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Assessment of Monitoring Strategies for Inhalation Exposure and Occupancy in Office Environments

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par

Seoyeon YUN

Acceptée sur proposition du jury

Prof. D. Khovalyg, présidente du jury
Prof. D. Licina, directeur de thèse
Prof. C. Miller, rapporteur
Prof. J. Laverge, rapporteur
Prof. A. Sonta, rapporteur

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polytechnique
fédérale
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Abstract

Given people's significant time spent indoors, ensuring good indoor air quality (IAQ) is essential because it significantly influences occupants' health and productivity. Office buildings consume about 50% of commercial building energy and 18% of total building stock, with HVAC systems contributing around 40% of the energy consumption. Despite the advent of low-cost smart building sensors, there is a lack of guidelines for optimal IAQ monitoring strategies particularly in offices with dynamically changing occupancy. This thesis investigates three research topics: 1) proxy methods for inhalation exposure assessment, 2) optimal air pollution sensor placement which captures inhalation exposures, and 3) sets of indicators for air inhalation exposure and occupancy detection in office environments.

Chapter 3 proposes proxy methods for detecting personal inhalation exposures to carbon dioxide (CO_2) and particulate matter (PM) in simulated office settings with dynamically changing occupancy. Three proxy sensing techniques were compared with the concurrent breathing zone measurements: stationary IAQ monitoring, wearable wristbands for physiological monitoring, and passive infrared (PIR) sensors for human presence detection. Combining three proxy techniques improved the CO_2 exposure detection by twofold compared to solely using a stationary IAQ monitor. Stationary PM monitors near the ventilation exhaust accurately estimated PM exposure, while CO_2 measurements at the front edge of the desk showed moderate accuracy for CO_2 exposure detection.

Chapter 4 investigates optimal sensor placement for detecting inhalation exposure in static and dynamic simulated office environments. It identifies suitable locations for accurate exposure estimation, considering occupancy dynamics. The findings show that differentiating between static/dynamic occupancy and sitting/standing activities enhanced the accuracy of exposure detection. Variables such as proximity of sensors to occupants and ventilation rate/strategy played significant roles in improving personal exposure detection. Desk- and wall-mounted CO_2 sensors, along with a ceiling-mounted PM sensor, provided the most accurate exposure detection.

Chapter 5 explores indicators for exposure and occupancy detection in two real office buildings in the western part of Switzerland. The method used a combination of stationary and wearable sensors, along with Decision Tree and correlation analyses. Occupancy strongly influenced air pollution gradients in different office spaces, with higher PM_{10} levels during lunch/coffee activities. Desk-mounted CO_2 sensors effectively detected CO_2, $PM_{2.5}$, and PM_{10} exposures in open-plan offices. CO_2 levels at the sidewall represented prolonged occupancy, while desk-mounted PM_{10} sensors captured transient occupancy. A single CO_2 sensor proved to be a cost-effective solution for both CO_2, $PM_{2.5}$ and PM_{10} exposure and occupancy detection. Air pollution data demonstrated up to 4× higher predictive power in detecting exposures and occupancy compared to indoor climate data.

The thesis proposes optimizing solutions for exposure and occupancy detection with smart building sensors under various office setups and occupancy scenarios. The findings could find application in enhancing IAQ management and occupant-centric HVAC control through integrated smart monitoring techniques that can be used in real-life occupancy conditions.

Keywords

Indoor air quality, Optimal sensor placement, Inhalation exposure detection, Occupancy dynamics, Office environments

Résumé

Du fait que la population passe une grande partie de leur temps à l'intérieur, il est essentiel de veiller à une bonne qualité de l'air intérieur (QAI) car cette dernière influence considérablement la santé et la productivité des occupants. Les immeubles de bureaux consomment environ 50 % de l'énergie des immeubles commerciaux et représentent 18 % du stock total de bâtiments. Les systèmes de chauffage, de ventilation et de climatisation (HVAC) contribuent à environ 40 % de cette consommation énergétique. Malgré l'avènement de capteurs à faible coût dans les bâtiments intelligents (*Smart buildings*), il manque des directives définissant les stratégies de surveillance optimale de la QAI, en particulier dans les bureaux où l'occupation varie fortement. Cette thèse explore trois sujets principaux de recherche : 1) les méthodes substitutives (proxy) permettant l'évaluation de l'exposition par inhalation, 2) le placement optimal de capteurs de pollution de l'air pour mesurer les expositions par inhalation, et 3) l'ensemble des indicateurs permettant la détection de l'exposition par inhalation et de l'occupation dans les environnements de bureau.

Le Chapitre 3 propose des méthodes de substitution pour détecter les expositions personnelles par inhalation au dioxyde de carbone (CO_2) et aux particules fines (PM) dans des environnements de bureau simulés avec une occupation en constante évolution. Trois techniques de détection par substitution ont été comparées aux mesures simultanées en zone respiratoire. Ces trois techniques sont 1) la surveillance stationnaire de la qualité de l'air intérieur, 2) les bracelets portables monitorant des données physiologiques et 3) les capteurs infrarouges passifs (PIR) détectant la présence humaine. La combinaison des trois techniques de substitution a permis d'améliorer de deux fois l'exposition au CO_2 par rapport à l'utilisation exclusive de capteurs stationnaires. Les moniteurs stationnaires de particules fines (PM) à proximité de la bouche de ventilation ont estimé avec précision l'exposition aux PM, tandis que les mesures de CO_2 à l'avant du bureau ont montré une précision modérée pour la détection de l'exposition au CO_2.

Le Chapitre 4 étudie le placement optimal des capteurs afin de détecter l'exposition par inhalation dans des environnements de bureau simulés dans des conditions statiques et dynamiques. L'Dans ce chapitre, les emplacements appropriés pour une estimation précise de l'exposition sont identifiés, tout en tenant compte de la dynamique d'occupation. Les résultats démontrent qu'inclure la distinction entre une occupation statique/dynamique puis des activités assises/debout permet d'améliorer la précision de l'estimation de l'exposition. Des variables telles que la proximité des capteurs par rapport aux occupants ainsi que le débit et la stratégie de ventilation jouent un rôle significatif dans l'amélioration de la détection de l'exposition personnelle. Des capteurs de CO_2 déposés sur les bureaux et accrochés aux murs, ainsi qu'un capteur de particules fines suspendu au plafond, ont permis une estimation de l'exposition la plus précise.

Le Chapitre 5 explore les indicateurs permettant la détection de l'exposition et de l'occupation dans deux bâtiments de bureau de Suisse Romande. La méthode combine des mesures effectuées par des capteurs stationnaires, portables, à une analyse statistique par arbres de décision et de corrélations. L'occupation influence fortement les gradients de pollution de l'air dans les différents espaces de bureau, avec des niveaux de PM_{10} plus élevés pendant les activités de déjeuner/café. Les capteurs de CO_2 déposés sur les bureaux ont efficacement détecté les expositions au CO_2, aux $PM_{2.5}$ et PM_{10} dans les bureaux en espace ouvert. Les niveaux de CO_2 au niveau des murs latéraux ont bien représenté l'occupation prolongée, tandis que les capteurs de PM_{10} déposés sur les bureaux ont capté l'occupation transitoire. Un seul capteur de CO_2 s'est avéré être une solution rentable pour estimer les expositions au CO_2, aux $PM_{2.5}$ et aux PM_{10}, ainsi que pour l'occupation. Les données sur la pollution de l'air intérieur ont démontré une puissance prédictive jusqu'à 4 fois plus importante pour l'estimer l'exposition et l'occupation par rapport aux données sur l'environnement intérieur.

Cette thèse propose des solutions d'optimisation pour l’estimation de l'exposition et de l'occupation avec des capteurs intelligents dans différentes configurations de bureaux et de scénarios d'occupation. Les résultats pourront être appliqués dans des conditions réelles de manière à améliorer la gestion de la qualité de l'air intérieur ainsi que le contrôle du système de chauffage, ventilation et d’air conditionné (HVAC) axé sur les occupants grâce à des techniques de surveillance intelligentes intégrées.

Mots-clés

Qualité de l'air intérieur, Placement optimal de capteurs, Estimation de l'exposition par inhalation, Dynamiques d'occupation, Environnements de bureaux

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Abbreviations

HVAC: Heating, Ventilation and Air-Conditioning

T_a: Air temperature

RH: Relative Humidity

T_{skin}: Skin temperature

HR: Heart rate

ACC: Resultant Acceleration ($\sqrt{ACC\_x^2 + ACC\_y^2 + ACC\_z^2}$)

PPD: Predicted Percentage of Dissatisfied

TVOCs: Total Volatile Organic Compounds

SVOCs: Semi-Volatile Organic Compounds

PM: Particulate Matter

$PM_{2.5}$: PM with particle diameter < 2.5 µm

PM_{10}: PM with particle diameter <10 µm

SBS: Sick Building Syndrome

HMM: Hidden Markov Model

MV: Mixing ventilation

DV: Displacement ventilation

NV: Natural ventilation

DCV: Demand Control Ventilation

PEM: Personal Exposure Monitors

MEM: Micro-environmental Exposure Monitors

ACH: Air Change Rate (/Hour)

IoT: Internet of Things

CO: Carbon monoxide

CO_2: Carbon dioxide

SO_2: Sulfur dioxide

SF6: Sulfur hexafluoride

NO_2: Nitrogen dioxide

PAHs: Polycyclic Aromatic Hydrocarbons

O_3: Ozone

MOx: Metal Oxide

PIR: Passive Infrared

RFID: Radio Frequency Identification

CFD: Computational Fluid Dynamic

OPC: Optical Particle Counter

BMS: Building Management System

PAQ: Perceived Air Quality

DT: Decision Tree

ANN: Artificial Neural Network

MLR: Multiple Linear Regression

DALYs: Disability-Adjusted Life Years

MPC: Model Predictive Control

EFs: Effect Factors

iF: Intake Fraction

Chapter 1 Introduction

1.1 Background and motivation

Carbon neutrality is a global trend which is accelerating [1]. Exclusive focus in it may end up compromising IAQ and cause elevated inhalation exposures and associated health risks [2]. Assuring ongoing and incoming carbon transformations applied to the buildings do not adversely impact IAQ and human health is necessary [3]. Office buildings represent a significant opportunity for improving energy efficiency, as they account for a substantial portion of energy consumption in commercial buildings [4]. Heating, ventilation, and air conditioning (HVAC) systems, in particular, contribute to a significant portion of energy usage in office buildings. Nonetheless, it is imperative to recognize that energy efficiency initiatives must not come at the expense of occupants' well-being and productivity.

The relationship between energy efficiency and indoor environmental quality (IEQ) is interconnected, requiring a holistic approach in building initiatives across all types [3,5]. Most of the conventional HVAC control loops typically rely on limited sensing of room air temperature (T_a), relative humidity (RH), and, in rare cases, carbon dioxide (CO_2) levels [6,7]. The traditional system-centric approach does not encompass various conditions that are relevant to occupants' health and well-being, such as human exposure to spatially- and temporally varying air pollutants particularly induced by occupant activities [8].

In environments particularly with imperfect mixing and significant air pollutant concentration gradients, the estimation of personal air pollution exposure can lead to considerable underestimation or overestimation [9–11]. This can result in inaccurate health risk assessments and highlights the utmost importance of addressing indoor inhalation exposures for ensuring optimal health, comfort, and productivity of occupants [12,13]. Therefore, it is essential to consider the degree of air mixing indoors as a more generic indicator for accurate air pollution exposure assessment. By doing this, a more nuanced understanding of how occupants are exposed to pollutants in real-world scenarios can be achieved. This approach accounts for the variability in pollutant distribution, considering factors such as the location of emission sources, indoor airflows, and occupant activities [14–16]. As a result, it enables a more accurate estimation of personal air pollution exposure, reducing the likelihood of underestimation or overestimation.

In contrast to conventional HVAC systems commonly found in offices, which inadequately address spatiotemporal air pollution, human-centered HVAC systems aim to prioritize occupant health, productivity, comfort, and well-being while maintaining energy efficiency [17,18]. The concept of "occupant-centric control" has emerged to describe building control strategies that actively utilize information about occupancy presence and occupant activities. Studies emphasized the significance of collecting occupant-related information, such as occupant numbers and activities, for designing and implementing occupant-centric control strategies [18–20]. With the advent of low-cost smart building sensors, real-time monitoring of indoor air quality (IAQ) and building occupancy has been enabled, providing opportunities to enhance energy efficiency while ensuring healthier and more productive indoor environments. However, there are challenges associated with the cost, accuracy and privacy implications of gathering such data [21,22]. Additionally, the utilization of multiple sensors rather than a single sensor has been favored in optimizing indoor environment control, allowing for better characterization of IEQ, occupancy presence, and satisfaction levels. While this approach shows promise, multiple questions remain unanswered about optimal sensing strategies for efficient detection of inhalation exposures and occupancy under realistic occupancy conditions [22].

To achieve an optimal inhalation exposure and occupancy monitoring that contribute to achieving occupant-centric building HVAC control, there is a clear need and value for a new paradigm that integrates holistic and intelligent IEQ sensing [17]. This paradigm should go beyond energy performance and consider human comfort, exposure to IAQ variations induced by occupancy and their activities. Hence, the motivation behind this thesis stems from the need to bridge these knowledge gaps and develop practical recommendations for achieving optimal inhalation exposure and occupancy monitoring strategies that can accurately characterize personal air pollution exposures under dynamic occupancies in office environments. Specifically, the thesis aims to enhance our understanding of inhalation exposure, occupancy dynamics, IAQ sensor placement, and optimal set of indicators for personal exposure and occupancy detection. By integrating advanced monitoring technologies that identify what to measure and how to strategically place sensors with a cost-effective yet accurate set of indicators, this thesis can provide a more comprehensive understanding of the dynamics of indoor environment and personal air pollution exposure characterizations. The outcomes of this research can have significant implications for improving IAQ, occupant health, and the development of effective guidelines for IAQ monitoring and HVAC control in office buildings, which can be helpful for building practitioners.

1.2 Scope of work

This thesis aims to propose optimal monitoring strategies for personal air pollution exposures and occupancy dynamics in office environments. The scope of the study includes two environmental chamber studies (Chapters 3 and 4) that simulated dynamic and static office environments in a controlled climate chamber, and one field study (Chapter 5) that is conducted in two office buildings in Swiss-Romandie region. The two chamber studies were conducted during two time periods (2020.07.13 – 2020.08.11; and 2021.09.20 – 2021.09.29) and one field study was conducted during the spring 2022. The target population in this thesis are the adults aged between 25 and 62 years who are in good health and do not have any respiratory issues. The scope of this thesis encompasses three key areas related to investigating human air pollution exposure and occupancy monitoring strategies in office environments.

The first controlled chamber study focuses on developing and evaluating proxy methods for characterizing inhalation exposure to CO_2, $PM_{2.5}$, and PM_{10} in simulated office environments with dynamically changing occupancy. This study identifies the best combination of physical parameters (environmental, contextual, and physiological) that represent inhalation exposures and propose proxy methods for personal air pollution exposure monitoring.

The second controlled chamber study focuses on determining the optimal stationary IAQ sensor placements for characterizing inhalation exposures in office environments, considering static and dynamic occupancy profiles. It investigates the influence of various categorical variables, such as occupancies, office layouts, ventilation types, and ventilation rates, on personal exposure detection. This study encompasses proposing practical recommendations for sensor placement to enhance exposure assessment accuracy and, consequently, improve occupant-centric HVAC control.

Lastly, the third field study includes various office space types and aims to identify key indicators for detecting personal exposures to air pollutants and occupancy dynamics in real buildings. It involves measuring personal-scale IAQ and activity data, room-scale IAQ and occupancy data, and building-scale occupancy data. This study involves exploring spatial gradients of personal exposures and conducting correlation and Decision Tree (DT) classification and regression analyses to identify the most significant sets of indicators for exposure and occupancy detection. The findings contribute to determining the minimum but sufficient indicators influencing personal exposure and occupancy detection, thereby addressing the cost-effectiveness of occupant-centric IAQ monitoring in real office settings.

Overall, the scope of this thesis is to bridge the knowledge gaps in monitoring strategies for personal air pollution exposures and occupancy dynamics in office environments. The thesis provides practical recommendations for proxy methods, sensor placement, and effective sets of physical indicators that can enhance occupant-centric IAQ monitoring approaches and ensure healthy and productive indoor environments for building occupants in office buildings.

Chapter 2 Literature review

2.1 Occupant-centric indoor environment and HVAC controls

The high energy consumption of HVAC systems in buildings emphasizes the need for effective HVAC management algorithms that not only reduce power consumption but also ensure an optimal indoor environment, taking into consideration occupants' health and well-being. Spaces with adequate ventilation strategies, including user control of the environment, have consistently been associated with higher occupant productivity and satisfaction indoors [23,24]. However, conventional measurement methods for environmental contexts in buildings have limitations in terms of size, cost, monitoring capabilities, and noise [25,26]. Advances in building automation, intelligent HVAC technologies, and low-cost IoT sensor-based control strategies offer solutions to overcome these limitations, enabling comprehensive and fine-grained IEQ monitoring [27–29]. This subsection aims to organize the existing research related to occupant-centric building HVAC, highlighting the need for a new paradigm of intelligent IEQ (including IAQ) sensing and control.

Figure 2.1 summarizes the state-of-art of occupant-centric building HVAC system, mainly ventilation control, sensing techniques and their implementations. From investigating previous studies [18,19,30–42], three main directions towards smart building ventilation system were identified: performance monitoring, rule-based control, and model predictive control (MPC). Rule-based control, often referred to as occupancy-based HVAC control, has received significant attention from previous studies [30–35]. Occupancy-based demand control ventilation (DCV), which utilizes various environmental and contextual parameters such as CO_2 [33,36], RH [37], T_a (indoor/outdoor) [38], total volatile organic compounds (TVOC) [39], and occupancy levels [35,40,41], is an emerging topic in advanced building HVAC technologies. The integration of occupancy-based control strategies with intelligent sensing technologies has paved the way for occupant-centric HVAC systems in buildings [18,19,42].

Recent advancements in sensing technologies have played a significant role in actualizing occupant-centric HVAC systems. Low-cost sensors and wireless sensing techniques, coupled with IoT sensors, enable real-time monitoring of different parameters in buildings on a large scale [43]. These advancements have facilitated the comprehensive measurement of diverse IEQ parameters, providing spatially and temporally resolved values. This level of monitoring can ultimately protect occupants from high concentrations of indoor air pollutants and transient thermal discomfort [27,44]. Despite the benefits of advanced sensing and monitoring strategies, the control loops governing HVAC system operations remain limited and primarily focused on energy performance in buildings. These control loops typically rely on limited sensing of room T_a, RH, and, in rare cases, CO_2 levels or other indoor air pollutants [45]. The traditional system-centric approach does not encompass certain contexts and conditions that are relevant to occupants, such as human exposure to spatial-temporal indoor air pollution variations mainly induced by occupant activities.

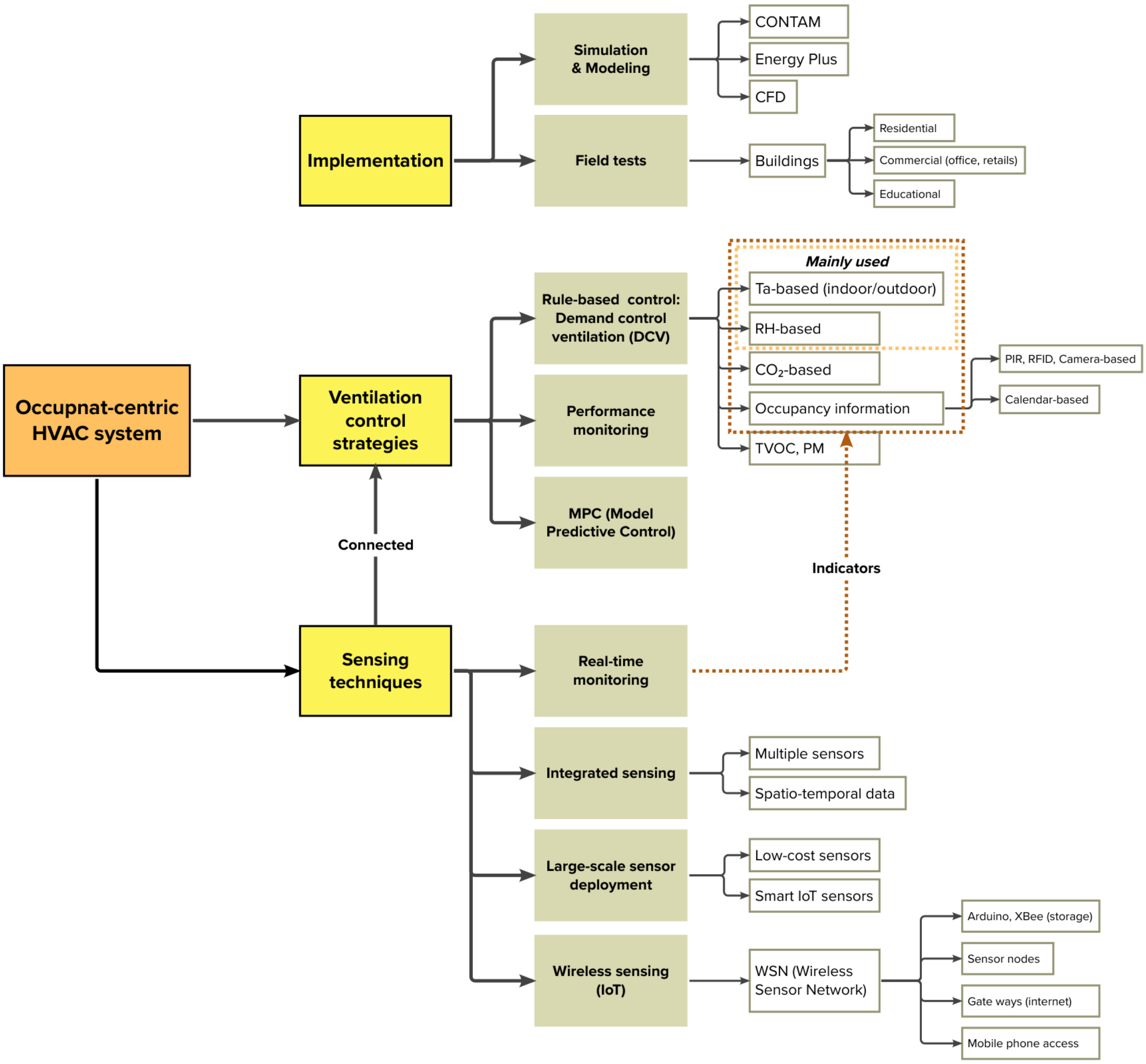

Figure 2.1 Overview of occupant-centric HVAC control system with various sensing techniques and indicators

To address the limitations of the current control loops and achieve occupant-centric HVAC control, there is a clear necessity for a new paradigm that integrates holistic and intelligent sensing on both energy-related and occupant health-related measures. This paradigm should go beyond energy performance and consider human exposure to indoor air pollution variations and contextual conditions. By incorporating advanced sensing technologies and expanding the range of monitored parameters, occupant-centric HVAC control can provide a more comprehensive understanding of IAQ and human air pollution exposures, enabling efficient and adaptive control strategies [18].

2.1.1 The value of occupant-centric building HVAC control

The value of occupant-centric building HVAC control lies in its ability to improve occupants' satisfaction, comfort, health and well-being while optimizing energy efficiency [46]. Historically, building automation and centralized control systems have excluded human-in-the-loop, leading to discomfort and dissatisfaction [17]. By incorporating occupant-centric controls, building systems can adapt to individual preferences and activities, providing personalized and responsive indoor environments [47]. One of the key benefits of occupant-centric control is the increased level of personal control over the indoor environment. Giving occupants the ability to adjust temperature, lighting, and other environmental factors or simply report their preferences about IEQ improves their satisfaction and comfort [48,49]. Another advantage is the ability to address irregular and partial occupancy and use this occupant-related factors in the control stage. Traditional building automation systems often provide the same conditions regardless of occupancy, leading to energy waste [50]. Occupant-centric controls can adapt to occupancy patterns, adjusting HVAC and lighting systems based on the presence or absence of occupants. Pang et al. [51] examined the energy-saving potential of occupant-centric HVAC controls in office buildings. Simulations were conducted across different building types, occupancy scenarios, building code versions, and climate zones. The results showed that both occupant presence and number counting sensors were effective in reducing energy consumption. Overall, the study shows that implementing occupant-centric HVAC controls can lead to significant energy savings in office buildings and contribute to sustainability goals. For instance, Huang et al. [52] employed a Hybrid Model Predictive Control (HMPC) scheme in an airport building ventilation, resulting in energy savings of approximately 41% and cost savings of about 13% compared to the baseline traditional control strategy. Similarly, Liu et al. [53] achieved monetary savings by implementing a multivariate MPC in a simulated office building, outperforming the baseline proportional-integral (PI) controller with 5.22% energy savings and 13.39% less CO_2 concentration over the set point. Lu et al. [54] summarized cost savings resulting from the implementation of CO_2-based DCV in various building types across different studies, revealing significant reductions of up to 80% compared to traditional ventilation systems. Furthermore, occupant-centric control allows for individualized control (direct/indirect) rather than relying on standardized settings or mean preferences of a large group of occupants [19,55]. By considering individual preferences and occupancy dynamics, building systems can provide tailored environmental conditions that enhance occupants' comfort and productivity.

Implementing occupant-centric control requires the integration of occupant knowledge into building automation systems [20]. This involves collecting data on the indoor environment, occupant interactions with the building (e.g., occupancy, light switches, thermostat usage), and occupant feedback on comfort and preferences [18]. This information is used to inform control actions and optimize the operation of HVAC and lighting systems. Despite the growing interest in occupant-centric control, there are challenges that need to be addressed, such as standardizing monitoring on key indicators and evaluation strategies for occupant comfort and energy savings, ensuring privacy and data protection, and developing consistent approaches for implementation across different building types and regions [18,20]. However, occupant-centric building HVAC control still provides a range of benefits, including improved occupant satisfaction, personalized control, energy efficiency, and sustainability. By considering occupants' preferences and activities, building systems can create comfortable and efficient indoor environments that enhance occupants' health and well-being. In conclusion, finding the right balance between energy efficiency and enhanced IAQ is important in ventilation control, while future IoT-based IAQ platforms should incorporate occupant-in-the-loop to create a more occupant-centric approach [56].

2.1.2 The impacts of occupant-centric HVAC control on human

Occupant-centric building HVAC control has a significant impact on human well-being, comfort, health, and productivity [17,49]. By prioritizing the needs and preferences of building occupants, HVAC systems can provide a more comfortable and conducive indoor environment. General impacts of occupant-centric HVAC control on humans are listed in the Table 2.1.

Table 2.1 Impacts of occupant-centric HVAC control on various human aspects

Impacts	**Description**
Comfort	Occupant-centric HVAC control aims to provide personalized comfort zones tailored to individual preferences. By adjusting temperature, humidity, and airflow to meet occupants' comfort requirements, it enhances thermal comfort and overall satisfaction [19,46,57].
Health	Occupant-centric control optimizes the schedule of HVAC system, air filtration and ventilation rates, improving indoor air quality and creating a healthy indoor environment [32,58,59]. Proper ventilation helps remove contaminants, allergens, and pollutants, reducing the risk of human respiratory issues and enhancing overall IAQ. Detailed health impacts of typical indoor air pollutants are discussed in the section 2.2.3
Productivity	A comfortable and healthy indoor environment provided by occupant-centric HVAC system directly impacts occupant productivity [60]. When individuals are in an environment that aligns with their comfort preferences and supports good health, they are more likely to concentrate, focus, and perform at their best [42,57].
Well-being	A comfortable and healthy indoor environment supported by occupant-centric HVAC system contributes to overall well-being [61]. When individuals feel comfortable and experience good IAQ, it positively impacts their mental and emotional state, promoting a sense of well-being and contentment [55].
User Control & Flexibility	Occupant-centric control gives individuals a sense of control directly or indirectly over their environment [62]. It allows occupants to adjust settings within predefined limits, providing a sense of empowerment and satisfaction [63].
Energy Efficiency	Occupant-centric control strategies, such as occupancy detection and predictive operations, lead to energy savings [50,64,65]. By adjusting HVAC operations and lighting based on occupancy patterns and predictive algorithms, unnecessary energy consumption is reduced. This, in turn, helps decrease environment carbon footprint and mitigates indirect impacts on human health.

Occupant-centric HVAC control can have a positive impact on reducing human air pollution exposures and improving IAQ, which of this thesis' key interests. By implementing strategies that prioritize occupant health, well-being and IAQ, occupant-centric control measures can help mitigate the negative effects of air pollution. From literature review, the features of occupant-centric HVAC control for mitigating indoor air pollution and exposures are listed in the Table 2.2.

Table 2.2 Features of occupant-centric HVAC control to mitigate indoor air pollution and exposures

Features	**Description**
Ventilation Management	Optimizes ventilation rates based on occupancy patterns [66–68] to ensure efficient intake of fresh outdoor air and reduce indoor air pollution. It reduces occupants' exposure to harmful substances by diluting and removing indoor air pollutants.
Air Filtration	Enhances air filtration systems using advanced technologies based on occupancy and pollutant levels [58,69]. It can effectively capture and remove particulate matter, allergens, and other airborne contaminants, improving IAQ by reducing their presence indoors [70,71].
Source Control	Addresses specific occupant-related pollution sources within the indoor environment through sensors and monitoring systems [27,72]. Detects and mitigates emissions from occupant-provoked sources like volatile organic compounds (VOCs), particulate matter, minimizing occupant inhalation exposure to pollutants.
Real-time Monitoring	Provides real-time monitoring of air quality and occupancy parameters, allowing building practitioners to be aware of the current air quality status and mitigate air pollution issues [42,73]. Enables necessary actions such as adjusting ventilation settings to mitigate exposures to pollutants and actively enhance indoor air quality.
Personalized Control	Allows individuals to personalize their indoor environment based on sensitivities, preferences or health conditions [74,75]. Enables adjustments to ventilation to reduce exposure to specific pollutants, promoting a healthier indoor environment for individuals.

By implementing occupant-centric indoor environment control strategies, the focus is placed on creating a healthier and cleaner indoor environment, reducing human exposure to indoor air pollution. This approach can significantly contribute to improving occupant health, reducing the risk of respiratory issues and other adverse health effects associated with poor IAQ. Overall, occupant-centric building HVAC control has the potential to enhance human experiences within buildings by prioritizing comfort, health, productivity, and overall well-being while not compromising energy-efficiency.

2.2 Indoor air quality studies in offices

Office indoor environments play a critical role in employee productivity, as it has been unequivocally demonstrated that poor indoor air quality can significantly impair work performance [76]. Specifically, better indoor temperature control and increased ventilation rates have been linked to improved productivity and health of employees [60,77]. Studies focusing on IAQ assessment in office environments have provided valuable insights into the relationship between IAQ, occupant health, symptoms, perceptions, and satisfactions. Sick Building Syndrome (SBS) has been recognized as a prevalent issue, particularly in offices and schools, since the 1970s [78]. SBS refers to a pattern of symptoms that have been seen repeatedly in indoor climate problem buildings defined by World Health Organization (WHO) [79,80]. Several studies [81–83] tried to assess IAQ in office buildings in order to identify potential factors contributing to SBS symptoms and implement appropriate measures to ensure a healthier and more productive work environment. A study by Apte [81] examined the relationship between indoor CO_2 levels and SBS symptoms in office buildings. The findings revealed a dose-response relationship, with higher CO_2 concentrations associated with increased prevalence of SBS symptoms, suggesting the importance of improving ventilation rates and controlling indoor air pollutants to mitigate these symptoms. A comprehensive study by

Burge [82] investigated SBS symptoms among office workers in various buildings and found that occupants in naturally or mechanically ventilated buildings without cooling or humidification reported fewer complaints about the indoor environment. Similarly, the study of Skov et al. [83] indicated a higher prevalence of SBS symptoms among occupants in mechanically ventilated office buildings compared to naturally ventilated ones. Within the European Health Optimisation Protocol for Energy-efficient Building (HOPE) research project, Bluyssen et al. [84] analyzed data from 5732 respondents in 59 office buildings to better understand the complex relationships between building, social, and personal factors and perceived comfort. The findings revealed that perceived comfort is strongly influenced by multiple personal, social, and building factors, suggesting that it encompasses more than just the average of perceived IAQ, noise, lighting, and thermal comfort responses. Under the HOPE project framework, Roulet et al. [85] also reported that there are strong correlations between perceived IAQ, thermal, acoustic, and lighting comfort, as well as significant correlations between perceived comfort and building-related symptoms, indicating that it is possible to design buildings that are both healthy, comfortable, and energy-efficient.

Previous studies [86–90] have extensively examined various pollutants and their sources to evaluate IAQ and mitigate indoor air pollution in office buildings. These investigations included field studies, controlled experiments and computational simulations.

Field studies are commonly conducted to directly monitor indoor air pollutants, providing real-time data on pollutant levels in order to identify the presence of specific pollutants and evaluate their concentrations. Factors such as ventilation rates, air exchange rates, distribution of airflow, and filtrations are also assessed to determine their impact on IAQ. For instance, Tham et al. [91] conducted field campaigns in call-center offices and found a 9% of improvement in operator performance when the outdoor air supply rate was increased. Another study of Wu et al. [92] investigated 37 small and medium commercial buildings and identified a combination of indoor and outdoor sources, along with occupant activities, as potential sources of VOCs, while carpets were identified as a possible source of bioaerosols. In this study, continuous monitoring of particle concentrations revealed an indoor-outdoor particulate matter (PM) ratio of less than one for most buildings, indicating the entry of outdoor particles due to the use of low-efficiency filters in the observed buildings. Saraga et al. [93] also highlighted the significant contribution of ventilation, faulty building envelopes, and windows to indoor PM concentrations. Under the European project OFFICAIR, Mandin et al. [94] investigated IAQ in modern office buildings, encompassing 37 buildings during the summer campaign and 35 buildings during the winter campaign. The study analyzed various pollutants, including VOCs, aldehydes, ozone (O_3), nitrogen dioxide (NO_2), and $PM_{2.5}$, revealing differences in pollutant concentrations between seasons and providing a preliminary evaluation of potential irritative and respiratory health effects, with some pollutants exceeding WHO air quality guidelines. Within the frame of OFFICAIR project, Szigeti et al. [95] highlighted the importance of long-term temporal PM monitoring and reported that monitoring $PM_{2.5}$ mass concentration alone might not adequately capture spatial variation in health-relevant PM characteristics like particulate oxidative potential (OP) and trace element concentrations within an office building. Challoner and Gill [96] examined $PM_{2.5}$ and NO_2 concentrations indoors and outdoors in ten commercial buildings in city center. They found that indoor $PM_{2.5}$ levels closely matched outdoor levels, and indoor NO_2 levels were influenced by street-level concentrations, suggesting the importance of increased air exchange at night time to reduce pollutant concentrations. Irga and Torpy [97] assessed various indoor air pollutants and airborne fungi in 11 office buildings in Sydney throughout a year, where they found that the ventilation type of the buildings influenced IAQ.

Controlled experiments while simulating office environments are usually conducted in order to systematically manipulate and measure various factors such as pollutant sources, ventilation strategies, and occupant activities to understand their effects on IAQ parameters and investigate effective strategies for improving IAQ. Melikov and

Kaczmarczyk [98] investigated air movement in relation to perceived air quality (PAQ) and SBS symptoms in a controlled climate chamber while exposing 124 human participants to various combinations of temperature, humidity, and air pollution levels. The results showed that air movement improved PAQ and freshness but did not reduce SBS symptoms caused by polluted air. Zhao et al. [99] conducted controlled experiments with 10 males and 10 females to analyze human response to thermal environment and PAQ in an office. The study compared individually controlled convective and radiant cooling systems, finding that the personalized ventilation system combined with radiant panel provided better thermal sensation and PAQ than the low velocity unit combined with radiant panel system. Both systems created micro-environments with slightly lower CO_2 concentrations, emphasizing the need for personalized control to ensure occupant satisfaction.

Simulation tools were used in several studies [100–102] to assess IAQ in offices. Martins and da Graça [100] investigated impact of airborne particle pollution on the potential for natural ventilation (NV) cooling in California office buildings while using building energy model “EnergyPlus” [103], where they showed that restricting NV usage to moments with outdoor particle levels below 12 $\mu g/m^3$ reduces the energy-saving potential to 20-60%, whereas use of NV resulted in a significant increase in indoor exposure to outdoor-origin $PM_{2.5}$, ranging from 400% to 500%. Rackes et al. [101] used CONTAM [104], a multi-zone airflow and contaminant transport analysis software, to evaluate the accuracy and spatial variability of different sensor placements for measuring CO_2 and VOCs in office environments. Computational fluid dynamic (CFD) simulations were often used to enable a detailed analysis of airflow patterns, heat transfer, and pollutant dispersion of indoor. This involves using computer simulations to numerically solve the equations governing airflow and pollutant distribution in buildings, providing a practical option due to limitations in experimental approaches. However, it is important to validate CFD results with carefully conducted experiments to ensure accuracy and reliability in predicting IAQ [105]. For instance, Staveckis and Borodinecs [106] explored using impinging jet ventilation (IJV) for indoor climate control in offices while using CFD simulations. They assessed the system's performance under different conditions, showing significant improvements in thermal comfort and IAQ with the circular air opening being more effective for contaminant removal and air exchange. The limitations of using simulation tools to assess IAQ in office environments include reliance on assumptions and simplifications, uncertainties in input data, and the accuracy of underlying mathematical models and algorithms. On the other hand, conducting field studies, including assessments of IAQ, and personal air pollution exposure, can be very challenging and time-consuming, requiring significant resources and personnel presence. However, advancements in sensor technologies have facilitated real-time indoor environment monitoring and getting occupant feedback, offering advantages for IAQ assessment over the conventional methods [9].

2.2.1 Typical indoor air pollutants

Office environments can be prone to a range of air pollutants that can affect the overall IAQ and potentially impact the health and well-being of the occupants. CO_2, PM, formaldehyde, VOCs, and O_3 are the most frequently investigated as common indoor air pollutants in office buildings [107], while specific pollutants can vary depending on various factors such as building materials, ventilation systems, and occupant activities.

CO_2 is a common indoor air pollutant in offices and often measured to estimate indoor air pollution because it serves as a reliable indicator of IAQ and building ventilation performance [108,109]. The common cause of elevated indoor CO_2 in office buildings is inadequate ventilation or poor air circulation, leading to a buildup of CO_2 emitted by occupants and other sources within the building [81]. Factors that can contribute to inadequate ventilation include poorly designed ventilation systems, improperly maintained HVAC systems, blocked air vents, or limited outdoor air intake. One of the primary concerns associated with high levels of CO_2 in office buildings is its impact on occupant comfort and productivity [110]. Increased CO_2 levels can lead to symptoms such as drowsiness, fatigue, difficulty concentrating, and reduced cognitive performance [111]. Hence, real-time monitoring of CO_2 levels is important in order to properly evaluate indoor air pollution and maintain proper ventilation rates for a healthy and comfortable working environment [112].

Particulate matter is a significant indoor air pollutant that can be found in office environments [113]. PM refers to tiny particles suspended in the air, and it can include a variety of substances such as dust, allergens, pollen, and other contaminants, originating from both outdoor and indoor sources [114]. Outdoor sources of PM in office environments may include vehicle emissions, construction activities, and industrial pollutants that infiltrate the indoor air. Indoor sources of PM can be occupant activities such as printing, photocopying, and the use of certain materials or equipment can release particles into the air. For instance, Horemans and Grieken [115] collected indoor and outdoor samples of PM_{10}, $PM_{2.5}$, and PM_1 in ten naturally ventilated office environments, finding higher indoor PM_1 concentrations during office hours, likely influenced by office printers, and particles with diameters between 1 and 2.5 µm and 2.5 and 10 µm were associated with distinct settling/resuspension periods. Inadequate air filtration systems or ventilation can also lead to higher levels of PM indoors [116]. Xing et al. [117] reported that fine particles with a diameter of less than 2.5 micrometers, known as $PM_{2.5}$, have the ability to penetrate deep into the lungs, causing irritation, corrosion of the alveolar wall, and ultimately leading to impaired lung function. Once inhaled, they can reach the lungs and potentially cause respiratory problems, trigger allergies, or worsen existing respiratory conditions such as asthma or bronchitis. Coarse particles, known as PM_{10}, have a diameter between 2.5 and 10 micrometers, are highly relevant to human activities indoors [118–120] and can still have adverse effects such as airway irritation and discomfort [121]. Particularly, occupant-related activities such as walking, cleaning, and vacuuming can contribute to the resuspension of particles from surfaces, leading to localized increases in PM concentration indoors [122]. Lappalainen et al. [123] investigated airborne particle concentrations (≥ 0.5 µm and ≥ 5.0 µm) in 122 Finnish office buildings with suspected indoor air problems, revealing higher particle counts in offices where occupants reported work-related symptoms compared to those with no symptoms. Quang et al. [124] mentioned that proper ventilation and air filtration systems are essential to mitigate the presence of PM in office environments. Regular maintenance of these systems, including filter replacement, can help remove or reduce the concentration of PM in the indoor air. Additionally, minimizing indoor sources of PM, such as controlling dust and using efficient printing and copying equipment, can contribute to better IAQ. Hence, real-time monitoring and assessment on PM levels in office is essential in order to maintain a healthy and comfortable workspace for employees [125].

VOCs are among the most prevalent indoor air pollutants in office environments. VOCs are emitted from a variety of sources, including building materials, furniture, carpets, adhesives, cleaning products, and office equipment. Common VOCs found in offices include formaldehyde, benzene, toluene, xylene, and various other organic compounds. Destaillats et al. [126] reviewed previous studies that report emission rates of VOCs from various office equipment such as computers, printers, copier machines, and other electronic devices. They find that the link between emissions from office equipment and indoor air concentrations is relatively well established for some pollutants, such as organophosphate flame retardants, whereas the source apportionment of indoor VOCs is more complex, as they can originate from multiple sources. Zuraimi et al. [127] analyzed VOC sources in five tropical air-conditioned office buildings in Singapore, attributing the highest contribution of TVOCs to ventilation systems (39.0%), followed by occupants and their activities (37.3%), and building materials (23.7%). They found that the ducted supply and return ventilation design had the lowest VOC emission rates, and some VOCs demonstrated sink effects, resulting in secondary emissions over time. Salonen et al. [128] investigated VOCs, formaldehyde, and ammonia concentrations in 176 Finnish office buildings and suggested guideline values for chemical measurements in offices with suspected indoor air problems. The most common VOCs found included toluene, xylene, 1-butanol, nonanal, and benzene, with guideline values of 70 $\mu g\ m^{-3}$ for TVOC, 7 $\mu g\ m^{-3}$ for most individual VOCs, 10 $\mu g\ m^{-3}$ for formaldehyde, and 12 $\mu g\ m^{-3}$ for ammonia, which can indicate the need for additional environmental investigations if exceeded, but should not be directly used for evaluating health risks. Kozielska et al. [129] compared VOC levels in offices, flats, and a residential building, finding higher concentrations of certain VOCs, including carcinogenic benzene, in the residential building. They reported that indoor sources such as paints, glues and varnishes were the main contributors to VOC contaminants, leading to high indoor-to-outdoor ratios.

Additionally, Spinazze et al. [130] reported that cleaning products, air fresheners, and even personal care products used by occupants contribute to the VOC levels in the office. TVOCs are a collective term used to describe the concentration of various VOCs in the air [131]. According to Sa et al. [132], researchers often used low-cost TVOC sensors to assess IAQ in offices since TVOC measurements provide an overall indication of the presence and level of VOCs in office environments, however, they have limitations for identifying specific individual chemicals, which can potentially lead to inaccurate representation of the true VOC concentration in the environment. Short-term exposure to VOCs can cause symptoms like irritation, headaches, and dizziness, while prolonged exposure can lead to chronic respiratory effects [133]. To manage TVOC concentrations in offices, measures like adequate ventilation, maintenance of ventilation systems, use of high-efficiency air filters, choosing low-VOC materials, and proper chemical storage can be implemented [130]. For instance, Painter et al. [134] proposed an approach of DCV that combines CO_2 and VOC monitoring to provide a beneficial ventilation solution for managing both occupant-related and building-related pollutants in office buildings.

Formaldehyde, a VOC mentioned earlier, deserves specific attention due to its prevalence in office environments. Salonen et al. [135] stated that formaldehyde is emitted from composite wood products, furniture, carpets, and other building materials, and prolonged exposure to this chemical can result in eye and respiratory irritation, allergic reactions, and potentially carcinogenic effects. Other potential indoor air contaminants in office settings were investigated such as O_3 generated by office equipment such as photocopiers and printers [136], as well as various allergens [137], such as mold spores and pollen, that can enter the indoor space through ventilation systems or open windows.

From the literature, it is acknowledged that implementation of effective ventilation systems, regular maintenance and cleaning practices, and the use of low-emission building materials and furnishings are important to mitigate various indoor air pollutants present in offices. Regular monitoring of IAQ and addressing potential pollutant sources can help mitigate the impact of indoor air pollutants on the health, well-being, and productivity of office occupants.

2.2.2 Typical air pollutant concentrations

The concentration of indoor air pollutants in office environments can vary depending on various factors such as building characteristics, ventilation systems, occupant activities, and external sources. Table 2.3 shows typical concentration ranges for common indoor air pollutants found in office buildings and the recommended threshold of existing standards and guidelines.

Table 2.3 Typical indoor air pollutant concentrations and recommended thresholds.

Pollutant	**Typical concentrations [references]**	**Recommended threshold**	**Standards/Guidelines**
Carbon Dioxide (CO_2)	380-500 ppm (Outdoor) [138] 450-3500 ppm (Indoor) [139–142]	< 1,000 ppm	ASHRAE 62.1 [143]
		< 800 ppm [during normal occupied hours]	RESET v2 [144], WELL v2 [145]
Particulate Matter (PM)	$PM_{2.5}$: 8.07 µg/m^3 [146][c]	< 5 µg/m^3 [Annual]	WHO [147]
		< 15 µg/m^3 [24-hour[a]]	
	PM_{10}: 16.74 µg/m^3 [146][c]	< 15 µg/m^3 [Annual]	
		< 45 µg/m^3 [24-hour[a]]	
Total Volatile Organic Compounds (TVOCs)	< 70 µg/m^3 [128]	< 500 µg/m^3 [30-minute average]	LEED v4 [148]
		< 300 µg/m^3 [8-hour average]	BREEAM [149]
Formaldehyde	< 10 µg/m^3 [128]	< 0.1 mg/m^3 (0.08 ppm) [30-min average]	WHO [147]
Ozone (O_3)	9.04 µg/m^3 [136][d]	60 µg/m^3 [Peak season[b]]	WHO [147]
		100 µg/m3 [8-hour[a]]	

[a] 99th percentile (i.e. 3-4 exceedance days per year).
[b] Average of daily maximum 8-hour mean O_3 concentration in the six consecutive months with the highest six-month running-average O_3 concentration.
[c] Average during only occupancy periods across 33 and 43 office field studies for $PM_{2.5}$ and PM_{10}, respectively.
[d] Calculated mean of reported average values across 13 office field studies.

Abdul-Wahab et al. [150] conducted a thorough review of IAQ guidelines and standard values set by international agencies, with a specific focus on major indoor air pollutants such as CO_2, NO_2, formaldehyde, CO, sulfur dioxide (SO_2), and PM. The study highlighted the significance of considering local regulations, building codes, and industry standards to establish precise recommendations for acceptable levels of indoor air pollutants, as these concentrations can vary based on specific circumstances. Hence, it is recommended to recognize that this list of pollutants and measurements serves as a guide and should be adapted based on specific objectives and research projects. Further, the selection of pollutants for measurement should be done with consideration of the specific indoor environment and occupancy dynamics [151].

2.2.3 CO_2, $PM_{2.5}$ and PM_{10} as proxy for ventilation performance and human health

In the context of IAQ studies in office environments, certain air pollutants can serve as proxies or indicators for assessing ventilation performance and evaluating their impact on human health. This section focuses on three key pollutants: CO_2 as a proxy for ventilation performance, and $PM_{2.5}$ and PM_{10} as key indicators related to burden of human chronic health impacts.

Elevated levels of CO_2 in indoor spaces can indicate inadequate ventilation [109]. While CO_2 itself is not a direct health threat at typical indoor concentrations, its measurement serves as a valuable indicator of ventilation effectiveness. For instance, Federspiel et al [152] examined the impact of ventilation rates on individual work performance in a call center by using CO_2 differential (indoor minus outdoor) and found that higher ventilation rates were associated with faster completion of talking tasks by office workers. Tsai et al. [153] reported that monitoring CO_2 as a proxy for ventilation performance can be a cost-effective method to improve IAQ, where they found high indoor CO_2 levels (>800 ppm) were associated with increased SBS symptoms, particularly eye irritation and upper respiratory symptoms, among office workers. These effects include impaired cognitive function, increased prevalence of headaches and fatigue, and negative perceptions of air quality, which indirectly impacts human health by affecting well-being, and productivity.

$PM_{2.5}$ and PM_{10} are airborne particles suspended in the indoor environment, and their presence can have significant health implications. These particles can originate from both outdoor and indoor sources, including combustion processes, dust, pollutants released from building materials, and occupant activities. Monitoring $PM_{2.5}$ and PM_{10} levels is essential for assessing their impact on human health. Inhalation of $PM_{2.5}$ and PM_{10} particles can lead to respiratory problems such as asthma exacerbation, bronchitis, and increased susceptibility to respiratory infections [117]. Moreover, fine particles can enter the bloodstream, contributing to cardiovascular issues like heart attacks, strokes, and other cardiovascular diseases [154]. Long-term exposure to elevated levels of $PM_{2.5}$ and PM_{10} has been associated with an increased risk of premature death due to respiratory and cardiovascular causes [155,156].

