationary sensor in a shared office in case of CO_2 compared to PM_{10}. Under static occupancies, however, the correlation r between stationary and BZ PM levels were higher than that of dynamic occupancies, where the greater particle mass exchange associated with exogenous sources (vigorous activity of other occupants) could strongly influence personal exposures to PM [5].

We also observed that specific sensor locations had stronger correlations with BZ levels than the others. For instance, the stationary CO_2 levels at the occupant desk correlated well with BZ CO_2 levels, and the stationary PM levels at Wall 2 showed a good correlation with BZ PM levels regardless of occupancy conditions. This is primarily due to the proximity effect – those two stationary sensors were located closer to the reference occupant than the other sensors.

As shown in Figs. S4–S5, the correlation r between stationary and BZ levels increased 1-4 × when we divided datasets into two occupant activities (sitting/standing) as opposed to the one of combined activities (sitting + standing).

3.3. Linear regression models for personal exposure detection

3.3.1. Regression models under dynamic and static occupancies

We constructed regression models for each sitting and standing activity under three different occupancy datasets: dynamic (32 runs), static (16 runs), and dynamic + static (48 runs) occupancies. The R-squared (R^2), RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) of each regression model are presented in Table 3. In general, the model for CO_2 exposure detection showed lower average accuracy on testing datasets ($R^2 \sim 0.2$) compared to the one of PM exposure detection ($R^2 \sim 0.7$). This is possibly due to a specific position of the CO_2 sampling point and its proximity to the highly unsteady exhalation pathway of the reference occupant. The model performance of detecting CO_2 exposures on testing datasets improved remarkably when we separated occupancy conditions to dynamic and static such as static-sitting and dynamic-standing activities ($R^2 \sim 0.4$). Similar pattern was observed for PM exposure detection. During static-sitting activities, the $PM_{2.5}$ and PM_{10} exposure detection models showed R^2 above 0.9 on both the training and testing datasets. Fig. S6 compared the actual values (measured in the experiment) with the predicted values from the developed models in the case of the highest model accuracy (bolded values in Table 3), where the lowest RMSE and MAE values were generally shown. For CO_2 and PM we considered the highest R^2 value, rather than the lowest RMSE/MAE values, for selecting the best performed model in order to avoid the uncertainty of instrument error (reported in Section 2.5) on RMSE/MAE values. Table S2 lists the coefficients and intercepts of the independent variables in the developed models. Our results support an interpretation that it is desirable to use a distinct model that considers the nature of occupant activities (e.g., static versus dynamic, and sitting versus standing) in order to increase the accuracy of exposure detection for the investigated air pollutants.

3.3.2. Optimal stationary locations for personal exposure detection

Using a machine learning technique called Decision Tree Classifier [64], our study assessed the contributions of examined input variables on the personal exposure detection. Table 4 reports top two optimal stationary locations for detecting personal exposures to CO_2, $PM_{2.5}$ and PM_{10} under occupant sitting/standing activities. During static-sitting activities, the wall- and front edge of desk-mounted CO_2 sensor adjacent to the reference occupant best characterized CO_2 exposures. During standing activities, the occupant desk and the front edge of the reference occupant desk were the best locations for detecting CO_2 exposures, partly because those two locations were adjacent to the standing reference occupant. The wall-mounted PM sensor immediately behind the seated reference occupant and the ceiling-mounted ventilation exhaust above the reference occupant were adequate locations for approximating personal PM exposures during occupant static-sitting and dynamic-standing activities, respectively. The results indicate that the