Assessing the health impacts of these pollutants in office environments is often done using Disability-Adjusted Life Years (DALYs), which quantifies the burden of disease by combining morbidity and mortality effects and provides a comprehensive measure of the health burden associated with various pollutants [157]. The specific magnitude of DALY losses depends on factors such as pollutant concentrations, exposure duration, and individual susceptibility. Morantes et al. [158] quantified and ranked the burden of household air pollution using DALYs. As shown in Figure 2.2, the effect factors (EFs) indicates that for every kilogram of examined pollutants inhaled by the exposed population, showing burden of chronic health impacts, measured in DALYs. Here, $PM_{2.5}$ is the standout contaminant with the highest EFs, signifying the most significant chronic health impact per unit intake of this pollutant. The study considered ten contaminants and estimates population-averaged annual DALY loss per 100,000 persons, with PM_{10} and $PM_{2.5}$ having the highest median DALY loss estimates, followed by PM_{coarse} ($PM_{2.5\text{-}10}$), formaldehyde, NO_2, radon, O_3, SO_2, acrolein, and mould-related bioaerosols. The estimation of population-averaged annual DALY loss due to chronic air contaminant inhalation in dwellings revealed that PM_{10} and $PM_{2.5}$ have the highest median DALY loss estimates, reaching magnitudes of 10^3. It is worth noting that PM_{10} includes the burden associated with the $PM_{2.5}$ fraction. Logue et al [159] also pointed out $PM_{2.5}$ as the highest detrimental non-biological air pollutants in residential settings, considering their majority of DALY losses on the population as a whole. By considering the DALYs lost, it becomes evident that $PM_{2.5}$ and PM_{10} are significant contributors to the overall health effects of indoor air pollutants. Sun et al [160] analyzed indoor air pollutants in office and school buildings in the Yangtze River Delta, China, and ranked the health risks based on DALYs lost. According to DALYs values, the impact of pollutants on health in offices was ranked as $PM_{2.5}$ > formaldehyde > ammonia > benzene > toluene > xylene, and inhalation of $PM_{2.5}$ resulted in a much higher DALYs lost compared to other pollutants such as formaldehyde, ammonia, benzene, toluene, and xylene. Over half of the office building samples exceeded current IAQ standards for pollutants like $PM_{2.5}$, formaldehyde, benzene, TVOC, and ammonia, emphasizing their importance in impacting human health. Monitoring indoor particles is thus important to properly implement measures to mitigate associated health risks of occupants.

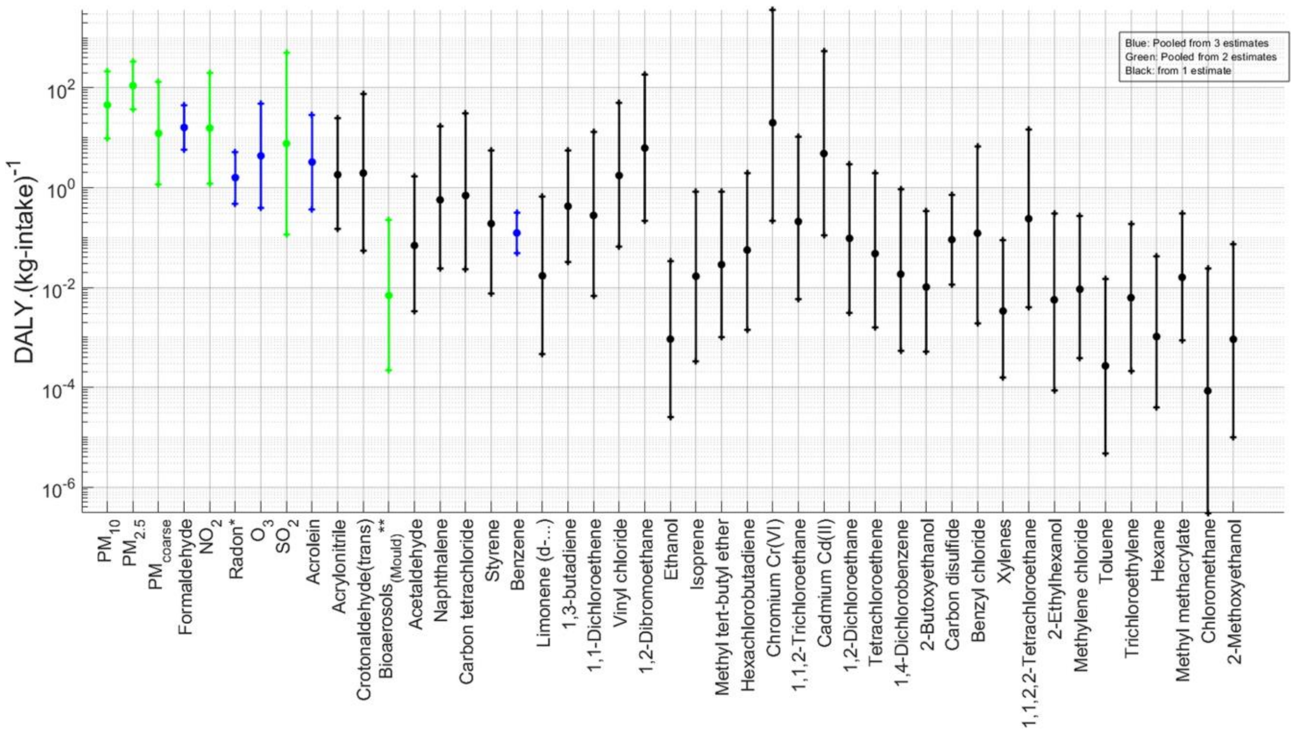

Figure 2.2 Pooled effect factors (EFs) in units of Disability-Adjusted Life Years per kilogram of intake (DALY/kg-intake^{-1}) for selected indoor air contaminants, adapted from Morantes et al [158]. The figure presents the estimated EFs for 45 contaminants, representing the chronic health impacts per kg inhaled by the exposed population in dwellings. EFs were calculated using the methodology described in the study, combining toxicological and epidemiological data. The EFs are shown as medians with 95% confidence intervals (CI). $PM_{2.5}$ stands out with the highest EF [1.1×10^2 (95% CI 3.6×10^1–3.3×10^2)], indicating the highest chronic health impact per unit intake of this pollutant. Other particulate matter such as PM_{10} and PM_{coarse} ($PM_{2.5-10}$), and certain chemicals like chromium, NO_2, and formaldehyde also have notable EFs, with values exceeding 101. The results represent an update to previous works on human toxicological and epidemiological effect and damage factors for carcinogenic and non-carcinogenic chemicals.

By monitoring and managing CO_2, $PM_{2.5}$, and PM_{10} levels, building operators and facility managers can gain insights into ventilation performance and the associated health risks of building occupants in office environments. The selection of these proxy pollutants is based on the thesis's scope, considering their relevance to health risk and ventilation strategies. Firstly, CO_2 and PM levels can be easily and accurately measured using low-cost sensors that are readily available in the market. These sensors provide real-time and reasonably accurate data, making it convenient for building operators and facility managers to assess IAQ regularly compared to other air pollutants. This approach also allows for widespread deployment of sensors, covering a larger number of locations within the building. Furthermore, CO_2 and PM are commonly regulated pollutants in indoor environments. Various organizations and standards have set guidelines for acceptable CO_2 and PM levels in office buildings, making them relevant parameters to monitor for compliance.

While VOCs, formaldehyde, NO_2, SO_2, O_3 and many other relevant indoor air pollutants are also important indicators of IAQ and occupant health, they often require more sophisticated and expensive monitoring methods to accurately assess the absolute concentration, which may not be feasible for large-scale deployment in office buildings. Hence, the focus on CO_2 and PM of this thesis as proxy pollutants allows for practical and efficient monitoring strategies, enabling building operators to make informed decisions to enhance occupant health and well-being.

2.3 Indoor air pollution and occupancy dynamics

The indoor environment and occupant dynamics have a significant impact on IAQ and personal inhalation exposures [8]. However, it is important to note that this dissertation also considers various other factors that influence IAQ, such as space layout, ventilation systems, air change rate, and outdoor and indoor climatic conditions. While this section primarily focuses on the impact of human activities on the spatial-temporal variation of indoor air pollutants, it should be understood within the context of a comprehensive assessment that encompasses multiple aspects of indoor environmental quality.

2.3.1 Spatial-temporal variation of indoor air pollutants

The spatial-temporal monitoring of indoor air pollution plays an important role in providing essential information about emission sources, air pollutant dynamics, ventilation effectiveness, and the resulting personal exposure levels [161]. For instance, indoor air pollutants can spatially and temporally vary by factors such as occupancy patterns, activity profiles (e.g. body posture, activity type and intensity), and ventilation schedules. During peak occupancy hours, when more individuals are present and engaging in activities, pollutant levels can increase. Changes in ventilation rates throughout the day, such as reduced ventilation during unoccupied periods or increased ventilation during periods of high occupancy, can also impact pollutant concentrations. Several studies [162–166] reported that the spatial-temporal variation of indoor air pollutants, such as CO_2, PM and TVOCs can be influenced by a combination of factors including human presence, activities, ventilation strategies, and the physical characteristics of the indoor environment. Sahu et al. [162] focused on assessing spatial-temporal air quality in the library in India, where higher concentrations of PM were found primarily attributed to movement activities within the library, specifically during cleaning, lunch hours and entry/exit times. Jung et al. [163] investigated the temporal and spatial variations of indoor air pollutants such as formaldehyde, CO_2, bacteria, and fungi in tropical and subtropical regions and concluded building condition and human activities were the major factor of air quality variations indoors. Another study of Ramos et al. [164] investigated the spatial and temporal variations of indoor air pollutants in a hospital building, with a specific focus on occupancy-related factors. The study found weak correlations between rooms for indoor air temperature, illuminance, and human occupancy/activity, whereas the strong temporal patterns and spatial correlations between rooms for RH, humidity ratio, and outdoor air fractions were found. Coleman and Meggers [165] demonstrated the effectiveness of in identifying spatial and temporal variations using low-cost distributed IAQ sensor networks, where they revealed higher levels of VOCs in the occupied spaces of office building. Shen et al. [166] investigated spatial-temporal variations of indoor air pollutants in an urban apartment, where the human metabolism and cooking were identified as the main indoor CO_2

sources, while the cooking activities specifically accounted for approximately 24% of indoor formaldehyde, 19% of indoor methane, and 25% of indoor VOCs.

The spatial distribution of indoor air pollutants can be influenced by ventilation strategies and airflow patterns within a building. Mahyuddin and Awbi [167] conducted a study using a controlled climate chamber to examine the distribution of CO_2 concentrations under various ventilation methods. They emphasized the significance of considering factors like room size, source location, ventilation rate, and the placement of air supply and extract devices when determining the optimal positioning of CO_2 sensors in a room. The effectiveness of ventilation systems in diluting and removing pollutants can vary across different areas, leading to spatial gradients. Ren et al. [168] analyzed the infection risk and ventilation strategies in offices using simulation model, where different ventilation modes, including mixing ventilation, zone ventilation, stratum ventilation, and displacement ventilation were compared to identify the optimal strategy for mitigating indoor airborne pollutants. The results showed that stratum ventilation showed excellent performance of air distribution and mitigation of airborne infection disease transmission, on the premise of providing sufficient supply air volume.

From the literature review, it is acknowledged that capturing the spatial-temporal variation of indoor air pollutants is of utmost importance for assessing inhalation exposures and implementing effective mitigation strategies. While various indoor environments have been studied, it is noteworthy that limited attention has been given to investigating the spatio-temporal variation of indoor air pollutants in various office settings specifically. Therefore, there is a critical need for further research in office environments to understand how occupancy patterns, activity profiles, and ventilation strategies impact indoor air pollution dynamics. Long-term real-time monitoring of pollutant levels across different locations within a building can provide valuable insights into the dynamics of indoor air pollution, enabling targeted interventions to improve IAQ and enhance the health and well-being of occupants.

2.3.2 Human air pollutant emissions

Important source of spatio-temporal variations of indoor air pollutants are humans. Human emissions are a significant contributor to indoor air pollution in various indoor environments including offices, particularly in terms of CO_2, PM and VOCs levels. Various human activities and physiological processes generate these pollutants, affecting IAQ and potentially impacting occupant health.

Indoor CO_2 levels are primarily influenced by human respiration [13]. The concentration of CO_2 from exhaled breath can increase rapidly in enclosed spaces with limited ventilation, such as offices, classrooms, or residential areas. Gall et al. [169] conducted real-time monitoring on CO_2 exposures of 16 individuals in Singapore, where they found that elevated CO_2 levels are commonly attributed to human metabolic emissions and recommended monitoring them to establish potential correlations with cognitive impacts in humans. Satish et al. [140] examined that the effects of increased CO_2 levels on decision-making performance in a controlled office-like chamber, where there were significant decrements in decision-making performance at higher CO_2 concentrations (1,000 ppm and 2,500 ppm), indicating potential adverse effects.

Humans and their activities also contribute significantly to the emission of indoor PM. In addition to respiratory emissions, humans are continuously emitting particles from their skin and clothing and their activities such as walking, sitting on furniture and using certain appliances can result in the generation and resuspension of particles from the surface [10,170]. Licina et al. [10] quantified the contribution of human particle emissions to personal exposure and the personal cloud effect in a simulated office environment. The study found that walking emitted an average of 20 million particles per hour, while seated occupants with moderate movement emitted an average of 8 million particles per hour. Sitting in a low-background climate chamber resulted in a personal PM exposure increment of 2-13 $\mu g/m^3$ due to the heterogeneously distributed PM. They also found that emissions from occupants' skin and clothing were significant sources of aerosol particles indoors, where the average emission rate associated with fabric manipulation was approximately 0.8 million particles per minute. These quantitative findings highlight the significant contribution of human activities, such as walking, seated movements, paper handling, and fabric manipulation, to PM concentrations in the indoor environment and personal exposure levels. The study by Wang et al. [171] focused on human PM emissions and activities in relation to indoor $PM_{2.5}$ pollution from ground fugitive dust. The concentration of human walking-induced indoor $PM_{2.5}$ resuspension reached a peak at approximately 1 minute for different dust loads. The study demonstrated that the resuspension fraction of $PM_{2.5}$ was 2.2×10^{-8}, and the diffusion rates of human walking-induced indoor $PM_{2.5}$ resuspension increased with higher indoor $PM_{2.5}$ dust loads. Furthermore, the movement and deposition of $PM_{2.5}$ were influenced by airflow and particle collisions, and increasing the number of people walking indoors led to an increase in indoor PM, emphasizing the importance of regular indoor dust cleaning to reduce secondary pollution from indoor activities. Ferro et al. [122] investigated personal, indoor, and outdoor PM concentrations using optical particle counters and filter samplers during different prescribed human activities in a residential setting. The study found that occupant activities involving the disturbance of dust reservoirs on furniture and textiles, such as dry dusting and folding clothes, resulted in the highest exposures to $PM_{2.5}$, PM_5, and PM_{10}. The vigor of activity and type of flooring also played a role in dust resuspension. As already mentioned, the fine particles have been associated with respiratory problems, allergies, and cardiovascular issues. Hence, monitoring and managing the sources of indoor PM, including human emissions, are required for reducing exposure and promoting human health and better IAQ.

In addition to CO_2 and PM, humans also emit other compounds and water vapors that can affect IAQ. The study by Tang et al. [172] focused on quantifying human VOC emissions in a university classroom by using a mass spectrometer. From the VOC concentrations measured during occupied and unoccupied periods, the study found that human-related VOC emissions, including those from personal care products and metabolic processes as the dominant source (57%) during occupied periods, followed by ventilation supply air (35%) and indoor non-occupant emissions (8%). The total occupant-associated VOC emission factor was determined to be 6.3 mg/h per person. Wang et al. [173] focused on measuring human-emitted VOCs in a controlled climate chamber. They investigated the emissions from breath, skin, and the whole body of seated human occupants under different conditions. The study found that without O_3, the total emission rate from the whole body was dominated by exhaled chemicals and was 2180 ± 620 µg/h per person. The presence of O_3 doubled the emission rate, mainly due to VOCs resulting from reactions between skin surface lipids and O_3, which increased with RH. Bekö et al. [174] examined the emissions from whole-body, exhaled breath, and dermal bioeffluents of human occupants under various conditions. The findings showed that acetone is one of the major VOCs present in the exhaled breath of healthy individuals. The emissions of acetone in breath were influenced by factors such as sex and age, although the differences among the groups were small. VOCs can have both short-term and long-term health effects, ranging from eye and respiratory irritation to potential carcinogenicity.

While the importance of VOCs was acknowledged through the review of related studies, the limitations in measuring them in real-time with high spatial resolution led to their exclusion as a parameter in the thesis studies. Measuring VOCs with high spatial resolution requires specialized and expensive analytical instruments, such as mass spectrometers or gas chromatographs. Furthermore, indoor environments are intricate, with various VOC sources, making it challenging to accurately distinguish and quantify individual compounds. Although low-cost metal oxide (MOx) sensors can offer a cost-effective solution for large-scale deployment in buildings to monitor

VOC levels, they have limitations in precisely reporting absolute concentrations. These sensors may not provide the level of accuracy required for discerning low-level VOCs in real-time. In conclusion, while VOCs are important contributors to indoor air pollution, their inclusion as a parameter in the thesis studies was not feasible due to the complexity and expense of high spatial resolution measurements, as well as the limitations of low-cost MOx sensors in reporting absolute concentrations effectively.

Office workers typically spend prolonged periods each day inside office buildings, often exceeding nine hours during their workdays [175]. Thus, managing human emissions and their impact on indoor air pollution requires a multifaceted approach, particularly in office settings. Adequate ventilation systems that supply fresh outdoor air and remove pollutants are essential for diluting and controlling air contaminants in office spaces. Proper source control measures, such as using low-emission personal care products and minimizing activities that generate air pollutants, can help reduce indoor air pollution levels. Overall, it is acknowledged that understanding the significance of human emissions is helpful for designing effective monitoring strategies to improve IAQ and protect occupant health in offices. By addressing these emissions and implementing appropriate mitigation measures, it is possible to create healthier and more comfortable indoor environments for office workers.

2.3.3 Impact of occupancy profiles on indoor air quality

In addition to human bodily emissions, occupants perform various activities which can result in elevated exposures indoors. In office environments, building occupancy play an important role in shaping air pollutant levels. Thus, understanding and characterizing occupancy profile including number and activities of building occupants is essential for accurately assessing and managing indoor air pollution in these settings. Occupant activities in office environments can vary widely throughout the day. Some common activities include sitting at desks, having a call, walking, having group meetings, using electronic devices, cleaning, operating coffee machines or kettles, eating and using different electrical appliances. Biernat et al. [175] assessed physical activity levels among office workers, while defining three physical activity categories: high, moderate, and low, based on human metabolic criteria. The study revealed that a significant proportion of office workers, including civil and local administration employees, and bank officials, fell into the low physical activity category. They also found that the average daily sitting time among participants was 9.7±1.7 hours, highlighting the sedentary nature of office work. Similarly, Clemes et al. [176] found that full-time office workers spend approximately 65% of their work time sitting. Tabak et al. [177] developed a model to predict intermediate activities in office spaces, which are often ignored in building simulations. These activities, such as getting a drink or taking short breaks, interrupt planned activities but contribute to the well-being of office employees. The study proposed probabilistic and S-curve prediction methods for capturing the occurrence and frequency of these intermediate activities.

Occupant office activities have the potential to influence IAQ through the generation and dispersion of pollutants [114,178,179]. One significant aspect of occupant activities is the resuspension of particles from indoor surfaces. Cheng et al. [114] examined indoor PM levels and size distributions in an office building at different times and found that indoor PM concentrations were influenced by outdoor air quality, ventilation system operation, and indoor human activities. Fine PM was the primary component of indoor PM in the air supply device. On working days, the size distributions displayed three modes, with prominent modes at approximately 0.33 µm, 2-4 µm, and 12-14 µm, indicating the presence of coarse particles related to indoor human activities. On holidays, the size distributions showed a stable double-mode pattern, indicating reduced coarse particles due to fewer indoor activities and sedimentation. Luoma and Batterman et al. [178] studied the relationship between occupant activities and indoor PM levels in a non-smoking office building. They recorded occupant activities and measured PM concentrations using OPCs and gravimetric methods. The study found that occupant activities explained a significant portion (24-55%) of particle number variations in the range of 1-25 µm. They developed statistical models to link PM concentrations with human activities, estimating that occupant activities contribute up to 10 µg/m^3 of PM concentrations per person. However, smaller particles showed little correlation with indoor activities, except for cigarette smoking, and were more influenced by outdoor levels. Operating coffee machines, kettles, or microwaves in cafeterias may contribute to elevated PM, VOCs, and humidity levels in the immediate vicinity. Hussein et al. [179] found that brewing coffee had the smallest impact on indoor aerosol concentrations, while using a toaster doubled the $PM_{2.5}$ concentration in dwellings. In this study, indoor cooking and combustion processes also increased levels of CO, NO_2, and VOCs.

Furthermore, understanding occupant activities is necessary to optimize energy consumption and ensure user comfort in building management system (BMS). Nguyen et al. [180] emphasized the need to examine occupant activity profiles in buildings for efficient energy and comfort management while proposing an ontological approach using low-cost, binary, and wireless sensors to rapidly recognize office activities in multiple-user, multiple-area settings. Their prototype achieved an average accuracy of over 92% in identifying seven typical office activities across three monitored areas. Ahmadi-Karvigh et al. [181] developed a framework to detect occupant activities and potential energy waste in buildings while highlighting the importance of examining occupant activity profiles for designing energy-efficient buildings and automation systems. For activity detection, they used a combination of plug meters to measure the power and energy consumption of appliances, light sensors to capture ambient light intensity, and binary motion sensors that were triggered by human motion, where the sensors were controlled through microcontrollers equipped with XBee modules in each prototype. The framework consisted of three sub-algorithms for action detection, activity recognition, and waste estimation, where they achieved high accuracy in action detection (97.6%) and activity recognition (96.7%). The study identified that an average of 35.5% of appliance or lighting system consumption could potentially be saved through optimized energy usage.

Understanding the type and intensity of different activities within an office setting is important for accurately assessing and managing IAQ. Occupant activity profiles can vary based on factors such as office layout, working hours, and the nature of the work being performed. For example, in open-plan offices and cafeteria, where individuals conduct various activities in a relatively bigger space, characterizing indoor air pollution and personal exposures may be difficult compared to individual offices or cubicles. By investigating occupant activity profiles and their impact on IAQ, strategies can be developed to mitigate the associated pollution risks in target office space. This may include implementing efficient ventilation systems, promoting awareness among occupants regarding pollutant-generating activities, and adopting suitable control measures to minimize pollutant emissions. Additionally, the use of real-time monitoring systems can provide valuable insights into the temporal patterns of occupant activities and corresponding changes in pollutant levels, enabling proactive measures to improve IAQ.

2.3.4 Personal cloud effect

Personal cloud effects refer to excess of air pollutant concentration in the breathing zone relative to stationary indoor or outdoor concentrations. The personal cloud effect results from localized and intermittent nature of air pollutants that occur in human vicinity, resulting in strong spatial-temporal gradients and elevated concentrations in the breathing zone [10,12,182]. The personal cloud of air pollution consists of pollutants from both endogenous and exogenous sources [13]. Endogenous sources include emissions from human breathing, skin, clothing, and personal care products, while exogenous sources encompass various human activities performed indoors such as cooking, cleaning and smoking. Specifically, activities like walking, vacuuming, and sitting on furniture can also emit coarse particles that contribute to the personal cloud [10,178,183]. Accounting for personal cloud effects is thus necessary for accurately assessing personal exposure levels and for implementing targeted control measures.

Several studies highlighted the significance of personal exposure assessment while considering personal cloud effects and the limitations of relying solely on stationary monitors to capture accurate personal air pollution exposures [10,12,13,122,182,184]. The study of Licina et al. [10] aimed to investigate personal exposures to airborne particles in a controlled chamber setting. They monitored particle levels with high temporal and particle-size resolution during various occupant activities and sampled directly from the breathing zone to characterize exposures. During sitting, the personal PM_{10} exposure increased by 1.6-13 μg/m^3 compared to room-average levels, highlighting the spatial variation of PM concentrations. The personal cloud effect was more noticeable for larger particles, indicating the shedding of particles from the skin and clothing. The study emphasized the importance of understanding the personal cloud effect for predicting and controlling personal exposures to enhance IAQ models and ventilation design. Ferro et al. [122] also reported that personal exposures to $PM_{2.5}$ and PM_5 were significantly higher compared to the indoor concentration measured by a stationary monitor, indicating the presence of a personal cloud effect. Pantelic et al. [12] examined the personal CO_2 cloud of 41 individuals during simulated office work. They found elevated levels (200-500 ppm) of median CO_2 concentration in the inhalation zone compared to room background levels in the seated occupants. The magnitude of the personal CO_2 cloud varied among subjects due to factors like posture and breathing patterns. The study highlights the need for localized measurements to understand the impact of the personal CO_2 cloud on human inhalation exposures.

Rodes et al. [184] examined the influence of personal activity sources (clouds) on exposure to indoor contaminants. They analyzed data from occupational and residential studies to assess the ratios of measurements between personal exposure monitors (PEM) and micro-environmental exposure monitors (MEM). They found that in occupational settings, the PEM to MEM ratios were typically 3 to 10, while in residential settings, the ratios ranged from 1.2 to 3.3. These ratios were shown to be log-normally distributed and primarily dependent on the proximity of the emission source to the receptors. In occupational settings, where individuals are often in close proximity to strong sources for extended periods, the PEM to MEM ratios can be significantly large. The findings showed that assumptions of well-mixed microenvironments may not hold true, emphasizing the need for further research and model development to better understand indoor concentration gradients and validate the existing exposure estimation models.

González et al. [185] investigated residential exposure to airborne pollutants in homes of 37 participants during the heating season. The findings showed that the personal cloud effect associated with CO_2 and particles was observed in most participants, indicating individual variations in exposure. They also revealed that sharing a residence, living with a smoker, and reduced window opening led to elevated air pollution exposures. Bedroom IAQ monitoring was found to best characterize exposure to CO_2 and particulate matter in the size range of 0.3–10 µm. Their findings enhance understanding of gaseous and particle pollutants in residences and could aid in refining procedures for residential air quality monitoring and inhalation exposure assessment.

Yang et al. [13] conducted a field experiment in a naturally ventilated office to assess occupants' exposure to common indoor air pollutants and investigate factors contributing to the personal cloud effect. Measurements were taken for endotoxin (a component of bacteria), VOCs, CO_2, and PM_{10} at both personal breathing zone sites and stationary room sites during a two-week period. The findings showed that the average magnitude of the personal cloud, irrespective of room concentrations, varied between 0–0.05 EU/m^3, 35–192 μg/m^3, 32–120 ppm, and

4–9 µg/m^3 for endotoxin, TVOC, CO_2, and PM_{10}, respectively. Each participant had distinct personal air pollution clouds, even though they shared the same office space. These findings highlight the significance of personal exposure assessments and the variability of air pollution levels within an office setting, emphasizing the importance of considering individual behaviors and activities when evaluating IAQ.

González and Licina [182] tracked participants during workdays using stationary air pollutant monitors at their homes and offices, as well as wearable personal monitors. Real-time measurements on CO_2, size-resolved particles and integrated samples on VOCs and aldehydes were collected. The study detected personal cloud effects as the magnitude of the PM_{10} cloud ranged from 5 to 37 µg/m^3, which was most noticeable in the larger, coarse particle size fraction. The study also found personal CO_2 clouds in living rooms and private or low-occupancy offices, with better prediction using stationary monitors placed in bedrooms. The findings highlighted the importance of considering personal exposures and the influence of different microenvironments on pollutant concentrations.

Overall, these studies emphasize the existence and significance of the personal cloud effect, particularly in relation to elevated PM and CO_2 concentrations around the human body. They underscore the limitations of relying solely on stationary monitors for exposure assessment and highlight the need to consider individual activities, postures, and micro-environmental factors to accurately evaluate personal exposures and mitigate potential health risks associated with indoor air pollution. In conclusion, the indoor environment and occupancy dynamics have a significant influence on IAQ and personal exposures to air pollutants. The spatial-temporal variation of indoor air pollutants, human emissions, occupant activity profiles, and personal cloud effects all play important roles in influencing IAQ and air pollution exposures.

2.4 Exposure assessment methods

Accurate estimation of the human air pollution exposures is required to better interpret health risks associated with inhaling air pollution. Several exposure assessment methods have been investigated and developed in the literature. This section explores proximity effect to the air pollution source and various techniques used for exposure assessment, including direct and indirect measures, and the utility of low-cost sensing technologies. The aim is to provide general understanding of the challenges and advancements in accurately measuring and characterizing human inhalation exposures to indoor air pollutants.

2.4.1 Proximity to the air pollution source

The proximity effect refers to the phenomenon where pollutant sources located in close proximity to individuals can result in elevated and highly variable personal exposure levels. Several studies have investigated this effect to better understand its implications for exposure assessment. McBride et al. [11] conducted series of experiments to quantify the proximity effect in a home environment using real-time measurements. They used different tracer pollutants, including sulfur hexafluoride (SF_6), CO, and particle-bound polycyclic aromatic hydrocarbons (PAHs), emitted from point sources. The results showed that when the source was emitting, concentrations of pollutants closest to the source were significantly higher and more variable compared to locations farther away. This effect was observed even at a distance of 2.0 m from the source under specific settings of air exchange rate and source strength. The study also identified transient elevations of concentrations, referred to as "microplumes," particularly near the source. Cheng et al. [186] focused on the proximity effect of indoor air pollution sources and the role of fan power in influencing human exposure. They performed 11 experiments in a residential garage and an office, where they varied the operating speeds of household fans in different locations to create varying air mixing conditions. They measured $PM_{2.5}$ levels at multiple points at different distances and angles from an emitting tracer particle source near the center of the room. They found that exposures close to these sources are significantly higher than those further away. By analyzing the relationship between fan power and the turbulent diffusion coefficient, they were able to predict the magnitude of the proximity effect. The study showed that introducing household fans can reduce proximity exposures, especially in environments with low natural air exchange rates. This information is valuable for assessing and mitigating the impact of air pollution on human health. Acevedo-Bolton et al. [187] investigated the proximity effect of air pollution exposure in residential homes. By releasing CO as a tracer gas from a central point source, they measured CO concentrations at different distances from the source under various ventilation conditions. The study found that concentrations in close proximity to the source (< 1 meter) exhibited high variability, with significant fluctuations attributed to short-duration peaks called microplumes. These microplumes contributed to concentrations near the source being 6 to 20 times higher than predicted well-mixed levels. These findings emphasize the importance of understanding and managing the proximity effect to mitigate air pollution exposure and promote IAQ.

Another study by Piedrahita et al. [188] focused on personal exposures to CO resulting from biomass burning for home energy use in Northern Ghana. They employed a Bluetooth low-energy beacon system to estimate participants' distances to their most-used cooking areas during sampling periods. They used proximity data (time-activity data) to improve exposure assessment modeling and predict personal exposures based on microenvironment air quality measurements. The results showed that incorporating proximity measurements improved the model fits and provided a better understanding of exposure and activities within and away from homes. The proximity sensing and exposure monitoring system developed in the study demonstrated its potential to customize exposure reduction strategies and assess the relative importance of pollutant sources. The technique showed broad applicability in various exposure monitoring domains, ranging from global health and development to occupational and industrial safety. It enabled the exploration of exposure variability within individuals and the identification of activities contributing to higher exposure levels. Hence, large-scale studies collecting such data hold great potential for evaluating intervention effectiveness and developing activity-focused exposure mitigation strategies.

Along with proximity effect to the source, the impact of source-receptor relationship [189–191] and room airflow interaction [192,193] on personal air pollution exposures can be significant. Complex interactions within indoor environments on contaminant dispersion are influenced by variables such as room geometry, the direction of principal air flows, and the presence and movements of occupants as indicated by previous studies [194–197]. These factors shape how pollutants are emitted, transported, and inhaled by individuals. Additionally, the study of Park and Kwan [198] emphasized the importance of considering spatio-temporal variability and individual mobility in exposure assessment. Human movement patterns can dictate the duration and intensity of exposure to different pollution sources. Fluid dynamics, in the context of indoor environments, can affect the dispersion and concentration of pollutants, impacting the exposure experienced by individuals [74,194]. Hence, investigations on source-reception relationship and room airflow interaction are helpful in understanding the mechanisms that determine personal exposure to air pollution.

Overall, the proximity effect plays a significant role in exposure assessment and understanding personal exposures to air pollutants. It highlights the need to consider the spatial relationships between pollutant sources and individuals when designing monitoring strategies and developing exposure models. Traditional approaches, such as placing sensors in specific locations far from the building occupants and use their direct readings to control the ventilation rate, may not effectively capture the variations in exposure due to incomplete air mixing and spatial-temporal variations of pollutants under dynamic occupancies. Hence, understanding the proximity effect is essential for developing more accurate exposure monitoring and assessment methods.

2.4.2 Existing methods for exposure assessment

Current practices for exposure assessment commonly involve the positioning of stationary IAQ monitors based on established practices [102,164,165,199–201], and standards [143,144,148,149,202]. While recommendations take into account factors such as ergonomics of the thermal environment, they may not accurately reflect the actual inhalation exposures of occupants. Furthermore, the focus has been on static occupancy, and only a few have delved into detecting exposure variations under dynamically changing occupancies. Commonly chosen locations for monitoring indoor air pollution include the middle of occupied zones, supply/exhaust ventilation grills, walls, and office desks [203,204]. According to previous studies [102], researchers prefer to place CO_2 monitors within occupied zones, usually at heights ranging from 1.0 to 1.2 m, corresponding to the height of the breathing zone (0.9 – 1.8 m) by California Title 24 Standard [202]. However, studies [10,12,13,122,182,184,185] have identified significant differences in concentrations recorded by stationary monitors compared to those recorded in the breathing zone of occupants. Moreover, the optimal sensor placement for specific air quality indicators remains unclear under dynamic occupancy conditions. Therefore, achieving optimal air quality monitoring should involve selecting the appropriate sensor location for monitoring necessary indicators, balancing cost and detection accuracy of sensors [205]. Previous studies have combined other methods, such as mobile wearable IAQ monitors [8,169,182,185,206–208] or occupancy detection techniques [209–211], with stationary IAQ monitoring to enhance the accuracy of exposure assessment.

The state-of-art personal air pollution exposure assessment methods can be broadly categorized into two main approaches: (1) direct measurement and (2) indirect measurement. These approaches are used to assess exposure to various air pollutants, including CO_2, PM, and VOCs. Direct personal air pollution assessment methods involve directly measuring the concentration of pollutants in the immediate vicinity of an individual. This approach provides real-time data on personal exposure levels. However, these direct measurement methods may have limitations such as the limited pollutant coverage, and the potential to disrupt normal daily activities due to the equipment's bulkiness, noises due to active sampling, and intrusiveness [212,213]. Some commonly used direct measurement methods are as follows:

- **Personal Monitoring Devices (Wearable IAQ sensors and passive samplers):** Personal monitoring devices are portable instruments that are worn or carried by individuals to measure pollutant concentrations in or nearby their breathing zone. Small and portable air quality sensors can be worn by individuals to monitor pollutant concentrations in real-time. These sensors can capture personal exposure levels by considering both indoor and outdoor environments. Data from wearable sensors can be combined with other parameters such as occupancy and activity information to estimate exposure. They provide continuous or time-resolved measurements of pollutants such as CO_2 [169,182], PM [182,206–208,214]. For instance, Gall et al. [169] conducted a study using portable CO_2 monitors to assess personal exposure in indoor environments. They found that the mode of bedroom ventilation significantly influenced CO_2 levels, with bedrooms employing ductless split air-conditioners showing higher median exposure levels (650 ppm) compared to naturally ventilated bedrooms (550 ppm, $p < 0.001$). McCreddin [206] examined the personal exposure to PM_{10} in office workers in Dublin, Ireland, where real-time measurements of 24-hour personal exposure were collected from 59 participants over a 28-month period. The sampling of personal exposure, activity, and location was performed using a real-time PM_{10} sampling device (Met One Aerocet-531 particle profiler), GPS tracking equipment (Garmin GPSMAP® 60CSx), and a personal activity diary. González and Licina [182] also assessed personal air pollution exposure using wearable CO_2 and PM monitors. They found that participants had detectable levels of PM_{10} and CO_2 clouds in their homes and offices, with particles associated with urban mix, traffic, and human activities as major contributors to PM_{10} exposure.

Passive samplers are small, lightweight devices that absorb or adsorb pollutants from the surrounding air over a specific period. Particularly, this methods were commonly used for estimating personal VOC exposures [185,215]. They are typically clipped onto clothing or placed in close proximity to the individual. After the sampling period, the samplers are analyzed in a laboratory to determine the pollutant concentrations. For instance, González et al. [185] investigated residential air pollutant exposure while using passive samplers to collect integrated measures of 36 VOCs and semi-volatile organic compounds (SVOCs) while having concurrent continuous stationary measurement. The findings showed that 13 out of the 36 detected VOCs and SVOCs had significantly higher concentrations in personal samples compared to stationary samples, highlighting the importance of considering personal exposure in residential air quality monitoring. O'Connell et al. [215] used silicone wristbands as personal passive samplers to measure bioavailable exposure to a diverse range of VOCs. In this study, the personal samplers effectively sequestered 49 compounds, including PAHs and other industrial compounds, demonstrating temporal and spatial sensitivity in occupational settings.

- **Thermal Breathing Manikins:** Several studies [216–219] used a thermal breathing manikin to simulate the thermal characteristics of a human body and human respiration, and to assess the inhalation exposure to pollutants in a controlled environment. By simulating human breathing patterns, thermal breathing manikins enable the direct measurement of pollutant concentrations in the breathing zone. This provides valuable information about the inhalation exposure of individuals in different environments or scenarios. Brohus and Nielsen [216] examined personal air pollution exposure in displacement ventilated rooms using thermal breathing manikins, where they proposed a personal exposure model considers gradients and the human thermal boundary layer, introducing new quantities to describe the person-ventilation interaction. Melikov and Kaczmarczyk [217] highlighted the sensitivity of a breathing thermal manikin in accurately measuring air characteristics inhaled by occupants, including temperature, humidity, and pollution concentration. They reported the simulation of breathing, especially exhalation, is important for studying the transport of exhaled air between occupants. The study provided recommendations for optimal simulation of human breathing with a thermal manikin, and standardizing the nose and mouth geometry for result comparisons. While using the thermal breathing manikin may have practical implications for assessing personal air pollution exposures and the spread of infectious agents in indoor environments, they may not fully capture the complexity of human respiration, human movement and individual variability in breathing rates or patterns [218,219].

Indirect personal air pollution assessment methods estimate personal exposures based on measurements taken in the ambient environment or other proxy measurements. These methods rely on simulation or proxy indicators from stationary IAQ measurement to infer personal exposure levels. Further, the methods provide a more holistic view of personal exposures by considering factors beyond immediate pollutant concentrations. They are often used when direct measurement methods are impractical, costly, or logistically challenging. However, these methods rely on assumptions and models, which can introduce uncertainties in exposure estimates. Some common indirect measurement methods are as follows:

- **Exposure Models by Simulations:** The utilization of human exposure simulators focused on air pollution is often used in epidemiological studies [220,221]. For instance, Chang et al. [220] developed a modeling framework using a spatial hierarchical model and a human exposure simulator to estimate the acute effects of personal exposure to air pollution. Applying the approach to $PM_{2.5}$ and daily mortality in New York City, a 2.32% increase in mortality per 10 µg/m^3 increase in personal $PM_{2.5}$ exposure from outdoor sources was observed, with higher risks during summer months. Berrocal et al. [221] utilized a stochastic simulator to estimate personal exposure to PM and its impact on birthweight, where the hierarchical model considers individual-level exposure, risk factors, and spatial effects. They analyzed data from 14 counties in North Carolina and found no significant effect of $PM_{2.5}$ on birthweight, but their modeling framework offers a template for studying personal exposure and long-term health outcomes.
- **Exposure Models by Proxy Indicators:** Personal exposure models integrate information on pollutant sources, indoor and outdoor concentrations measured by stationary air quality monitors, occupancy and individual time-activity patterns. Several studies [182,191,222,223] conducted stationary IAQ measurement while combining this data with occupancy and activity information and pollutant decay models to estimate personal exposures indoors. Licina et al. [191] investigated the impact of indoor emission locations on inhalation intake fraction (iF) of airborne particles using three stationary PM monitors. They found that near-occupant releases resulted in significantly higher iF compared to other indoor locations, highlighting the importance of emissions-receptor proximity and the influence of the thermal plume. González and Licina [182] assessed indoor air pollution exposure using stationary IAQ monitors while considering the time-activity information of the occupants, where they found that the stationary CO_2 and PM monitors placed in bedrooms were more accurate predictors of personal exposure to CO_2 and PM_{10}. Xiang et al. [224] examined a hybrid sensor network architecture based on the combination of stationary and mobile IAQ sensors, where the hybrid sensor network showed a 40.4% reduction in error compared to traditional stationary sensor network, leading to a 35.8% improvement in personal exposure measurement accuracy. Ashmore and Dimitroulopoulou [222] reviewed the use of personal exposure modeling to assess individual exposures to air pollutants, where they reported that probabilistic models are developed to capture the variation in individual activity patterns and air pollution concentrations in different microenvironments, allowing the identification of factors associated with high exposure levels in children. Klinmalee et al. [223] used personal exposure modeling based on indoor pollutant concentrations and time-activity data of occupants in a university campus and a shopping center, where they revealed high exposure to $PM_{2.5}$ (max 70 µg/m^3), particularly for people working in the shopping center during weekend.

Previous studies often use a combination of direct and indirect measurement methods to obtain a comprehensive understanding of personal air pollution exposure. From the literature review, this thesis acknowledged the importance of choosing exposure assessment method depending on various factors, including the specific pollutant of interest, research objectives, available resources, and the study population. Further, it is important to explore personal exposures in realistic office scenarios, with diverse stationary sensor placements and occupancy profiles, which extends beyond studies conducted under steady-state conditions with limited sensor placements.

2.4.3 Utility of low-cost sensing for exposure assessment

Low-cost sensing has gained significant attention in the field of air pollution exposure assessment due to its potential to provide widespread and affordable monitoring capabilities. It involves the use of inexpensive sensors that are capable of measuring various air pollutants, allowing for more localized and fine-scale monitoring compared to traditional monitoring methods. Low-cost air quality sensors typically utilize compact and portable designs, making them suitable for real-time monitoring of indoor air pollution in various settings. Several studies explored the effectiveness of low-cost air quality monitors for assessing IAQ and exposure. Morawska et al. [22] reported that low-cost IAQ sensing technologies have the potential to revolutionize air pollution monitoring although there are still uncertainties regarding their performance and recommended usage. The study also highlighted further advancements of low-cost sensing are required for source apportionment and wide-scale monitoring of personal exposures.

These sensors are capable of measuring indoor climate (T_a, RH) and a range of air pollutants such as CO_2, PM, TVOCs, CO, NO_2, and O_3. Some sensors are designed for specific pollutants, while others offer multi-pollutant detection capabilities. For instance, Piedrahita et al. [225] developed and validated low-cost air quality monitors called M-Pods, that includes MOx sensors for measuring CO, O_3, NO_2, and TVOCs, along with non-dispersive infrared sensors for measuring CO_2. Zhuang et al. [226] introduced AirSense, a portable and cost-effective device that monitors T_a, RH, $PM_{2.5}$ levels, geographical information using GPS sensor, and user activity using an accelerometer sensor, where they verified the capability of AirSense in effectively monitoring ambient air quality in daily life and potential applications of the context-sensing platform. Moreno-Rangel et al. [227] evaluated the precision, accuracy, and usability of a low-cost IAQ monitor ('Foobot') that measures T_a, RH, TVOCs, CO_2 equivalents, and $PM_{2.5}$ in residential environments. The findings demonstrated that Foobot provided reliable data for T_a, RH, TVOCs, and $PM_{2.5}$, but caution was advised when interpreting the CO_2 equivalent measurements. The study concluded that low-cost monitors like Foobot are suitable for identifying high pollutant exposures, providing data at a high granularity level, and have potential for both user and scientific applications. Demanega et al. [228] evaluated eight low-cost environmental monitors and eight single-parameter sensors for IAQ monitoring. The results showed that most of the tested units could be used for measurement-based IAQ and comfort management. The Awair 2nd edition (retail price: $199, USA) performed the best in accurately measuring multiple environmental parameters among the low-cost units. While there were disparities in quantitative accuracy for certain pollutants, most of the tested low-cost devices demonstrated potential for detecting pollution events and were strongly correlated with reference data, making them suitable for IAQ management.

There are several advantages of using low-cost sensing in exposure assessment. Firstly, low-cost sensors are significantly cheaper compared to traditional monitoring equipment, enabling the deployment of sensor networks over larger spatial scales and increasing the density of monitoring stations. This affordability makes it feasible to conduct exposure assessments in areas that lack extensive monitoring infrastructure. For instance, Gaskins and Hart [229] discussed the opportunities of using low-cost air pollution monitors (‘AirBeam2©’) in two reproductive epidemiology studies. The advantages of the personal monitor include its low cost, ability to collect multiple size fractions of PM data, portability, GPS tracking, and real-time exposure information for participants, which highlights the potential of novel methods for short-term air pollution exposure assessment in reproductive epidemiology studies. Secondly, the low-cost and portable nature of these sensors allow for their deployment in dense networks, enabling more localized monitoring of air pollution. This high spatial resolution helps capture spatial variability and identify pollution hotspots within a given area, providing a more detailed understanding of exposure patterns. Shen et al. [230] used low-cost sensors to monitor spatial-temporal variation of indoor $PM_{2.5}$, where they found that indoor PM mainly originated from outdoor infiltration and cooking emissions, with variations in different rooms depending on their distance from the sources. Thirdly, low-cost sensors often provide real-time or near real-time data, allowing for immediate feedback on air pollution levels. This real-time information can be valuable for personal exposure monitoring, enabling individuals or BMS to make informed decisions to reduce their exposure and minimize health risks. Palmisani et al. [231] conducted extensive monitoring of TVOCs, $PM_{2.5}$, and CO_2 in oncology units using low-cost sensors, where they demonstrates the potential of low-cost sensors for real-time monitoring and detection of pollution events, providing valuable information for personal exposure monitoring to minimize health risks in oncology units.

However, there are still some challenges and concerns of utilizing low-cost sensing in exposure assessments raised by previous studies [21,229,232]. For instance, low-cost sensors may have lower accuracy and precision compared to reference-grade instruments. Calibration and validation of these sensors are essential to ensure the reliability and accuracy of the collected data. Proper calibration techniques and periodic maintenance are needed to maintaining sensor performance. Jiang et al. [232] evaluated the performance of a low-cost OPC ('PMS 7003') for PM measurements where they found significant deviations of low-cost sensors compared to reference high-accuracy sensor and concluded careful calibration of the low-cost sensors before deployment. Further, low-cost sensors may have limitations in terms of battery life, sensitivity, selectivity, and response time. Gaskins and Hart [229] discussed the disadvantages of low-cost air pollution monitors, AirBeam2©, including limited battery life, incompatibility with iOS-based smartphones, and frequent connection issues. Additionally, environmental factors such as T_a, RH, and cross-sensitivity to other pollutants can impact sensor performance. Castell et al. [21] examined the performance of commercial low-cost sensors ('AQMesh v3.5') in measuring gaseous pollutants (NO, NO_2, O_3, CO) and PM ($PM_{2.5}$ and PM_{10}). The findings showed that the sensors performed well in the laboratory, showing high correlations between sensors, whereas their performance was significantly lower in real-world conditions. These limitations need to be considered when interpreting the data and estimating exposure levels accurately. Hence, ensuring the quality of data from low-cost sensors is important, especially when using the data for exposure assessments. Validation techniques, such as collocation studies with reference instruments, cross calibration, data quality checks, and statistical analyses, can help assess and improve the reliability of the collected data. Additionally, proper data management, quality control, and advanced data analysis techniques, such as data fusion, spatial interpolation, and machine learning algorithms, are required to extract meaningful exposure information from the collected sensor data [233,234]. Low-cost sensing has the potential to revolutionize exposure assessment by providing more localized, real-time, and cost-effective monitoring solutions. While there are challenges associated with accuracy, calibration, and data quality, ongoing advancements in sensor technology and data analysis techniques are continually improving the reliability and usability of low-cost sensing for exposure assessment.

To conclude, by considering the proximity effect, exploring current practices for exposure assessment, and harnessing the potential of low-cost sensing technologies, it is possible to improve the accuracy and reliability of human exposure estimation to indoor air pollutants for ultimately enhancing IAQ and promoting occupant health and well-being in buildings.

2.5 Occupancy assessment methods

Understanding and assessing occupancy is important for analyzing indoor environments, especially in buildings with varying occupancy conditions such as office buildings. Having information about the number of occupants and their activities at the room or building level is essential for managing IAQ, energy efficiency, and occupant comfort. This section of the thesis examines current practices in occupancy assessment and explore two specific methods: stationary occupancy sensors and wearable occupancy sensors.