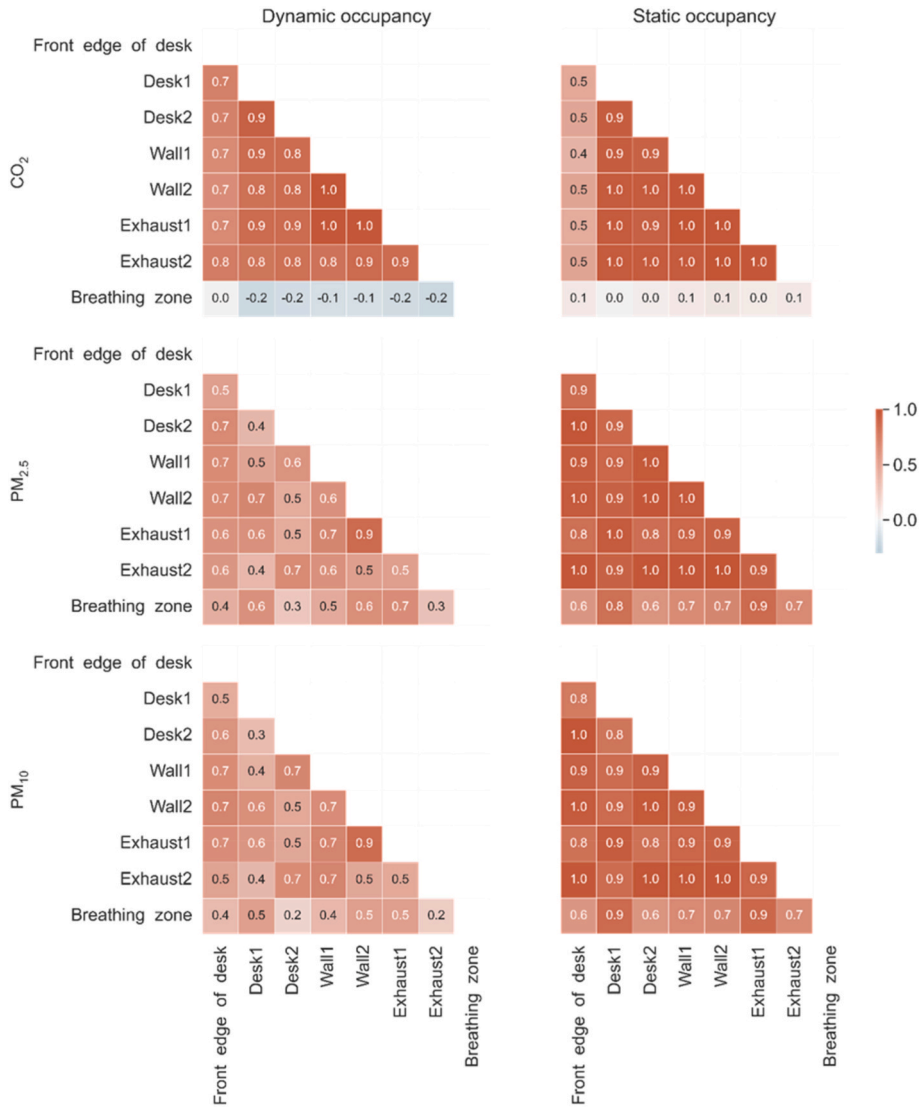

Fig. 6. Pearson correlations between stationary and BZ measurements of CO_2, $PM_{2.5}$, and PM_{10} under dynamic and static occupancies. Correlation r is annotated in each heat map.

Table 3
Evaluation of developed personal exposure detection models by using randomly selected training and testing datasets under sitting/standing activities in dynamic and static occupancies. Bolded values show the best accuracy (R^2) of a model for each pollutant type during occupant sitting/standing activities. RMSE stands for Root Mean Square Error and MAE stands for Mean Absolute Error.