2.5.1 Current practices for occupancy assessment

Current practices for occupancy assessment in buildings rely on various methods and sensors. Rueda et al. [235] categorized and analyzed techniques for estimating building occupancy information, considering factors such as performance, occupancy resolution, sensor types, building types, and energy-saving potential. Occupancy resolution in this study captured detailed information about individuals' presence, identification, and activity, enabling improved resource management, energy efficiency, and occupant comfort, where they mentioned that accurate assessment of this data empowers building managers to optimize space utilization and create tailored environments for occupants' needs. Occupancy data in buildings could be collected through variety of methods, including visual observation by staff (i.e. manual surveys) [236], occupancy sensors (i.e. PIR sensors) [237], cameras [238], and indoor air pollution [210,239,240]. The latter one was studied in the context of CO_2 [210,240], PM [239], and VOCs [241]. Specifically, Pantazaras et al. [240] examined the use of CO_2 sensors for occupancy estimation, where the findings showed that CO_2 levels and occupancy can be accurately estimated with minimal impact from sensor placement, offering a decision tool for balancing air quality and energy consumption in a university lecture theatre. Cali et al. [210] developed and validated an algorithm for detecting the presence of occupants indoors using CO_2 concentration as a proxy. The algorithm was tested in both residential and office buildings, achieving a correct detection of general occupancy up to 96% of the time and accurately identifying the exact number of occupants up to 81% of the time. Weekly et al. [239] approximated human activity from the values of low-cost PM sensor and found a statistical correlation between the human activity and measured PM concentrations. Ekwevugbe et al. [241] developed a data fusion technique to estimate occupancy patterns while using data from RH, illuminance, T_a, CO_2, and VOC sensors. Their proposed sensor fusion model offers a novel methodology for accurate occupancy detection by monitoring indoor climatic variables, indoor events, and energy data in non-domestic buildings. To conclude, occupancy-related indoor air pollutants could serve as reliable indicators of personal air pollution exposure, occupancy, and occupant activities. However, challenges remain regarding the cost and scalability of deploying multiple sensor types on a large scale, as well as concerns about intrusiveness and privacy. Current practices highlight the necessity for enhanced methods that can capture occupancy characteristics and deliver more precise and comprehensive occupancy information in a cost-effective and less intrusive manner.

2.5.2 Stationary occupancy sensors

Occupancy sensors offer a promising approach to assess occupancy presence and activity at different scales in buildings. These sensors detect the presence or absence of occupants in a given space and can provide real-time information about occupancy patterns. Various types of stationary occupancy sensors are available, including PIR sensors, ultrasonic sensors, CO_2 sensors, cameras, audio, and radio frequency identification (RFID) systems, as summarized in Table 2.4.

Table 2.4 Overview of occupancy sensing technologies and their capabilities

Occupancy Sensing Technology [reference]	**Description**	**Information Captured**	**Limitations**
Passive Infrared (PIR) Sensors [242,243]	Detect changes in infrared radiation caused by moving warm human bodies	Binary output (occupied/unoccupied)	Lack fine-grained occupant activity information
Ultrasonic Sensors [244]	Emit ultrasonic waves and measure the time it takes for them to bounce back	Occupancy based on movement	Limited information about occupant activities
CO_2 Sensors [36,102,245]	Measure CO_2 concentration in the air, which indirectly indicates occupancy	Indirect occupancy indication	Slow response times, influenced by environmental conditions
Cameras [238,246]	Provide visual information about occupancy and detailed occupant activities	Fine-grained occupancy details	Privacy concerns, image processing challenges
Audio [238]	Capture occupancy information by analyzing sound patterns and detecting human presence based on audio cues	Occupancy activities	Background noise, privacy concerns, audio signal processing
Radio Frequency Identification (RFID) Systems [247]	Use radio frequency signals to track RFID tags carried by occupants	Accurate occupancy information	Requires occupants to carry RFID tags
Plug Loads and Electronic Equipment Tracking [248–250]	Monitor electrical usage and power consumption patterns of plug loads and electronic devices	Data on device activation and usage	Limited in capturing human presence when devices are inactive, may not differentiate between occupants and devices

In order to achieve energy efficiency in office buildings, it is important to have accurate information about space utilization and building occupancy. Wahl et al. [242] focused on using strategically placed PIR sensors and algorithms to estimate people count per office space. The performance of the proposed sensor model was evaluated in an office setting, and simulations of realistic occupant behaviors confirmed the accuracy of the estimation algorithms in predicting people count, where they highlighted the potential of PIR sensors to enable dynamic control of lighting, climate, and appliances in office spaces. Milenkovic and Amft [251] also reviewed PIR sensors for detecting office worker activities and estimating people count in office buildings. By employing finite state machines and probabilistic models, they achieved high accuracy in recognizing desk-related activities and estimating people count in real office environments. The results indicate potential energy savings of 21.9% and 19.5% by integrating activity sensing into building energy management systems. Andrews et al. [243] developed MI-PIR, a novel approach that overcomes the limitations of PIR sensors for detecting stationary occupants in indoor spaces. In this study, they achieved accurate room occupancy classification, estimation of occupant count, and prediction of location and differentiation of human targets by mounting a PIR sensor on a moving platform and utilizing an artificial neural network (ANN). The results demonstrated potential applications for tracking and monitoring at-risk patients in indoor settings.

Ultrasonic sensors, widely available and cost-effective, are commonly employed to regulate lighting systems within buildings [252]. Unlike PIR sensors, they possess the advantage of not requiring a direct line of sight for detecting presence. Jin et al. [244] explored occupancy detection in commercial buildings using ultrasonic sensors, acceleration sensors, WiFi access points, and individual power monitoring and developed a semi-supervised learning algorithm based on power measurement for space security, occupancy behavior modeling, and energy savings in plug loads.

CO_2 sensors are commonly employed as explicit detection mechanism for occupancy detection in buildings [36]. Since the amount of CO_2 generated by occupants varies, CO_2 can act as a proxy for estimating the number of people present [253]. Lam et al. [254] examined various parameters (CO_2, CO, TVOC, lighting, T_a, RH, motion, and acoustics) to detect occupancy numbers in open-plan offices, where they found the highest correlation between the number of occupants in the space and CO_2 and acoustic parameters, which can be attributed to the characteristics of the open office plan. For this reason, CO_2 sensors are primarily utilized for DCV purposes in buildings [102,245]. One drawback of CO_2 sensors is their slower response time compared to PIR and ultrasonic sensors [209].

Jalal et al. [246] developed a depth-based life logging human activity recognition system for monitoring the activities of elderly individuals. They utilized depth video sensors to capture depth silhouettes and generate human skeletons with joint information for activity recognition. The developed system demonstrated satisfactory recognition rates compared to conventional approaches, where they showed potential applications in elderly monitoring systems and examining indoor activities in various settings, such as homes, offices, and hospitals. The study of Kreiss et al. [255] proposed a new bottom-up method called PifPaf, utilizing Part Intensity Fields (PIF) and Part Association Fields (PAF) for multi-person 2D human pose estimation from the recorded video, particularly well-suited for occupancy detection in urban mobility scenarios like self-driving cars and delivery robots, outperforming previous methods in challenging conditions. Wojek et al [238] presented a method for multi-person activity recognition in an office environment using audio and video features obtained from a simple setup of cameras and microphones. The approach involved employing a multilevel hidden Markov model (HMM) framework to simultaneously track users at the room-level, demonstrating promising results in unconstrained real-world data recorded in multiple offices. However, using camera or audio for detecting occupancy faces challenges such as high computational complexity, susceptibility to illumination conditions, and privacy concerns as reported by Chen et al. [256].

Li et al. [247] proposed an RFID-based occupancy detection system to facilitate demand-driven HVAC operations by tracking multiple stationary and mobile occupants in various spaces. The system accurately estimated the thermal zones where occupants are located and provided real-time reports on the number of occupants in each zone. Their field tests demonstrated an average zone-level detection accuracy of 88% for stationary occupants and 62% for mobile occupants, supporting the integration of the occupancy detection system with energy-saving strategies to reduce HVAC energy consumption.

Occupancy detection through plug loads and electronic equipment tracking in offices involves monitoring electrical usage and power consumption patterns of devices such as computers, printers, and other office equipment [248]. When occupants are present and actively using these devices, they draw power and generate electrical signatures [250]. By analyzing these signatures, it is possible to infer occupancy, as the devices are typically used when people are at their workstations. However, it is important to note that this method may not reliably differentiate between occupants and devices when equipment is in standby mode or inactive, requiring additional sensors or data sources for more accurate detection [249].

From the literature review, combining multiple sensors and integrating their outputs can improve the accuracy and reliability of occupancy assessment methods. However, the balance between cost and accuracy of deployed multiple sensors and privacy concerns of the deployed sensors remains a consideration.

2.5.3 Wearable occupancy sensors

Wearable sensors (e.g. smartwatches, accelerometers, gyroscopes, etc.) offer a novel approach to assess occupancy profiles in office buildings. These sensors are typically worn by occupants and can provide continuous monitoring of various physiological parameters of humans. By measuring parameters such as body movement, heart rate, respiration rate, and skin temperature, wearable sensors can infer occupancy presence, identify specific activities, and provide personalized exposure assessments. For instance, smartwatches equipped with sensors such as skin temperature, heart rate monitors, accelerometers, and gyroscopes can provide valuable insights into occupancy patterns and occupant activities. Weiss et al. [257] compared smartwatch and smartphone-based activity recognition and highlighted the advantages of smartwatches in identifying specialized hand-based activities, such as eating. The skin temperature and heart rate monitoring can provide information about the intensity of physical activities, such as walking, running, or sitting, and can help identify different occupant activities and infer occupant comfort [258]. Accelerometers and gyroscopes can detect motion and movement patterns, allowing for the recognition of specific activities, such as walking, standing, or cleaning. For instance, Liu et al. [259] developed an unobtrusive and automatic monitoring system for housekeeping tasks for healthcare applications by using wearable accelerometers and gyroscopes, where they achieved high accuracy (90.67%) in recognizing housekeeping tasks and accurately classifies activity levels (94.35%), demonstrating its reliability for long-term monitoring.

The advantage of utilizing wearable sensors for occupancy assessment is their ability to capture individual-level information in real time [260], providing detailed and personalized data on occupant activities, postures, and interactions with the indoor environment. This fine-grained information enables a more comprehensive understanding of occupancy dynamics and activity patterns within buildings, which can be utilized as one lever for occupant-centric HVAC system. However, the use of wearable sensors for occupancy assessment also presents challenges such as data privacy, intrusiveness, user acceptance, and sensor accuracy, which needs to be addressed [261].

In conclusion, occupancy assessment methods are essential for understanding indoor environments and optimizing building performance. Current practices based on stationary sensors have limitations in capturing comprehensive occupancy characteristics. Occupancy sensors, such as PIR sensors, ultrasonic sensors, CO_2 sensors, cameras, audio and RFID systems, offer opportunities to improve occupancy assessment accuracy. Furthermore, wearable sensors provide a promising avenue for capturing fine-grained occupancy information and personalized exposure assessments. Further research and development are needed to refine and integrate these methods into practical and cost-effective solutions for assessing occupancy presence, number, and activities in office buildings.

2.6 Knowledge gap, research questions, and hypotheses

The literature review in this thesis highlights the need for more effective methods and indicators to detect personal inhalation exposure and assess occupancy in office environments. Specifically, there is a lack of research on capturing the spatial-temporal variation of indoor air pollutants and occupancy dynamics in offices, which is essential for understanding and mitigating the impact of indoor air pollution on occupant health and well-being. Additionally, exploring the potential of low-cost smart sensing technologies and wearable sensors could lead to practical and cost-effective solutions for both exposure and occupancy assessment in office buildings. In short, the overall knowledge gap lies in the exploration of effective methods and indicators for detecting personal inhalation exposure and occupancy in static and dynamic office environments.

Specifically, a significant knowledge gap emerges in determining the most effective proxy method for detecting personal inhalation exposure in office settings. Past research has explored various indicators and sensor technologies, but a comprehensive understanding of which method provides the most accurate and reliable exposure assessment remains elusive. In addition, previous studies lack a clear consensus on the optimal sensor locations within office spaces for characterizing inhalation exposure to indoor air pollution. Research in this area often follows existing guidelines (e.g., breathing zone height) and lacks specificity, leaving uncertainty regarding where to position sensors for the most precise and comprehensive monitoring of inhalation exposure. Lastly, another critical knowledge gap pertains to the identification of the minimum but sufficient sets of indicators necessary for effective inhalation exposure and occupancy detection. While previous studies have explored various sensor combinations for IAQ monitoring, there is a lack of standardized guidelines and conclusive findings on which indicators are essential and which may be redundant. Bridging these research gaps are essential for enhancing exposure assessment strategies and developing cost-effective and practical solutions of IAQ monitoring in office buildings.

The thesis proposes three key research questions to be answered through various experiments and data analysis to gain insights into the factors that significantly impact inhalation exposure and occupancy estimation in office buildings.

[Research Question 1]

There is a lack of exploration regarding proxy methods for detecting personal exposures to CO_2 and PM under dynamic office environments. Hence, the study hypothesized that certain physical parameters act as better proxies for inhalation exposures to CO_2, $PM_{2.5}$, and PM_{10} than others, and that a combination of physical parameters may better represent inhalation exposures than a single parameter in a simulated office environment with dynamically changing occupancy profiles. A specific research question is as follows:

- ***"What combination of physical parameters (environmental, contextual, and physiological) best represents inhalation exposures to CO_2, $PM_{2.5}$, and PM_{10} in a simulated office environment with dynamic occupancy profiles?"***

[Research Question 2]

The existing research lacks studies on optimal stationary IAQ sensor placement considering dynamic occupancy profiles in office settings. Hence, the study hypothesized that stationary sensor positioning affects the accuracy of personal exposure detection, and that the optimal sensor placement for exposure detection may vary based on building ventilation and occupancy profiles. Specific research questions are as follows:

- ***"What are the suitable stationary IAQ sensor placements that can best approximate personal CO_2, $PM_{2.5}$ and PM_{10} exposures under dynamic and static occupancy conditions?"***
- ***"How do categorical variables (occupant number, activity, office layout, ventilation type, ventilation rate) influence personal exposure detection?"***

[Research Question 3]

The identification of indicators for detecting personal exposures to indoor air pollutants and building occupancy in real-life office settings is an underexplored area of research. Hence, the study hypothesized certain sets of indicators may serve as better proxies in approximating personal exposures and office occupancy relative to others while considering their cost-effectiveness. Specific research questions are as follows:

- ***"How do spatial gradients of personal CO_2, $PM_{2.5}$, and PM_{10} exposure in offices relate to various occupant activity profiles?"***
- ***"Which indicators serve as the most effective proxies for personal air pollution exposure and occupancy in different office types?"***
- ***"What are the minimum but sufficient indicators for characterizing personal exposures and occupancy in real office settings?"***

By addressing these research questions, this thesis aims to enhance the understanding of spatio-temporal variations of common office pollutants, improve exposure assessment accuracy, and propose cost-effective recommendations for occupant-centric IAQ monitoring and occupancy detection. Ultimately, this thesis presents an important step towards contributing to improved occupant health and well-being in office buildings.

Building upon these questions, the thesis formulates hypotheses that propose potential answers and hypotheses that aim to advance our understanding of the complex dynamics of IAQ, inhalation exposures, and occupancy in office buildings.

- **Hypothesis 1: A combination of multiple physical parameters, including environmental, contextual, and physiological factors, will yield more accurate representations of inhalation exposures to CO_2, $PM_{2.5}$, and PM_{10} in office environments compared to relying on individual parameters alone.**

- **Hypothesis 2: The accuracy of personal exposure detection in office environments will be influenced by stationary sensor positioning, and optimal sensor placement will vary based on building ventilation, office layout, and occupancy profiles.**
- **Hypothesis 3: Certain sets of indicators, chosen for their cost-effectiveness, will serve as better proxies for approximating personal exposures to indoor air pollutants and office occupancy relative to others, depending on office layout and occupancy conditions.**

2.7 Research objectives

The objectives of this thesis are to propose: (1) proxy methods for characterizing inhalation exposure to CO_2, $PM_{2.5}$ and PM_{10} in simulated office environments, (2) optimal sensor placement for estimating personal CO_2, $PM_{2.5}$ and PM_{10} exposures in simulated static and dynamic office environments, (3) minimum but sufficient indicators for detecting personal CO_2, $PM_{2.5}$ and PM_{10} exposures and occupancy dynamics using smart sensors in real office environments, and (4) practical recommendations for building practitioners to achieve cost-effective monitoring strategies for personal air pollution exposures and occupancy dynamics in office environments. Each of the proposed research objectives corresponds to one thesis chapter, as follows:

Chapter 3: Proxy methods for detection of inhalation exposure in simulated office environments

- Identify the best proxy methods that represent inhalation exposures to CO_2, $PM_{2.5}$, and PM_{10} in a simulated office environment with dynamic occupancy profiles.

Chapter 4: Optimal sensor placement for personal inhalation exposure detection in static and dynamic office environments

- Determine the suitable stationary IAQ sensor placement that best characterizes personal air pollution exposures under different occupancy conditions (dynamic and static).
- Evaluate the influence of categorical variables (occupant number, activity, office layout, ventilation type, ventilation rate) on personal exposure detection.

Chapter 5: Investigation of indicators for personal exposure and occupancy in offices by using smart sensors

- Examine spatial gradients of personal CO_2, $PM_{2.5}$, and PM_{10} exposure in offices associated with various activity profiles (body posture, activity type, and activity intensity).
- Identify minimum but sufficient sets of indicators for characterizing personal air pollution exposures and occupancy in various office settings using correlation and Decision Tree (DT) classification and regression analysis.

Chapter 6: Discussions

- Propose integrative discussions of thesis findings.
- Articulate limitations of thesis findings.
- Provide perspectives for research and practice.

Chapter 7: Conclusions

- Address and answer research questions.
- Provide future research outlook.

2.8 Thesis structure

The structure of this thesis that corresponds to the next chapters is presented below as Figure 2.3.

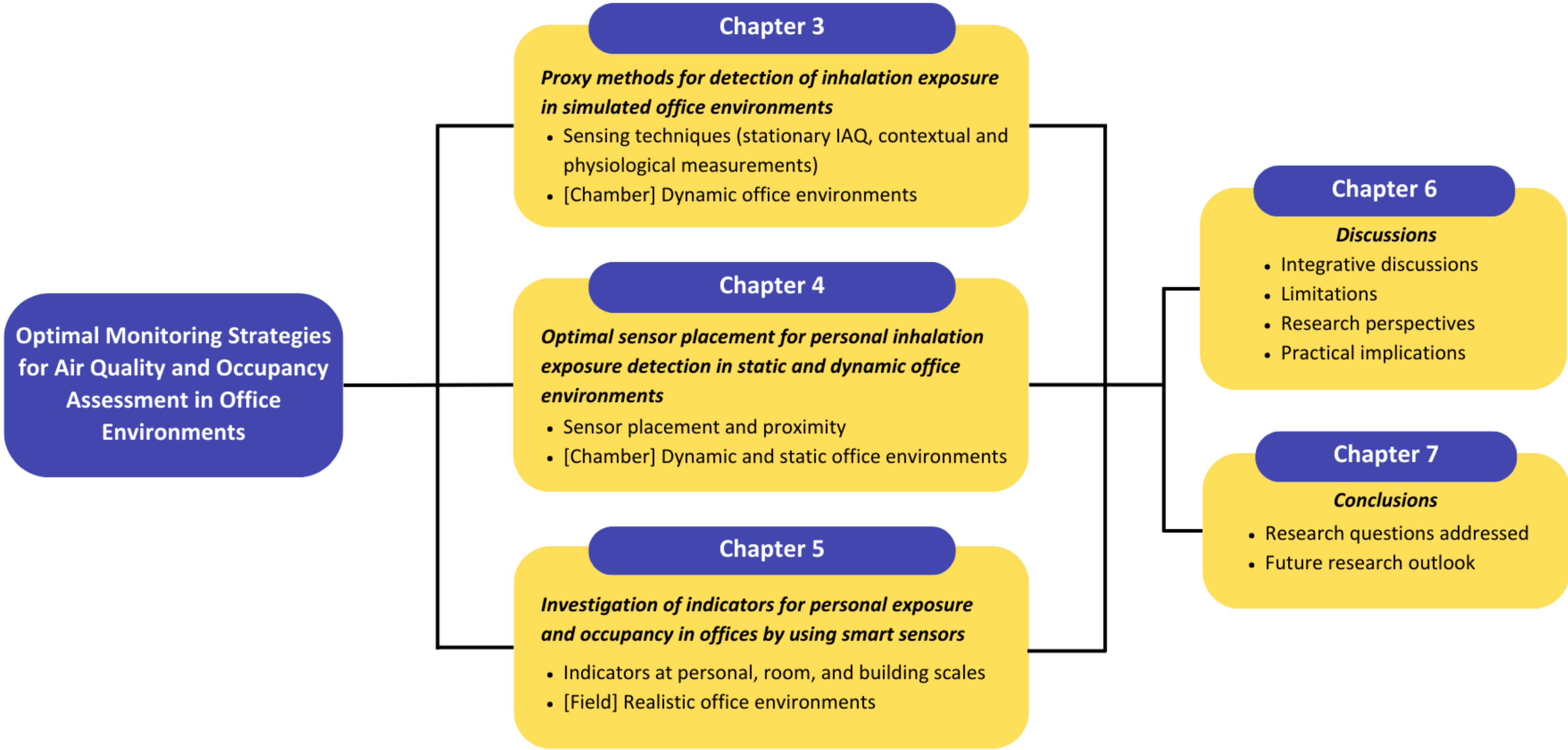

Figure 2.3 Structure and summary of the thesis chapters

Chapter 3 Proxy methods for detection of inhalation exposure in simulated office environments

Seoyeon Yun[1*], Salin Zhong[2], Hamed S. Alavi[3], Alexandre Alahi[4], Dusan Licina[1]

[1] Human-Oriented Built Environment Lab, School of Architecture, Civil and Environmental Engineering, École Polytechnique Fedérale de Lausanne, Switzerland

[2] Human-IST Institute, Department of Informatics, University of Fribourg, Switzerland

[3] Digital Interactions Lab, Institute of Informatics, University of Amsterdam, Netherlands

[4] Visual Intelligence for Transportation, School of Architecture, Civil and Environmental Engineering, École Polytechnique Fedérale de Lausanne, Switzerland

[*]Corresponding author: seoyeon.yun@epfl.ch

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Edit: the introduction has been incorporated into Chapter 2, and the references and caption numbers of figures, tables, and equations have been edited to align with the respective thesis chapter number.

Abstract

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. The study aimed to examine the feasibility of several proxy methods for estimating inhalation exposure to CO_2, $PM_{2.5}$, and PM_{10} in simulated office environments. 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. Segregating data onto sitting and standing activities could lead to improved accuracy of exposure estimation model for CO_2 and PM by 9 - 60% during sitting activities, relative to combined activities. Stationary $PM_{2.5}$ and PM_{10} 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 CO_2. Combining different sensing techniques improved the CO_2 exposure detection by twofold, whereas the improvement for PM

exposure detection was small (~10%). 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.

3.1 Specific objectives

As previously noted, methods for characterizing personal exposures to CO_2 and PM under dynamic indoor environments are largely unexplored. The specific objective of this study was to examine the feasibility of proxy methods for estimating inhalation exposure to CO_2, $PM_{2.5}$, and PM_{10} in simulated office environments. The study aimed to compare different sensing techniques, including stationary IAQ monitoring, individual physiological monitoring using wearable wristbands, and human presence detection using PIR sensors. The study also sought to determine the accuracy of these proxy methods by comparing the results from stationary IAQ measurements with concurrent IAQ measurements taken in the breathing zone of a reference participant. The study examined the effects of different office activities (sitting and standing) of occupant on exposure estimation accuracy and explore the optimal combination and placement of monitors for improved estimation of inhalation exposures to CO_2, $PM_{2.5}$, and PM_{10}. Additionally, the study aimed to investigate the benefits of combining multiple inputs (environmental, physiological, and contextual parameters) for improving exposure estimation. Finally, the study provided recommendations on the optimal combination and placement of monitors in order to assist stakeholders in gaining a better understanding of spatial air pollutant gradients indoors, ultimately improving the control of IAQ.

3.2 Research methodology

3.2.1 Chamber description and office layouts

The experiments were conducted in a controlled climate chamber (floor area: 24.8 m^2, volume: 60 m^3), where air temperature and relative humidity were controlled within narrow ranges, 24.9±0.4℃ and 54.3±4%, respectively. To simulate typical mechanically-conditioned office spaces, the study selected the mixing ventilation strategy, which is the most common air distribution method applied in commercial office buildings [262]. Here, the conditioned air was supplied and exhausted through the two swirl type diffusers at the ceiling of the chamber (Figure 3.1). The air change rate was constant (2.4 – 2.6 h^{-1}), which was confirmed by the CO_2 tracer gas decay method [263]. The corresponding air change rate matched the recommendation value (ventilation rate of 144 – 156 m^3/h for four persons and a floor area of 24.8 m^2) from the European standard of EN16798-1 (Non-residential building; Category 1) [264]. 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. The study examined 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 (Figure 3.1). The details of each floor plan with furniture organization are presented in Figure S3.1.

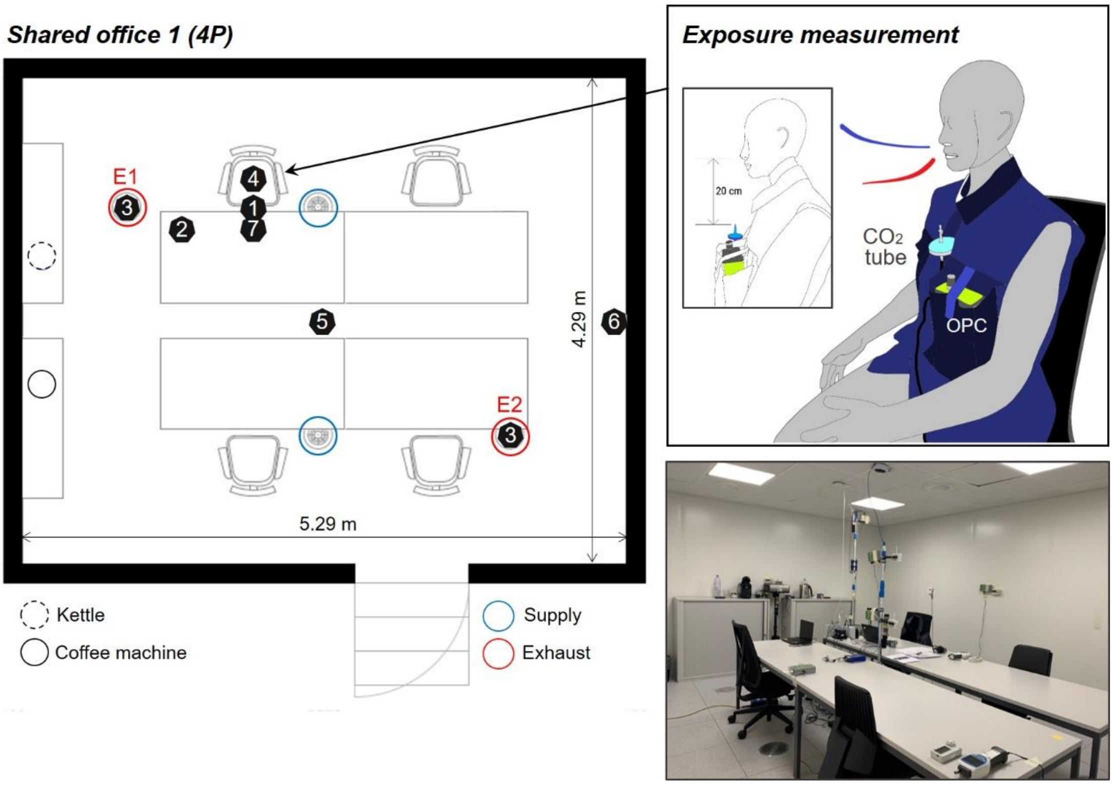


Figure 3.1 Example of monitor placement in the Shared office 1 (4 participants) and exposure measurement (CO_2, PM) in the breathing zone of the reference participant. Each monitor location is marked with an ID number which is described in Table 3.1. Notes: E1 = Exhaust 1, E2 = Exhaust 2.

3.2.2 Human occupants

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 [264]. The age of participants was between 26 – 31 and the average BMI ranged within 20.3 – 23.8 kg/m^2 for females and 25.1 – 31.8 kg/m^2 for males. The study distributed the number of males and females equally in each experiment to minimize the impact of gender on human CO_2 emission [12,265] and maintained the same participants throughout the experiments. The participants wore typical office summer clothing (average 0.4 *clo*). One female participant (28 years old, BMI = 22.4 kg/m^2) was designated as a reference participant for inhalation exposure measurements.

3.2.3 Experimental design

The study conducted a total of 11 chamber experiments during the summer period (13.07.2020 – 11.08.2020, Table S3.1). Each experiment was replicated two times except the cafeteria scenario. The measurements included the following three categories: air quality parameters (CO_2, $PM_{2.5}$, and PM_{10}), 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. The study determined seven sensor placements (IDs 1–7, Table 3.1) based on the literature and current best practices [101,102,266]. One example of monitor placement for the Shared office 1 is shown in Figure 3.1, whereas the others are shown in Figure S3.1. For breathing zone measurements, the reference participant wore one CO_2 and one OPC at the sampling point located 20 cm below the nose (Figure 3.1). The sampling tube connected to the CO_2 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 the ground-truth occupancy information.

Table 3.1 Monitor ID, measurement parameters and placements.

<table>
<tr><th>ID</th><th>Parameters measured</th><th>Measurement placement (No. of monitors)</th><th>Measurement method</th></tr>
<tr><td>1</td><td rowspan="4">CO₂,
Size-resolved particle number concentration</td><td>Front edge of participant desk (1)
Front edge of desk near an abdomen of the reference participant</td><td>CO₂ monitor, OPC</td></tr>
<tr><td>2</td><td>Desk (1)
On each participant's desk</td><td>CO₂ monitor, OPC</td></tr>
<tr><td>3</td><td>Exhaust (2)
Ceiling-mounted exhaust diffusers, 2.4 m:
• Exhaust 1 (E1, Figure 3.1): near the reference participant
• Exhaust 2 (E2, Figure 3.1): additional placement</td><td>CO₂ monitor, OPC</td></tr>
<tr><td>4</td><td>Breathing zone (1)
20 cm below from the reference participant's nose</td><td>CO₂ monitor, OPC</td></tr>
<tr><td>5</td><td rowspan="2">Participant presence, number, body posture, and type of office activity</td><td>Ceiling (2)
Ceiling in the center of the chamber, 2.4 m</td><td>PIR, Network camera</td></tr>
<tr><td>6</td><td>Wall (2)
Side wall, 1.4 m and 2.0 m</td><td>PIR, Network camera</td></tr>
<tr><td>7</td><td>Participant presence</td><td>Below the desk (1)
Below the participant desk</td><td>PIR</td></tr>
</table>

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 Figure S3.2. Duration of each activity spanned from 5 to 25 min. All the participants exited the chamber after 60 minutes of the experiment and the chamber was sealed for 30 minutes 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.

3.2.4 Research instrumentation

Two types of monitors were deployed to measure stationary indoor and breathing zone CO_2 concentrations. Three 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 were deployed at the Exhaust 1 and at the Breathing zone of the reference participant. To capture size-resolved particle number concentration, the study used four stationary and one wearable OPCs. Stationary monitors included: Met One 804 (Met One 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 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, >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. The study also introduced one wearable wristband (E4, Empatica Inc., USA, frequency range: 32 Hz) that measured physiological state of the reference participant. Lastly, the study installed two network cameras (M1065-LW and M3057-PLVE, Axis communications, Sweden, frequency range: 64 Hz) inside the chamber. All IAQ data was obtained at 1-min time interval except for the CO_2 measurements at breathing zone, which was measured at 0.5-second interval. The PIRs recorded occupancy information as binary code at 1-minute time interval. Skin temperature was measured at 4 Hz frequency (0.25 seconds), heart rate at 1 Hz frequency (1 seconds) and acceleration at 32 Hz frequency (0.03125 seconds).

3.2.5 Data analysis

Kierat et al. [267] proposed that accurate CO_2 exposure assessment requires breathing zone measurements to be performed during the inhalation period only. To eliminate the effect of human exhalation, the study selected only a single minimum value (Figure S3.3) out of one respiratory cycle, where each cycle typically had 6 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/m^3) was estimated from measured number concentration by assuming that particles are spherical with density of 2.5 g/cm^3, and by supposing that the mass-weighted size distribution, dM/d(log d_p), is constant within each particle size group [268]. As density of indoor particles is typically in the range 1-2.5 g/cm^3, the reported particle mass concentrations are likely to be upper-bound estimates [122].

The study removed the contribution of the former activity to the CO_2 and PM concentrations due to multiple participant activities conducted in a relatively short time period. The study firstly estimated CO_2 concentration by removing preceding 5-min average CO_2 concentration from each time stamp (Figure S3.4). For PM, the study followed data processing approach described in [183] where the evolution of PM level from the former activity was calculated and removed (Figure S3.5).

Pearson correlation r value indicates existence of association between the measured variables, where stronger linear relationship appears as the r value approaches ±1 [269]. Our study examined r value between the measured IAQ parameters in order to identify the strength of the correlation between them. Through MLR analyses, the study 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} (Figure 3.2). Firstly, the study composed a regression model by using input variable from each data category: 1) air quality; 2) contextual; 3) physiological. The study 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, the study 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 [270,271]. Further, the study 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.

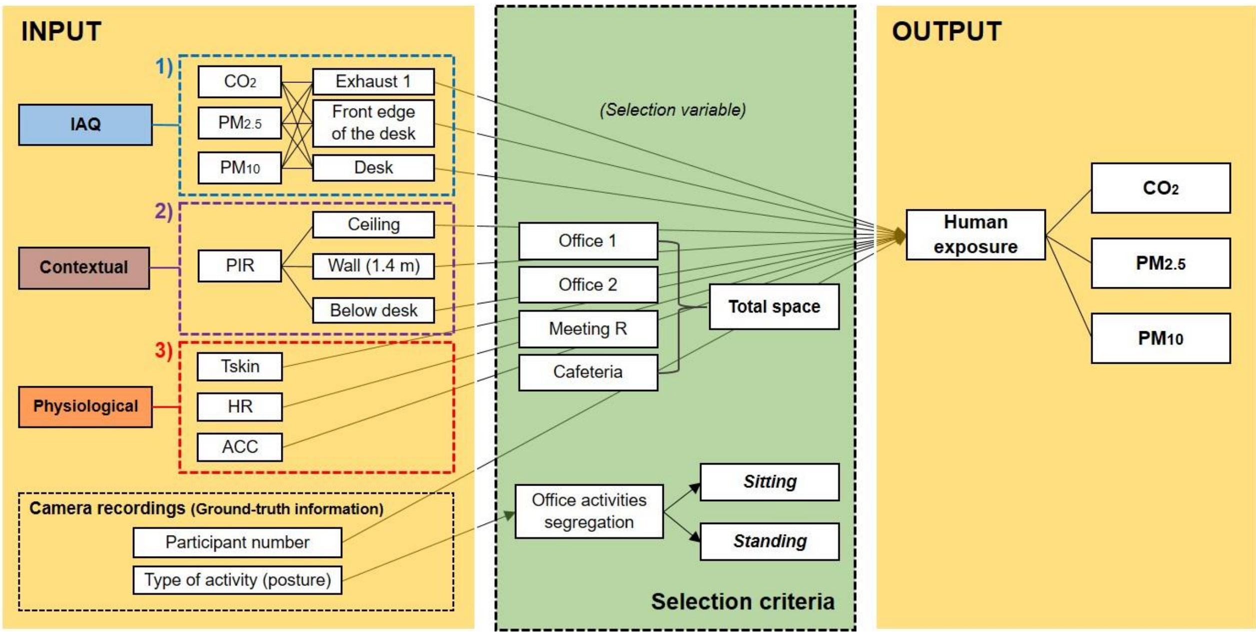


Figure 3.2 Input and output variables in composing MLR models. Selection criteria were applied while separating the collected data into sitting and standing activities. Notes: Exhaust 2 was not included as input in MLR analysis. T_{skin} stands for skin temperature, HR for heart rate, and ACC for resultant acceleration $\sqrt{ACC\_x^2 + ACC\_y^2 + ACC\_z^2}$). Description of sitting and standing activities is shown in Figure S3.2.

3.2.6 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 HHPC 6+) were compared against the high-accuracy OPC (Mini-WRAS 1371). Adjustment factors of the side-by-side instrument performance tests are shown in Table S3.2.

3.3 Results and discussion

3.3.1 Summary of descriptive statistics and correlations of IAQ measurements

In order to understand spatial IAQ variations in the chamber, the study examined variations of studied air pollutant concentrations in relation to monitor placement. Figure 3.3 shows minimum, first quartile, median, third quartile, maximum and average CO_2, $PM_{2.5}$, and PM_{10} 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 CO_2 concentrations of the reference participant were approximately two times higher than the ones from stationary monitors. This finding showed a notable increase of breathing zone CO_2 concentration compared to a study of Melikov et al. [272], where CO_2 concentration inhaled by a breathing thermal manikin was only 16% higher than in the room exhaust. The average $PM_{2.5}$ and PM_{10} showed 6.7× and 6.8× higher concentrations at the breathing zone than the ones at stationary monitors, respectively.

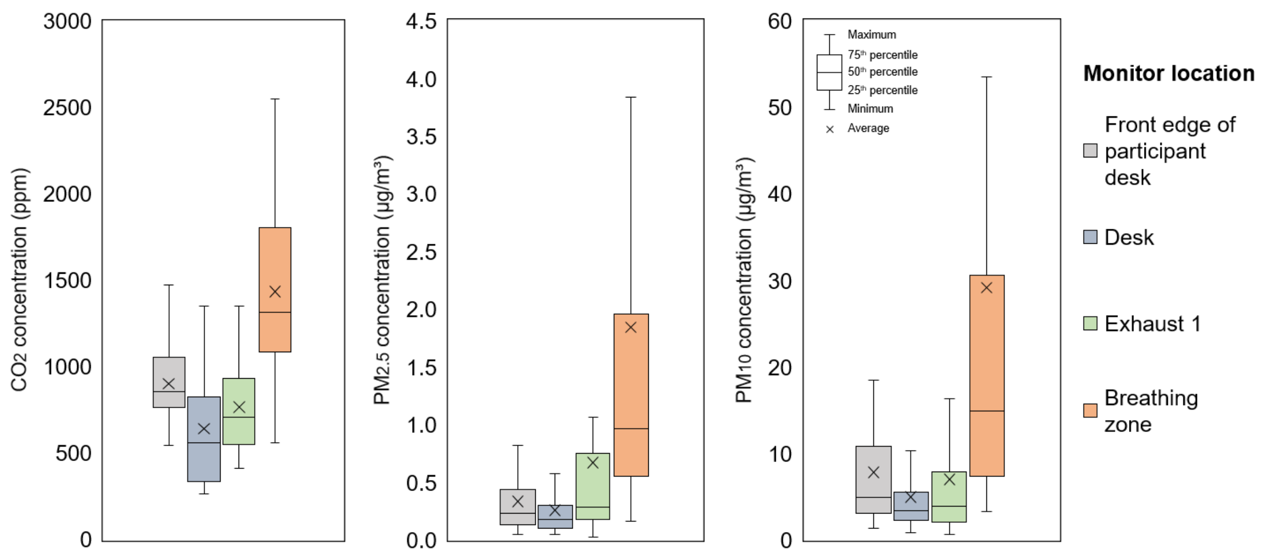
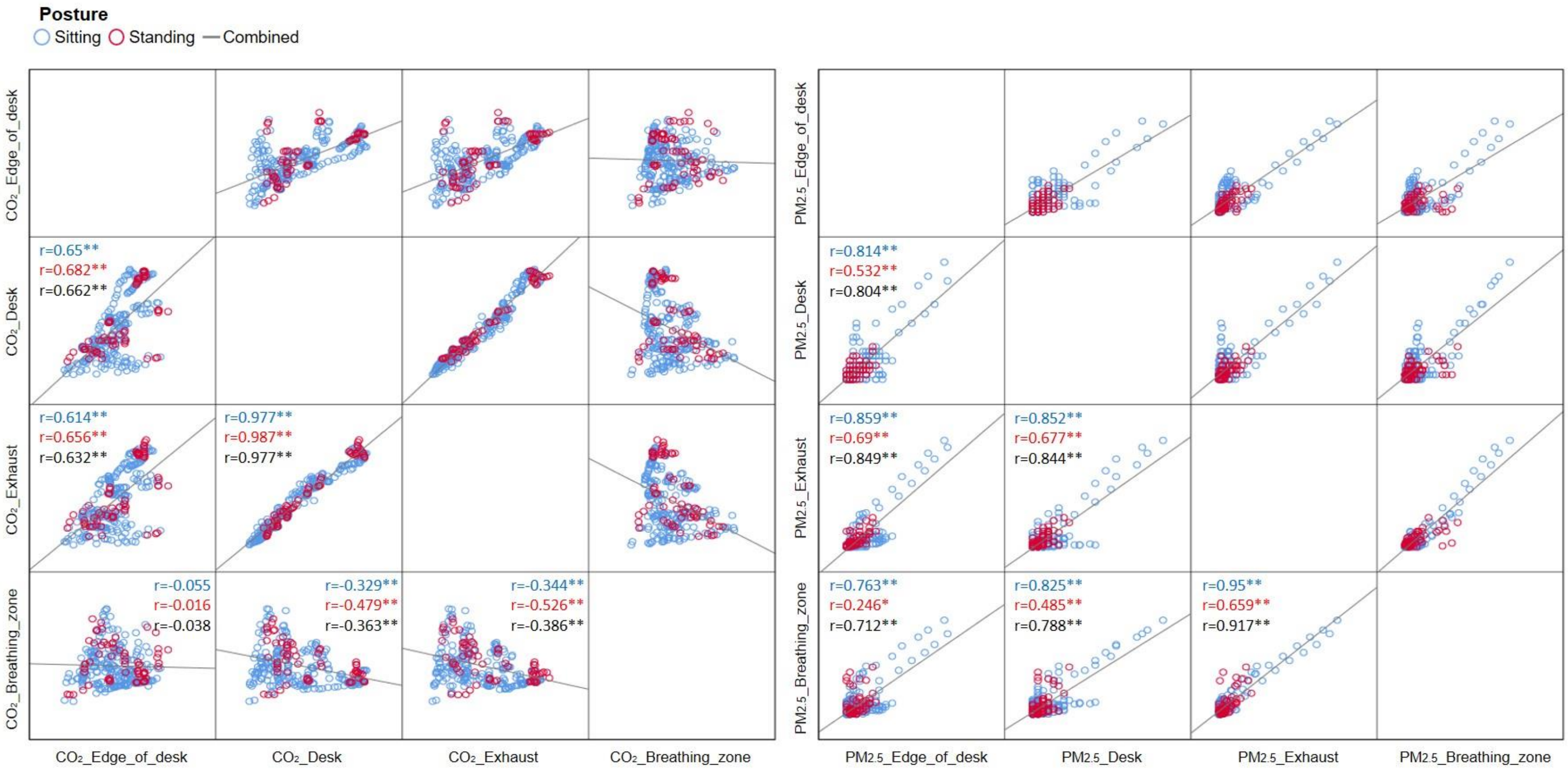


Figure 3.3 The CO_2, $PM_{2.5}$ and PM_{10} concentration at different stationary monitors across all activities and experiments.

The highest average CO_2 and PM_{10} 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 CO_2 jet that propagates downwards during *sitting* activities, as well as human thermal plume that transports locally generated airborne particles to the breathing zone [273]. 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, the study compared the absolute mean CO_2 and PM_{10} concentration between the Exhaust 1 and Exhaust 2 (Figure S3.6), where difference and variation of mean concentration was trivial in case of CO_2, while it was significant in case of PM_{10}.

Figure 3.4 shows the Pearson correlation r values between stationary indoor and breathing zone CO_2 and PM concentrations during *sitting*, *standing* and *combined* (*sitting* and *standing*) activities. Relative to *combined* activities, r values for CO_2 were often higher when the study segregated participant activity into *sitting* and *standing* activities. The correlation r between the CO_2 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. CO_2 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 of Pei et al. [102] who reported CO_2 measured at the room exhaust well correlates with the inhalation exposure to CO_2 under mixing ventilation. The two highest correlations between breathing and stationary CO_2 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 CO_2 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. [33] also recognized that inconsistent patterns of CO_2 concentrations in breathing zone of occupants may contribute to discrepancies of correlations between room exhaust and breathing zone CO_2 level.

The correlation r between stationary and breathing zone $PM_{2.5}$ and PM_{10} measurement improved marginally during *sitting* activities (4-7%) and did not improve during *standing* activities compared to *combined* activities (Figure 3.4). *Sitting* activities had better correlation for $PM_{2.5}$ and PM_{10} 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 $PM_{10.}$ Low correlation between stationary and breathing zone PM level 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 the human activity and its intensity [10,191]. Further, the study compared correlation r between the two exhausts with the Breathing zone measurement (Table S3.3). In case of PM_{10}, 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.



**. Correlation is significant at the p=0.01 level (2-tailed)
*. Correlation is significant at the p=0.01 level (2-tailed)

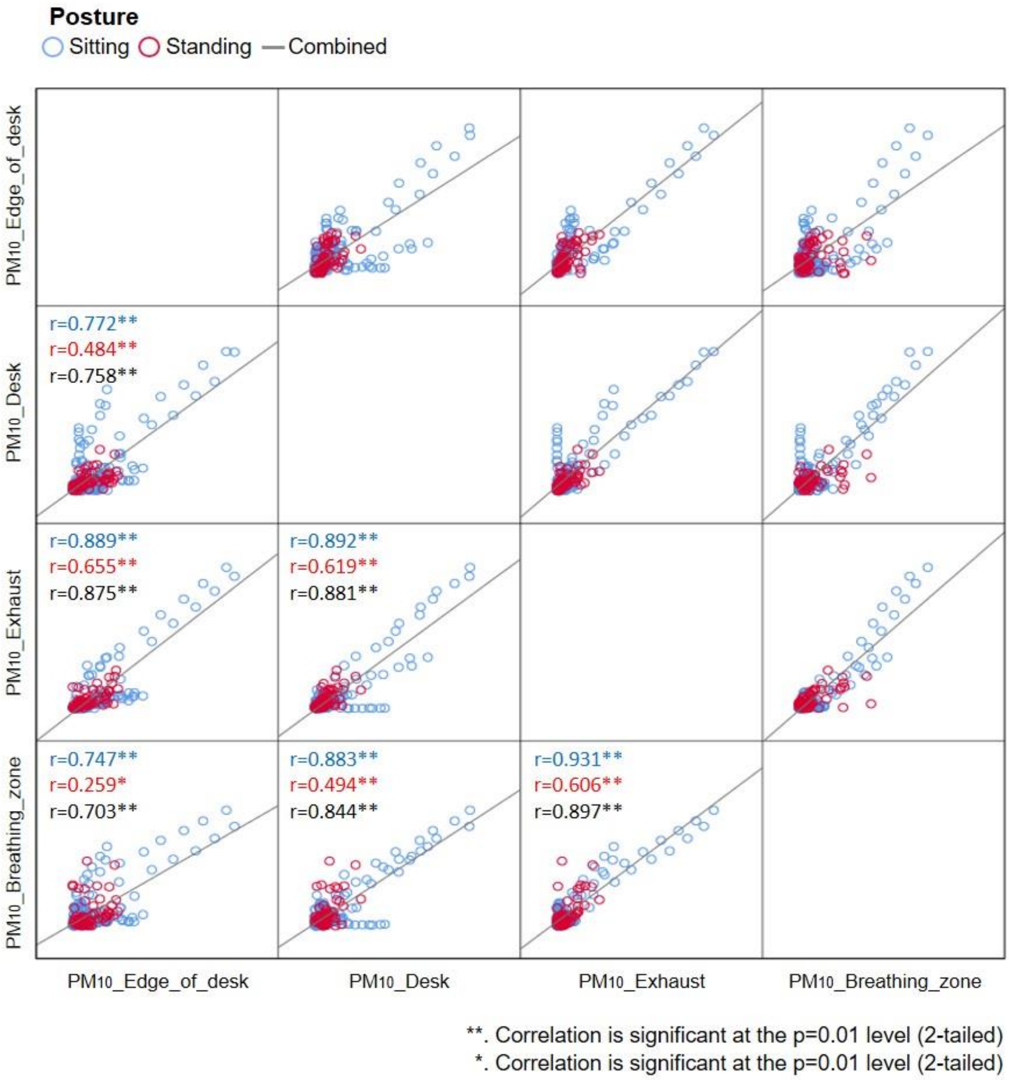


Figure 3.4 Pearson correlations of CO_2, $PM_{2.5}$, and PM_{10} measurements during *sitting*, *standing*, and *combined* participant activities.

3.3.2 Multiple linear regression models for estimating human exposure

3.3.2.1 MLR models based on stationary IAQ measurements

The study investigated the accuracy of human exposure estimation to CO_2, $PM_{2.5}$ and PM_{10} 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 3.2 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 CO_2 inhalation exposure was 77% higher compared to one under *combined* activities. This result agrees with the previous report (Figure 3.4) of significant improvement of correlation between stationary and breathing zone CO_2 measurements when participants' activities were separated. Accuracy of $PM_{2.5}$ and PM_{10} 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. [10] also identified personal cloud effect with elevated PM concentration in breathing zone of seated occupant 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 PM_{10} 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.

Table 3.2 Adjusted R^2 value of MLR models for IAQ exposure estimation by using different number and combinations of stationary CO_2 and PM measurements during *combined* and separated activities (*sitting* and *standing*). Bolded values have moderate or strong correlation (R^2 > 0.5).