Parameter			Sitting			Standing		
Occupancy			Dynamic	Static	Dynamic + Static	Dynamic	Static	Dynamic + Static
CO_2	R^2	Training	0.21	**0.26**	0.19	**0.38**	0.19	0.42
		Testing	0.16	**0.37**	0.05	**0.41**	0.26	0.10
	RMSE	Training	198	251	218	174	250	215
		Testing	225	254	236	189	229	231
	MAE	Training	162	218	180	141	197	169
		Testing	187	224	199	158	176	182
$PM_{2.5}$	R^2	Training	0.6	**0.9**	0.6	0.5	0.7	**0.8**
		Testing	0.7	**0.9**	0.7	0.4	0.7	**0.8**
	RMSE	Training	1.0	0.2	1.0	1.1	3.8	2.9
		Testing	1.2	0.2	0.8	1.0	3.6	2.6
	MAE	Training	0.6	0.1	0.6	0.7	3.0	1.9
		Testing	0.7	0.1	0.5	0.7	2.6	1.8
PM_{10}	R^2	Training	0.5	**1.0**	0.3	0.5	0.7	**0.7**
		Testing	0.6	**1.0**	0.4	0.5	0.8	**0.8**
	RMSE	Training	25.2	0.6	15.0	18.4	22.1	18.9
		Testing	25.8	0.6	14.0	15.8	20.3	16.4
	MAE	Training	13.4	0.4	8.1	11.6	16.9	14.2
		Testing	14.3	0.4	7.7	11.4	14.2	12.4

Table 4
Top optimal stationary sensor locations for personal CO_2, $PM_{2.5}$ and PM_{10} exposure detection under sitting/standing activities in dynamic and static occupancies. L1 (Location 1) and L2 (Location 2) are ordered by the magnitude of their contribution to exposure detection. Bolded sensor placements show the optimal locations in case of the best model accuracy.

		Sitting			Standing		
		Dynamic	Static	Dynamic+ Static	Dynamic	Static	Dynamic + Static
CO_2	**L1**	Front edge of desk	**Wall2**	Front edge of desk	**Desk2**	Desk1	Wall1
	L2	Exhaust1	**Front edge of desk**	Wall2	**Front edge of desk**	Front edge of desk	Desk1
$PM_{2.5}$	**L1**	Desk1	**Wall2**	Exhaust1	Wall1	Exhaust1	**Exhaust1**
	L2	Front edge of desk	**Exhaust1**	Wall1	Desk2	Desk1	**Desk2**
PM_{10}	**L1**	Front edge of desk	**Wall2**	Desk1	Desk2	Desk1	**Exhaust1**
	L2	Exhaust1	**Front edge of desk**	Front edge of desk	Front edge of desk	Exhaust1	**Desk2**

distance between the target occupant and the IAQ sensor affects the accuracy of the inhalation exposure detection.

Our results point toward interpretation that a precise stationary sensor placement is important in the spaces with highly dynamic occupancies. The current building practices and standards neither specify the optimal sensor placement for each air pollutant type nor consider occupancy characteristics. For instance, both WELL v2 [10] and RESET v2 [11] propose to install the air quality sensor in the breathing zone height and locate them at wall or in the center of the space away from operable windows and air diffusers. This placement aligns with one of our proposed sensor locations (wall), however, these guidelines could be improved based on contextual space characteristics which take into account occupancy location and distance from the installed sensors. According to several studies [65–67], the proximity of the sensors to active sources (in our case, occupants) and dominant occupant activities should be carefully considered as determinants when selecting an optimal IAQ sensor placement. Piedrahita et al. reported that the accuracy of detecting exposures to carbon monoxide improved when the occupant activity data with time duration was considered in the space where high spatial indoor air pollution variation existed [65]. Furthermore, Jiang et al. reported that in high-density occupancy spaces, a small distance between the sensor and target occupant is necessary in order to achieve an effective personalized IAQ monitoring [66]. The study of Pollard et al. [68] reported that the occupants' air pollution exposures in the office area were strongly correlated with the occupants movements lasting more than 10 s, which underlines the importance of considering the nature of occupant activities (static vs. dynamic).