Number of variables	**IAQ stationary monitor placement**	***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	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

* All models included participant number as one input variable

The CO_2 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 3.2). Furthermore, the $PM_{2.5}$ and PM_{10} exposure estimations by using a single OPC during *standing* activities was also not accurate (average adjusted R^2 of 0.24 and 0.22 across all single OPCs, Table 3.2). The results indicate that the single stationary IAQ monitoring location recommended by standards and guidelines [274–276] 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 PM_{10} 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 CO_2 exposure estimation, where there was no difference between using single and multiple variables. Further, the study reported regression coefficients of the models (Table S3.4) consisted of a single stationary IAQ measurement and participant number as input variables with the best estimation accuracy. The regression equations (Equation 3.1-3.3) are listed based on the models (Table S3.4) composed with one stationary IAQ measurement and participant number ($part_{num}$) as inputs. A negative correlation between participant number and CO_2 inhalation exposure was observed, while a positive correlation between CO_2 level at the Front edge of participant desk and CO_2 inhalation exposure was detected during *standing* activities (Equation 3.1). As indicated in Equation 3.2 and Equation 3.3, two inputs ($part_{num}$, $PM_{exhaust}$) had a positive correlation with output (inhalation exposure to $PM_{2.5}$ and PM_{10}) during *sitting* activities. Interestingly, inhalation exposure to PM_{10} was more dependent on the participant number than the stationary PM_{10} measurement at the ventilation exhaust, while the opposite aspect was shown for inhalation exposure to $PM_{2.5}$.

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

Equation 3.1

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

Equation 3.2

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

Equation 3.3

3.3.2.2 MLR models based on contextual measurements

The study derived the MLR models by using input variables obtained from PIRs installed at three different placements; ceiling, wall, and below the participant desk. Table 3.3 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 CO_2 during *standing* activities. Our results point towards conclusion that the PIR alone is able to detect human presence in the space (see β=0.26, Table S3.5), but none of the three PIRs showed a sufficient ability to estimate inhalation exposure solely.

Table 3.3 Adjusted R^2 value of MLR models for IAQ exposure estimation by using different combinations of PIRs measurements during *combined*, *sitting* and *standing* activities. Bolded values have moderate correlation ($R^2 > 0.5$).

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

3.3.2.3 *MLR models* based on physiological measurements

The study 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 3.4. In general, physiological measurements gave poor estimate of inhalation exposures for the investigated scenarios except the CO_2 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 [277,278] that indicated a complex relationship of human physiological status and indoor CO_2 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 PM_{10} exposure by multiple inputs showed 5 and 10% increase in sitting activities and showed 10% increase in standing activities in case of CO_2 compared to the model with a single input. However, overall model accuracy by physiological inputs was still insufficient to estimate inhalation exposures. Further, the study reported regression coefficients of a model that best estimated CO_2 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 S3.6).

Table 3.4 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. Bolded values have moderate correlation (R^2 > 0.5).

Number of variables	Wearable wristband parameters*	*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	T_{skin}	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	T_{skin} + HR	0.459	0.04	0.014	0.475	0.118	0.062	**0.594**	-0.022	-0.019
	T_{skin} + 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	T_{skin} + HR + ACC	0.457	0.043	0.018	0.474	0.127	0.07	**0.589**	-0.038	-0.032

* T_{skin}: skin temperature, HR: Heart rate, ACC: resultant acceleration ($\sqrt{ACC\_x^2 + ACC\_y^2 + ACC\_z^2}$)

3.3.2.4 MLR models based on multiple parameter measurements

The study 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. The study 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 section 3.3.2.1. Adjusted R^2 values of each model were reported with relevant input variables listed in parentheses (Table 3.5). 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 CO_2 measurement. When participants were moving around, CO_2 exposure estimation was better by integrating stationary CO_2 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 PM_{10} 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 PM_{10} exposure while heart rate (HR) was useful in estimating both $PM_{2.5}$ and PM_{10} exposures. By combining IAQ with wearable and PIR measurements, adjusted R^2 for $PM_{2.5}$ and PM_{10} 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.

Table 3.5 Adjusted R^2 value (relevant input variables) of MLR models with combined input parameters for IAQ exposure estimation during *sitting* and *standing* activities. The best parameter or a combination of parameters to estimate inhalation exposure is colored in grey. The last row (colored as blue) indicates how much percent increase (%) was obtained in terms of estimation accuracy when using combined parameters compare to using a single IAQ parameter.

Combinations of parameters* *(used as input variables)*	**Adjusted R^2 of composed MLR model (relevant input variables**)**					
	Sitting			***Standing***		
	CO_2 estimation	**$PM_{2.5}$ estimation**	**PM_{10} estimation**	**CO_2 estimation**	**$PM_{2.5}$ estimation**	**PM_{10} estimation**
Single IAQ	0.26 (Part_num, CO_2_Front edge of participant desk)	0.91 (Part_num, $PM_{2.5}$_Exhaust 1)	0.87 (Part_num, PM_{10}_Exhaust 1)	0.579 (Part_num, CO_2_Front edge of participant desk)	0.442 (Part_num, $PM_{2.5}$_Exhaust 1)	**0.363** (Part_num, PM_{10}_ Exhaust 1)
IAQ + E4	0.492 (Part_num, CO_2_Desk, Exhaust 1, T_{skin})	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, T_{skin}, HR)	0.594 (Part_num, T_{skin}, HR)	**0.503** ($PM_{2.5}$_ Front edge of participant desk, Exhaust 1)	0.363 (Part_num, PM_{10}_ Exhaust 1)
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)	0.503 ($PM_{2.5}$_ Front edge of participant desk, Exhaust 1)	0.363 (Part_num, PM_{10}_ Exhaust 1)
IAQ + E4 + PIRs	**0.524** (Part_num, CO_2_Desk, Exhaust 1, T_{skin}, 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, T_{skin}, HR)	0.594 (Part_num, T_{skin}, HR)	0.503 ($PM_{2.5}$_ Front edge of participant desk, Exhaust 1)	0.363 (Part_num, PM_{10}_ Exhaust 1)
Improvement of estimation accuracy *(Single IAQ vs combination of parameters, percent increase %)*	101	3.2	6.3	6.2	13.8	0

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

** Part_num: number of participants, T_{skin}: skin temperature, HR: heart rate

Except a notable improvement (twofold increase) of using combined parameters in CO_2 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 Equation S3.1-S3.5. The study also included normality test of the final regression models (Figure S3.7) in order to make valid future inferences of the models. Lastly, the study presented additional regression models that used single and combined parameters during *combined* (*sitting* + *standing*) activities (Table S3.7). As expected, the best model accuracy for estimating personal exposure to CO_2, $PM_{2.5}$ and PM_{10} was not apparent when participants' activities were mixed. This finding confirms the importance of having contextual information, particularly occupant activities, for evaluating personal exposures.

3.4 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, the study 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 recordings, which would not be possible in a real life scenario due to intrusiveness and privacy issues [209,279]. To tackle these limitations, one promising technology is a novel camera-based human activity detector algorithm named PifPaf [255] that gives information about total number of participants and estimates posture of participants containing 17 joints, without violating privacy issues.

3.5 Conclusions

Considering 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, the study deployed three different sensing techniques (stationary IAQ, contextual and physiological measurements) to detect breathing zone CO_2, $PM_{2.5}$ and PM_{10} concentrations.

The accuracy of estimating inhalation exposures was contingent upon occupant number, activities and positioning of sensors. Firstly, occupant number was a 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 CO_2 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 CO_2 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 CO_2 and the ventilation exhaust for PM. Specifically, the Front edge of the desk showed a moderate accuracy (adjusted R^2=0.58) for CO_2 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 PM_{10} of a seated participant. By combining multiple inputs (environmental, physiological, and contextual parameters), the model estimation on inhalation exposure to CO_2 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 [10,12,267]. 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 [236,280,281].

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.

Chapter 4 Optimal sensor placement for personal inhalation exposure detection in static and dynamic office environments

Seoyeon Yun*, Dusan Licina

Human-Oriented Built Environment Lab, School of Architecture, Civil and Environmental Engineering, École Polytechnique Fedérale de Lausanne, Switzerland

*Corresponding author: seoyeon.yun@epfl.ch

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Edit: the introduction has been incorporated into Chapter 2, and the references and caption numbers of figures, tables, and equations have been edited to align with the respective thesis chapter number.

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.

4.1 Specific objectives

The study aimed to address the lack of research on optimal stationary sensor placement in office settings considering dynamic occupancy profiles. In order to shed light on effective stationary sensing strategies that can accurately capture inhalation exposures in dynamic and static occupancy settings, the study have formulated two research questions: 1) What are the suitable locations for stationary IAQ sensor placement to best approximate personal exposures under dynamic and static occupancy conditions? 2) How do categorical variables such as occupancies, office layouts, ventilation types, and ventilation rates impact personal exposure detection? The hypothesis was that the optimal sensor placement for personal exposure detection may vary depending on the building's ventilation and occupancy characteristics. To answer these research questions, the study developed a regression model that detects personal air pollution exposures while evaluating the contributions of studied input variables: occupancies (occupant number and activities), office layouts, and ventilation strategies/rates. The study goal was to compare the levels of CO_2, $PM_{2.5}$, and PM_{10} in the breathing zone (BZ) with stationary air pollution levels using seven stationary sensors placed throughout the space. Additionally, the study developed linear regression models to identify key indicators for personal exposure detection and proposed optimal placements for stationary IAQ sensors. The findings from this chapter could be useful for improving the accuracy of exposure assessment, for contributing to the advancement of guidelines for continuous IAQ monitoring, and more broadly, for enhancing occupant-centric building HVAC controls.

4.2 Research methodology

4.2.1 Chamber description and office layouts

The study 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. The study examined 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 [282], 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 [263]. 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) [264]. 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 Figure S4.1 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.

4.2.2 Human occupants

In each experiment, the study 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 [283]. The study kept the same occupant composition for the scenarios with the same number of occupants. The average age of the occupants was between 26 – 34, with BMI ranging between 20.3 – 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. The study 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.

4.2.3 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 4.1. These experiments consisted of 32 runs with dynamic occupancy and 16 runs under static occupancy. In the experiments, the study 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 [284]. 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.

Figure 4.1 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. The ethical and safety considerations of the experiments were approved by the Human Research Ethics Committee of EPFL.

Table 4.1 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*	Shared office 1	2 vs. 4	2.4 – 2.6 h^{-1}	Half vs. Full	6-7 combined activities designed for each office layout (Figure 4.1)	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}			

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

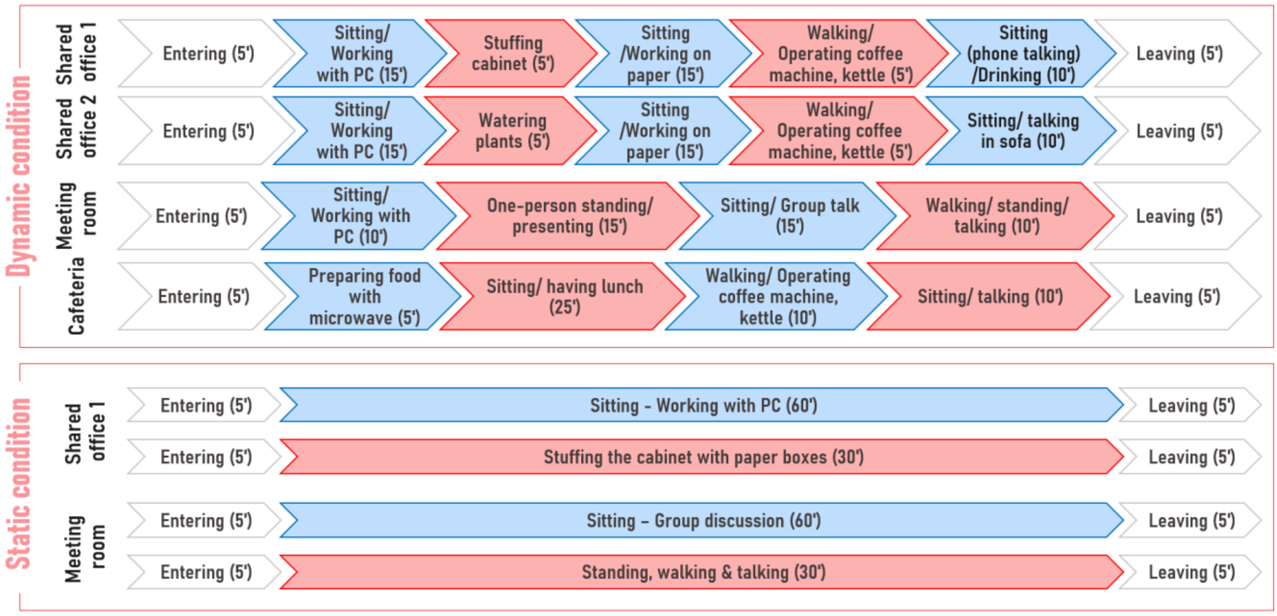

Figure 4.1 Occupants' office activities (duration in minutes) in each simulated office layout and occupancy condition. Sitting activities are marked as blue shading while standing activities are marked as red shading. "Entering", "Leaving" and "One-person standing/presenting" activities were excluded in data analysis.

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 minutes, whereas it lasted 30 or 60 minutes for static occupancy. After each case of the experiment, all occupants exited the chamber. The chamber was sealed for 30 minutes 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.

4.2.4 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 [102,164,165,199–201]. Seven stationary (IDs 1-4) and one breathing zone monitoring location (ID 5) for IAQ sensors are described in Table 4.2. 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 seconds.

Table 4.2 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	

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 Figure 4.2. 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.

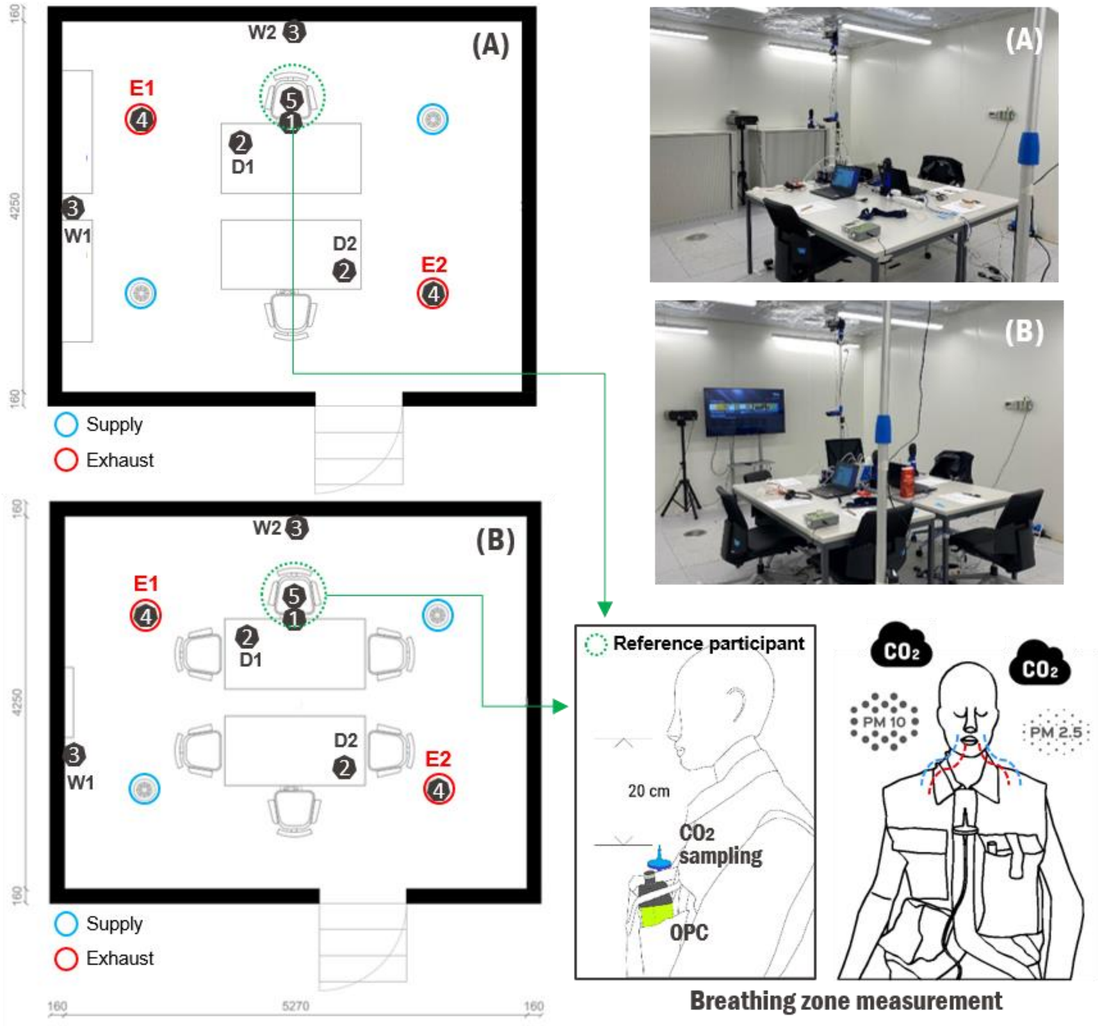

Figure 4.2 Example of sensor placement (A) in the Shared office 1 with two occupants and (B) in the Meeting room with six occupants. The lower right part of the figure illustrates exposure measurement (CO_2, PM) in the BZ of the reference occupant. Each sensor placement is marked with an ID that is described in Table 4.2. 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.

4.2.5 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.

4.2.6 Data analysis

Accurate assessments of CO_2 exposure requires sampling in the BZ during the inhalation period only [285,286]. Our study followed the same method of the study of Yun et al. [287], 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 seconds depending on the activities. By selecting only the minimum sampling point within one respiratory cycle, the study could minimize the effect of human exhalation. The study 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 (µg/m^3) was estimated from the measured number concentration by assuming that particles are in spherical shape with density of 1.0 g/cm³, and the mass-weighted size distribution, dM/d(log d_p), is constant within each particle size group [268].

In case of dynamic occupancies, the air pollution contribution of a 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 1h experiment, the study introduced the data processing approach described in [183,287]. The study 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, the study calculated the CO_2 concentration by subtracting the 5-min average CO_2 concentration from each time stamp.

After data processing, the study used two sample t-test [288] 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 [269]. 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, the study executed a multiple linear regression analysis [289] by using Python 3.10.7 with scikit-learn library [290] as a programming language. In the regression model presented in Figure 4.3, 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, the study categorized occupant posture into two categories (sitting and standing). The study 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). The study 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), the study presented the R^2 value of the produced regression models. The study 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, the study applied a Decision Tree Classifier, a data mining method for developing classification based on multiple covariates [291,292], which allowed us to evaluate the contribution of each input variable that enhances the exposure detection. Input parameters of Decision Tree classification were stationary CO_2, $PM_{2.5}$ and PM_{10} measurement at different locations and categorical variables as shown as Figure 4.3, whereas output parameter was inhalation exposure to investigated indoor air pollutants (CO_2, $PM_{2.5}$, and PM_{10}). Decision Tree classification model was developed under occupants' sitting and standing scenario, respectively.

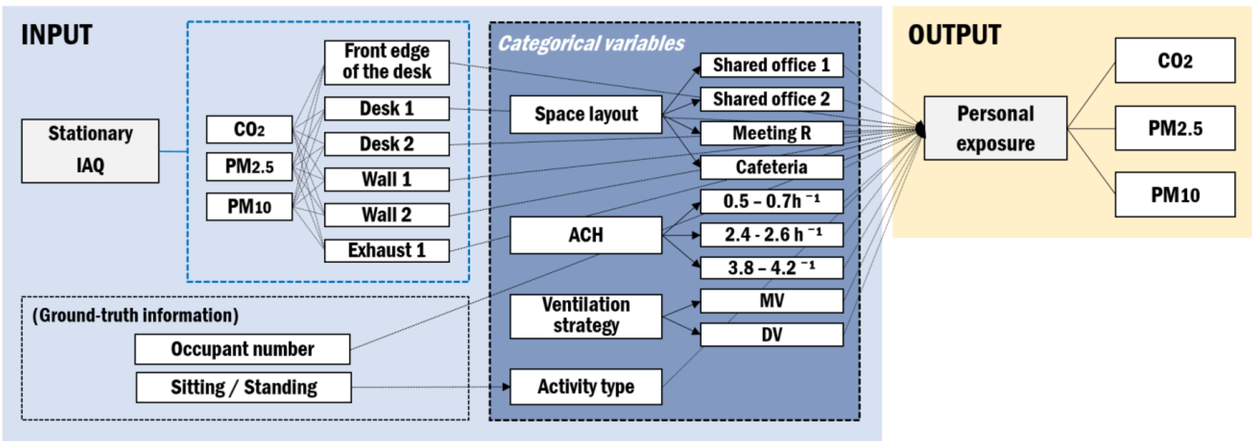

Figure 4.3 Input and output variables used to compose the linear regression models for detecting personal exposures to CO_2, $PM_{2.5}$, and PM_{10}. Categorical variables were introduced using dummy variables. Note: Exhaust 2 was excluded from the regression analysis because of its limited dataset.

4.2.7 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 S4.1. 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%.

4.3 Results and discussion

4.3.1 Descriptive IAQ statistics under different categorical variables

The study first examined spatial concentration variations of the studied air pollutant in the chamber. Figure 4.4 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 Figure 4.4. 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 ($p > 0.05$).

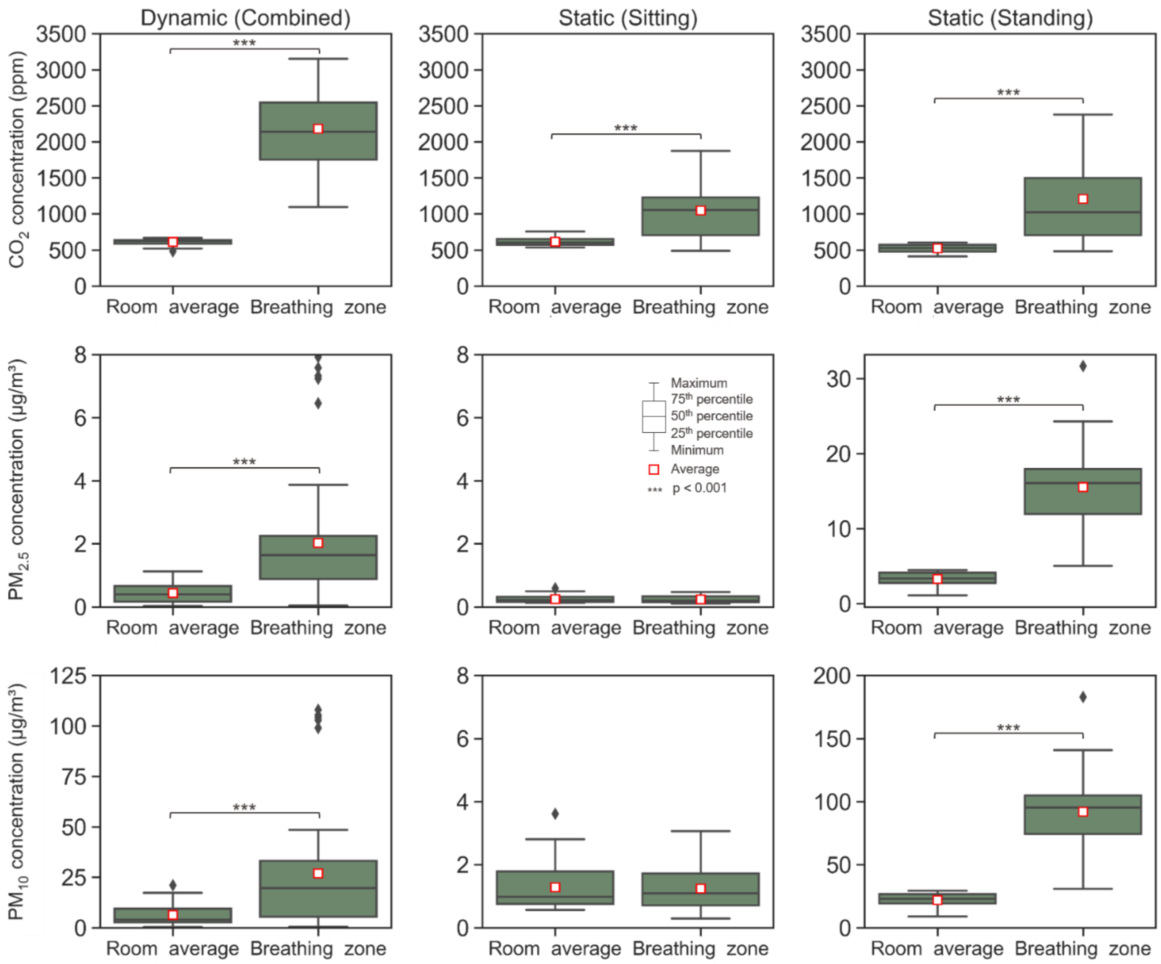

Figure 4.4 Boxplot of room average and BZ CO_2, $PM_{2.5}$ and PM_{10} concentrations as a function of dynamic and static occupancy. The results are presented for the selected scenario of Shared office 1 (two people) under the mixing ventilation with a fixed ACH of 2.4 – 2.6 h^{-1}. The p-value from the t-test is star-marked.

Figure 4.5 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-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. The study 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 in case of two occupant scenario was expectedly negative and mostly linear.

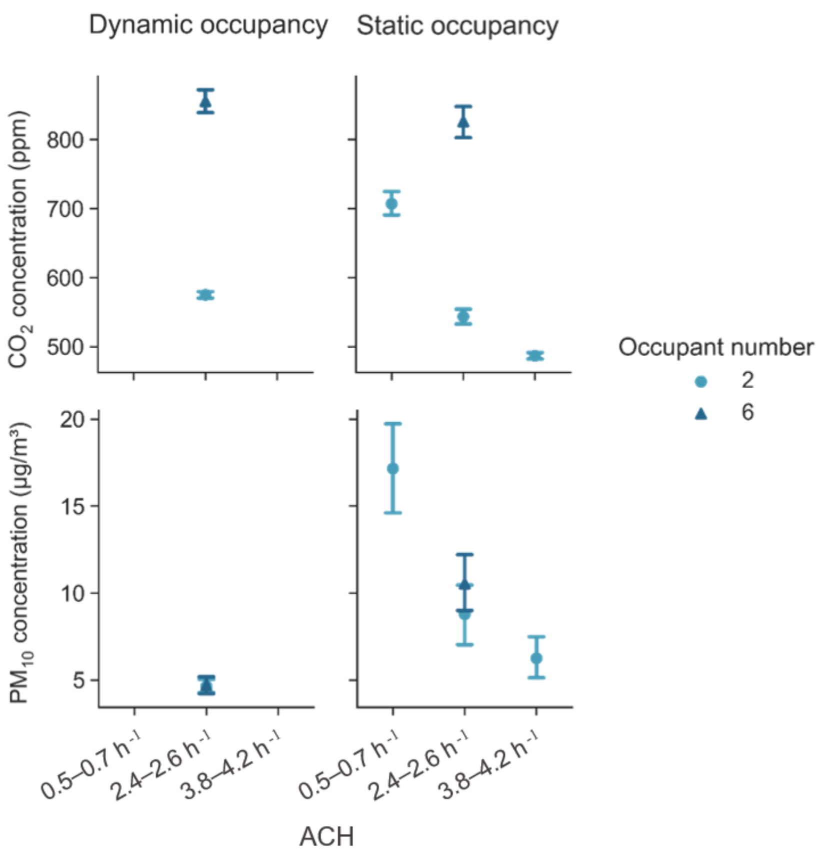

Figure 4.5 Room average CO_2, $PM_{2.5}$, and PM_{10} concentration as a function of air change rate and occupant number in dynamic and static occupancies. Markers represent the average values while the vertical bars indicate standard deviation.

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. Figure S4.2 presents the room average and BZ CO_2 level as a function of three ACHs during occupant sitting or standing activities. Figure S4.3 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.

4.3.2 Correlations between stationary and BZ sensors

Figure 4.6 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 [102] 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 lower correlation between stationary and BZ levels compared to the $PM_{2.5}$ and PM_{10}. A Similar result was reported in a study of González Serrano et al [182], 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 [10].

The study 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 Figure S4.4-S4.5, the correlation r between stationary and BZ levels increased 1-4× when the study divided datasets into two occupant activities (sitting/standing) as opposed to the one of combined activities (sitting+standing).

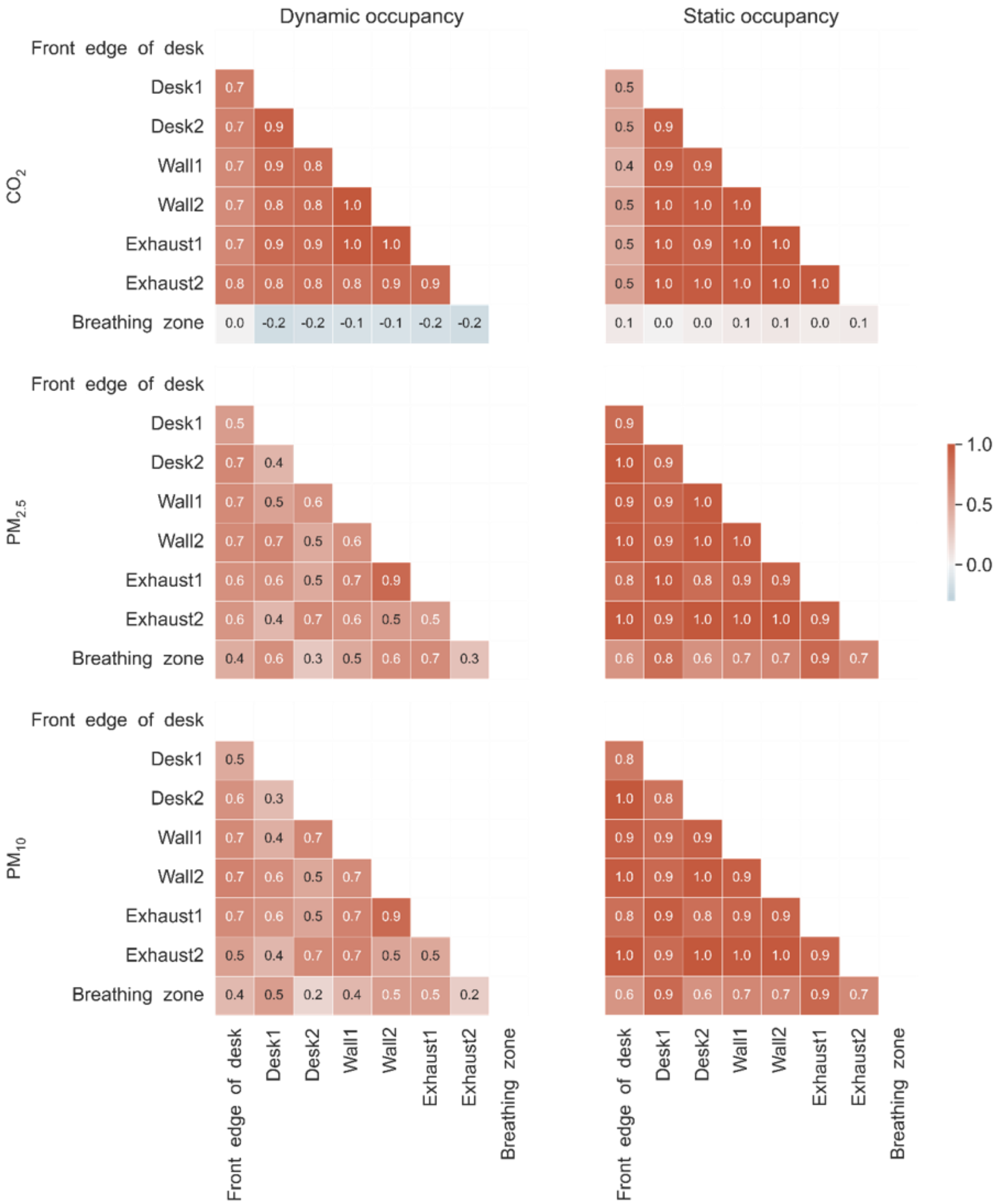

Figure 4.6 Pearson correlations between stationary and BZ measurements of CO_2, $PM_{2.5}$, and PM_{10} under dynamic and static occupancies. Correlation r is annotated in each heat map.

4.3.3 Linear regression models for personal exposure detection

4.3.3.1 Regression models under dynamic and static occupancies

The study 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 4.3. In general, the model for CO_2 exposure detection showed lower average accuracy on testing datasets (R^2 ~ 0.2) compared to the one of PM exposure detection (R^2 ~ 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 the study separated occupancy conditions to dynamic and static such as static-sitting and dynamic-standing activities (R^2 ~ 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. Figure S4.6 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 4.3), where the lowest RMSE and MAE values were generally shown. For CO_2 and PM the study 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 4.2.5) on RMSE/MAE values. Table S4.2 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.

Table 4.3 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 \ Occupancy			Sitting			Standing		
			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

4.3.3.2 Optimal stationary locations for personal exposure detection

Using a machine learning technique called Decision Tree Classifier [293], our study assessed the contributions of examined input variables on the personal exposure detection. Table 4.4 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 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 [145] and RESET v2 [144] 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 [187,188,294], 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 CO improved when the occupant activity data with time duration was considered in the space where high spatial indoor air pollution variation existed [188]. 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 [294]. The study of Pollard et al. [295] reported that the occupants' air pollution exposures in the office area were strongly correlated with the occupants movements lasting more than 10 seconds, which underlines the importance of considering the nature of occupant activities (static vs. dynamic).

Table 4.4 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**

4.4 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 [216,296], 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 [297,298].

4.5 Conclusions

Concerning limited practical solutions for detecting personal inhalation exposures directly in the breathing zone, 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, the study 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.

The study 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 discernable 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, the study 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.

This thesis chapter 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 [299]. Until this technology is applied, the proposed method can be used for more efficient personal air pollution exposure detection.

Chapter 5 Investigation of indicators for personal exposure and occupancy in offices by using smart sensors

Seoyeon Yun*, Dusan Licina

Human-Oriented Built Environment Lab, School of Architecture, Civil and Environmental Engineering, École Polytechnique Fedérale de Lausanne, Switzerland

*Corresponding author: ysy7477@gmail.com

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Edit: the introduction has been incorporated into Chapter 2, and the references and caption numbers of figures, tables, and equations have been edited to align with the respective thesis chapter number.

Abstract

Despite the advent of smart building sensors, real-time methods for capturing inhalation exposure and occupancy are limited. This study utilized stationary and wearable environmental sensors, along with Decision Tree and correlation analyses, to determine the optimal set of indicators for approximating dynamic inhalation exposures and occupancy in office environments. In a 2-week field campaign in two Swiss office buildings, real-time measures of air temperature, relative humidity, CO_2, and size-resolved particle concentrations were taken at two scales: personal – via personalized vests with sensors for personal exposure detection; and room – via stationary sensors at sidewalls and office desks. Occupancy and activity profiles were collected at three scales: personal – via smartwatches; room – via visual inspections; and building – via a cloud-based location service system. A desk-mounted CO_2 sensor in the center of an office was an effective indicator of personal exposures to CO_2, $PM_{2.5}$, and PM_{10}. Sidewall CO_2 measurements accurately captured room occupancy in open-plan offices, while desk-mounted PM_{10} sensors were effective in areas with transient occupancy (e.g., cafeteria). Findings from this study aid improved understanding of the complex dynamics of air pollutants in offices, and could support the development of refined methods for smart building monitoring and ventilation control.

5.1 Specific objectives

The study aimed to explore effective sets of indicators for detecting personal exposures to indoor air pollutants and building occupancy in real-life office settings, which have received limited attention thus far. The research question posed was: "What are the minimum but sufficient indicators for characterizing personal CO_2, $PM_{2.5}$ and PM_{10} exposure and occupancy in real office settings?" The hypothesis was that certain indicators among multi-scale sensor data would serve as better proxies for approximating personal exposures and office occupancy compared to others, consequently defining the number and type of required indicators for real-time personal air pollution and occupancy monitoring in various office settings. Firstly, the study was structured to compare stationary and personal air quality sensor measurements. Secondly, the study investigated spatial gradients of personal exposure to CO_2, $PM_{2.5}$, and PM_{10} associated with different occupant activity profiles (body posture, activity type and intensity). Further, through correlation and Decision Tree (DT) classification and regression analyses, the study sought to identify the most significant sets of indicators for personal air pollution exposure and occupancy in each of examined office settings. In details, the study objective was to emphasize the importance of tailoring sensor placement, selecting appropriate indicators, and utilizing suitable monitoring technology based on the specific characteristics of examined office spaces and occupancy profiles. By employing a different combination of environmental indicators at optimal placement, the study aimed to obtain a comprehensive and accurate understanding of both occupancy and personal exposure in real-life office scenarios. In this study, the challenges of accurately detecting exposure in relation to occupancy and occupant activities were also addressed. The importance and benefits of implementing real-time monitoring using customized cost-effective IAQ monitoring solutions in different office environments are addressed to enhance IAQ management and occupant health and well-being.

5.2 Research methodology

5.2.1 Study sites

The study conducted a 2-week long field campaign in each of the two modern Swiss office buildings located in the Romandie region of Switzerland in spring 2022. The HVAC system of the Building 1 was operational 24h (7 days a week) with occasional window opening by the building occupants, while the HVAC system of the Building 2 was only operated during 06-21h (5 workweek days) without the possibility of window opening. The ventilation strategy of the Building 1 was mixing ventilation, which is the most common air distribution method applied in commercial office buildings in Europe [282], where the air was supplied and exhausted through the diffusers at the ceiling. In Building 2, air was supplied through diffusers at the floor and exhausted through diffusers in the restrooms. The supply air temperature of both buildings was 22°C during the measurement period. As a result of the work-from-home requirement during the Covid-19 pandemic, both buildings were required to regulate the capacity of each facility to up to 50% of its maximum occupancy, excluding the external visitors. Building 1 and Building 2 had similar numbers of occupants (20-30) throughout the measurement week, which corresponded to only a quarter of the occupancy density in typical open-plan offices as defined by Standard EN15251 [284]. Table 5.1 presents the main characteristics of the two office buildings studied.

Table 5.1 Characteristics of building pairs selected as case studies.

	Building 1	Building 2
Construction year	2015	2008
Area (m^2)	1’257	1’194
No of employees	47	52
No of workstations	70	67
Mean occupancy rate (%)	30-40	40-50
Ventilation type*	Hybrid (MV+NV)	MV
Ventilation operation	24h (7 days)	06–21h (5 workweek days)
Ventilation standard compliance	SIA 382/1	
Heating/Cooling	Fan-coil floor heating Radiant ceiling (Meeting room)	Active slab + additional fan coil in the raised floor
Target areas	Open-plan office, Meeting room, Cafeteria	Open-plan office, Meeting room, Singular office

*MV: Mechanical ventilation, NV: Natural ventilation

As illustrated in Figure S5.1 of the supplementary information (SI) file, the three target areas in each of the two buildings were examined: Open-plan office (both buildings), Meeting room (both buildings), Cafeteria (Building 1), and Singular office (Building 2). The Open-plan offices were furnished with standard office furniture and middle-height dividers to separate the workstations. The Singular office of the Building 2 was a cubic shaped single-occupancy office with one desk and a chair. The Meeting room was used for occasional group meetings. The Cafeteria in the Building 2 was equipped with a coffee machine, a sink, a refrigerator, and tables for lunch.

5.2.2 Human participants

In each office building, the study recruited four office workers (“reference participants”) for personal exposure assessment and activity tracking. All participants were in a good health without any respiratory issues. Except for one case, where one participant worked in the Singular office, all participants spent most of their working hours in the Open-plan office. The participants' ages ranged from 25 to 62 years. The only female participant's BMI was 22.4 kg/m^2, whereas the BMI of all other male participants ranged from 24.8 to 31.8 kg/m^2. The participants wore a regular office spring attire (average total 0.75 Clo, including wearable experimental apparatus) and this factor was not controlled.

5.2.3 Field campaign design

To examine spatio-temporal variability of air pollution in the target areas of the two office buildings, the study performed a real-time stationary measurement of air temperature (T_a), relative humidity (RH), CO_2, and size-resolved airborne particles represented by $PM_{2.5}$ and PM_{10}. Table 5.2 summarizes the air pollutants monitored, sensor placements, measurement methods, instrument models and accuracy. The room-scale CO_2, $PM_{2.5}$ and PM_{10} measurements were taken at three stationary locations (IDs 1-3) of each examined target area: a) at two different sidewalls and b) at a single desk. Their selection was based on the established best practice in the field [102,164,165,199–201]. In addition to the stationary measurements, personal-scale CO_2, $PM_{2.5}$ and PM_{10} measurements were taken from four participants in each building by means of customized vests (ID 4). The personal vest was worn indoors during working hours. An example of the sensor placements in the Singular office of Building 2 as well as the personal vest with the mounted CO_2 and PM sensors is shown in Figure 5.1. Photos of the instrumentation in each target area are presented in Figure S5.2.

Table 5.2 Summary of IAQ sensor placement and description.

<table>
<tr><th>ID</th><th>Sensor placement</th><th>Description (Height)</th><th>Parameters monitored</th><th>Method</th><th>Model and accuracy</th></tr>
<tr><td>1</td><td>Wall 1</td><td>Sidewall (1.4 m)</td><td rowspan="4">1) Carbon dioxide (CO_2), also includes air temperature (T_a) and relative humidity (RH) records
2) Size-resolved particle number concentration</td><td rowspan="4">1) Non-dispersive infrared CO_2 sensor
2) Optical particle counter that sizes particles based on light scattering</td><td rowspan="3">1) Arve, Switzerland, measurement range: 0 to 5’000 ppm ±50 ppm
2) OPC-R2, Alphasense, 16 size bins, size range: 0.3 – 12.4 µm</td></tr>
<tr><td>2</td><td>Wall 2</td><td>Sidewall near corridor/entrance (1.4 m)</td></tr>
<tr><td>3</td><td>Desk</td><td>Desk at the center of every examined spaces (1.0 m)</td></tr>
<tr><td>4</td><td>Personal vest</td><td>Fixed in the side pocket of the experimental vest</td><td>1) HOBO MX1102, Onset Computer Corporation, USA, measurement range: 0 to 5’000 ppm, accuracy: ±50 ppm
2) OPC-R2, Alphasense, 16 size bins, size range: 0.3 – 12.4 µm</td></tr>
</table>

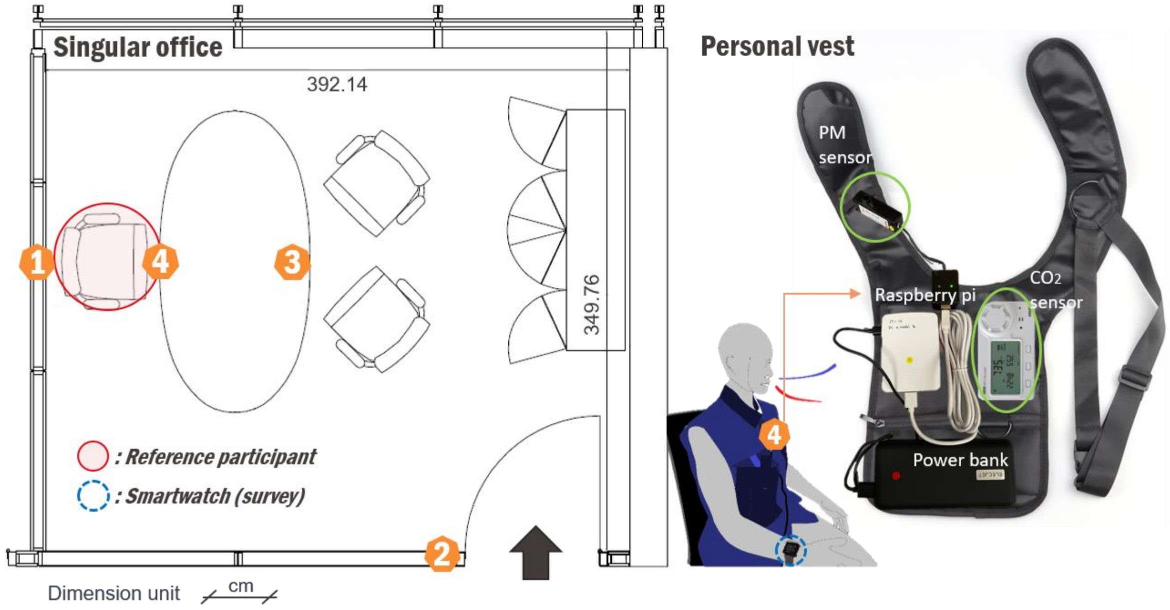


Figure 5.1 Example of sensor placement in the Singular office of Building 2 (left), and personal CO_2 and PM exposure measurement of the reference participants by using the personal vest (right). Each sensor placement is marked with an IDs which are described in Table 5.2 and in Figure S5.1. The reference participants also wore a smartwatch to report activity profiles through survey.

The study collected three types of data regarding the building occupancy number and their activities at three different scales. At the building scale, a real-time building occupancy (a total number of occupants in the entire building) was monitored at 1-min intervals by cloud-based location services (a wireless tracking service based on the IP address of present electronic devices present through access points installed in the building). This system was unable to characterize individual-room occupancy. At the room scale, one reference participant per building conducted a visual inspection of the number of room occupants at the moment of counting 3× per day. At the individual scale, four reference participants were surveyed through smartwatches with occupant feedback application called Cozie [300]. They were asked to complete a point-in-time survey concerning a body posture, activity type, and activity intensity. The detailed survey questions are presented in Figure S5.3. The survey notification was sent to the participants' smartwatches hourly from 8:00 a.m. to 18:00 p.m. using a vibration feature.

Four reference participants per building were given a general instruction on the field campaign prior to the measurements. Upon arrival at the office building, the participants were instructed on how to wear the personal vest and how to use the smartwatch. Instruments utilized in this study had one or more features of smart sensors, including real-time data collection, wireless connectivity, occupancy detection, localization and tracking, energy efficiency, user-friendly interface, and wearable solutions. In the case of the Arve environmental sensor and occupancy sensors, data was acquired wireless via a data cloud platform (i.e. Grafana). For OPC-R2, the PM data was first stored in raspberry pi and transferred later to the main laptop wirelessly using Virtual Network Computing (VNC) for data analyses. CO_2 data stored in HOBO sensors was extracted using HOBOware after the measurement, as the sensor itself did not have wireless capability. The ethical and safety considerations for the field campaigns were approved by the Human Research Ethics Committee of EPFL.

5.2.4 Data analysis

The study included data collected during business hours only (07-19h) and during the time when workers wore their personal vests. The obtained personal CO_2 and PM data was split into each target area based on the participants' location response on their smartwatches, which corresponds to ~10% of the total amount of data collected. The building occupancy data acquired per minute interval was averaged into 5 minutes in order to remove noisy data, which corresponds to ~20% of the total amount of data collected. Python 3.10.7 with scikit-learn library [290] was used as a programming language.

The study first compared stationary and personal CO_2, $PM_{2.5}$ and PM_{10} measurements. The study then investigated the personal air pollution exposures in relation to their activity profiles (body posture, activity type, and activity intensity). The study presented heat maps with Pearson correlation r values between stationary CO_2 and PM_{10} measurements and building and room occupancy to further examine the correlation between the investigated parameters. When the Pearson r coefficient is close to ±1, there is likely to be a strong linear relationship between the measured variables [269].

The study introduced Decision Tree (DT) classification and regression analysis, which is a machine learning algorithm that builds a tree-like structure of if-else conditions based on input indicators to make predictions about the class or category of a given instance [292,301]. This algorithm splits the data recursively based on the most informative indicators, where the indicator that appears at the top of the tree, or at earlier splits, is considered more informative, as it has the most significant impact on the classification decision. DT analysis can be more useful than other machine learning models, such as Random Forests, in certain situations because it provides a transparent and interpretable decision-making process. This makes it easier to understand the logic behind predictions and identify the most influential features in the dataset. Furthermore, Decision Trees are non-parametric models, which means they make no assumptions about the distribution of data. This flexibility was specifically advantageous for this thesis that include field tests where the data may be non-linear or have complex relationships.

Before implementing DT analyses, datasets were prepared as clean sets while handling missing values, and encoding categorical variables. In DT classification, all indicators (also called variables) defining each scenario are first described (as input data) prior to choosing an indicator that will serve as a decision for the given problem (output data) [301]. *Max_depth* is parameter in the Decision Tree Classifier determines the maximum depth or the maximum number of levels the decision tree can grow. While constructing DT model, the study experimented different *max_depth* values to avoid overfitting the model and to find the optimal *max_depth* for our models. The *criterion* parameter specifies the function used to measure the quality of a split when constructing the DT, where the study chose *entropy* as our *criterion*. *Entropy* is a measure of impurity or disorder in a set of data. When building the tree, the algorithm aims to reduce *entropy* at each split. In other words, it selects the features that minimize *entropy*, leading to a more informative and effective split. The *accuracy_score* in a DT classification model is a metric that quantifies the proportion of correctly classified instances out of the total number of instances, providing a measure of the overall prediction accuracy of the model [302,303]. For instance, an *accuracy_score* of 0.85 means that the model predicted the correct class for 85% of the instances. Based on the practice in the field, the study defined "moderate", "good", and "excellent" accuracies of the DT classification model as *accuracy_score* of "0.5–0.7", "0.7–0.9", and ">0.9", respectively [304–306]. Two DT classification analyses were carried out independently to ascertain the most beneficial indicator for each output, as shown in Figure 5.2. To be utilized as inputs alongside the physical factors in a classification, dummy variables were generated for categorical parameters.

While using same input and output variable as explained above, the study conducted DT regression analysis. The study randomly divided the data into two parts – 80% for training and 20% for testing the model, as is frequently recommended [307,308]. The performance of developed regression model was presented as R^2 score (coefficient of determination). R^2 provides a measure of how well your regression model explains the variability in the target variable. It ranges from 0 to 1, where 0 indicates that the model does not explain any variability, and 1 indicates a perfect fit. The regression analyses were separately conducted for estimating the two outputs: 1) personal exposure and 2) occupancy. The data collected from two Open-plan offices and two Meeting rooms from each building were pooled to construct separate DT models for personal exposure detection – one for the Open-plan office and the other for the Meeting room.