3.4. Study limitations

Our findings are subject to several limitations. The study replicated multiple typical office scenarios, however, the results are constrained to selection of four office scenarios only. The simulated office activities were varied, but still unable to cover all possible human activities that may occur in office settings. Additionally, stationary sensor placements were abundant (7) but case-specific. This suggests that the proposed models might not be fully applicable to different office contexts and stationary sensor locations. Furthermore, the reference participant wore measurement equipment but the obtained results could not be considered to fully represent true exposure levels which should be based on direct sampling in the inhaled air. Our results may also not correspond to the general population considering that BZ measurements were performed on a single female occupant with specific respiration pace and nose/mouth geometry. Since the measurements were not taken in the breathing zone of each participant, our results may not be representative of the overall exposures. According to several researches [69,70], the personal-level air pollution assessments may not accurately reflect the population exposures in the occupied spaces which are characterized by spatial air pollution gradients. Additional measurement in the breathing zones of multiple people of different sex, age can be a valuable step towards provision of more generic findings. Furthermore, given the high level of measurement invasiveness to the reference occupant (i.e., wearing the bulky IAQ sensor), our experimental apparatus might not be relevant to real-life settings. Wearable sensors (smart watches) and portable IAQ sensors with user-friendly designs could be deployed in the future for more effective quantification of personal exposures in real office buildings [71,72].

4. Conclusion

Concerning limited practical solutions for detecting personal inhalation exposures indoors, it is valuable to explore the utility of optimal placement of stationary IAQ sensors. In a controlled chamber resembling office settings with dynamic and static human occupancy, we sought to identify stationary sensor locations that best approximate inhalation exposures to CO_2, $PM_{2.5}$ and PM_{10} of a reference occupant under a set of different occupancies, office layouts and environmental conditions.

We consistently found higher breathing zone concentrations, 500–1500 ppm for CO_2, 0.7–2.9 μg/m^3 for $PM_{2.5}$, and 13–16 μg/m^3 for PM_{10} compared to those measured by stationary sensors, highlighting the importance of identifying stationary sensor locations that highly correlate with the breathing zone measurements. The study also found a discernible impact of different ventilation types and air change rates on the BZ concentrations of the studied air pollutants.

A linear regression model, characterizing personal air pollution exposures for studied office scenarios (varied combinations of sitting/standing activity and dynamic/static occupancy), showed that inhalation exposure prediction could be improved by separating static from dynamic occupant activities. By using Decision Tree Classifier, we found that the sidewall immediately behind the reference occupant (<1 m) and the desk of the reference occupant best approximated CO_2 exposures under static-sitting and dynamic-standing condition (R^2~0.4). For particles, average detection accuracy of exposure with stationary sensors across different occupancy conditions was higher (R^2~0.7). The best stationary PM sensor locations in the best detection accuracy (R^2 = 0.8–0.9) scenarios were the sidewall immediately behind the reference occupant and ceiling-mounted ventilation exhaust near the reference occupant (<1–1.5 m).

The investigation of personal exposures in realistic office scenarios with a variety of stationary sensor placements and occupancy profiles goes beyond studies conducted under steady-state conditions with limited sensor placements. The proposed regression models should be further developed by additional in-depth investigations of building occupancy, occupant activities and stationary sensor locations in actual office buildings.

Our study suggests that positioning a stationary IAQ sensor in a proper location could be an effective strategy for estimating human inhalation exposures in office spaces. The proposed personal exposure detection method, which is based on the optimal deployment of stationary IAQ sensors, is intended to provide building practitioners with a realistic and affordable solution for attaining occupant-centric building HVAC control. Within the next ten years, it is expected that portable and affordable real-time air pollution sensors will be commercially available [73]. Until this technology is applied, the proposed method can be used

for more efficient personal air pollution exposure detection.

Approval for research on human subjects

The Human Research Ethics Committee of EPFL approved the ethical and safety considerations of the experiments (approval number: HREC 039–2020).

CRediT authorship contribution statement

Seoyeon Yun: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dusan Licina:** Resources, Methodology, Investigation, Funding acquisition, Conceptualization, Writing – review & editing.

Declaration of competing interest

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.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

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