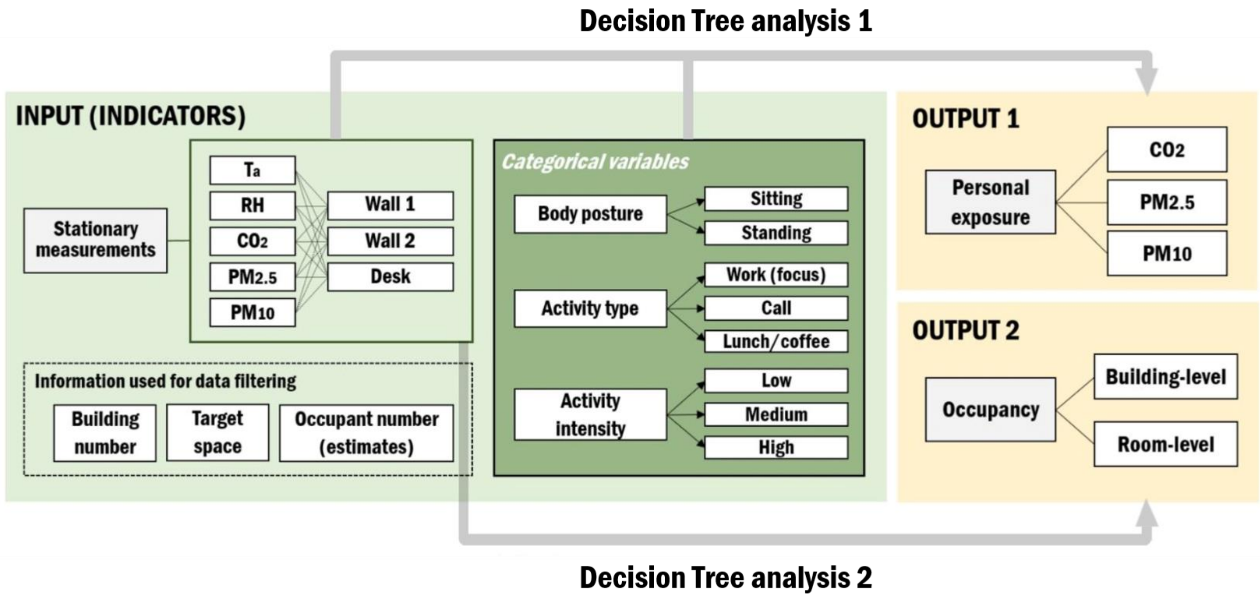


Figure 5.2 Input and output variables for composing Decision Tree classification and regression models for detecting personal CO_2, $PM_{2.5}$, and PM_{10} exposures and occupancy. Categorical variables were only used as indicators in case of Decision Tree analysis 1.

Finally, the study reported the type and number of the best indicators orderly ranked by their feature importance (predictive power, described by *accuracy_score*) for characterizing personal exposure and occupancy. This analysis is useful for determining the optimal number and type of indicators (sensors) in various office settings.

5.2.5 Quality assurance

All air quality sensors were calibrated ahead of the field campaign in a controlled climate chamber. Four HOBO® MX CO_2 loggers and 18 ARVEs were inter-calibrated based on the linear correlation with the high-accuracy CO_2 analyzer (LI-850, LI-COR Biosciences GmbH, Germany, measurement range: 0 to 20’000 ppm, accuracy: ±1.5%). The particle counters (four OPC-R2s and 18 ARVEs) were compared against the reference high-accuracy optical particle counter (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). The PM mass concentration (µg/m^3) of the reference high-accuracy particle counter was estimated from the measured number concentration by assuming that particles are in spherical shape with a 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 [268]. The obtained mass concentrations were compared against those directly reported by the particle counters used in the study. The correction factors obtained from the side-by-side instrument performance tests are presented in Table S5.1.

Previous studies [285,286] have shown that only measurements in the inhalation zone (nose or mouth) during the inhalation phase can accurately represent CO_2 exposures. However, such measurements are practically challenging in field tests involving human participants. To understand the associated uncertainty, this study compared the CO_2 levels measured by a sensor attached to the personal vest with the measurements taken directly in the breathing zone by the high-accuracy CO_2 gas analyzer (Li-COR) on one reference participant (Figure S5.2). From the high-accuracy CO_2 sensor, the study obtained the CO_2 exposure results by selecting only the minimum CO_2 sampling point within one respiratory cycle, as proposed by Yun et al. [287]. The differences between the high-accuracy CO_2 gas analyzer and the personal vest were relatively small – 30 ppm mean and 150 ppm median (Figure S5.4).

5.3 Results

Section 5.3.1 reports descriptive results comparing stationary and personal measurements in all target areas of the two buildings. The section 5.3.2 summarizes the variation of personal air pollution exposure results with various occupant activity profiles. The section 5.3.3 investigates linear correlation between stationary CO_2, PM_{10} and occupancy. Finally, section 5.3.4 presents DT classifications and regression models developed for characterizing personal air pollution exposures (section 5.3.4.1) and estimating building and room occupancy (section 5.3.4.2) while highlighting the optimal set of the indicators, namely their type and number.

5.3.1 Comparison of stationary and personal sensors measurements

The study firstly examined the spatial variation of air pollutant concentrations measured at the personal locations of four participants and at different stationary locations in each of the two office buildings (Table 5.3). The time-averaged CO_2, $PM_{2.5}$ and PM_{10} concentrations in each space type were generally low, which the study attributed to the large office volume, reduced occupancy and ventilation system. The air pollutant concentrations were substantially lower than those measured in other offices [94–96,309]. Among the stationary placements, the average CO_2 mixing ratios were in the range of 430-510 ppm range, which was within the recommended CO_2 threshold (800 ppm) proposed by green building standards [144,145]. The average $PM_{2.5}$ levels were in the range of 2-5 µg/m^3 and PM_{10} in the range of 3-8 µg/m^3, which were kept lower than the annual limits for $PM_{2.5}$ and PM_{10} (<5 µg/m^3 and <15 µg/m^3, respectively) recommended by the World Health Organization (WHO) [147]. The study observed ~1.5× higher average stationary PM_{10} levels in the Cafeteria in which occupant activities were more dynamic compared to the Meeting room.

As shown in Table 5.3, the average personal concentrations were 1.2–1.3× higher than stationary concentrations for CO_2 and 1.8–2.5× higher for PM_{10}, as would be expected due to localized respiratory emissions (CO_2) and coarse particle emissions through shedding and resuspension (PM_{10}). The variability (SD) of CO_2 and PM_{10} levels at the personal level was 2–3× higher and 6–11× higher, respectively, than that of stationary placements, as expected for highly unsteady microenvironments around a human body [13,191,310]. The study further presents box plot statistics of CO_2, $PM_{2.5}$ and PM_{10} levels at nine stationary sensor placements (Figure S5.5) and at the personal levels of four reference participants (Figure S5.6) in each building.

Table 5.3 Average ± standard deviation concentrations of CO_2, $PM_{2.5}$ and PM_{10} recorded with three stationary sensors in each target area and with personal vests of four participants in each building. The reported values refer to business hours only.

Sensor placement			CO_2 (ppm)	$PM_{2.5}$ (µg/m^3)	PM_{10} (µg/m^3)
Building 1	Stationary	Cafeteria	430 ± 40	4.7 ± 2.4	7.7 ± 4.0
		Open-plan office	490 ± 50	4.4 ± 2.1	7.2 ± 3.5
		Meeting room	480 ± 70	3.0 ± 1.6	4.9 ± 2.7
	Personal vest		630 ± 150	2.6 ± 2.5	12.4 ± 18.0
Building 2	Stationary	Singular office	440 ± 50	2.1 ± 1.3	3.4 ± 2.1
		Open-plan office	490 ± 50	2.4 ± 1.5	3.9 ± 2.5
		Meeting room	510 ± 70	3.0 ± 2.9	5.0 ± 4.7
	Personal vest		590 ± 100	1.6 ± 1.6	10.4 ± 23.6

5.3.2 Personal exposure in relation to occupant activities

The study compared the air pollution exposure information collected from the reference participants' personal vests with their activity profile data (body posture, activity type and activity intensity) collected from their smartwatches. Figure 5.3 shows that the personal PM_{10} concentrations of four participants were generally strongly influenced by the participants' body posture, activity type and activity intensity. Compared to sitting, standing resulted in 1.5-1.8× higher average personal PM_{10} levels. These concentrations were also significantly higher compared to the whole-day time-averaged concentrations reported in Table 5.3. The higher intensity of occupancy activities is usually associated with standing activities, which are linked to increased dermal emissions of particles from humans and resuspension from the floor and furniture [120,311–313]. The average personal PM_{10} levels of the participants during the lunch/coffee and call activities were 1.5-1.9× higher than during the basic work activity.

In Figures S5.7 and S5.8, the study presents the average and SD of the personal $PM_{2.5}$ and CO_2 concentrations of four participants in relation to their activity profiles. The results for $PM_{2.5}$ were relatively similar to those reported for PM_{10}. Interestingly, for CO_2, the personal-level concentrations were higher during sedentary activities. The study hypothesizes that localized respiratory emissions of CO_2, combined with reduced air mixing during sitting, resulted in stronger spatial gradients around the participants, as has been similarly documented in previous studies [10,13,286].

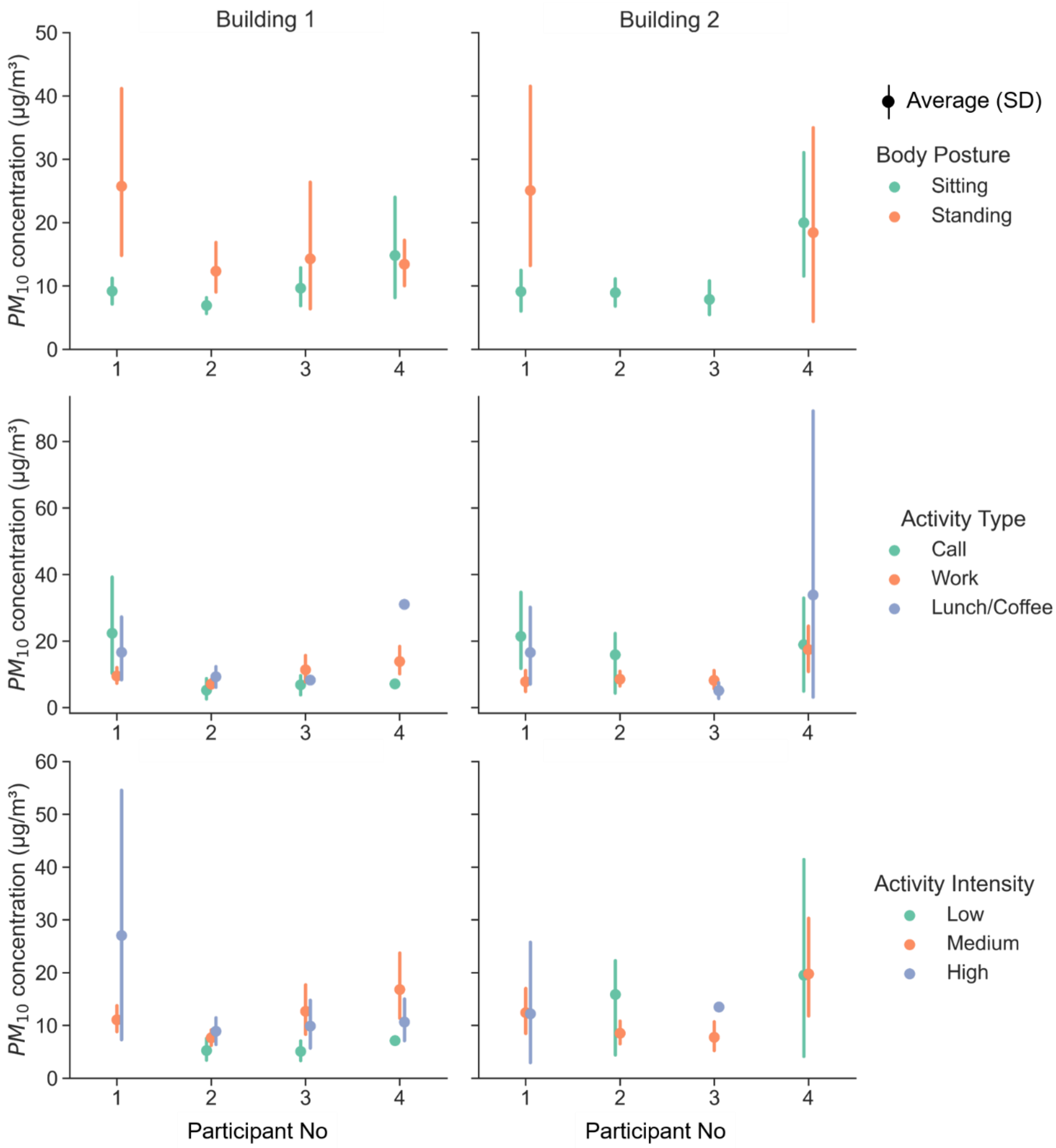


Figure 5.3 Average and standard deviation of personal-level PM_{10} concentration in relation to point-in-time activity profiles of four participants (Participant No. 1-4) in the two office buildings.

5.3.3 Correlation analysis between stationary CO_2, PM_{10} and occupancy

CO_2 and PM_{10} were selected to be correlated with occupancy because CO_2 is a good marker of human metabolic emissions and PM_{10} is primarily derived from the resuspension of coarse particles due to human activities. Figure 5.4 provides heat maps illustrating the correlation values (annotated as "r") between the examined parameters, including building and room occupancy, CO_2, and PM_{10}, for the three target office areas in Building 1. The correlation heat maps for Building 2 are shown in Figure S5.9.

Overall, the correlation between building occupancy (Building_occ) and the stationary CO_2 or PM_{10} levels in individual rooms was limited (r ~ 0.3), indicating that the specific room environmental conditions do not linearly encompass the number of occupants in the entire building. However, the study observed an average correlation 1.6× higher between stationary CO_2/PM_{10} levels and room occupancy (Room_occ) than those of building occupancy. Notably, in the Open-plan office and the Meeting room, room CO_2 levels exhibited a significant correlation ($r > 0.7$) with Room_occ. In the Cafeteria, where occupancy changes frequently, the PM_{10} levels measured at the desk (lunch table) showed a strong correlation ($r > 0.7$) with room occupancy, while the correlation between occupancy and CO_2 levels was low ($r < 0.3$). The occurrence of negative correlation coefficients (r values) might arise from discrepancies between the timing of occupancy detection and environmental sensor readings, or from the heterogeneity in the distribution of air pollutants within office spaces.

Overall, the placement of stationary sensors within a space significantly influenced the correlation with room occupancy, with up to 40% variation for CO_2 and up to 350% variation for PM_{10}. This highlights the importance of sensor placement for accurate room occupancy detection. Room CO_2 levels proved to be a useful proxy for room occupancy in spaces where there was sufficient time for CO_2 to accumulate due to prolonged occupancy, such as in the Open-plan office and Meeting room. Conversely, in spaces like Singular offices occupied by a single individual, the desk-mounted PM_{10} sensor outperformed the CO_2 sensor in inferring the room occupancy.

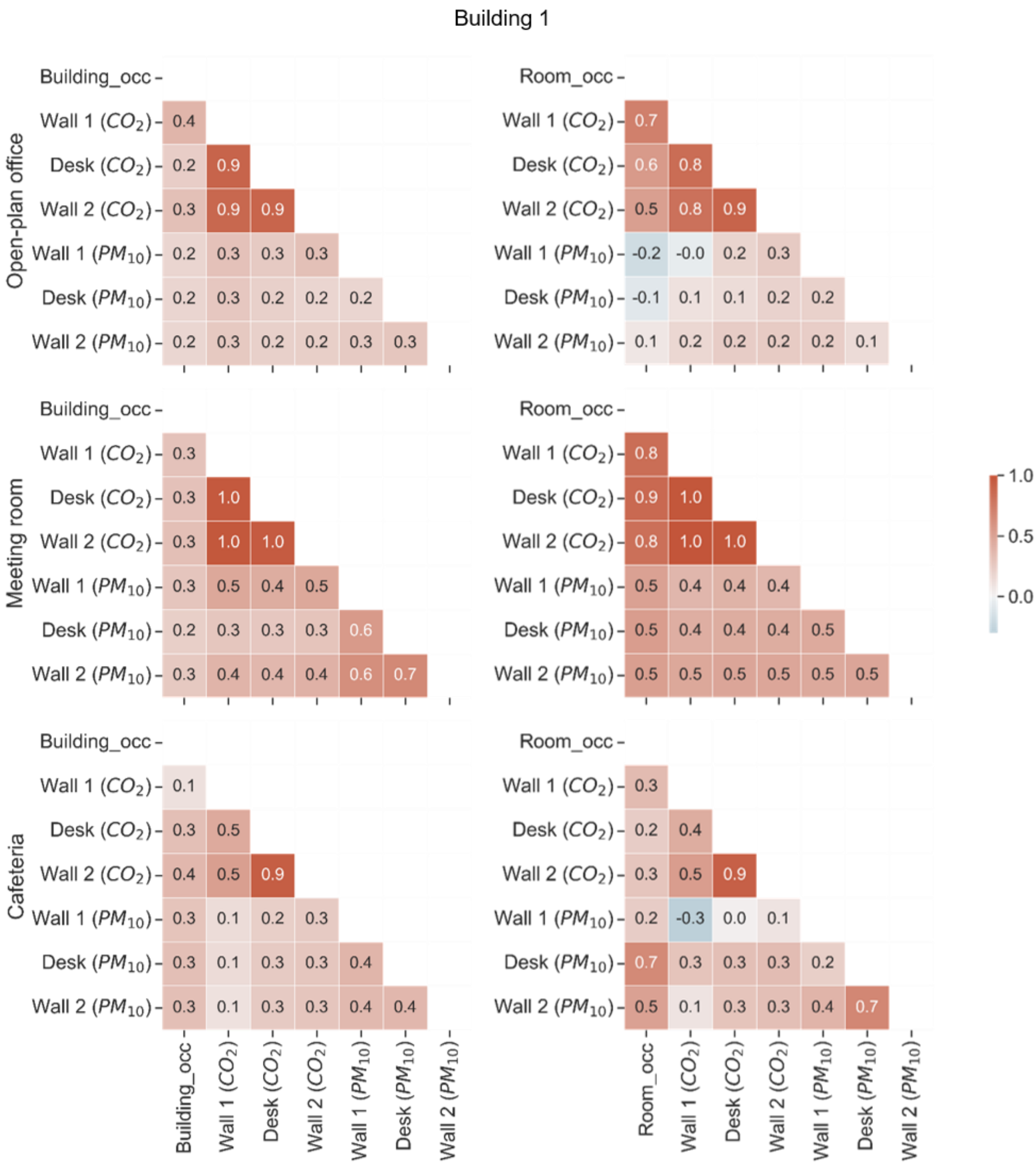


Figure 5.4 Heat maps annotated with correlation r values between building occupancy (Building_occ), room occupancy (Room_occ), CO_2 and PM_{10} levels at three different stationary placements of each examined target area of Building 1.

5.3.4 Decision Tree classification and regression analyses

5.3.4.1 Decision Tree classification and regression for personal exposures

Classification models were developed to estimate personal air pollution exposures to CO_2, $PM_{2.5}$ and PM_{10} in each of the office area studied. Room-stationary T_a, RH, CO_2, $PM_{2.5}$ and PM_{10} levels measured at three stationary locations of each target area and activity profile data of four participants (body posture, activity type and activity intensity) were utilized as the inputs, while the personal-level CO_2, $PM_{2.5}$ and PM_{10} concentrations were used as the output variables. Data from two Open-plan offices and two Meeting rooms in Building 1 and Building 2 were combined and used to create separate DT models for the Open-plan office and the Meeting room. Figure 5.5 shows the number and type of indicators used for characterizing personal CO_2, $PM_{2.5}$ and PM_{10} exposures in the Open-plan office along with their accuracy scores. On the x-axis, the input parameters are sequentially numbered from 1 to 18 based on their relative importance in contributing to the model's accuracy. On the y-axis, the accuracy score is plotted against the number of indicators utilized in the model. Figure S5.10 shows the corresponding results for the Meeting room, the Singular office, and the Cafeteria. Along with all indicators, the study presents the minimum but sufficient set of indicators that surpass the defined “good” accuracy (*accuracy_score* > 0.7).

Overall, the performance of the generated DT models was strong (R^2 > 0.9) on both the training and testing datasets, except for the Cafeteria where the average model performance on the testing data was relatively low (R^2 ~ 0.5). Figure 5.5 shows that the stationary CO_2 sensor positioned at the occupant desk in the center of the room was the most effective indicator for detecting the inhalation exposures to CO_2, $PM_{2.5}$ and PM_{10} in the Open-plan office. In contrast to $PM_{2.5}$ exposure prediction, where one stationary monitor was sufficient, an additional monitoring of CO_2 levels in the target room (on the sidewall) was required to achieve a sufficient accuracy (*accuracy_score* > 0.7) in detecting inhalation CO_2 and PM_{10} exposures. This is because CO_2 and PM_{10} are major occupancy-associated air pollutants, and thus contribute to higher spatial gradients as shown in Table 5.3 and in other studies [10,95,182,314,315]. Furthermore, the study results indicate that in the Open-plan office, the inclusion of stationary RH sensors could further enhance the accuracy of exposure detection. However, the study results show that the room air pollution data (CO_2 and PM_{10}) were on average 1.1-4x more useful than the indoor climate data (T_a, RH) for capturing personal air pollution exposures to CO_2, $PM_{2.5}$ and PM_{10} in terms of individual predictive power (Table S5.2).

Figure S5.10 illustrates that achieving “good” accuracy in exposure estimation (*accuracy_score* > 0.7) was feasible with one or two environmental indicators among CO_2, RH, and PM_{10} levels in the Meeting room and the Singular office. In the Cafeteria, at least four to five indicators, including occupant activity profiles were required to achieve "good" accuracy in estimating personal CO_2 and PM_{10} exposures. A stationary PM_{10} sensor has proven to be particularly effective in detecting personal exposure to both CO_2 and PM_{10}. This effectiveness can be attributed to the strong correlation observed between PM_{10} levels and occupant activities [10,183,316,317]. This highlights the importance of monitoring both air quality indicators and occupant activities for estimating personal air pollution exposures in the spaces with transient occupancy spaces (e.g., cafeteria).

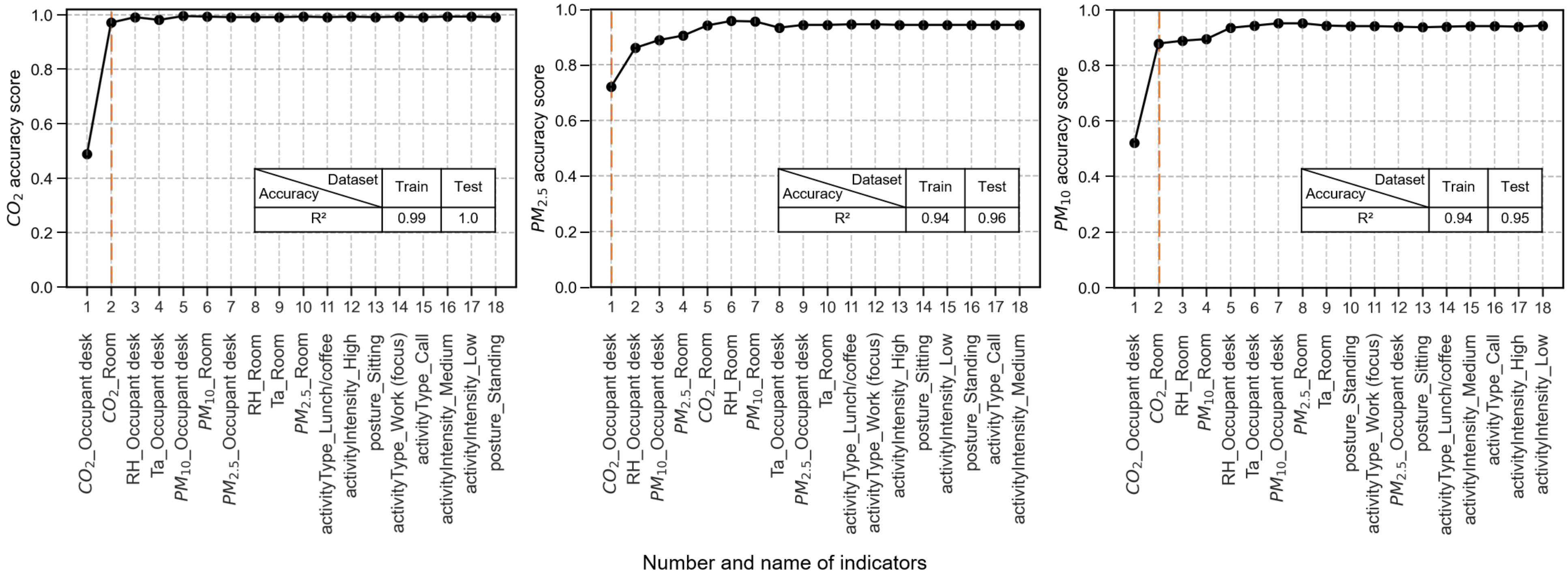


Figure 5.5 Number and name of the indicators and their accuracy scores for characterizing personal CO_2, $PM_{2.5}$ and PM_{10} exposures in Open-plan office. The data from two Open-plan offices of Building 1 and Building 2 were used in constructing presented DT model. The indicators are named based on either type/placement of environmental sensors or occupant activity profiles, and they are ranked in order of their importance, from the highest (left) to the lowest (right). The vertical dashed lines indicate the minimum but sufficient set of indicators that can capture personal exposures to CO_2, $PM_{2.5}$ and PM_{10} with a "good" accuracy (*accuracy_score* > 0.7). The estimation performance (R^2) of proposed Decision Tree regression model in the best case (*accuracy_score* > 0.7) using train (80%) and test (20%) dataset is shown as a table.

5.3.4.2 Decision Tree classification and regression for occupancy

The study also developed the DT classification and regression models for estimating building and room occupancy (number of occupants) based on stationary environmental sensors. The datasets were split into each target area of the two examined buildings. The number and type of indicators used for characterizing occupancy at building and room scale are presented with their accuracy scores in Figure 5.6 (Open-plan office) and Figure S5.11 (Meeting room, Singular office, and Cafeteria). On the x-axis, the input parameters are sequentially numbered from 1 to 15 based on their relative importance in contributing to the model's accuracy. On the y-axis, the accuracy score is plotted against the number of indicators utilized in the model.

The DT model exhibited an average accuracy that was higher when estimating room occupancy (R^2 = 1.0) than when estimating building occupancy (R^2 = 0.85). This difference in accuracy can be attributed to the utilization of a cloud-based location software for capturing the number of occupants in an entire office floor, which resulted in poorer estimation accuracy compared to direct visual inspection of room occupancy. Furthermore, the building occupancy encompassed short-term external visitors, potentially undermining the correlation between occupancy and environmental conditions, whereas room occupancy predominantly pertained to the number of occupants engaged in prolonged stays in specific areas.

The study findings indicate that accurate occupancy estimation can be achieved at both building and room levels using a single indicator, namely CO_2 levels, with a consistently "good" accuracy (*accuracy_score* > 0.7). Specifically, Figure 5.6 shows that the installation of a single CO_2 sensor on the sidewall of the Open-plan office can effectively estimate the number of occupants at both room and building levels. The detection of room occupancy had "excellent" accuracy (*accuracy_score* > 0.9) in all the offices examined. This finding supports previous studies that have also established the reliability of CO_2 levels as a measure of occupancy in office buildings [210,318,319].

In addition to the sidewall-mounted CO_2 sensor being the most reliable single indicator, Figure S5.11 demonstrates that a PM_{10} sensor mounted on a desk was also effective in detecting the number of occupants in the Meeting room, Singular office, and Cafeteria. These findings align with previous studies that have explored the relationship between coarse particle levels and occupancy patterns [120,320–322].

Table S5.3 lists the key indicators in order from the highest to the lowest contribution to the estimation accuracy of the models. It shows that the stationary T_a and RH levels could also be useful for inferring the building occupancy in offices, but were the less optimal indicators by 70% and 40% respectively compared to the stationary CO_2 or PM_{10} levels.

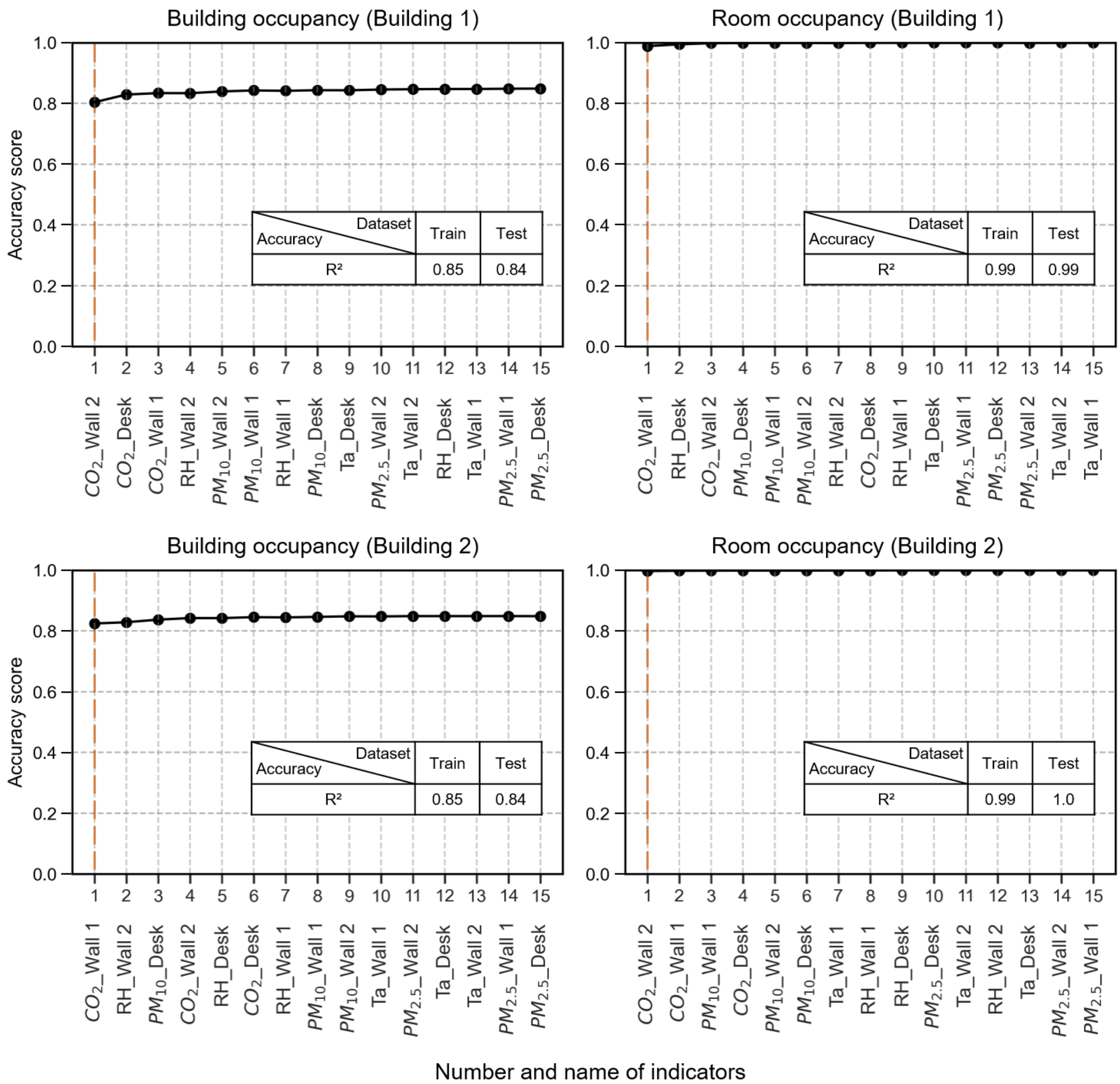


Figure 5.6 Number and name of the indicators and their accuracy scores for characterizing occupancy at building and room scale in Open-plan office of Building 1 and Building 2. The indicators are named based on the type and placement of the sensor, and they are ranked in order of their importance, from the highest (left) to the lowest (right). The vertical dashed lines indicate the minimum but sufficient set of indicators that can capture personal exposures to CO_2, $PM_{2.5}$ and PM_{10} with a "good" accuracy (*accuracy_score* > 0.7). The estimation performance (R^2) of proposed Decision Tree regression model in the best case (*accuracy_score* > 0.7) using train (80%) and test (20%) dataset is shown as a table.

5.4 Discussions

5.4.1 Practical insights for exposure and occupancy detection

The study findings provide valuable insights into exposure and occupancy detection in offices by using proxy indicators. The results could be used to drive cost-effective decision making related to the importance of sensor placement and the number of sensors. Desk-mounted CO_2 sensors were particularly useful for detecting air pollution exposures in the Open-plan office, as they were located close to the breathing zone of seated occupants. A single sidewall-mounted CO_2 sensor accurately indicated room occupancy in areas with prolonged human presence, such as open-plan offices and meeting rooms. Monitoring additional CO_2 or RH levels at the sidewall or desk in open-plan offices did not meaningfully enhance the accuracy of occupancy estimation. Desk-mounted PM_{10} sensors proved valuable for inferring room occupancy and personal PM_{10} exposures in areas with episodic occupancy, such as the Cafeteria, by capturing fluctuations in particulate matter concentrations caused by occupant presence and activity. The study findings revealed that while indoor climate data controlled by HVAC systems, such as room T_a and RH, were not as effective as air pollution data in exposure or occupancy detection, they offered supplementary information. Since office buildings commonly have T_a monitoring in place, leveraging this existing dataset can be valuable in combination with air pollution data to improve the accuracy of personal air pollution exposure and occupancy detection.

In the future, wearable sensors such as smart watches and user-friendly portable IAQ sensors may be utilized to enhance the accurate measurement of personal exposures in office buildings [323,324]. Until wearable technology reaches a more advanced stage, the study can continue to rely on stationary sensors for quantifying personal exposures effectively in real office buildings. The study recommends the installation of a single stationary monitor with a CO_2 sensor on the sidewall in spaces with prolonged occupancy (e.g., open-plan offices), as a comprehensive and cost-effective solution for personal air pollution detection. In office spaces with dynamic occupancy changes, monitoring occupant activities along with CO_2 or PM_{10} concentrations at stationary locations can provide valuable insights. By utilizing a combination of sidewall-mounted CO_2 sensors, desk-mounted PM_{10} sensors, and indoor climate data, a comprehensive and accurate understanding of personal exposure and occupancy can be achieved in all office spaces.

The implications of this study extend beyond immediate monitoring benefits, offering valuable insights for various building stakeholders for workspace design and building HVAC management. Firstly, the findings underscore the significance of adopting an occupant-centric approach, facilitated by the utilization of smart sensors. These sensors provide real-time personal exposure and occupancy data at different scales, enabling building designers and facility managers to optimize spatial layouts, ventilation strategies, and resource allocation, ultimately fostering healthier and more comfortable office environments that cater to the diverse occupant needs. Secondly, this study introduces a data-driven decision-making paradigm for office settings. By leveraging insights from sensor data, building owners and facility managers can implement targeted interventions based on evidence, such as adjusting ventilation, encouraging appropriate occupant action (e.g. window opening), or controlling sources. Ultimately, building occupants could gain improved indoor comfort, health, and well-being, enhancing productivity and satisfaction. Building owners benefit from optimized energy use through improved HVAC control, potential cost savings, enhanced IAQ, higher tenant retention, and a positive real estate market reputation. However, this study also recognize potential challenges. Initial costs for smart sensor deployment, data management, and maintenance may pose a concern. Integrating new technologies could necessitate organizational and employee adjustments. Ensuring data privacy and security is essential due to ethical and regulatory considerations. Hence, careful planning and stakeholder engagement are necessary to maximize positive impacts while mitigating potential negatives, as with any technology implementation.

5.4.2 Study limitations

Several limitations could interfere with generalizing the study results. The study was restricted to the two case study buildings with a particular orientation, layout, interior design, and occupancy profile; therefore, the findings may not be generalizable to other types of office buildings. The present study has solely focused on indoor environmental factors within the office buildings, without concurrent monitoring of the corresponding outdoor environmental conditions. The results could not be extrapolated to the whole population due to the limited number of reference participants (four per building). Personal-level measurements could misrepresent the true exposure, as measurements were not made directly in the breathing zone, as reported in several studies [216,296,325]. The study accounted for this effect for CO_2 by supplementary measurements directly in the breathing zone (Figure S5.4). In the context of an Open-plan office (Figure 5.5), the study found that the Decision Tree model for exposure detection had a higher R^2 value on the testing dataset compared to the training dataset. This discrepancy could be due to the Decision Tree model being overly complex, leading it to capture noise within the training data and consequently struggle to make accurate generalizations when applied to the test data. Additionally, the experimental solution may not be applicable in a real office setting given the high degree of measurement intrusiveness to the participants (e.g., a wearing a personal vest in offices). Wearable sensors (smart watches) and portable IAQ sensors with user-friendly designs could be employed in future studies to analyze personal exposures in real office settings [297,298].

5.5 Conclusions

Occupancy and occupant activities are drivers of spatial and temporal indoor air quality (IAQ) variations which pose challenges for accurate exposure detection. In this study, both personal exposures and office building occupancy were approximated by real-time measurements at three scales: personal (using customized IAQ vests and smartwatches), room (using stationary IAQ sensors and visual inspections), and building (using a cloud-based monitoring system). By combining the multi-scale sensor data with Decision Tree classification and regression analyses, the study identified the most effective indicators of personal inhalation exposure and occupancy.

The study found that occupancy triggers strong spatio-temporal gradients of CO_2 and PM_{10}, emphasizing the importance of ubiquitous real-time monitoring in office buildings. Participants' body posture, activity type, and activity intensity were strongly linked to personal exposure. Correlation analyses revealed that room CO_2 levels can act as a reliable indicator of room occupancy in spaces with prolonged occupancy (e.g., open-plan offices), while desk-mounted PM_{10} sensors are more effective in determining occupancy in areas with transient occupancy (e.g., cafeteria). The DT analyses showed that the most cost-effective solution for both personal exposure and occupancy detection was to install an environmental monitor, including CO_2 sensor, on the sidewalls in the areas with prolonged occupancy. Indoor climate data (T_a, RH) were less effective indicators for detecting exposures and occupancy than air pollution data, with up to 4× less predictive power.

This research provides real-time estimation of personal exposure and occupancy using smart sensing technologies in offices, offering insights to improve IAQ management and promote healthier working environments. The findings support the implementation of occupant-centric building ventilation strategies to enhance IAQ, occupancy management, and energy efficiency. By utilizing indirect indicators such as IAQ metrics for occupancy detection, privacy concerns associated with traditional methods (e.g., camera-based systems) can be minimized.

Moving forward, there are several avenues for future research. One area of exploration could involve validating the findings in different office spaces with various ventilation rates/strategies to assess the generalizability of the identified indicators. Additionally, analyzing occupant activity profiles with consideration of gender and age could lead to more customized HVAC solutions tailored to specific demographic groups. Further investigations could also delve into the potential integration of real-time sensor data with building automation systems, enabling dynamic adjustments in response to dynamic occupancy patterns and needs. Furthermore, investigating the long-term financial implications of enhanced indoor air quality on occupant health and productivity has the potential to quantify the broader significance of occupant-centric ventilation strategies. This analysis could provide a monetary perspective that encourages stakeholders to invest in these strategies, recognizing the tangible benefits they offer. As smart sensing technologies continue to evolve, future studies could bring the potential of advanced data analytics and machine learning techniques for even more precise exposure and occupancy predictions.

In conclusion, this study offers guidance for building management stakeholders on the optimal indicators for accurate detection of personal air pollution exposures and occupancy, while considering cost-effectiveness. These insights are instrumental in establishing occupant-centric ventilation control strategies in energy-efficient office buildings, ultimately contributing to healthier and more productive indoor environments.

Chapter 6 Discussions

This thesis significantly contributes to understanding inhalation exposures and occupancy dynamics in buildings, with a particular focus on detecting human air pollution exposures and occupancy in diverse office environments. While the findings offer practical implications for field application, it is important to acknowledge certain limitations that should be considered for future implementation. Section 6.1 provides serves as a general discussion to integrate and mutually analyze the results and findings from Chapters 3, 4, and 5, addressing the key shortcomings identified in the thesis. Section 6.2 presents broader perspectives on research and practical implications.

6.1 Integrative discussions and limitations

Indoor spaces are subject to spatio-temporal variations in pollutant concentrations due to factors such as occupancy patterns, ventilation, and emission sources. The significant difference between inhalation exposure of an occupant and room air pollution levels was also identified. Regarding occupancy dynamics, the thesis has demonstrated the importance of differentiating static from dynamic indoor environments and considering occupancy profiles when characterizing exposures to CO_2, $PM_{2.5}$, and PM_{10}. Previous studies [12,191] have also emphasized the significance of occupant activities on evaluating personal air pollution exposures. Therefore, a more accurate assessment of inhalation exposure requires accounting for these variations in occupancy dynamics.

The investigation conducted in this thesis has highlighted the limitations of assuming indoor spaces to be well-mixed. For instance, the detected spatio-temporal variation of indoor air pollution in office environments (both controlled chamber experiments and field tests) indicates that air pollutant concentrations can vary significantly according to different zones of a building and occupancy dynamics. Hence, the assumption of well-mixed air in indoor environments might oversimplify the actual distribution of pollutants. To address this, multi-zone modeling for DCV based on parameters [326,327] can be considered to optimize ventilation air volumes of individual room and primary air handling unit of office buildings. This approach divides spaces into different zones based on ventilation characteristics, sources and occupancy density. CFD simulation can be also helpful to be combined with the actual measurement indoors to provide more accurate representations of pollutant dispersion and help in identifying areas of higher exposure risk [105,328,329]. By understanding spatio-temporal variations with appropriate measures, building managers can implement targeted IAQ strategies for specific zones to improve inhalation exposure estimation and overall IAQ.

The thesis underscores the feasibility and effectiveness of proxy methods for estimating inhalation exposures to CO_2, $PM_{2.5}$ and PM_{10} in typical office environments. These proxy methods, including stationary IAQ monitoring, wearable physiological measurements, and human presence detection, offer valuable alternatives to traditional stationary IAQ measurements. For instance, the significant advancement in CO_2 exposure detection, especially when combining human physiological parameters, can be attributed to human metabolism, as both human CO_2 emission and physiological markers such as skin temperature and heart rate exhibit a positive linear relationship with human metabolic rate [330,331]. By combining multiple sensing techniques, stakeholders can gain a better understanding of real human exposure to air pollutants and enhance IAQ management in buildings. Optimal placement of a single stationary air quality monitor can be a practical solution, minimizing initial costs and maintenance fees. However, the adoption of combined monitoring strategies, integrating environmental, physiological, and contextual parameters, can further minimize potential errors resulting from suboptimal monitor placement.

The thesis's findings align with previous researches [11,102,186–188] on sensor proximity to the reference occupant and ventilation rate/strategy, which influence exposure detection accuracy, while highlighting the significance of sensor positioning when it comes to accurately measuring indoor air pollution and exposure levels. The proximity effect observed between the sensor and the target occupant emphasizes the need for thoughtful and strategic sensor placement. Placing sensors nearby target occupants in areas with prolonged occupancy can yield more representative measurements of inhalation exposure levels in office buildings, thus enabling better-informed decisions for IAQ management. For instance, identified best locations for stationary air quality sensors were desk-mounted CO_2 sensors and ceiling-mounted exhaust for PM sensors near target occupant (< 1–1.5 m), can accurately approximate personal exposures in simulated office environments. This proposition complies with recommended sensor placement by previous studies [102] and common practices [203,204]. As previous researchers noted [332–334], incorrect sensor placement can lead to erroneous HVAC adjustments and result in occupant discomfort and increased energy demand. Therefore, implementing these optimal sensor locations can lead to more efficient and cost-effective methods for estimating human inhalation exposures while securing human health and well-being in offices.

The thesis discusses the minimum yet sufficient sets of indicators that can be applied in real-life office settings, overcoming the limitations of controlled chamber studies mentioned in Chapters 3 and 4. These indicators serve as practical recommendations for inhalation exposure and occupancy detection in various office environments while considering the cost-effectiveness of sensors and implementation feasibility. The thesis proposes the most effective sets of indicators that can be used to approximate inhalation exposure and occupancy in each of the various office settings. Desk-mounted CO_2 sensors were found to be particularly valuable in detecting exposures in open-plan offices, located close to the breathing zone of seated occupants, and strongly correlated with personal exposure to pollutants such as CO_2, $PM_{2.5}$, and PM_{10}. Therefore, in spaces with often prolonged occupancy, the thesis recommends the installation of a single stationary environmental sensor at the sidewall, including CO_2 measurement, as it offers a comprehensive and cost-effective solution for personal air pollution detection. This proposition aligns with previous studies [335,336] proposing real-time CO_2 measurement as a cost-effective solution for controlling HVAC in commercial buildings. However, in areas characterized by sporadic occupancy patterns like cafeterias, achieving accurate exposure detection necessitated four times the number of indicators, including PM_{10} levels and dominant occupancy profiles, compared to open-plan offices. As other researchers proved the strong correlation between occupant activity and coarse particles [10,92,114,123,178], PM_{10} monitoring in addition to CO_2 measurements in areas with fluctuating occupancy may be beneficial for improving the exposure detection accuracy.

For occupancy detection, the thesis found that CO_2 measurements at the sidewall accurately indicated occupancy (occupant number) at room and building scale in areas with prolonged human presence, such as open-plan offices. Therefore, placing a sidewall-mounted CO_2 sensor can serve as a reliable indicator of occupancy in office buildings. This agrees with previous studies[210,254,337–340] that highlighted the effectiveness of using CO_2 for building occupancy detection. Monitoring additional CO_2 or relative humidity levels at the sidewall or desk did not significantly enhance the accuracy of occupancy estimation. Therefore, to minimize costs and simplify implementation, a single sidewall-mounted CO_2 sensor in open-plan offices could be sufficient for occupancy detection. In areas with transient occupancy, such as cafeterias, desk-mounted PM_{10} sensors proved valuable in inferring both room occupancy and personal PM_{10} exposures mainly because they capture fluctuations in PM concentrations caused by occupant presence and activities [10,182]. Thus, in spaces with dynamic occupant changes, desk-mounted PM_{10} sensors can provide valuable insights for both occupancy and personal exposures to coarse particles.

While indoor climate data controlled by HVAC systems, such as room air temperature and relative humidity, were not as effective as air pollution data for exposure or occupancy detection, they still offer supplementary information. Leveraging existing air temperature and humidity data commonly monitored in office buildings could help enhance the accuracy of personal exposure and occupancy detection when combined with IAQ data.

The results of this thesis provide valuable insights into the detection of human air pollution exposures and occupancy dynamics in office environments. While the primary focus has been on office spaces, the principles and methodologies presented here can be expanded and applied to different types of mechanically ventilated buildings. The protocols and insights gained from this thesis can serve as a foundation for investigating and optimizing IAQ management strategies, particularly for better understanding of inhalation exposures and occupancy dynamics in various built environments, such as schools, hospitals, commercial spaces, and residential buildings. By adapting and validating the identified indicators and sensor locations, the applicability of these findings can be extended to a broader range of indoor settings, contributing to improved air quality and occupant well-being in diverse built environments.

While this thesis significantly contributes to the understanding of inhalation exposures and occupancy dynamics in buildings, it is essential to acknowledge several limitations. Firstly, the proposed models and investigations are limited to simulated office environments and a few case buildings, and the applicability of identified indicators and sensor locations in real-world office settings still need a validation. Varying ventilation strategies and occupant activities in different buildings may influence the effectiveness of the proposed methods. In addition, although the thesis explores the potential of proxy methods for exposure estimation, such as stationary IAQ monitoring, wearable physiological measurements, and human presence detection, it is essential to recognize that these methods may have limitations in capturing localized and episodic air pollutant emissions from human. Further research is needed to explore the performance of these proxy methods under diverse real-world conditions to assess their reliability and accuracy in estimating human air pollution exposures in office environments. The development of improved exposure estimation models considering dynamically changing occupancy and spatial air pollutant gradients is a promising avenue, but it requires additional research and refinement with more varying office conditions. A judicious approach to implementing various models for the detection of inhalation exposure and occupancy is essential to mitigate the risk of overfitting. Generalizing the regression models across various spatial contexts is necessary to ensure the wider applicability and robustness of the proposed approach. Additionally, privacy concerns are paramount in the development of automatic occupancy detection systems. The limitations of the thesis include limited sample size, specific participant characteristics, exploration of various breathing zone air pollution measurement methods, which should be addressed in future research. Future investigations must address these concerns while striving to establish a more comprehensive and secure approach for accurately evaluating human air pollution exposure and occupancy detection in buildings.

6.2 Perspectives for research and practice

Section 6.2.1 – 6.2.2 include research perspectives towards achieving occupant-centric building HVAC control and practical implications of the thesis findings for building practitioners for real-world applications.

6.2.1 Research perspectives towards the future of occupant-centric building HVAC controls

Moving closer towards achieving occupant-centric HVAC in the future, this thesis emphasizes the importance of balancing costs and accuracy while taking air pollution exposures of building occupants and ventilation rate of building into account. MacNaughton et al. [341] explored the economic, environmental, and health implications of enhanced ventilation in office buildings. They demonstrated that current building ventilation standards based on minimum requirements overlook the significant human health benefits associated with increased ventilation rates. The research highlighted the positive impact of enhanced ventilation on human decision-making performance, leading to increased productivity among office workers. Specifically, by increasing the ventilation rate, the performance of workers improves by 8%, equivalent to a $6500 increase in employee productivity each year. Additionally, enhanced ventilation is associated with reduced absenteeism and improved overall health. Thus, achieving a balance between costs and human health requires prioritizing the health benefits associated with enhanced ventilation rates and detection accuracy.

Figure 6.1 depicts the qualitative relationship between inhalation exposure and various factors influencing it. Among these factors, the primary ones are ventilation rate and costs associated with ventilation operation and sensors. Higher ventilation rates result in increased operational costs, as indicated by previous researches [342,343] as depicted as double-dashed orange line in Figure 6.1. Ventilation cost includes installation, operation and maintenance fee. Whereas, the costs of sensors (dotted orange line) rise linearly with the number of sensors installed in the building unit, where relatively lower cost is expected than the one of building ventilation. Hence, the combined cost (solid orange line) incurred from ventilation operation and sensors follows an exponential relationship. The accuracy of inhalation exposure estimation (green line) does not strictly follow a linear trend and may exhibit an exponential pattern when a sufficient number of indicators (sensors) are effectively utilized in the space.

When deciding on ventilation and sensor costs, it is essential to strike a balance between reducing occupant inhalation exposure and improving exposure detection accuracy. These two parameters are critical for maintaining a healthier indoor environment. Figure 6.1 highlights the optimal region (yellow shaded area) for the total costs where both low inhalation exposure and good exposure detection accuracy can be achieved. Therefore, building stakeholders should carefully consider costs, inhalation exposure risks as a health indicator, and detection accuracy, aiming to position themselves within the yellow shaded area in Figure 6.1 based on their budget and desired outcomes.

Relying solely on cost and exposure considerations may lead to limited accuracy in detecting inhalation exposures, which can negatively impact IAQ management and human health. On the other hand, prioritizing detection accuracy and exposure risks might result in exaggerated operational costs and increased energy consumption. Hence, finding the right balance is essential for effective and efficient IAQ management and occupant-centric building HVAC control solutions.

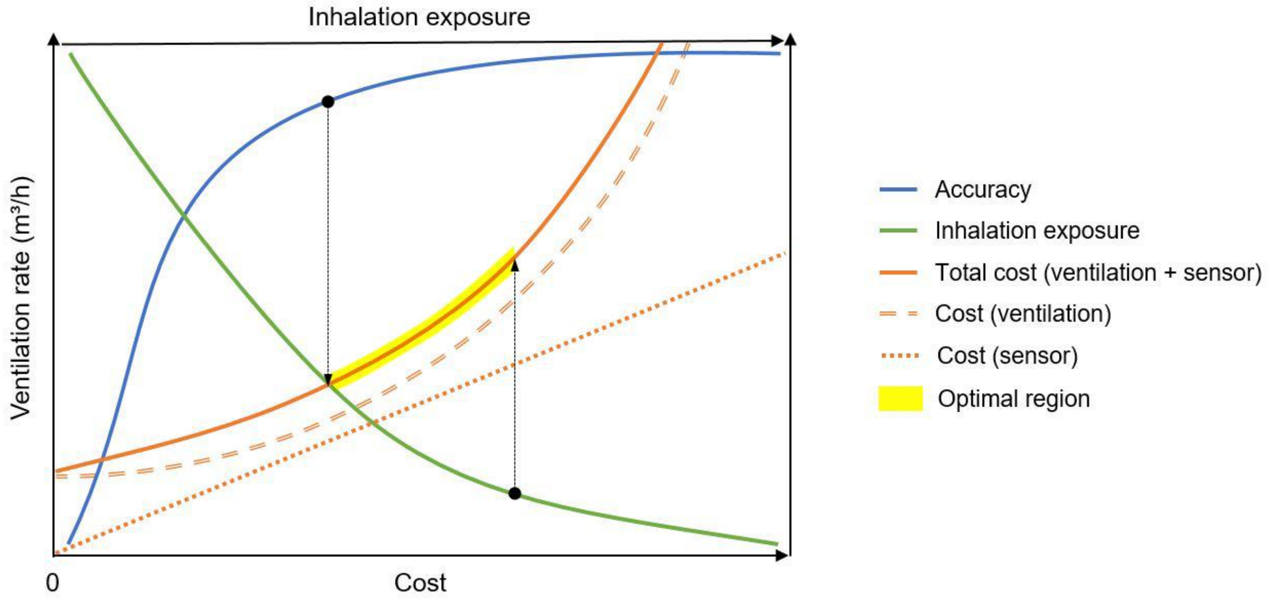


Figure 6.1 Qualitative representation of decision-making factors in indoor ventilated spaces. The y-axis represents ventilation rate (m^3/h), while the two x-axes display cost and inhalation exposure. The blue line depicts the accuracy of inhalation exposure estimation according to the number of sensors, and the green line indicates inhalation exposure of building occupant (a health indicator) depending on the ventilation rate. The double-dashed orange line represents the cost of ventilation operation sourced from previous studies [342,343]. The dotted orange line shows sensor costs depending on the number of sensor purchased and installed in building unit. The solid orange line represents the combined cost incurred from both ventilation and sensors installed in building unit. Optimal region for total cost is the yellow shaded area, where the balance between inhalation exposure risks and exposure detection accuracy is found. The yellow shaded area highlights the optimal region that building stakeholders should target, taking into account ideal costs for sensor and ventilation that secure low inhalation exposure risks and good exposure estimation accuracy to ultimately secure healthier office environments and occupant health and well-being.

In order to achieve a balance between costs and accuracy regarding indoor air pollution exposure monitoring and management in the future, several areas require attention. Firstly, it is imperative to prioritize generalization and standardization. This entails developing estimation models and sensor placement recommendations that can be effectively applied across diverse office contexts, accounting for variations in building layouts, occupancy characteristics, and ventilation systems, which partly has been proposed in this thesis. The further establishment of standardized guidelines and protocols can aid building practitioners in implementing efficient strategies.

In addition to prioritizing generalization and standardization, addressing the scalability and real-world testing of the techniques developed in this thesis is essential for advancing occupant-centric building HVAC controls. To conduct large-scale field-based data collection and experimental testing across population in multiple cities worldwide, several key innovations and technologies would be needed.

Firstly, the deployment of a comprehensive network of advanced sensors capable of continuously monitoring IAQ in real-time is necessary. These sensors should be integrated into a centralized system that can collect, process, and analyze data from various locations simultaneously. Additionally, leveraging the IoT technology and cloud computing infrastructure can facilitate remote monitoring and data management.

Secondly, to ensure widespread participation and data collection, collaboration with building owners, managers, and occupants would be essential. Developing user-friendly interfaces and mobile and wearable applications for occupants to report their experiences and preferences regarding IAQ can enhance engagement. Strategies such as incentivizing participation through rewards could also encourage active involvement in data collection.

Lastly, to analyze the collected data on a global scale, machine learning and artificial intelligence (AI) algorithms could be employed to identify patterns, correlations, and optimize HVAC control strategies. This would require access to powerful computing resources and data analytics expertise. Collaborations with research institutions and technology companies specializing in AI and data analytics could be beneficial.

Furthermore, conducting comprehensive cost-effectiveness analyses is equally important before developing occupant-centric HVAC solutions [344]. This analysis should consider both the costs of ventilation operations and expenses related to sensors. Additionally, assessing the impact of these measures on health-related costs is essential [341,345–347]. By evaluating the long-term health benefits and potential energy savings resulting from enhanced air pollution exposure management, stakeholders can make well-informed decisions to strike a balance between costs and desired benefits (outcomes) [348].

Lastly, promoting collaboration and interdisciplinary research is paramount. Bringing together researchers, building practitioners, HVAC professionals, and other stakeholders can integrate expertise from various fields. This collaborative approach fosters the development of innovative solutions that consider the intricate dynamics of IAQ, human exposures, occupant health, energy efficiency, and cost implications. By addressing these aspects, healthier indoor environments while finding the optimal balance between costs and benefits can be achieved.

Achieving occupant-centric building HVAC controls on a global scale would necessitate a multi-faceted approach involving advanced sensor networks, IoT technology, cloud computing, user engagement strategies, and collaboration with relevant stakeholders. By systematically tackling these technological and logistical challenges while incorporating cost-effectiveness analysis, it becomes possible to rigorously test and implement the innovative techniques proposed in this thesis across diverse office environments worldwide, ultimately leading to healthier indoor spaces.

6.2.2 Practical implications

The thesis has provided valuable insights into the estimation of personal air pollution exposures and occupancy detection in office settings. While each study has its own limitations, when considering the findings collectively, several general implications and potential avenues for further research can be proposed as follows:

1. **Contextual and Physiological Parameters:** The inclusion of contextual and physiological parameters, such as occupant numbers, activities, body posture, presence and absence, in the estimation of human inhalation exposure has shown promising results. The studies highlight that considering these factors alongside traditional environmental monitoring can improve the accuracy of exposure estimation. This implies that future research should continue exploring the integration of cost-effective contextual and physiological parameters in exposure models, potentially leveraging technologies such as low-cost wearable sensors and camera-based human activity detection algorithms.

2. **Integration of Multiple Indicators and Sensing Techniques:** Combining multiple indicators, including environmental, physiological, and contextual parameters, has demonstrated the potential to improve the accuracy of exposure estimation. Pantelic et al. [349] emphasized the significance of IoT sensing at urban, building, and personal scales, highlighting the need for data convergence across all three scales. The thesis also advocates for the integration of information across different scales, which holds great potential for advancing the understanding of the relationship between the environment and individuals. For instance, the thesis demonstrates the potential of integrating multiple sensing techniques, such as stationary IAQ monitoring, wearable devices, and occupancy sensors, to obtain a comprehensive understanding of indoor air pollution and occupancy dynamics. This perspective encourages the development of advanced sensor technologies, data fusion techniques, and IoT-based systems for real-time IAQ monitoring and management, contributing to a more sustainable and healthier indoor environment.

3. **Sensor Placement and Monitoring Strategies:** The optimal placement of stationary IAQ sensors has been identified as a key factor in approximating personal exposure and occupancy. The studies provide insights into the effective locations for stationary IAQ sensors, such as desk edges, sidewalls, and ventilation exhausts depending on the target air pollutant type for exposure estimation in specific office setting. These findings can inform stakeholders, including building practitioners, on the practical strategies for sensor deployment to enhance exposure and occupancy detection accuracy. Further investigations should aim to generalize the estimation models and sensor placement recommendations in different office contexts, considering variations in space/furniture layouts, occupancy profiles, and ventilation strategies.

4. **Improved Exposure Estimation:** The thesis highlights the potential of proxy methods and optimal sensor placement for enhancing the estimation of personal inhalation exposures to air pollutants. One of the key findings emphasized in the research is the importance of sensor proximity to the target occupants and the understanding of dominant occupant activities within the room, as these factors play a crucial role in accurately estimating exposure levels. By addressing these aspects, the thesis holds practical implications for comprehending and mitigating health risks associated with indoor air pollution in office settings. Further, the research sheds light on the spatio-temporal variation of indoor air pollutants, an aspect that is often overlooked in conventional monitoring strategies. Indoor environments are dynamic [228,350], and pollutants can exhibit significant variation in concentration across different locations and time periods.

Ignoring this variation can lead to a misrepresentation of the actual exposure levels experienced by individuals. The thesis proposes strategies to account for the spatio-temporal dynamics of pollutants while acknowledging the problematic nature of relying solely on well-mixed representation of indoor environments, where previous researches [10,184] also addressed the same concern. By considering both sensor proximity and spatio-temporal variation, the research opens up new avenues for achieving more accurate exposure estimations. This improved accuracy, in turn, enables a more comprehensive calculation of potential health impacts arising from indoor air pollution. Armed with such precise estimations, policymakers and building managers can develop targeted strategies to mitigate health risks effectively.

5. **Real-time Occupant-centric IAQ Monitoring:** The thesis emphasizes the importance of occupant-centric ventilation strategies and real-time monitoring in promoting healthier work environments. The optimal sensor placement recommendations and insights from the thesis can inform building managers and stakeholders about effective approaches to improve IAQ monitoring and apply adequate HVAC control. This includes the identification of key indicators with appropriate sensor placements for detecting personal exposure and occupancy, facilitating targeted interventions to mitigate possible air pollution risks.

6. **Real-Life Applications:** While the studies of this thesis were conducted in controlled experimental settings and two case study buildings, the implications extend to real-life office environments. The proposed methods and strategies can provide useful insights for personal air pollution exposure monitoring to leverage HVAC control strategies in real-life office buildings. As wearable sensors and low-cost stationary and portable IAQ devices become more advanced and affordable, their deployment in real office settings can enhance the measurement of personal exposures and facilitate more effective exposure detection.

7. **Cost Effective Applications for Stakeholder Guidance:** The thesis findings have practical implications for stakeholders involved in managing indoor air pollution and occupant health. The optimal placement of stationary IAQ sensors, as recommended by the thesis, can guide building practitioners in cost-effective strategies for exposure and occupancy detection. These insights can be tailored to the development of occupant-centric ventilation control strategies, aiming to improve air quality, occupancy monitoring, and energy efficiency in office buildings.

Overall, the thesis contributes to advancing the understanding of proxy methods, optimal sensor placement, and the integration of smart sensing technologies with effective indicators for accurate detection of personal inhalation exposures and occupancy dynamics in office environments. The implications and perspectives presented in the thesis provide a foundation for further research and offer practical insights for stakeholders, policymakers, and building practitioners to improve IAQ, exposure management, occupant health and well-being in office buildings.

Chapter 7 Conclusions

7.1 Research questions addressed

This thesis encompasses holistic investigation of the effectiveness of proxy methods with optimal sensor placement and indicators for estimating personal inhalation exposures to air pollutants and occupancy dynamics in office environments. It includes exploration of multiple sensing techniques, including stationary IAQ monitoring, wearable devices, and occupancy sensors, to improve the accuracy of exposure estimation under both static and dynamic occupancy profiles. The thesis proposes the method of identifying the most effective sets of indicators at the proper sensor locations for detecting personal exposure and occupancy, aiming to enhance IAQ management in office environments through reduced inhalation exposures and to promote health of office workers while balancing the cost and accuracy of sensors The research questions outlined in section 2.6 of this thesis are answered in the following manner.

[Research Question 1]

- ***"What combination of physical parameters (environmental, contextual, and physiological) best represents inhalation exposures to CO_2, $PM_{2.5}$, and PM_{10} in a simulated office environment with dynamic occupancy profiles?"***

In order to address the research question posed, this thesis explored different proxy sensing techniques for estimating inhalation exposure to CO_2, $PM_{2.5}$ and PM_{10} in simulated office environments. The study aimed to address the limitations of traditional stationary air pollution measurements by examining the feasibility of alternative methods under dynamically changing occupancy profiles. The study conducted experiments in a controlled climate chamber that mimicked various office setups. Human participants performed scripted sitting and standing office activities while three proxy sensing techniques were tested: stationary IAQ monitoring, individual monitoring of physiological status using wearable wristbands, and human presence detection using PIR sensors. The results showed that segregating data based on occupant sitting and standing activities led to improved accuracy in exposure estimation for CO_2 and PM by 9-60%. Stationary CO_2 and PM monitors positioned at specific locations, such as the front edge of the desk and ceiling-mounted ventilation exhaust respectively, estimated inhalation exposure accurately. Combining three sensing techniques (stationary IAQ monitoring, wearable wristbands for physiological monitoring, and PIR sensors for human presence detection) improved the detection of CO_2 exposure by twofold, while the improvement for PM exposure detection was smaller (~10%).

[Research Question 2]

- ***"What are the suitable stationary IAQ sensor placements that can best approximate personal CO_2, $PM_{2.5}$ and PM_{10} exposures under dynamic and static occupancy conditions?"***
- ***"How do categorical variables (occupant number, activity, office layout, ventilation type, ventilation rate) influence personal exposure detection?"***

This thesis addressed two research questions posed above while focusing on detecting personal inhalation exposures using stationary IAQ sensors in office environments. Firstly, it explored suitable sensor placements that best approximate personal CO_2, $PM_{2.5}$, and PM_{10} exposures under dynamic and static occupancy conditions. The study was conducted in a controlled climate chamber that mimicked various office settings, considering factors like occupant number, activities, and ventilation type. Breathing zone concentrations were found to be higher than those recorded by stationary sensors, emphasizing the importance of identifying sensor locations closely correlated with breathing zone exposure levels. Optimal sensor locations were identified, including the sidewall immediately behind the occupant (<1 m) and the ceiling-mounted ventilation exhaust (<1-1.5 m from the occupant), showing the highest correlation with breathing zone CO_2 and PM_{10} measurements, respectively.

Secondly, the thesis investigated how categorical variables such as occupant number, activity, office layout, ventilation type, and ventilation rate influence personal exposure detection. The study found that separating static from dynamic occupancy and differentiating between sitting and standing activities were important in improving the accuracy of inhalation exposure estimation. As the number of occupants increased, indoor air pollution levels also increased. The air change rates exhibited a linear negative correlation with the room average concentration of CO_2, $PM_{2.5}$, and PM_{10}. Additionally, the proximity of sensors to target occupants and the ventilation rate/strategy played a significant role in detecting personal exposure accurately. Overall, the research provides valuable insights into the effectiveness of stationary IAQ sensors for approximating personal inhalation exposures, guiding optimal sensor placements, and understanding the impact of various factors on exposure detection in office environments.

[Research Question 3]

- ***"How do spatial gradients of personal CO_2, $PM_{2.5}$, and PM_{10} exposure in offices relate to various occupant activity profiles?"***
- ***"Which indicators serve as the most effective proxies for personal air pollution exposure and occupancy in different office types?"***
- ***"What are the minimum but sufficient indicators for characterizing personal exposures and occupancy in real office settings?"***

This thesis addresses three research questions posed above by focusing on the integration of smart sensing techniques at personal, room, and building scales to identify effective indicators for inhalation exposure and occupancy detection in real office settings while considering cost-accuracy aspects of the deployed sensors. Firstly, to explore the spatial gradients of personal CO_2, $PM_{2.5}$, and PM_{10} exposure in offices related to various occupant activity profiles, real-time measurements were conducted at personal, room, and building scales. The study utilized customized IAQ vests, smartwatches, stationary IAQ sensors, visual occupancy inspections, and a cloud-based occupancy monitoring system. Through correlation and Decision Tree classification and regression analyses, the most effective sets of physical indicators for personal exposure detection and occupancy detection in different office settings were identified. The study revealed that occupancy triggers spatial-temporal air pollution gradients, highlighting the significance of real-time monitoring on both IAQ and occupancy profiles.

Secondly, to determine the most effective proxies for personal air pollution exposure and occupancy in different office types, the thesis recommended specific sensor placements and monitoring strategies for different areas within office buildings. For instance, in open-plan offices with prolonged occupancy, the installation of a single environmental sensor including CO_2 monitoring at the sidewall was found to be the most cost-effective way to capture both exposure and occupancy, which can be utilized for future occupant-centric HVAC control to maintain healthier office environments.

Last but not the least, the minimum but sufficient sets of indicators for detecting personal air pollution exposure and occupancy in various office settings include monitoring CO_2 levels at sidewalls in areas with prolonged occupancy (e.g. open-plan offices), desk-mounted PM_{10} sensors for areas with episodic occupancy (e.g. cafeterias), and a combination of indoor climate data and air pollution data to improve detection accuracy. These findings provide valuable insights for optimizing sensor placements and monitoring strategies for better characterizing inhalation exposure to indoor air pollution and occupancy dynamics in real office environments.

In conclusion, this thesis has undertaken a comprehensive investigation of the effectiveness of proxy methods, optimal sensor placement, and indicators for estimating personal inhalation exposures to air pollutants and occupancy dynamics in office environments. By exploring multiple sensing techniques, including stationary IAQ monitoring, wearable devices, and occupancy sensors, the thesis aimed to improve the accuracy of exposure estimation under both static and dynamic occupancy profiles. The thesis successfully identified the most effective sets of indicators and sensor locations for detecting personal exposure and occupancy, contributing to enhanced IAQ management in office settings while considering the balance between cost and accuracy of sensors. The findings of this thesis emphasize the importance of real-time monitoring of IAQ and occupancy profiles to accurately estimate personal inhalation exposures in office environments. By implementing the recommended sensor placements and monitoring strategies, building stakeholders can achieve better IAQ management and promote the health and well-being of office workers. Furthermore, these insights contribute to the ongoing development of occupant-centric HVAC control systems for maintaining healthier office environments while optimizing resource utilization. Overall, this thesis represents a significant step forward in advancing the understanding of monitoring personal inhalation exposures and occupancy dynamics in office spaces, and its recommendations provide valuable guidance for researchers, policymakers, and building managers aiming to create healthier and more sustainable indoor environments.

7.2 Future research outlook

The thesis conclusions highlight the importance of considering different indoor environment representations, occupancy profiles, and sensor positioning, selection of effective indicators while developing occupant-centric HVAC solutions. The thesis sets a foundation for further research in the field of inhalation exposure and occupancy assessment, offering practical insights for building managers and stakeholders to enhance occupant well-being in office buildings. Following, the research conducted in this thesis opens up several avenues for future investigations, addressing further need for development of proper assessment methods for indoor air pollution exposures and occupancy dynamics in various building types. The following research outlook outlines key areas for future exploration:

- **Real-world Office Settings Validation:** The applicability and effectiveness of the identified indicators and sensor locations need validation in real-world office environments. Future studies should explore different types of both mechanically and naturally ventilated buildings, considering varying ventilation rates, air distribution strategies, occupant activities, and spatial contexts to assess the reliability and accuracy of the proposed methods and amend the developed protocols according to condition of interests.

- **Proxy Methods Performance:** Further research is needed to explore the performance of proxy methods, such as stationary IAQ monitoring, wearable physiological measurements, and human presence and activity detection, in capturing localized and episodic emissions in real-world office settings. Investigating their reliability and accuracy under different indoor air pollution scenarios is essential in refining exposure estimation models.

- **Improved Exposure Estimation Models:** The development of improved exposure estimation models while utilizing and combining various assessment methods (direct/indirect) should be a focus for future research. For instance, further research can combine CFD simulation of inhalation exposures in office environments in addition to the physical measurement with human subjects in offices. This enables opening up the opportunities of testing various conditions of dynamic occupancy and spatial air pollutant gradients, which ultimately enhances the accuracy of exposure assessments in indoor environments. These models could consider various parameters apart from physical environment, such as human activity and metabolism, to better predict personal air pollution exposures.

- **Spatio-Temporal Variations and Multi-Zone Modeling:** Understanding spatio-temporal variations in indoor air pollution is essential. Future studies should consider adopting multi-zone modeling and CFD simulations to optimize ventilation strategies in individual rooms and air handling units for various building types.

- **Generalizing Regression Models and Assessment Protocols:** To ensure wider applicability, future research should focus on generalizing regression models and protocols for assessing inhalation exposure and occupancy dynamics across various spatial contexts and building types. Understanding how different factors influence indoor air pollution dynamics in diverse settings leads to more robust and adaptable exposure estimation approaches.

- **Sensor Positioning Strategies:** Further investigations should focus on optimizing sensor positioning strategies in real-world indoor environments. Identifying the best locations for stationary IAQ sensors, considering the proximity effect and various occupant activities, leads to more effective and cost-efficient methods for estimating human inhalation exposures.

- **Sample Size and Participant Characteristics:** Addressing the limitations of sample size and specific participant characteristics is essential for future research. Further studies should strive to include a more diverse range of buildings and occupants (different groups of sex, age, and ethnicity) to ensure the findings can be applied broadly.

- **Automatic Occupancy Detection:** Future research should consider the advancement of automatic occupancy detection systems, building upon existing researches [210,235,351–354]. More importantly, ensuring that privacy concerns are adequately addressed is essential for establishing a more comprehensive and secure approach for occupancy detection in buildings.

- **Practical Applications in Diverse Built Environments:** The insights gained from this study can serve as a foundation for investigating and optimizing IAQ management strategies in various built environments, such as schools, hospitals, commercial spaces, and residential buildings. Future research should extend the applicability of the identified indicators and sensor locations to contribute to improved air quality, occupant health and well-being in diverse indoor settings.

In conclusion, future research in this field should focus on validating the identified indicators and sensor locations in real-world office settings, improving exposure estimation models, addressing limitations, and considering the complexities of various indoor environments. By exploring these areas, the field of inhalation exposure and occupancy dynamic assessments can advance significantly, leading to more effective strategies for enhancing indoor air quality and protecting occupant health.

Supporting information

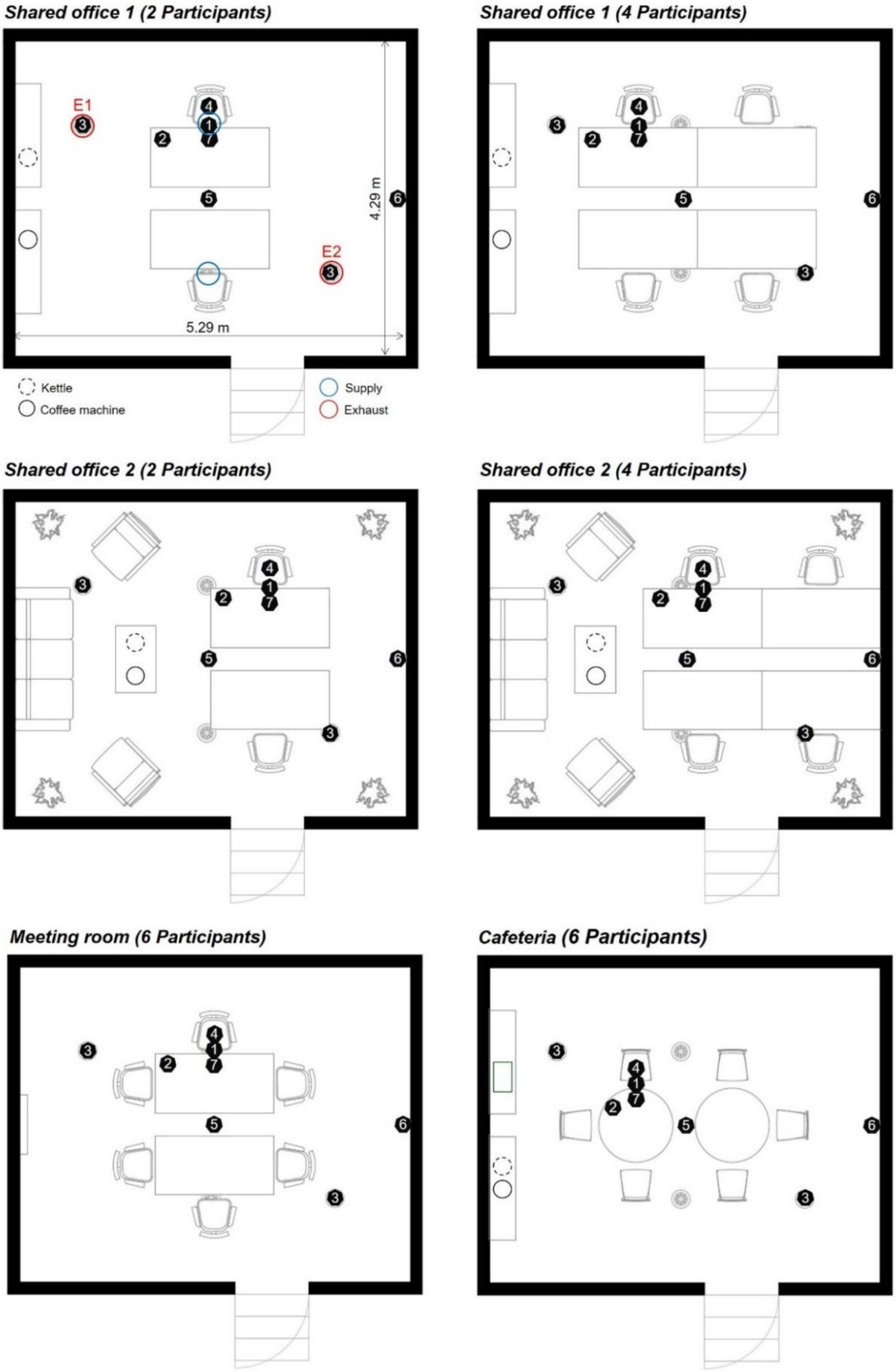
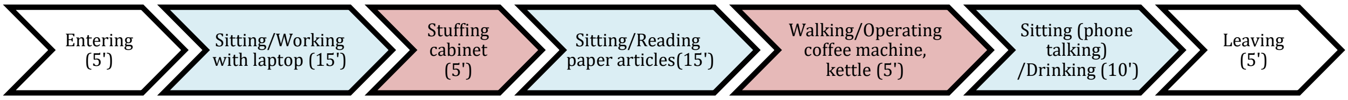
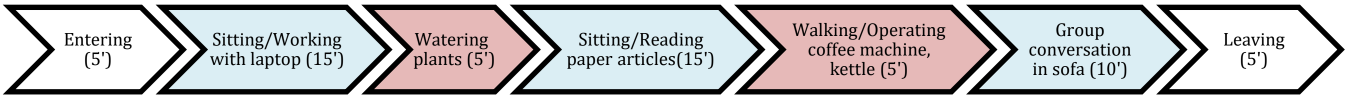


Figure S3.1 Floor plan and monitor placement IDs (1 -7). The dimension of the space and supply/exhaust diffuser placement are all the same in every space as shown in the Shared office 1 (2 Participants). The Shared office 1 consisted of two or four office desks/chairs depending on the number of participants (two and four), and kettle and coffee machine on two cabinets. In Shared office 2, the office desk/chair setup was similar to Shared office 1 but it had a common space where the participants could sit on fabric sofa and have coffee/tea from a table. The Meeting room (six participants) was equipped with two desks with six office chairs and TV screen to simulate actual group meeting activity. The Cafeteria (six participants) was composed of two lounge tables in the middle of the space with six chairs with two cabinets to place coffee machine, kettle, and microwave.

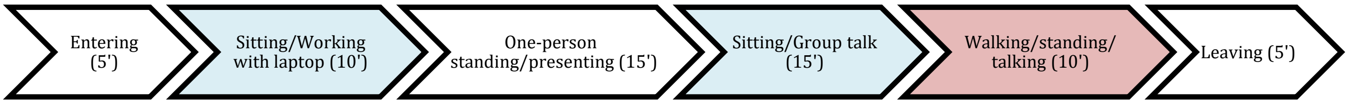
(i) Activity scenario for Shared office 1 (w/o common space)



(ii) Activity scenario for Shared office 2 (w/ common space)



(iii) Activity scenario for Meeting room



(iv) Activity scenario for Cafeteria

Figure S3.2 Participants' office activities (duration in minutes) in each space type. *Sitting* activities are marked as blue shading while *standing* activities are marked as orange shading. "Entering", "Leaving" and "One-person standing/presenting" activity were excluded in regression analyses.

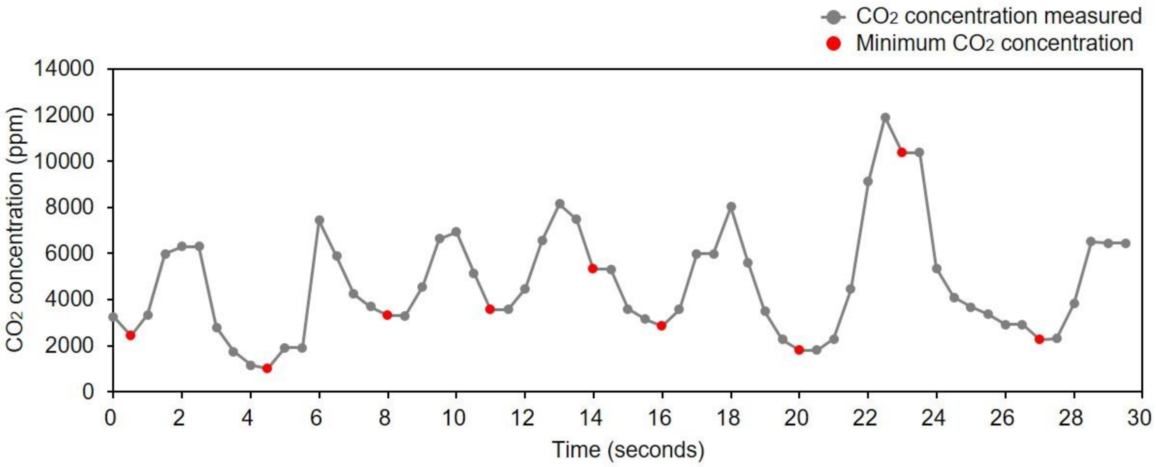


Figure S3.3 Calculation of inhaled CO_2 concentration during 30-second breathing cycle of the reference participant. The red dots were taken into account for calculating inhaled CO_2 concentration.

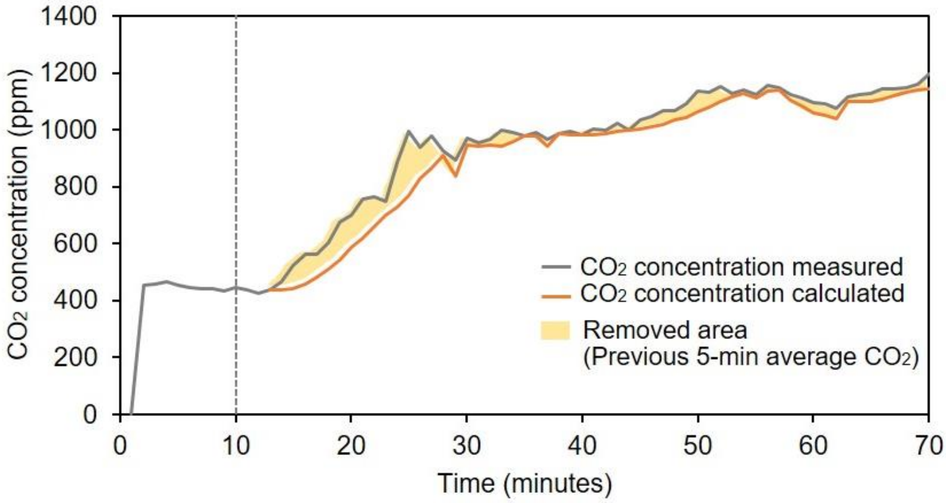


Figure S3.4 Calculated CO_2 concentration based on subtracting former 5-minute CO_2 concentration from each time stamp. (e.g. calculated CO_2 concentration at 40 minutes: measured CO_2 concentration at 40 minutes – average measured CO_2 concentration from 35 to 39 minutes)

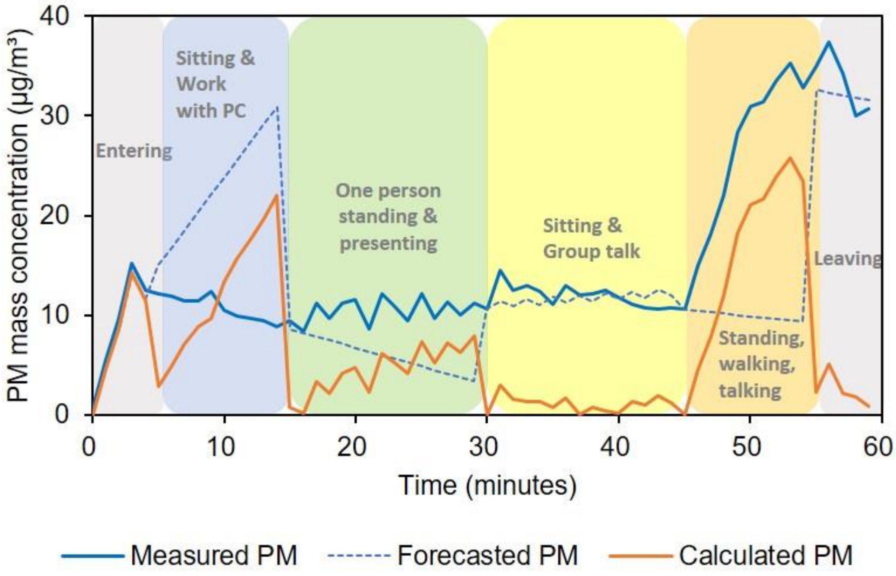


Figure S3.5 Calculated PM mass concentration for each participant activity by using forecast curve based on the data of the former activity and removing the gap between measured and predicted PM value from the measured PM value. Forecasted PM has been processed using the FORECAST.ETS function (target_date, values, timeline) in Excel, where the contribution of forecasted PM has been removed from measured PM so that the study could minimize the contribution of former activity on the latter PM value from another activity.

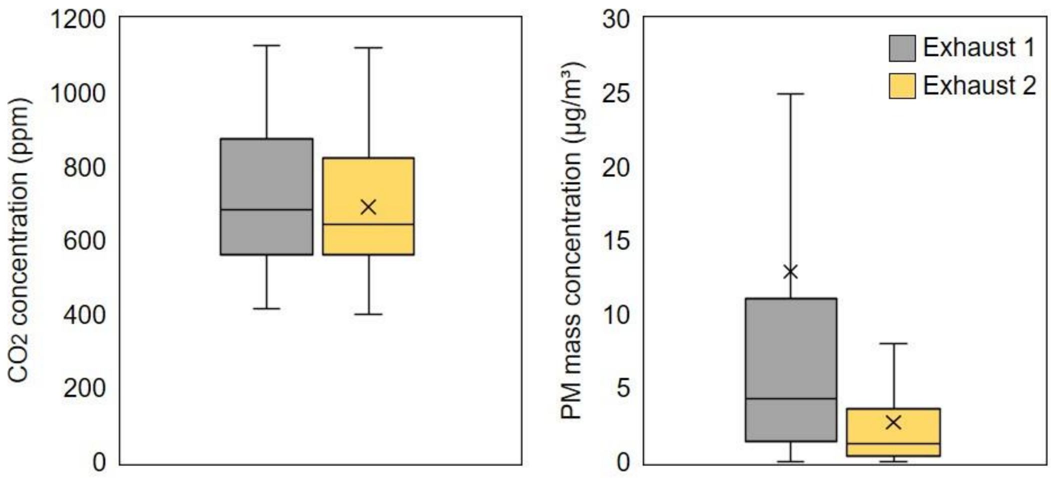
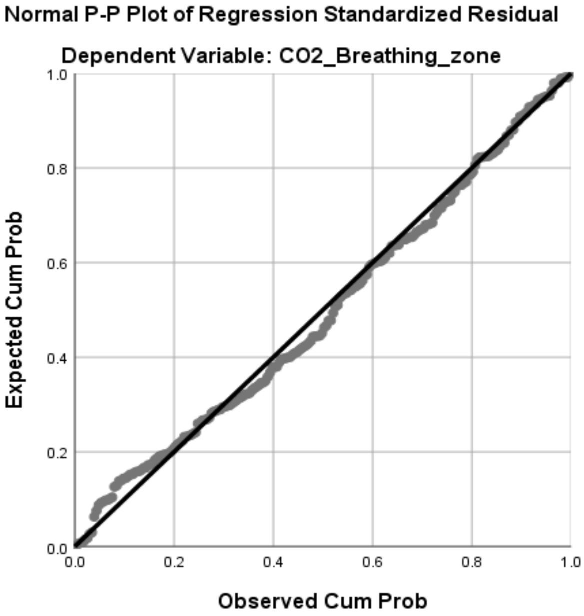
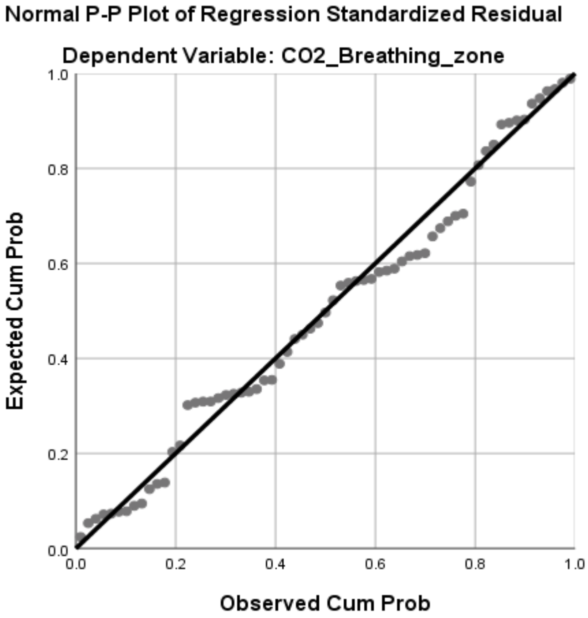


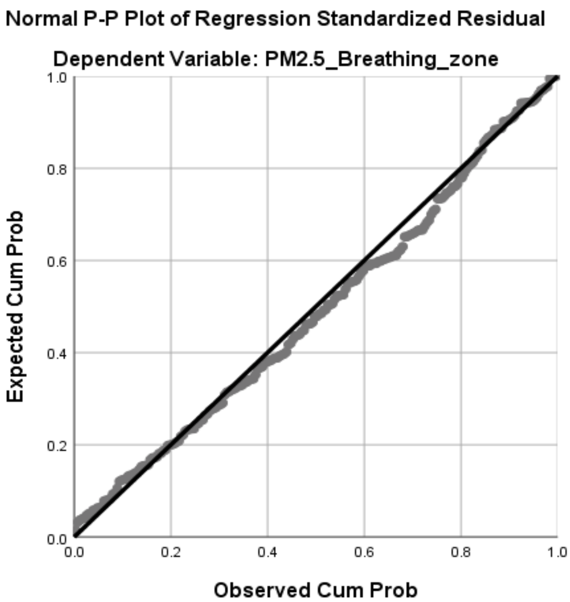
Figure S3.6 Comparison of mean CO_2 and PM_{10} concentration at two exhausts for *combined* activities (*sitting* and *standing*) in the space. The higher PM_{10} concentration at the Exhaust 1 compared to the Exhaust 2 was likely attributed to vigorous activities (i.e., stuffing the cabinet with paper boxes) that occurred near the Exhaust 1.

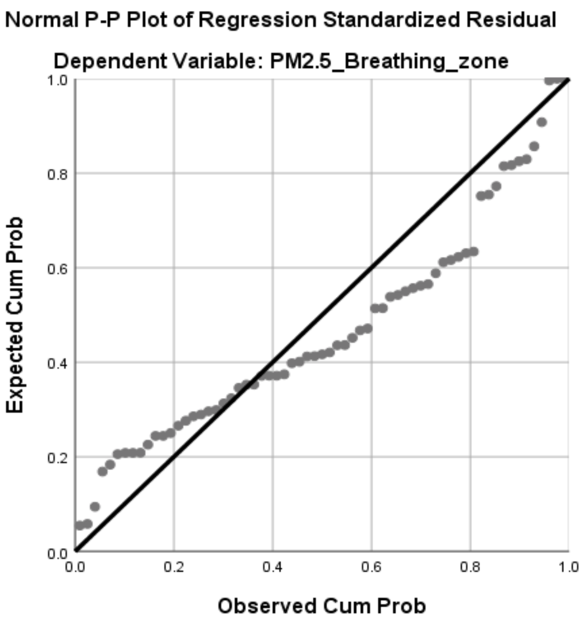
(i) Normal P-P plot for CO_2 exposure estimation model (left: *sitting activities*, right: *standing* activities)





(ii) Normal P-P plot for $PM_{2.5}$ exposure estimation model (left: *sitting activities*, right: *standing* activities)





(iii) Normal P-P plot for PM_{10} exposure estimation model (*sitting* activities)

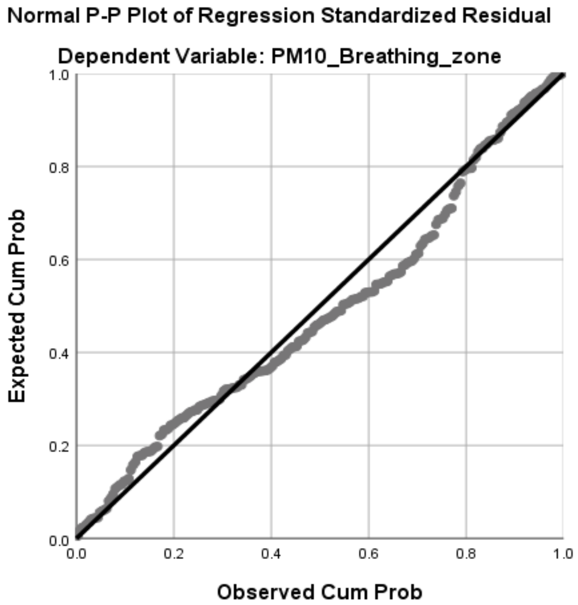


Figure S3.7 Normal P-P plot of composed regression models: test for normal distribution of residuals. Test for PM_{10} exposure estimation model in *standing* activities was excluded.

Table S3.1 List of experimental runs, associated occupancy and environmental conditions.

Experimental ID	Space type	No. of participants	ACH	T, RH
1	Shared office 1	2	2.4 - 2.6 h^{-1}	24.9±0.4 °C, 54.3±4 %
2		2		
3		4		
4		4		
5	Shared office 2	2		
6		2		
7		4		
8		4		
9	Meeting room	6		
10		6		
11	Cafeteria	6		

Table S3.2 Adjustment factors to mutually correct IAQ instruments. Reference instrument is shown in the bracket.

Monitor placement		Adjustment factors		
ID	Description	CO_2	PM	
			$PM_{2.5}$	PM_{10}
1	Front edge of participant desk	1.177	0.8565	1.618
2	Desk	1.124	1 (reference, Mini-WRAS 1371)	
3	Exhaust 1	1 (reference, LI-850)	1.1021	1.4971
4	Breathing zone	0.986	1.2435	1.6801

Table S3.3 Correlation r comparison between the two Exhausts and the Breathing zone.

Stationary monitor location	*Sitting* activities		*Standing* activities	
	Breathing zone CO_2	Breathing zone PM_{10}	Breathing zone CO_2	Breathing zone PM_{10}
Exhaust 1	-0.344**	0.931**	-0.526**	0.606**
Exhaust 2	-0.517**	0.551**	-0.491**	-0.106
Difference (Exhaust 2 compared to Exhaust 1, percent increase %)	50.3 %	-40.8 %	-6.7 %	-82.5 %

**. Correlation is significant at the p=0.01 level (2-tailed)

Table S3.4 Regression coefficients for estimating CO_2, $PM_{2.5}$, and PM_{10} exposure using one stationary IAQ monitor and participant number. Notes: B stands for unstandardized regression coefficient, Std. Error for unstandardized standard error of the B, β for standardized regression coefficient, t for t-value, and p for p-value.

Model coefficients[a,b,c]

Variable*	B	Std. Error	β	t	p
(Constant)	1983.328	214.483		9.247	0.000
Participant_number	-281.51	29.675	-0.828	-9.486	0.000
CO_2_ Front edge of participant desk	0.829	0.25	0.289	3.316	0.002

[a.] Dependent variable: CO_2_Breathing_zone

[b.] R^2_{adj} = 0.579 (N = 65, p = 0.000)

[c.] CO_2 exposure estimation model for *standing* activities

* B: unstandardized regression coefficient, Std. Error: unstandardized standard error of the B, β: standardized regression coefficient, t: t-value, p: p-value

Model coefficients[a,b,c]

Variable*	B	Std. Error	β	t	p
(Constant)	-0.007	0.182		-0.037	0.971
Participant_number	0.172	0.043	0.081	3.954	0.000
$PM_{2.5}$_Exhaust 1	1.795	0.039	0.949	46.319	0.000

[a.] Dependent variable: $PM_{2.5}$_Breathing_zone

[b.] R^2_{adj} = 0.91 (N = 220, p = 0.000)

[c.] $PM_{2.5}$ exposure estimation model for *sitting* activities

* B: unstandardized regression coefficient, Std. Error: unstandardized standard error of the B, β: standardized regression coefficient, t: t-value, p: p-value

Model coefficients[a,b,c]

Variable*	B	Std. Error	β	t	p
(Constant)	1.098	3.482		0.315	0.753
Participant_number	2.497	0.833	0.073	2.997	0.003
PM_{10}_Exhaust 1	1.652	0.043	0.929	38.294	0.000

[a.] Dependent variable: PM_{10}_Breathing_zone

[b.] R^2_{adj} = 0.91 (N = 220, p = 0.000)

[c.] PM_{10} exposure estimation model for *sitting* activities

* B: unstandardized regression coefficient, Std. Error: unstandardized standard error of the B, β: standardized regression coefficient, t: t-value, p: p-value

Table S3.5 Regression coefficients for estimating CO_2 exposure using one input [PIR_Wall (1.4 m)] from PIRs and participant number under *standing* activities.

Model coefficients[a,b]

Variable*	B	Std. Error	β	t	p
(Constant)	1842.901	270.202		6.82	0.000
Participant_number	-265.276	28.731	-0.78	-9.233	0.000
PIR_Wall (1.4 m)	831.186	275.675	0.255	3.015	0.004

[a.] Dependent variable: CO_2_Breathing_zone

[b.] R^2_{adj} = 0.568 (N = 65, p = 0.000)

* B: unstandardized regression coefficient, Std. Error: unstandardized standard error of the B, β: standardized regression coefficient, t: t-value, p: p-value

Table S3.6 Regression coefficients for estimating CO_2 exposure using two inputs [T_{skin} + HR] from wearable wristband and participant number under *standing* activities.

Model coefficients[a,b]

Variable*	B	Std. Error	β	t	p
(Constant)	-9517.293	3809.79		-2.498	0.015
Participant_number	-170.997	35.304	-0.503	-4.844	0.000
T_{skin}	305.227	100.885	0.323	3.025	0.004
HR	9.832	2.968	0.287	3.313	0.002

[a.] Dependent variable: CO_2_Breathing_zone

[b.] R^2_{adj} = 0.594 (N = 65, p = 0.000)

* B: unstandardized regression coefficient, Std. Error: unstandardized standard error of the B, β: standardized regression coefficient, t: t-value, p: p-value

Table S3.7 Adjusted R^2 value (relevant input variables) of MLR models with combined input parameters for IAQ exposure estimation during *combined* activities. The last row (colored as blue) indicates how much percent increase (%) was obtained in terms of estimation accuracy when using combined parameters compare to using a single IAQ parameter.

Combinations of parameters* *(used as input variables)*	**Adjusted R^2 of composed MLR model (relevant input variables**)**		
	Combined activities		
	CO_2 estimation	**$PM_{2.5}$ estimation**	**PM_{10} estimation**
Single IAQ	0.326 (Part_num, CO_2_Front edge of participant desk)	0.861 ($PM_{2.5}$_Front edge of participant desk, Desk, Exhaust 1)	0.842 (PM_{10}_Front edge of participant desk, Desk, Exhaust 1)
IAQ + E4	0.474 (Part_num, CO_2_Front edge of participant desk, T_{skin}, HR)	0.862 ($PM_{2.5}$_Front edge of participant desk, Desk, Exhaust 1)	0.845 (PM_{10}_Front edge of participant desk, Desk, Exhaust 1)
IAQ + PIRs	0.338 (Part_num, CO_2_Front edge of participant desk, PIR_Ceiling)	0.863 (Part_num, $PM_{2.5}$_Front edge of participant desk, Desk, Exhaust 1)	0.843 (PM_{10}_Front edge of participant desk, Desk, Exhaust 1, PIR_ceiling)
IAQ + E4 + PIRs	0.49 (Part_num, CO_2_Front edge of participant desk, T_{skin}, HR, PIR_Wall, Desk)	0.865 (Part_num, $PM_{2.5}$_Front edge of participant desk, Desk, Exhaust 1)	0.846 (PM_{10}_Front edge of participant desk, Desk, Exhaust 1)
Improvement of estimation accuracy *(Single IAQ vs combination of parameters, percent increase %)*	50.3	0.5	0.5

* IAQ: Stationary IAQ measurement, E4: Physiological measurement, and PIRs: Contextual measurement

** Part_num: participant number, T_{skin}: skin temperature, HR: heart rate

Equation S3.1-S3.5 Multiple regression equations for human exposure estimation to indoor air pollutants under both *sitting*/*standing* activities by using combinations of different parameters: IAQ monitor, wearable wristband, and PIR.

1. *Sitting* activities

(i) Regression equation for CO_2 exposure estimation

$$CO_{2,exposure} = -137.768 part_{num} - 1.653 CO_{2,desk} + 2.09 CO_{2,exhaust} + 872.547 T_{skin} - 293.286 PIR_{wall} + 227.358 PIR_{desk} - 29636.191$$

Equation S3.1

(ii) Regression equation for $PM_{2.5}$ exposure estimation

$$PM_{2.5,exposure} = 0.297 part_{num} - 1.302 PM_{2.5,front\ edge\ of\ participant\ desk} + 1.946 PM_{2.5,desk} + 1.764 PM_{2.5,exhaust} + 0.04 HR - 0.527 PIR_{wall} - 0.413 PIR_{desk} - 2.617$$

Equation S3.2

(iii) Regression equation for PM_{10} exposure estimation

$$PM_{10,exposure} = 1.475 part_{num} - 1.465 PM_{10,front\ edge\ of\ participant\ desk} + 0.941 PM_{10,desk} + 1.876 PM_{10,exhaust} - 10.272 T_{skin} + 0.87 HR + 313.329$$

Equation S3.3

2. *Standing* activities

*PM_{10} exposure estimation was excluded (low accuracy of a regression model)

(i) Regression equation for CO_2 exposure estimation

$$CO_{2,exposure} = -293.061 part_{num} + 0.713 CO_{2,front\ edge\ of\ participant\ desk} + 689.008 PIR_{wall} + 1466.035$$

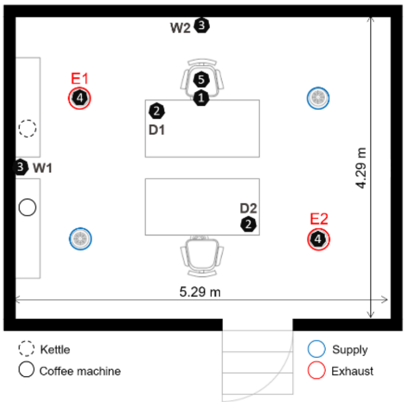
Equation S3.4

(ii) Regression equation for $PM_{2.5}$ exposure estimation

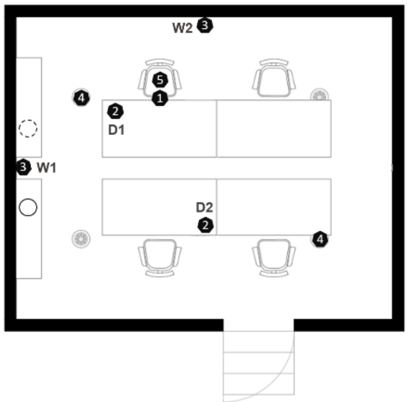
$$PM_{2.5,exposure} = -4.156 PM_{2.5,front\ edge\ of\ participant\ desk} + 3.165 PM_{2.5,exhaust} + 1.036$$

Equation S3.5

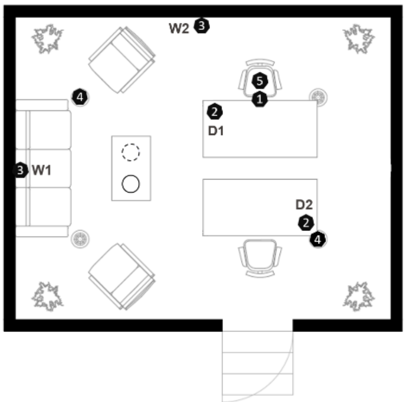
Shared office 1 (2 Participants)



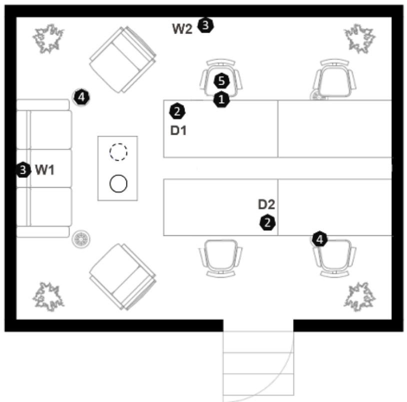
Shared office 1 (4 Participants)



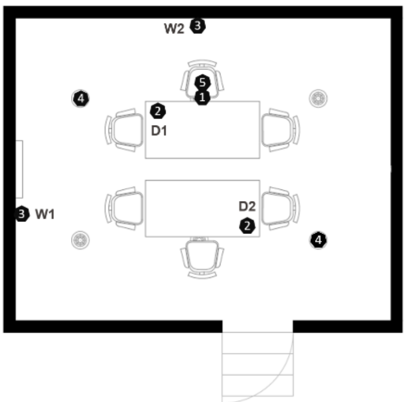
Shared office 2 (2 Participants)



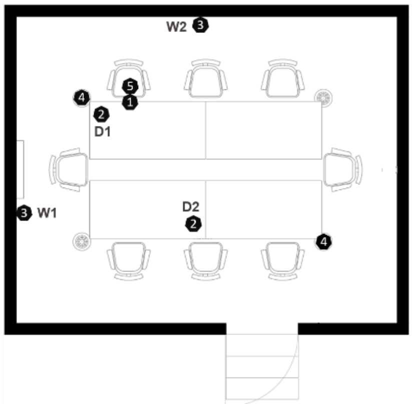
Shared office 2 (4 Participants)



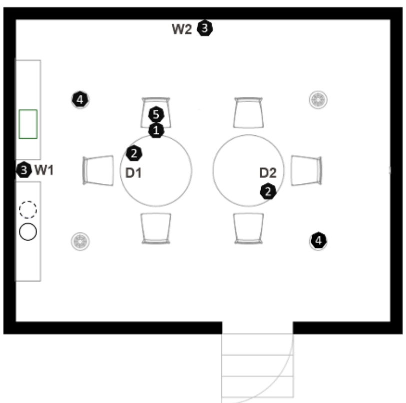
Meeting room (6 Participants)



Meeting room (8 Participants)



Cafeteria (6 Participants)



Cafeteria (8 Participants)

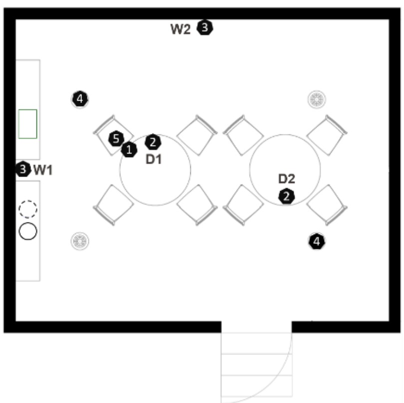


Figure S4.1 Floor plan and monitor placement IDs (1-5). The dimension of the space and supply/exhaust diffuser placement were the same in every space as shown in the Shared office 1 (2 Participants). The Shared office 1 consisted of two or four office desks/chairs depending on the number of participants (two and four), and a kettle and coffee machine on two cabinets. In Shared office 2, the office desk/chair setup was similar to Shared office 1 but it had a common space where the participants could sit on a fabric sofa and have coffee/tea from a table. The Meeting room (six and eight participants) was equipped with two desks with six/eight office chairs and TV screen to simulate actual group meeting activity. The Cafeteria (six and eight participants) was composed of two lounge tables in the middle of the space with six/eight chairs with two cabinets to place the coffee machine, kettle, and microwave. Note: E1 = Exhaust 1, E2 = Exhaust 2. W1 = Wall 1, W2 = Wall 2. D1 = Desk 1, D2 = Desk 2.

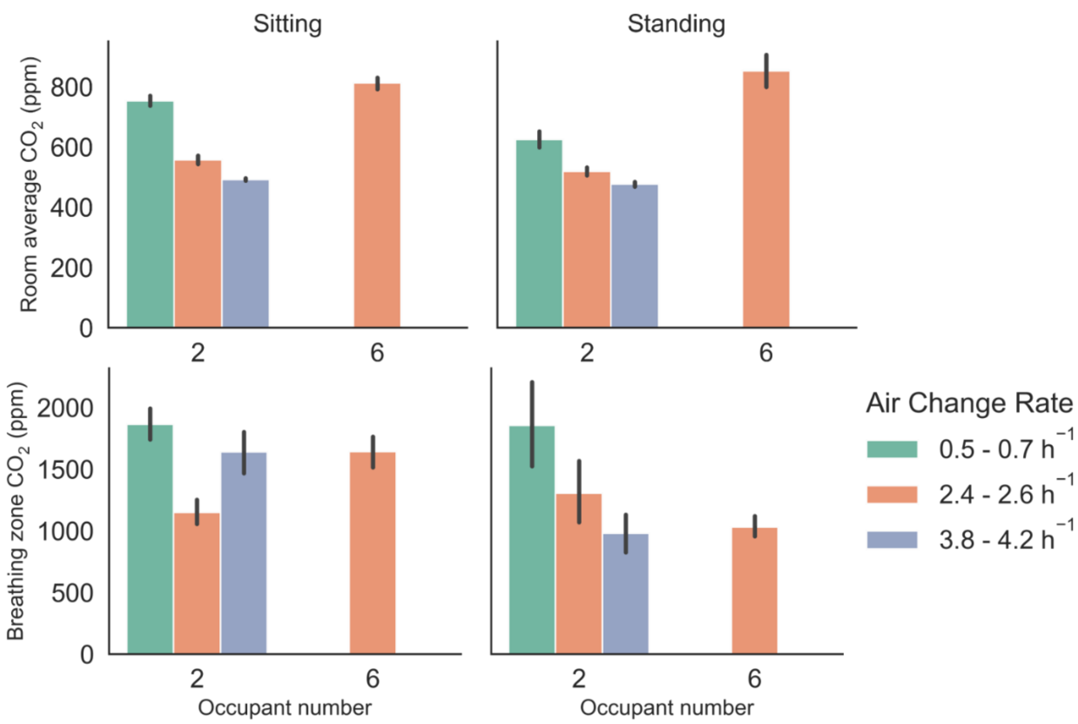


Figure S4.2 Room-average and breathing zone CO_2 concentration depending on three different air change rates and occupancy number during *sitting* and *standing* activities in static occupancies.

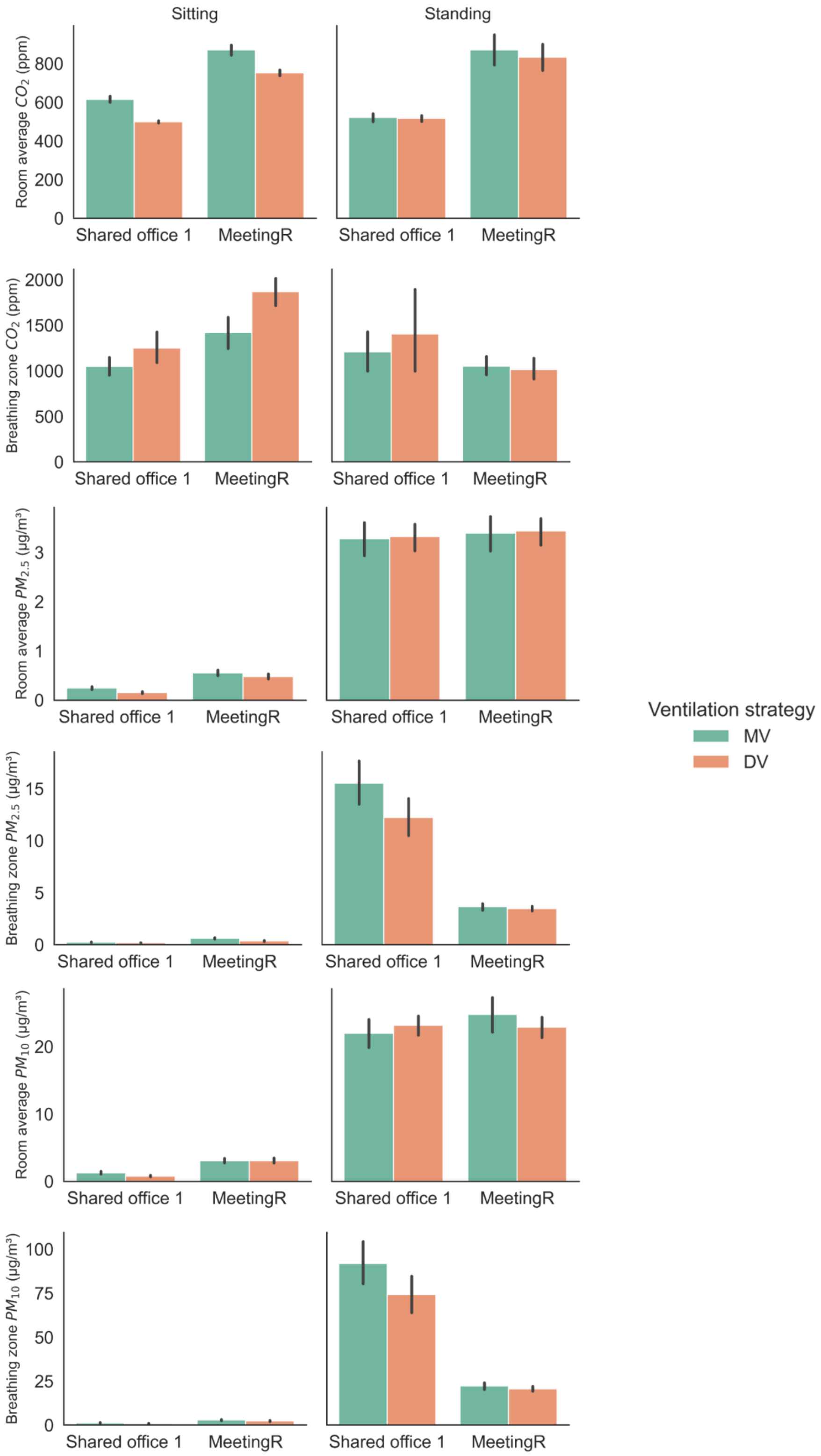


Figure S4.3 Room-average and breathing zone CO_2, $PM_{2.5}$, and PM_{10} concentration during sitting and standing activities depending on ventilation strategies (MV, DV) in static office and meeting room occupancies (two and six participants) at fixed air change rate of 2.4 – 2.6 h^{-1}. The DV scenarios had 200 – 350 ppm higher BZ CO_2 level and 0.7 – 0.85× lower BZ PM level than those of MV scenarios during the vigorous occupant activity.

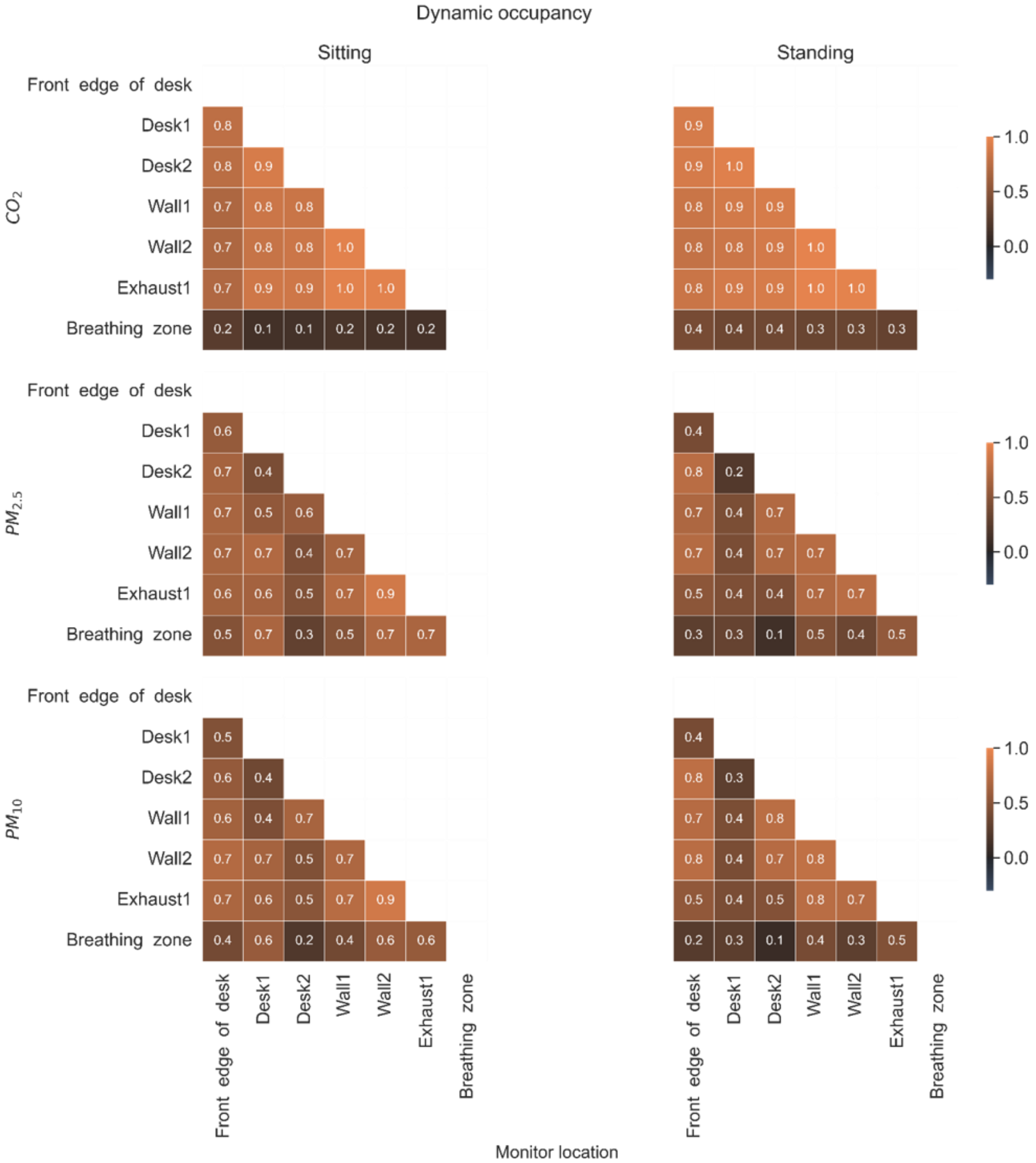


Figure S4.4 Pearson correlations of CO_2, $PM_{2.5}$, and PM_{10} measurements between stationary and breathing zone monitors during *sitting* and *standing* activities in dynamic occupancies.

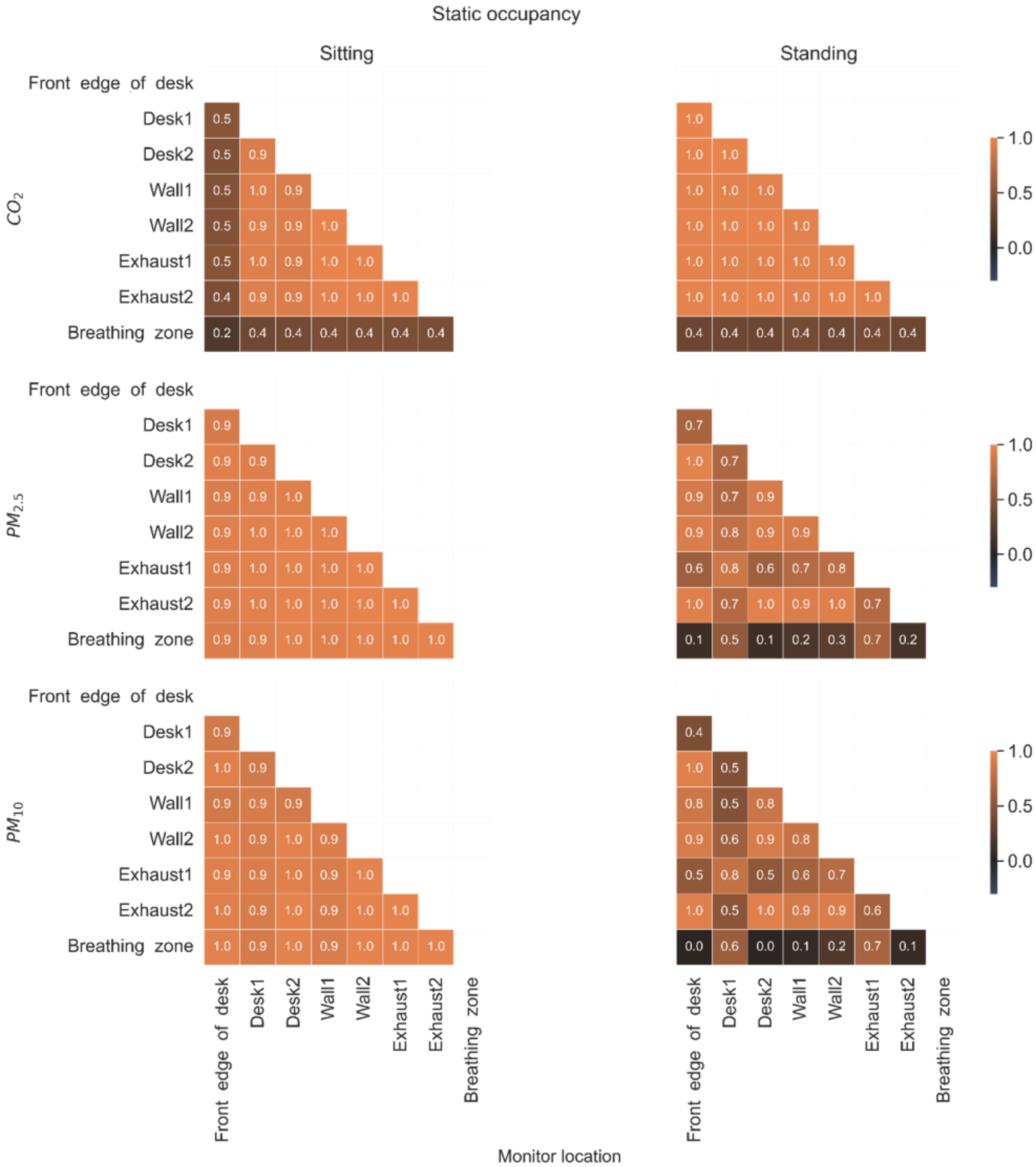


Figure S4.5 Pearson correlations of CO_2, $PM_{2.5}$, and PM_{10} measurements between stationary and breathing zone monitors during *sitting* and *standing* activities in static occupancies.

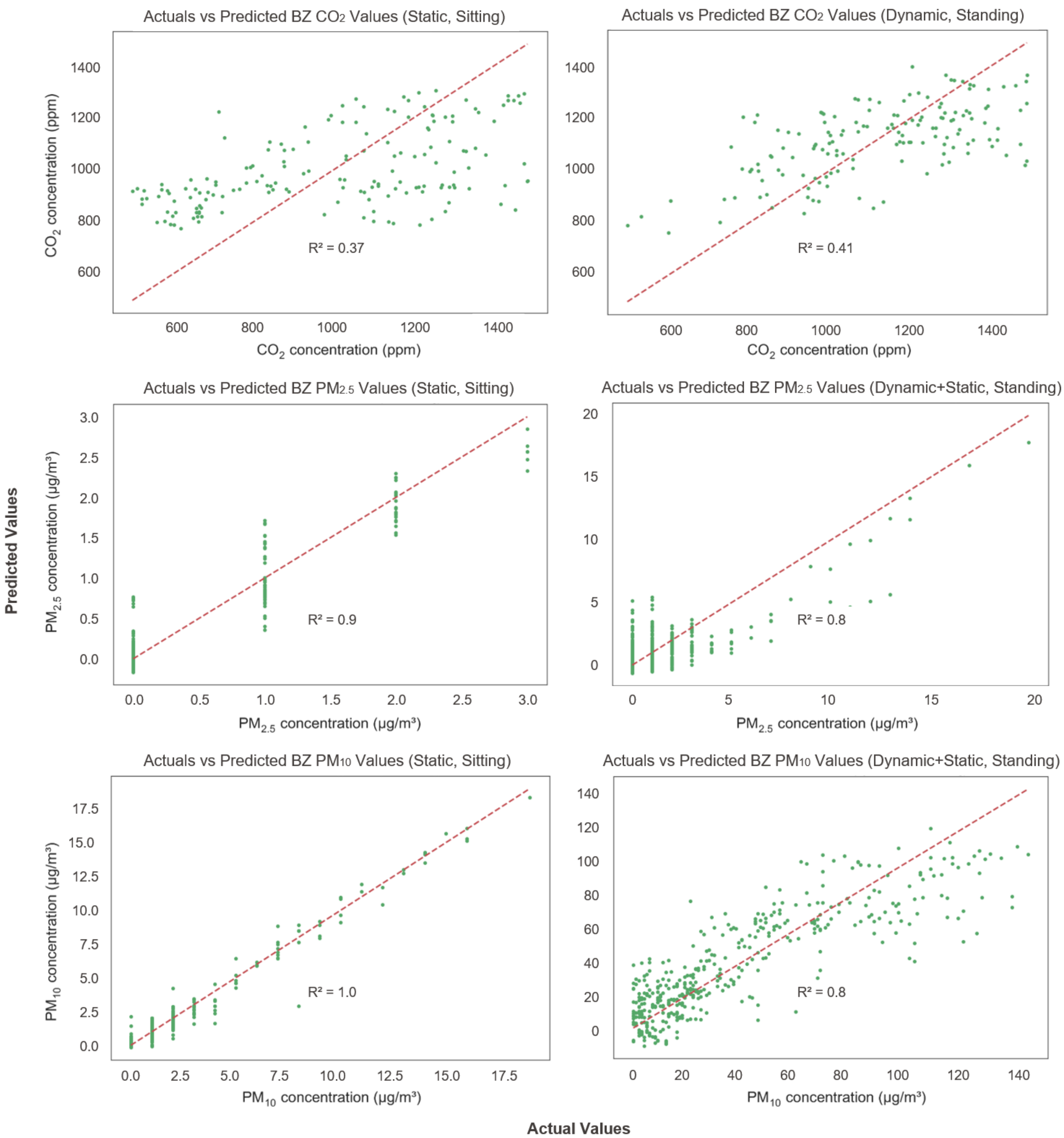


Figure S4.6 Comparison between actual (measured) and predicted personal exposures to CO_2, $PM_{2.5}$, and PM_{10} from the developed regression model in case of best accuracy (R^2) in the combination of occupancy profiles.

Table S4.1 Adjustment factors to mutually correct IAQ instruments. Reference instrument is shown in the parentheses.

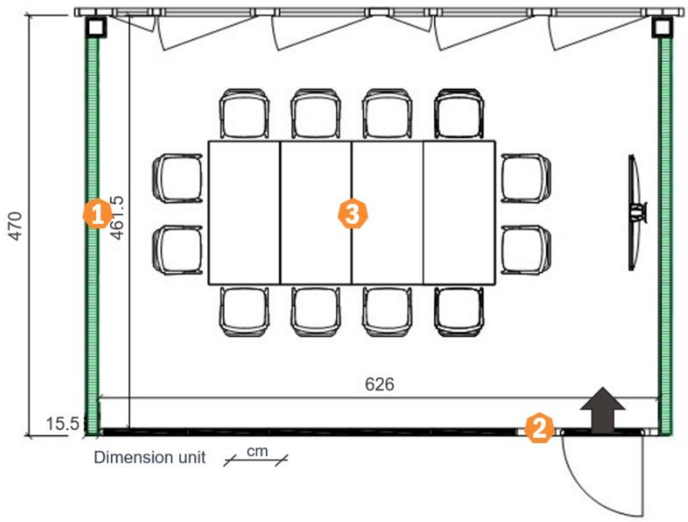
Monitor placement		Adjustment factors		
No	Description	CO_2	PM	
			$PM_{2.5}$	PM_{10}
1	Front edge of participant desk	1.01	2.0665	1.0645
2	Desk1	0.989	0.626	0.634
3	Desk2	0.963	2.0221	1.0537
4	Wall1	0.967	1 (reference, Mini-WRAS 1371)	
5	Wall2	0.964	1.9978	1.0981
6	Exhaust1	1.12	1.9637	1.0182
7	Exhaust2	0.987	2.0019	1.0141
8	Breathing zone	1 (reference, LI-850)	1.6816	0.9045

Table S4.2 The coefficients and intercepts of independent variables of the developed regression models in the best cases.

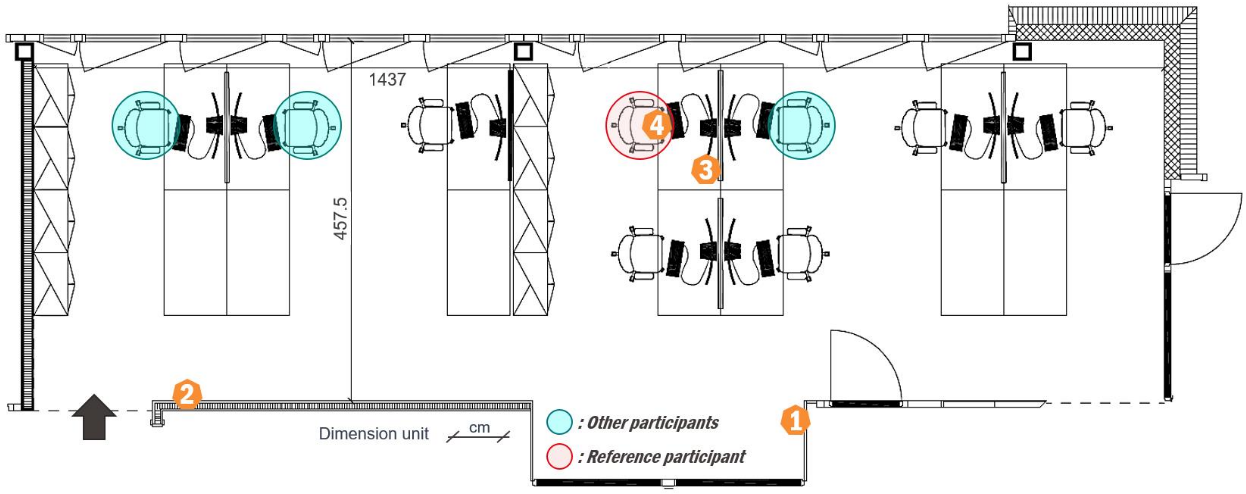
Occupancy	**Static Sitting**						**Dynamic Standing**					
Parameter	**CO_2**		**$PM_{2.5}$**		**PM_{10}**		**CO_2**		**$PM_{2.5}$**		**PM_{10}**	
Intercept		925.43		-0.12		-0.20		492.37		0.86		14.92
Coefficient*	**Wall2**	**-1.3**	**Wall2**	**0.73**	**Wall2**	**0.23**	**Desk2**	0.06	**Exhaust1**	**1.82**	**Exhaust1**	**1.09**
	FEOD	**0.1**	**Exhaust1**	**-0.18**	**FEOD**	**0.19**	**FEOD**	0.17	**Desk2**	**-0.02**	**Desk2**	**-0.19**
	Desk2	1.1	Wall1	0.51	Desk2	0.10	Desk1	0.78	Wall1	-0.57	Wall2	-0.93
	Wall1	1.1	FEOD	-0.02	Wall1	0.07	Wall2	0.91	FEOD	-0.29	Desk1	0.58
	Desk1	-0.2	Desk2	-0.05	Exhaust1	0.04	Exhaust1	-0.74	Desk1	3.53	Act_4	15.14
	Exhaust1	-0.5	Desk1	-0.41	Desk1	0.23	Wall1	-0.41	OccNum_2	0.77	Wall1	0.28
	DV	21.4	ACH_2	-0.09	ACH_2	-0.23	Act_12	-50.36	Wall2	-0.99	FEOD	0.34
	MV	-21.4	Act_3	0.00	ACH_3	-0.18	Act_In_2	-33.85	MV	0.77	MV	3.38
	OccNum_2	-16.8	Act_In_1	0.00	MV	0.02	OccNum_6	-70.73	Act_In_1	0.52	ACH_2	-4.58
	ACH_2	-93.8	ACH_1	0.19	Space_2	-0.05	DV	63.62	DV	-0.77	Act_In_1	7.62
	ACH_1	273.1	ACH_3	-0.10	Act_3	0.00	OccNum_8	-46.15	ACH_3	-0.03	DV	-3.38
	ACH_3	-179.3	MV	-0.01	Act_In_1	0.00	Act_In_1	33.85	OccNum_6	-0.44	Space_4	1.93
	Act_3	0.0	DV	0.01	ACH_1	0.41	Space_3	-13.54	OccNum_8	0.38	OccNum_6	-6.01
	Act_In_1	0.0	Space_1	0.05	DV	0.02	Act_6	8.74	Act_12	-0.15	Act_In_2	-7.62
	Space_1	-16.8	Space_2	-0.05	Space_1	0.05	Act_8	139.02	Space_1	-0.14	ACH_1	5.98
	Space_2	16.8	OccNum_2	0.05	OccNum_2	0.05	ACH_3	-55.04	Act_4	1.37	Space_3	5.32
	OccNum_6	16.8	OccNum_6	-0.05	OccNum_6	-0.05	Space_1	130.42	OccNum_4	-0.71	OccNum_2	6.14
							Space_2	-50.36	Act_6	-0.58	OccNum_8	5.45
							OccNum_2	116.83	ACH_2	-0.56	Act_8	-11.91
							Act_4	-30.87	Act_13	1.07	Act_12	-2.49
							MV	-63.62	Act_15	-0.98	Act_15	-14.79
							Act_13	1.57	Act_8	-0.73	Act_6	-2.66
							Act_15	-68.09	Act_In_2	-0.52	ACH_3	-1.40
							ACH_2	55.04	ACH_1	0.59	Space_2	-2.49
							Space_4	-66.52	Space_2	-0.15	OccNum_4	-5.58
							OccNum_4	0.06	Space_3	0.20	Act_13	16.72
									Space_4	0.08	Space_1	-4.76

*FEOD: Front edge of desk, OccNum_2, 4, 6, 8: Occupant Number (2, 4, 6, 8 people), Space_1, 2, 3, 4: Shared office1 (1), Shared office 2 (2), Meeting room (3), Cafeteria (4), ACH_1, 2, 3: Air Change Rate of 0.5 – 0.7 h^{-1} (1), 2.4 – 2.6 h^{-1} (2), 3.8 – 4.2 h^{-1} (3), MV: Mixing ventilation, DV: Displacement ventilation, Act_In_1, 2: Activity Intensity Full (1), Half (2), Act_3, 4, 6, 8, 12, 13, 15: sitting and working with laptop (3), stuffing cabinet with paper boxes (4), walking around and operating coffee machine/kettle (6), walking around and watering the plants (8), walking around, standing, talking (12), operating microwave and preparing lunch box (13), cleaning after lunch and operating coffee machine/kettle (16). Bolded values show the top two key features for each regression models.

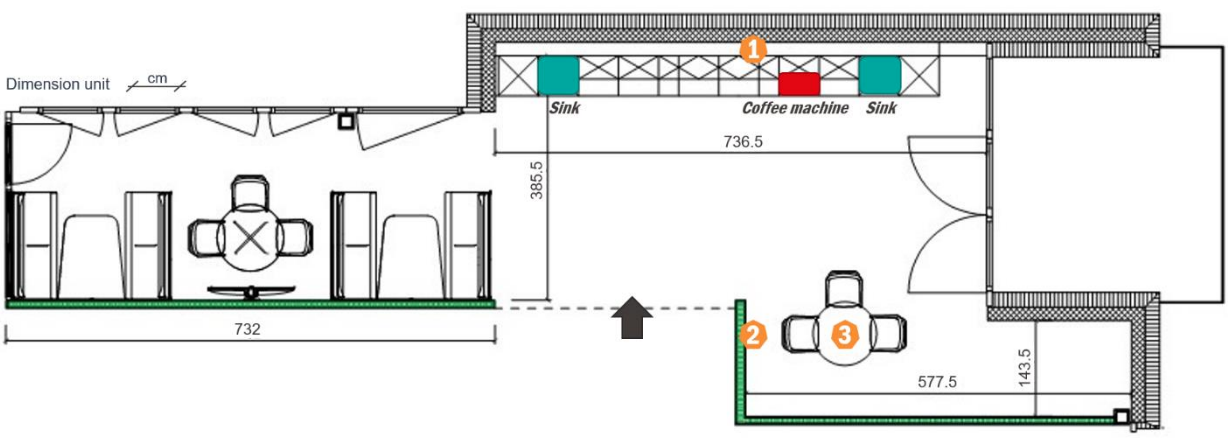
1) Building 1 – Meeting room



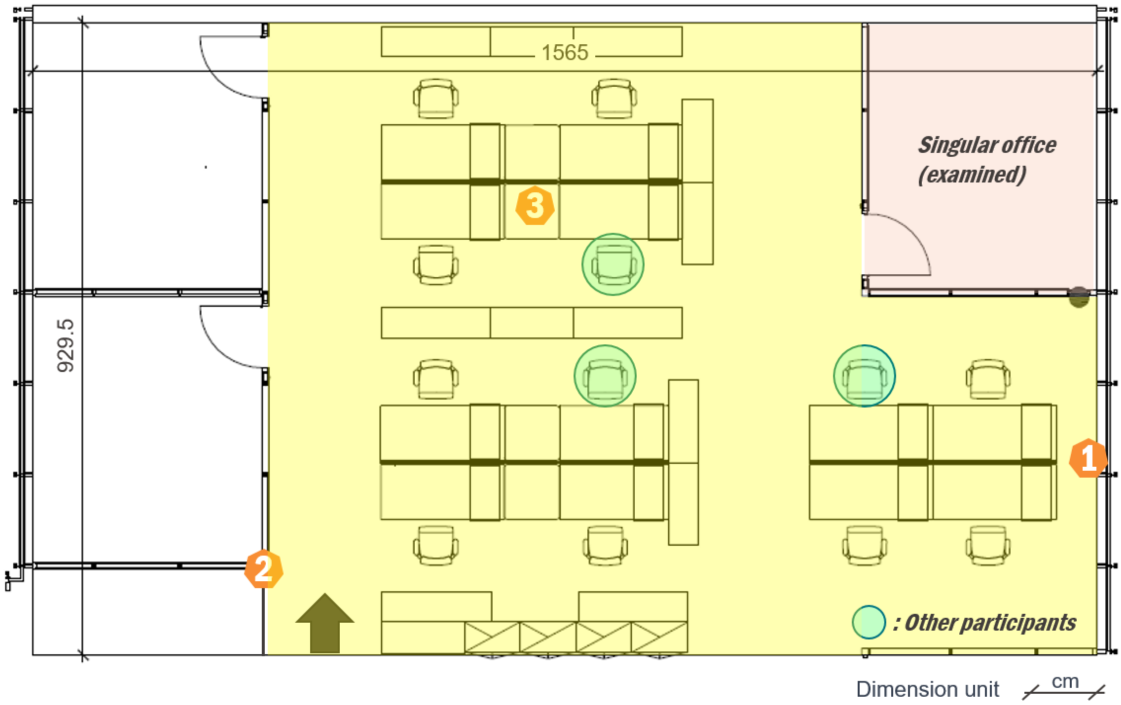
2) Building 1 – Open-plan office



3) Building 1 – Cafeteria



4) Building 2 – Open-plan office (coloured in yellow)



5) Building 2 – Meeting room

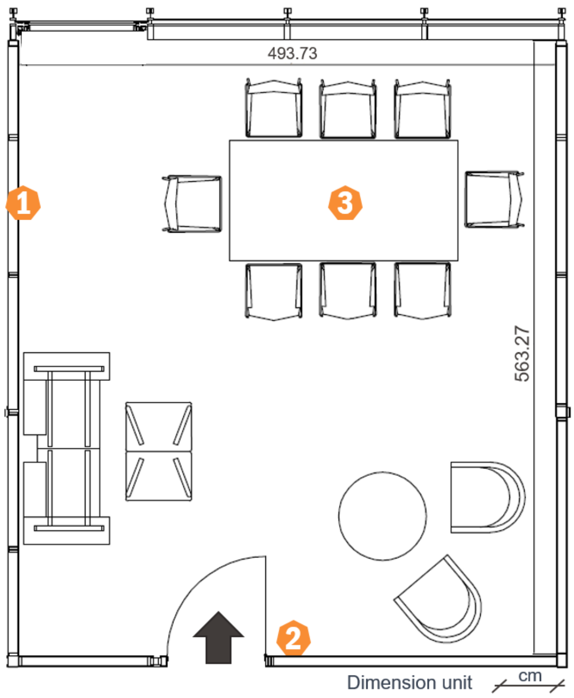
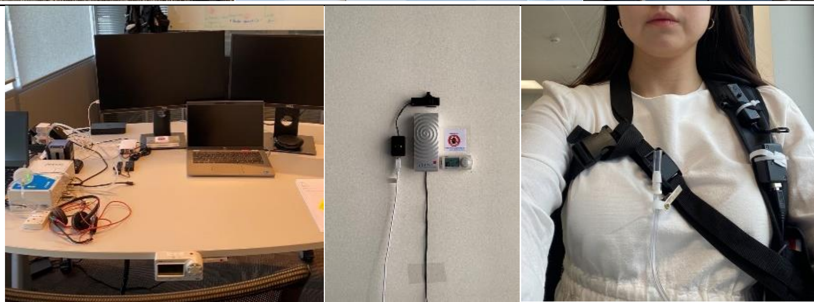
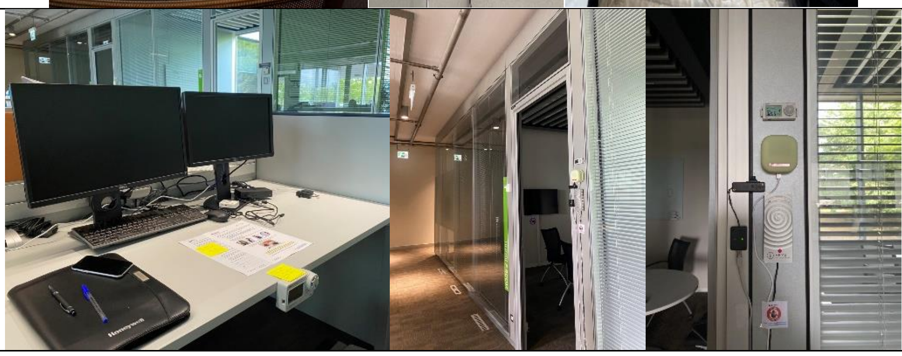


Figure S5.1 Floor plan and sensor placement IDs (1-4) of the examined target office areas in Building 1 and Building 2 except the singular office of Building 2 which is presented in Figure 5.1. ID 1: Wall 1, ID 2: Wall 2, ID 3: Desk, and ID 4: Personal vest, where T_a, RH, CO_2, $PM_{2.5}$ and PM_{10} levels are monitored.

Building No.	Target space	Picture
1	Open-plan office	
	Meeting room	
	Cafeteria	
2	Singular office	
	Open-plan office	

	Meeting room	

Figure S5.2 Detailed pictures of the target office areas in Building 1 and 2 with the installed sensors. When seated at workstation, one reference participant had an additional CO_2 sampling tube attached in the personal vest 20 cm below the nose to obtain estimated inhalation exposure to CO_2 only during seated posture as shown in the Singular office.

Figure S5.3 Questions of a point-in-time survey with application Cozie on participants' smartwatches.

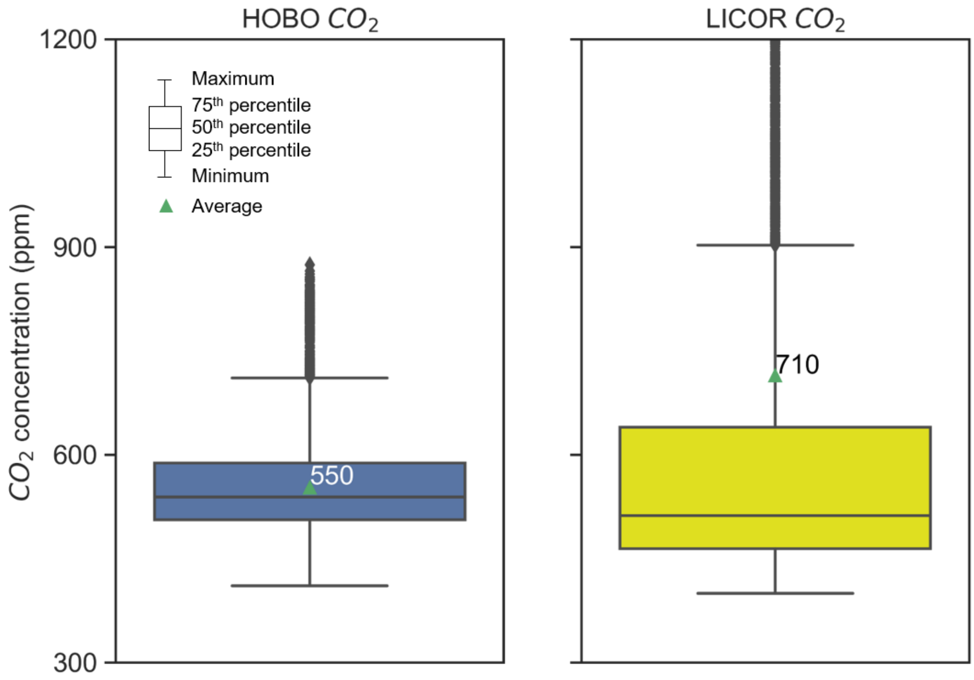


Figure S5.4 Comparison between personal and inhalation CO_2 exposure concentrations of the reference participant measured by the personal vest with HOBO CO_2 logger and by CO_2 sampling tube (with Li-COR gas analyzer), respectively.

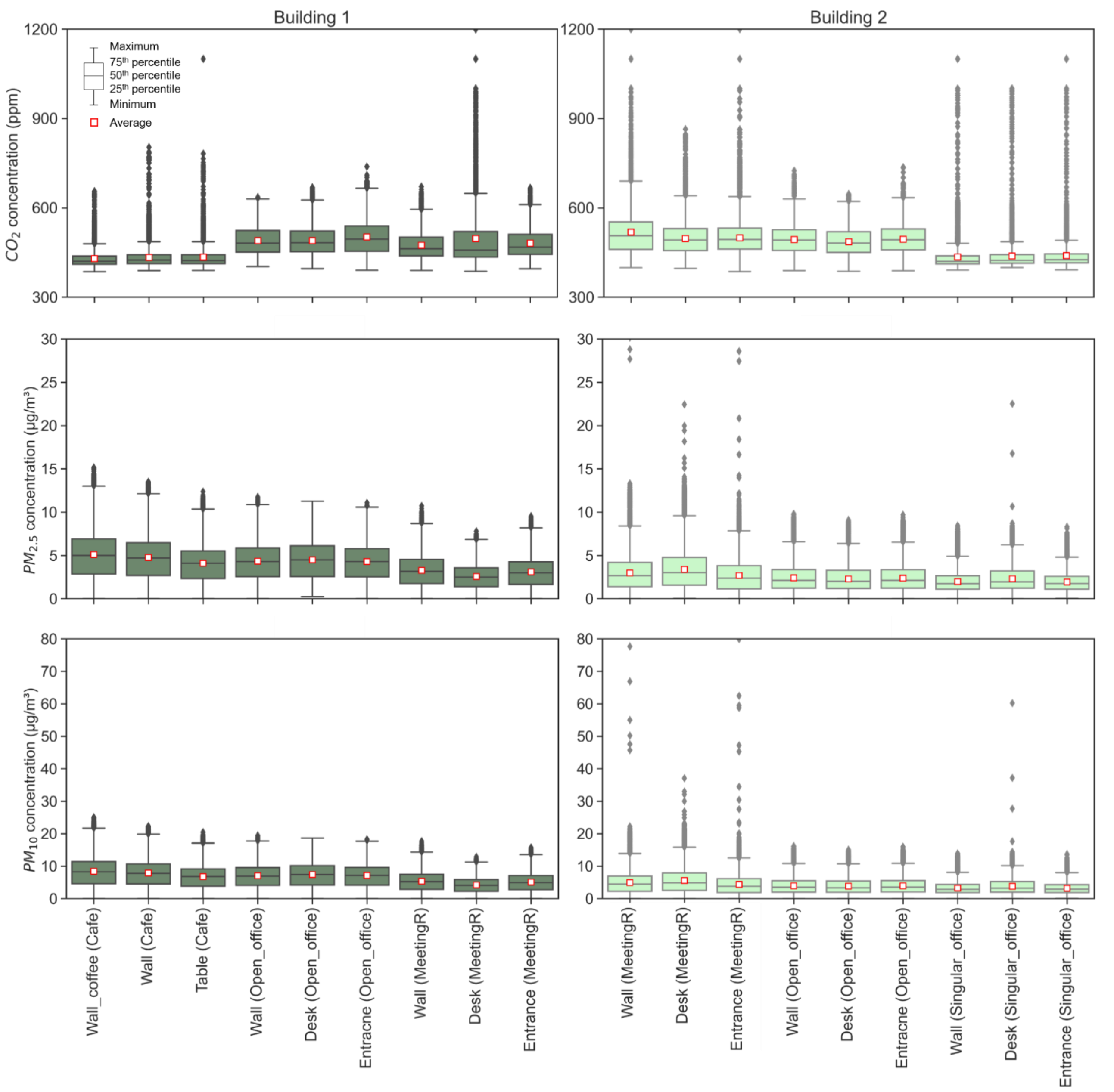


Figure S5.5 Stationary CO_2, $PM_{2.5}$, and PM_{10} measurements at various stationary locations of the examined target areas in the two office buildings. The figure shows the minimum, first quartile, median, third quartile, maximum and average concentrations.

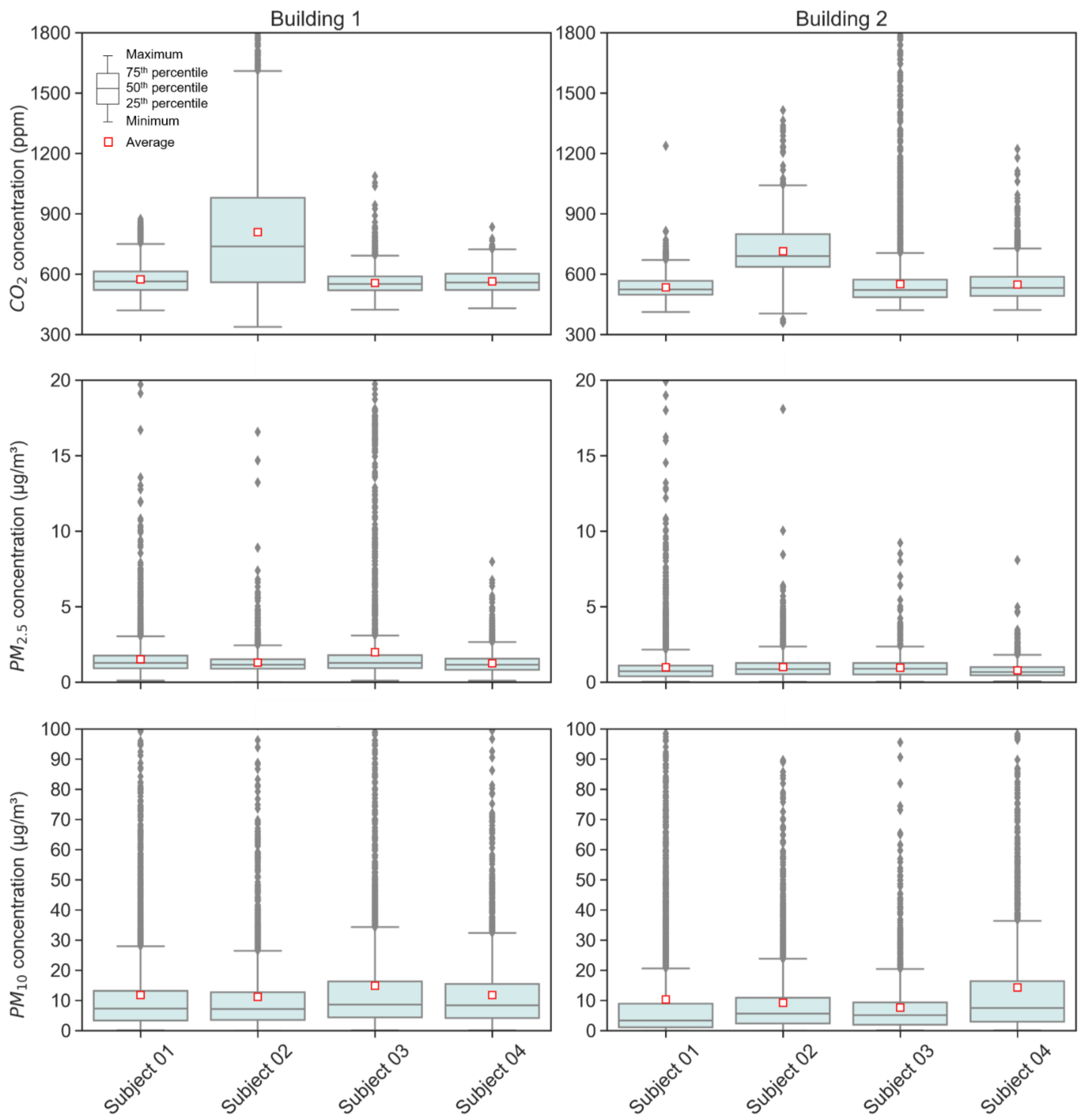


Figure S5.6 Personal CO_2, $PM_{2.5}$, and PM_{10} exposures of four participants monitored by their personal vests in the two office buildings. The figure shows the minimum, first quartile, median, third quartile, maximum and average concentrations.

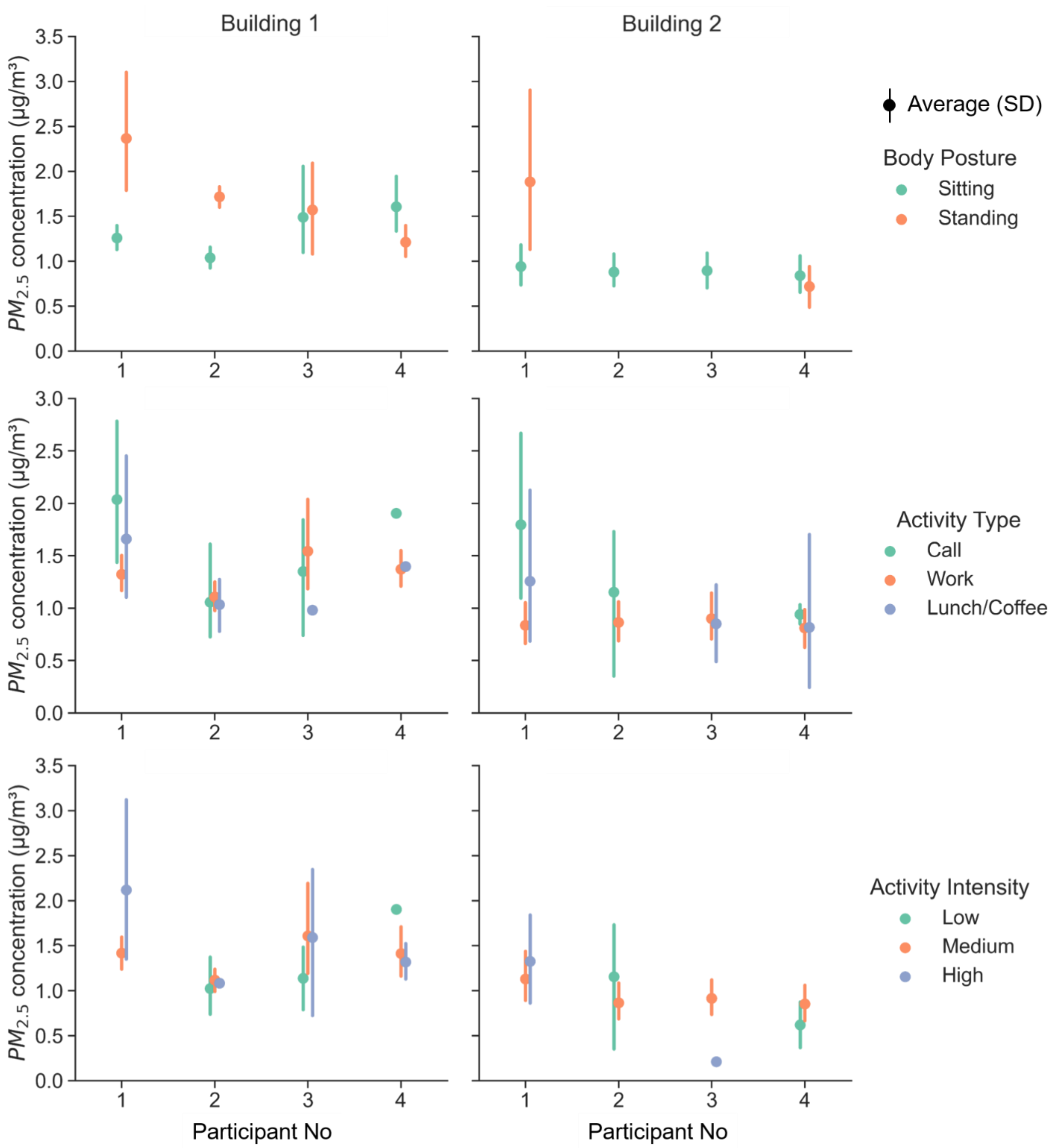


Figure S5.7 Average and standard deviation of personal-level $PM_{2.5}$ concentration in relation to point-in-time activity profiles of four participants (Participant No. 1-4) in the two office buildings.

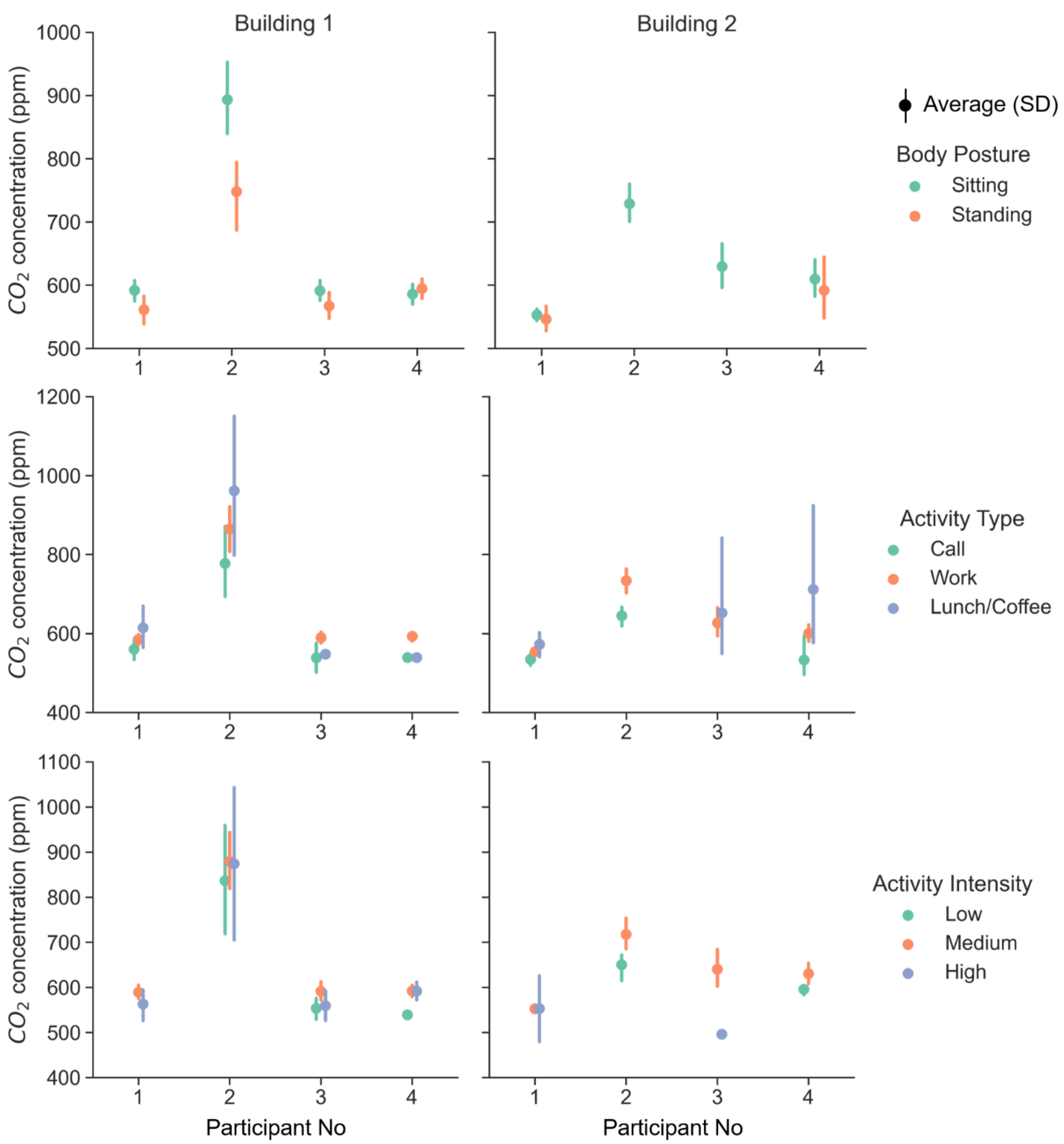


Figure S5.8 Average and standard deviation of personal-level CO_2 concentration in relation to point-in-time activity profiles of four participants (Participant No. 1-4) in the two office buildings.

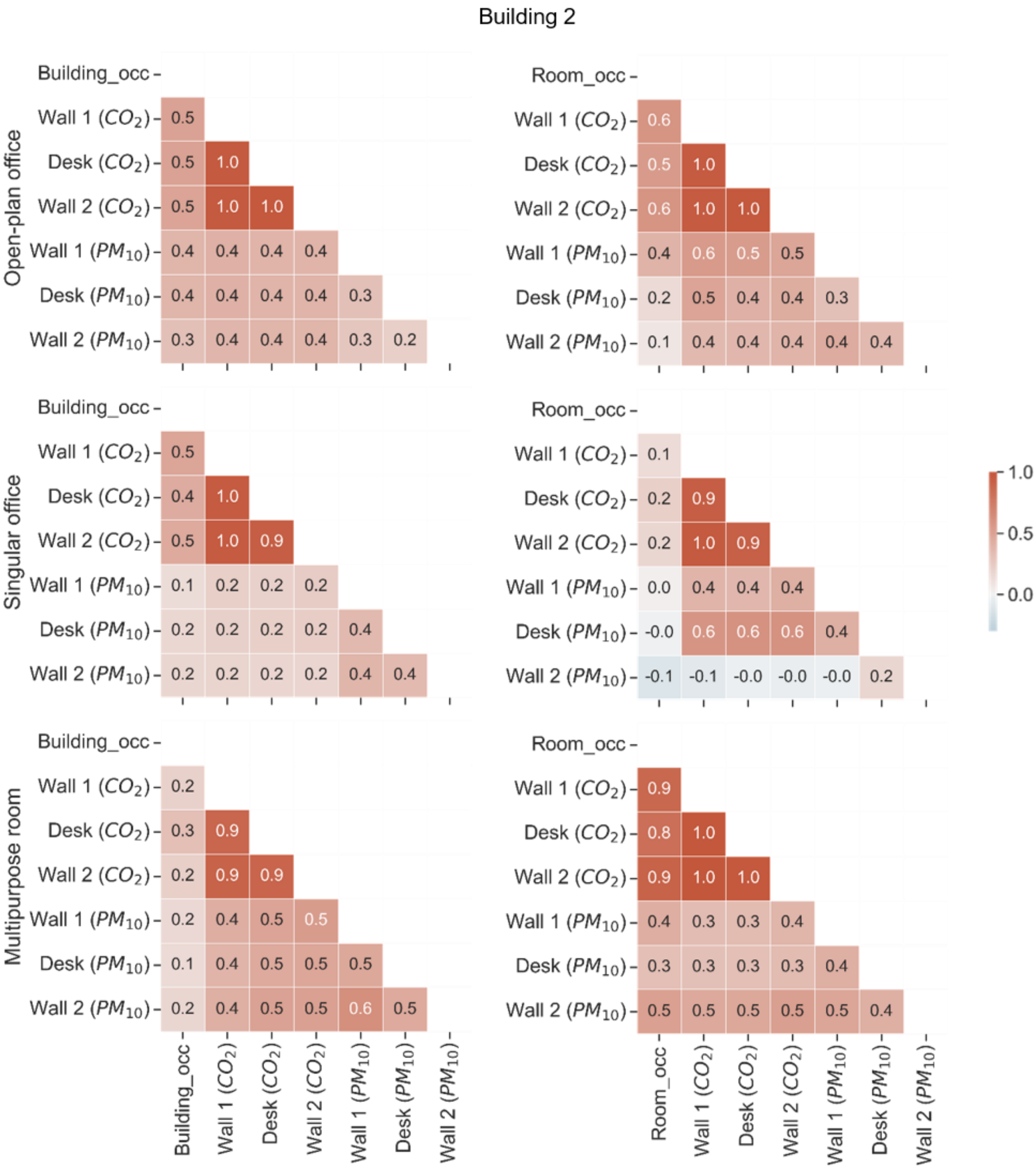
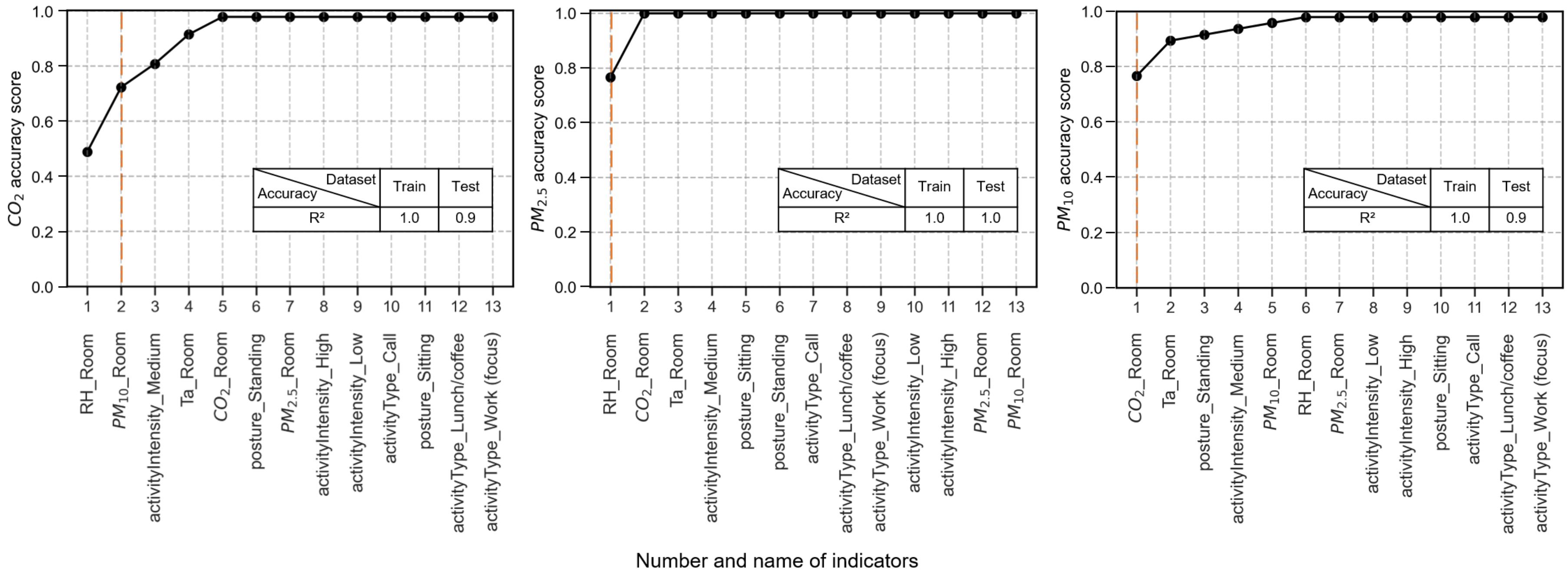
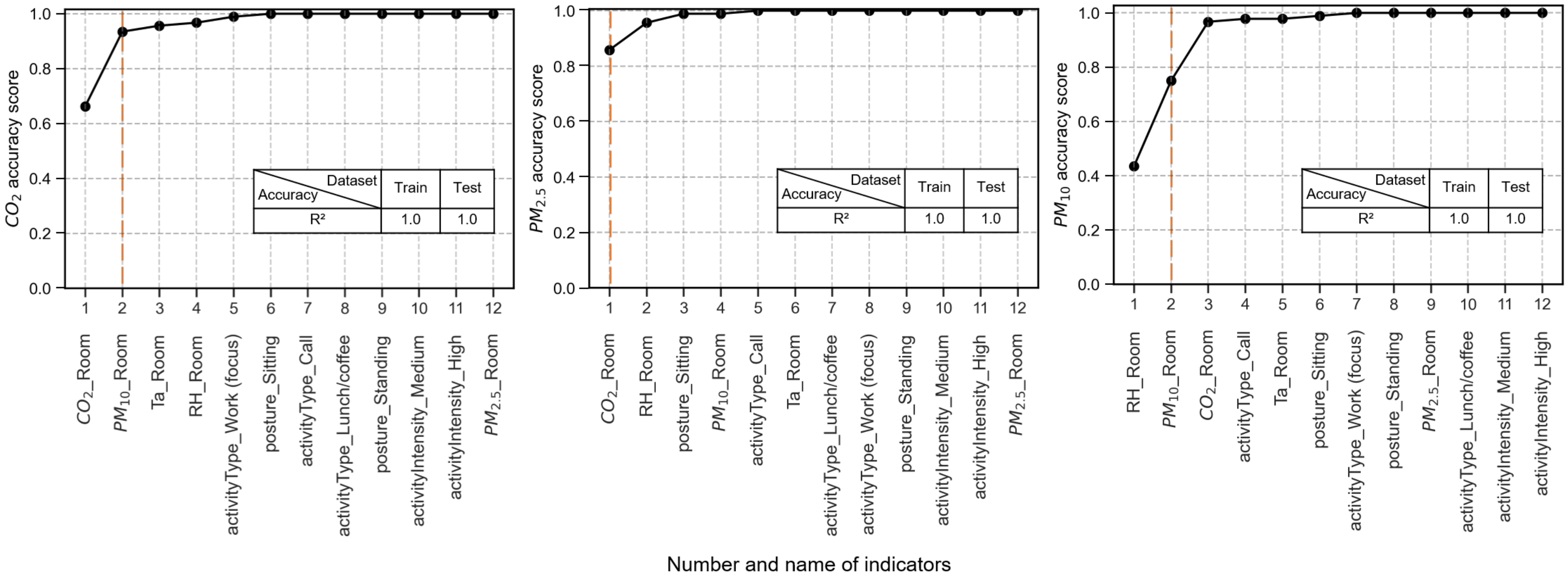


Figure S5.9 Heat maps annotated with correlation r values between building and room occupancy (Building_occ and Room_occ), CO_2 and PM_{10} levels at three different stationary locations of each examined target area of Building 2.

- **Meeting room**



- **Singular office**



- **Cafeteria**

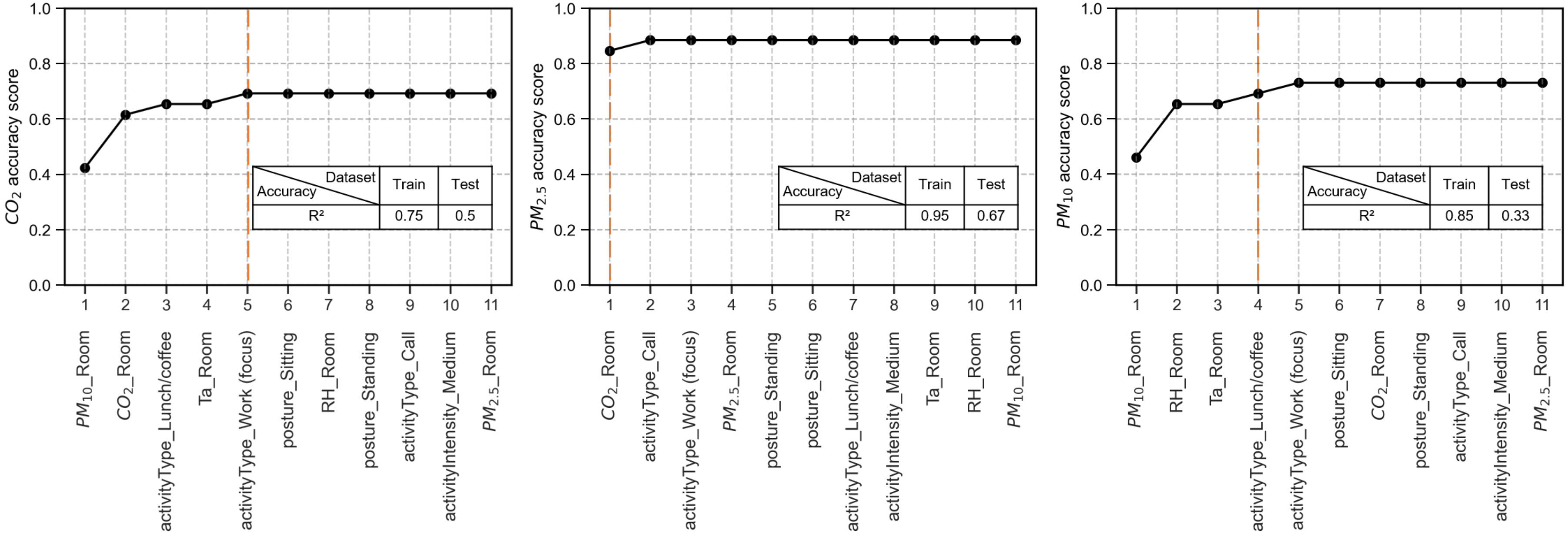
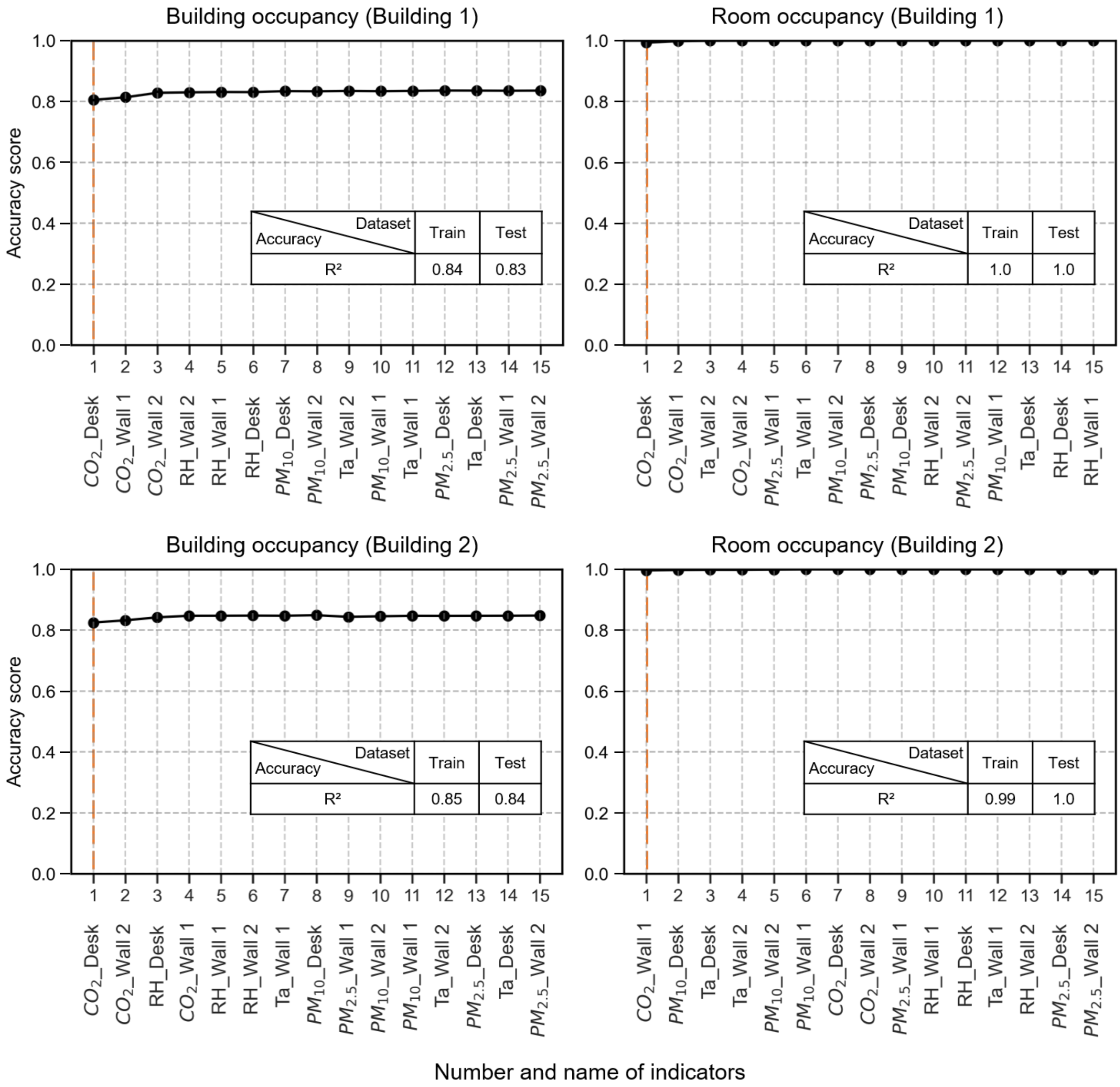
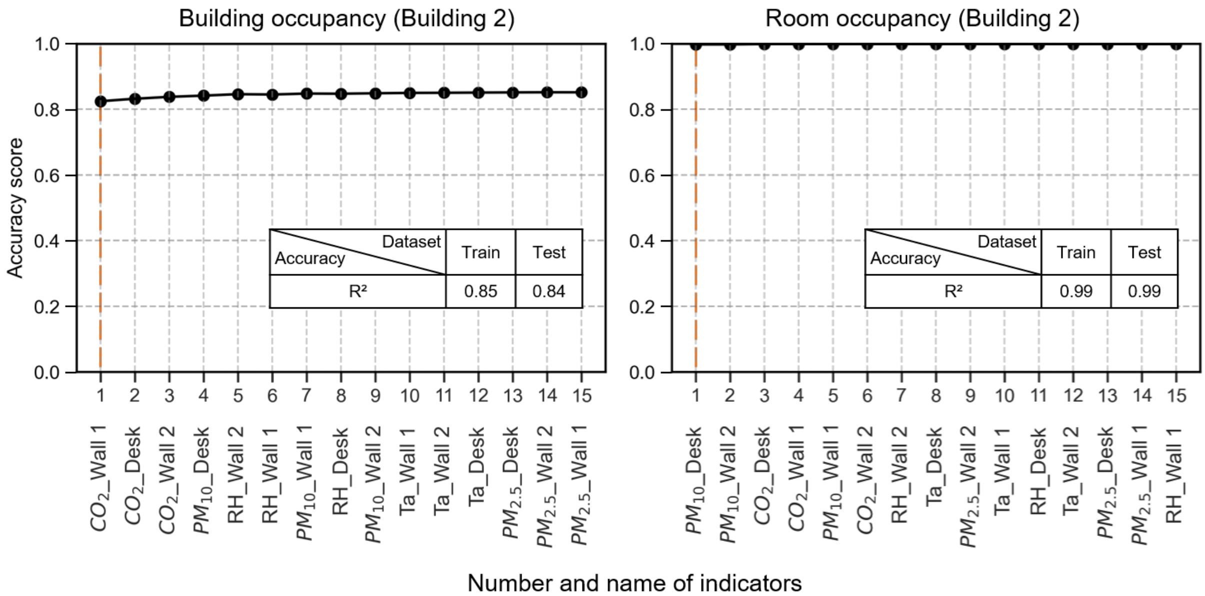


Figure S5.10 Number and name of the indicators and their accuracy scores for characterizing personal CO_2, $PM_{2.5}$ and PM_{10} exposures in Meeting room, Singular office, and Cafeteria. In case of Meeting room, the data from two Meeting rooms of Building 1 and Building 2 were used in constructing presented DT model. The indicators are named based on either type/placement of environmental sensors or occupant activity profiles, and they are ranked in order of their importance, from the highest (left) to the lowest (right). The vertical dashed lines indicate the minimum but sufficient set of indicators that can capture personal exposures to CO_2, $PM_{2.5}$ and PM_{10} with a "good" accuracy (*accuracy_score* > 0.7). The estimation performance (R^2) of proposed Decision Tree regression model in the best case (*accuracy_score* > 0.7) using train (80%) and test (20%) dataset is shown as a table.

- **Meeting room**



- **Singular office**



- **Cafeteria**

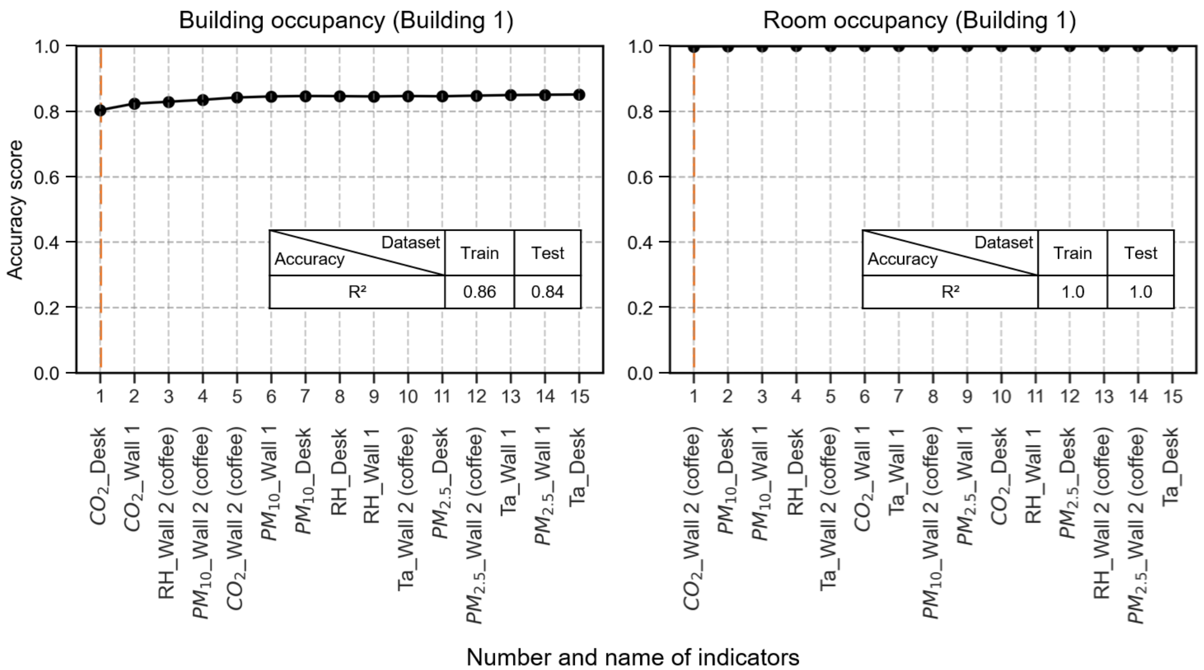


Figure S5.11 Number and name of the indicators and their accuracy scores for characterizing occupancy at building and room scale in Meeting room, Singular office, and Cafeteria in Building 1 and Building 2. The indicators are named based on the type and placement of the sensor, and they are ranked in order of their importance, from the highest (left) to the lowest (right). The vertical dashed lines indicate the minimum but sufficient set of indicators that can capture personal exposures to CO_2, $PM_{2.5}$ and PM_{10} with a “good” accuracy (*accuracy_score* > 0.7). The estimation performance (R^2) of proposed Decision Tree regression model in the best case (*accuracy_score* > 0.7) using train (80%) and test (20%) dataset is shown as a table.

Table S5.1 Adjustment factors to mutually correct IAQ instruments. Reference instrument is shown in the last row of the table with parentheses.

Building	Target space	Placement	Monitor	Adjustment factors (R^2)		
				CO_2	PM	
					$PM_{2.5}$	PM_{10}
1	Cafeteria	Wall 1	ARVE 1	0.99	0.98	0.84
		Wall 2	ARVE 2	0.99	0.987	0.865
		Desk	ARVE 3	0.99	0.98	0.829
	Open-plan office	Wall 1	ARVE 4	0.99	0.982	0.88
		Wall 2	ARVE 5	0.99	0.983	0.863
		Desk	ARVE 6	0.99	0.98	0.87
	Meeting room	Wall 1	ARVE 7	0.99	0.984	0.84
		Wall 2	ARVE 8	0.99	0.988	0.845
		Desk	ARVE 9	0.99	0.972	0.848
2	Singular office	Wall 1	ARVE 16	0.99	0.978	0.868
		Wall 2	ARVE 17	0.99	0.979	0.881
		Desk	ARVE 18	0.99	0.978	0.829
	Open-plan office	Wall 1	ARVE 13	0.99	0.987	0.906
		Wall 2	ARVE 14	0.99	0.983	0.94
		Desk	ARVE 15	0.99	0.982	0.79
	Meeting room	Wall 1	ARVE 10	0.99	0.985	0.885
		Wall 2	ARVE 11	0.99	0.982	0.928
		Desk	ARVE 12	0.99	0.986	0.886
1 & 2	Personal IAQ bag	Subject 1	HOBO 1	0.9216		
		Subject 2	HOBO 2	1.0452		
		Subject 3	HOBO 3	0.926		
		Subject 4	HOBO 4	0.9336		
		Subject 1	OPC-R2 1		0.976	0.817
		Subject 2	OPC-R2 2		0.978	0.952
		Subject 3	OPC-R2 3		0.986	0.794
		Subject 4	OPC-R2 4		0.99	0.908
Reference				**1 (LI-850)**	**1 (Mini-WRAS 1371)**	

Table S5.2 Averaged feature importance (F) in proposed Decision Tree model for detecting inhalation exposure to CO_2, $PM_{2.5}$ and PM_{10} by using stationary CO_2, $PM_{2.5}$, PM_{10}, T_a, and RH respectively.

	Average F value across deployed stationary monitors				
Parameter	**CO_2**	**$PM_{2.5}$**	**PM_{10}**	**T_a**	**RH**
CO_2 exposure detection	0.258	0.025	0.120	0.132	0.148
$PM_{2.5}$ exposure detection	0.377	0.035	0.064	0.085	0.193
PM_{10} exposure detection	0.185	0.032	0.195	0.136	0.199

Table S5.3 All indicators (I_n) ordered by the largest feature importance (F) in proposed Decision Tree model for detecting occupancy at building and room scale in each target area of each of the two office buildings.

Building_ occupancy model	**Building 1**						**Building 2**					
	Open-plan office	**F**	**Meeting room**	**F**	**Cafeteria**	**F**	**Open-plan office**	**F**	**Meeting room**	**F**	**Singular office**	**F**
I1	Wall 2_CO_2	0.162	Desk_CO_2	0.205	Desk_CO_2	0.165	Wall 1_CO_2	0.16	Desk_CO_2	0.161	Wall 1_CO_2	0.146
I2	Desk_CO_2	0.122	Wall 1_CO_2	0.161	Wall 1_CO_2	0.158	Wall 2_RH	0.121	Wall 2_CO_2	0.137	Desk_CO_2	0.128
I3	Wall 1_CO_2	0.118	Wall 2_CO_2	0.146	Wall 2 (coffee)_RH	0.11	Desk_PM_{10}	0.104	Desk_RH	0.122	Wall 2_CO_2	0.112
I4	Wall 2_RH	0.1	Wall 2_RH	0.108	Wall 2 (coffee) _PM_{10}	0.09	Wall 2_CO_2	0.096	Wall 1_CO_2	0.12	Desk_PM_{10}	0.091
I5	Wall 2_PM_{10}	0.079	Wall 1_RH	0.069	Wall 2 (coffee) _CO_2	0.088	Desk_RH	0.094	Wall 1_RH	0.089	Wall 2_RH	0.09
I6	Wall 1_PM_{10}	0.076	Desk_RH	0.068	Wall 1_PM_{10}	0.085	Desk_CO_2	0.086	Wall 2_RH	0.071	Wall 1_RH	0.083
I7	Wall 1_RH	0.07	Desk_PM_{10}	0.055	Desk_PM_{10}	0.072	Wall 1_RH	0.081	Wall 1_Ta	0.054	Wall 1_PM_{10}	0.074
I8	Desk_PM_{10}	0.064	Wall 2_Ta	0.042	Desk_RH	0.058	Wall 1_PM_{10}	0.07	Wall 1_$PM_{2.5}$	0.05	Desk_RH	0.072
I9	Desk_Ta	0.046	Wall 2_PM_{10}	0.042	Wall 1_RH	0.042	Wall 2_PM_{10}	0.062	Desk_PM_{10}	0.05	Wall 2_PM_{10}	0.069
I10	Wall 2_$PM_{2.5}$	0.042	Wall 1_PM_{10}	0.03	Wall 2 (coffee)_Ta	0.038	Wall 1_Ta	0.048	Wall 2_PM_{10}	0.048	Wall 1_Ta	0.061
I11	Wall 2_Ta	0.035	Wall 1_Ta	0.029	Desk_$PM_{2.5}$	0.024	Wall 2_$PM_{2.5}$	0.031	Wall 1_PM_{10}	0.046	Wall 2_Ta	0.032
I12	Desk_RH	0.033	Desk_$PM_{2.5}$	0.022	Wall 2 (coffee) _$PM_{2.5}$	0.023	Desk_Ta	0.026	Wall 2_Ta	0.027	Desk_Ta	0.027
I13	Wall 1_Ta	0.023	Desk_Ta	0.019	Wall 1_Ta	0.021	Wall 2_Ta	0.01	Desk_$PM_{2.5}$	0.015	Desk_$PM_{2.5}$	0.012
I14	Wall 1_$PM_{2.5}$	0.022	Wall 1_$PM_{2.5}$	0.003	Wall 1_$PM_{2.5}$	0.02	Wall 1_$PM_{2.5}$	0.009	Desk_Ta	0.006	Wall 2_$PM_{2.5}$	0.003
I15	Desk_$PM_{2.5}$	0.009	Wall 2_$PM_{2.5}$	0.001	Desk_Ta	0.008	Desk_$PM_{2.5}$	0.002	Wall 2_$PM_{2.5}$	0.005	Wall 1_$PM_{2.5}$	0.001
Room occupancy model	**Building 1**						**Building 2**					
	Open-plan office	**F**	**Meeting room**	**F**	**Cafeteria**	**F**	**Open-plan office**	**F**	**Meeting room**	**F**	**Singular office**	**F**
I1	Wall 1_CO_2	0.307	Desk_CO_2	0.6	Wall 2 (coffee) _CO_2	0.321	Wall 2_CO_2	0.203	Wall 1_CO_2	0.383	Desk_PM_{10}	0.156
I2	Desk_RH	0.255	Wall 1_CO_2	0.163	Desk_PM_{10}	0.221	Wall 1_CO_2	0.14	Desk_PM_{10}	0.118	Desk_CO_2	0.128
I3	Wall 2_CO_2	0.162	Wall 2_Ta	0.118	Wall 1_PM_{10}	0.078	Wall 1_PM_{10}	0.102	Desk_Ta	0.116	Wall 2_PM_{10}	0.128
I4	Desk_PM_{10}	0.06	Wall 2_CO_2	0.046	Wall 2 (coffee)_Ta	0.069	Desk_CO_2	0.088	Wall 2_Ta	0.081	Wall 1_CO_2	0.117
I5	Wall 1_PM_{10}	0.043	Wall 1_$PM_{2.5}$	0.03	Desk_RH	0.069	Wall 2_PM_{10}	0.082	Wall 2_PM_{10}	0.077	Wall 1_PM_{10}	0.109

I6	Wall 2_PM_{10}	0.041	Wall 1_Ta	0.023	Wall 1_CO_2	0.068	Desk_PM_{10}	0.079	Wall 1_PM_{10}	0.076	Wall 2_CO_2	0.099
I7	Wall 2_RH	0.038	Wall 2_PM_{10}	0.014	Wall 1_Ta	0.031	Wall 1_Ta	0.065	Desk_CO_2	0.052	Wall 2_RH	0.097
I8	Wall 1_RH	0.028	Wall 2_RH	0.002	Wall 2 (coffee) _PM_{10}	0.03	Wall 1_RH	0.064	Wall 2_CO_2	0.028	Desk_Ta	0.061
I9	Desk_CO_2	0.028	Desk_$PM_{2.5}$	0.002	Wall 1_$PM_{2.5}$	0.028	Desk_RH	0.059	Wall 1_$PM_{2.5}$	0.023	Wall 2_$PM_{2.5}$	0.048
I10	Desk_Ta	0.016	Desk_PM_{10}	0.002	Wall 1_RH	0.023	Desk_$PM_{2.5}$	0.043	Wall 1_RH	0.019	Wall 1_Ta	0.028
I11	Wall 1_$PM_{2.5}$	0.011	Desk_Ta	0	Desk_CO_2	0.023	Wall 2_Ta	0.033	Desk_RH	0.013	Desk_RH	0.015
I12	Desk_$PM_{2.5}$	0.01	Wall 1_RH	0	Desk_$PM_{2.5}$	0.022	Wall 2_RH	0.023	Wall 1_Ta	0.008	Wall 2_Ta	0.014
I13	Wall 2_$PM_{2.5}$	0.002	Desk_RH	0	Wall 2 (coffee)_RH	0.016	Desk_Ta	0.013	Wall 2_RH	0.006	Wall 1_RH	0
I14	Wall 1_Ta	0	Wall 2_$PM_{2.5}$	0	Desk_Ta	0	Wall 2_$PM_{2.5}$	0.007	Wall 2_$PM_{2.5}$	0	Wall 1_$PM_{2.5}$	0
I15	Wall 2_Ta	0	Wall 1_PM_{10}	0	Wall 2 (coffee) _$PM_{2.5}$	0	Wall 1_$PM_{2.5}$	0	Desk_$PM_{2.5}$	0	Desk_$PM_{2.5}$	0

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Curriculum Vitae

Seoyeon Yun
Email: ysy7477@gmail.com, ORCiD: 0000-0001-6022-7520
Tel: +41 76 379 47 17
Date of Birth: 07. May. 1992
Nationality: Republic of Korea

Education

Ph.D. **Civil and Environmental Engineering,** EPFL, Switzerland. 11/2019 – 10/2023

Advisor: Prof. Dusan Licina

M.S. **Interior architecture & Built Environment,** Yonsei University, Seoul, Korea. 03/2016 – 02/2018

Advisor: Prof. Chungyoon Chun

B.S. **Interior architecture & Built Environment,** Yonsei University, Seoul, Korea. 03/2011 – 02/2016

Experiences

Project Lead	**Honeywell International Sarl,** Rolle, Switzerland	01/2022 – 10/2023
Scientific Lead	**EPFL,** Lausanne, Switzerland	11/2019 – 10/2021
Research Collaborator	**Hyundai Motor Company,** Namyang, South Korea	03/2018 – 09/2019
Project Lead	**Hyundai Motor Company,** Namyang, South Korea	12/2015 – 12/2017
CSR Group Assistant	**POSCO E&C,** Songdo, South Korea	02/2013 – 02/2014

Activities

- **ENAC-week Student Project Supervisor,** Mission Asclepios: Terrestrial Lunar Base, EPFL. (2023)
- **Ph.D. Student Representative,** EDCE (Environmental and Civil Engineering), EPFL. (2021-2023)
- **Tutor,** Swiss-Korean student exchange program ARC-HEST (Architecture for human environment with smart technologies). (2020, 2023)
- **Semester Project Supervisor,** Indoor environmental quality investigation in a simulated spacecraft cabin, Asclepios, EPFL. (2022)
- **Smart Living Lab Student Incubator,** Cofounder of PAir (Personal Air Quality Monitor). (2022)
- **Talent Kick Entrepreneurship,** Cofounder of Syncus (Meeting Assistant for Hybrid Team). (2022)
- **Teaching Assistant,** MS course “Indoor air quality and ventilation”, EPFL. (2021)
- **Teaching Assistant,** BS course “Theory of indoor environment”, Yonsei University. (2016-2017)
- **USAC Exchange Student,** Universita degli Studi della Tuscia, Viterbo, Italy. (2014-2015)

Honors and Awards

- **Doctoral Fellowships "EPFLinnovators",** MCAA, EU Horizon Europe 2020. (2019-2023)
- **Best Short Paper Awards,** Healthy Building Europe Conference, Oslo, Norway. (2021)
- **MSc Full Scholarships "Brain Korea 2021",** National Research Foundation of Korea, South Korea. (2016-2018)
- **Excellent Journal Presentation Awards,** AIK (Architectural Institute of Korea), South Korea. (2018)
- **Young Researchers Awards,** KSAE (Korean Society of Automotive Engineers), South Korea. (2017)
- **Best BSc Graduation Exhibition Awards**, Yonsei University, South Korea. (2016)
- **BSc State Scholarships**, Korea Student Aid Foundation, South Korea. (2013)

Peer-reviewed Publications

1. **Yun, S.**, & Licina, D. (2023). Investigation of indicators for personal exposure and occupancy in offices by using smart sensors, *Energy and Buildings,* 298, 113539.
2. **Yun, S.**, & Licina, D. (2023). Optimal sensor placement for personal inhalation exposure detection in static and dynamic office environments, *Building and Environment,* 110459.
3. **Yun, S.**, Zhong, S., Alavi, H. S., Alahi, A., & Licina, D. (2022). Proxy methods for detection of inhalation exposure in simulated office environments. *Journal of Exposure Science & Environmental Epidemiology*, 1-11.
4. **Yun, S.**, Chun, C., Kwak, J., Park, J. S., Kwon, C., Kim, S., & Seo, S. (2021). Prediction of thermal comfort of female passengers in a vehicle based on an outdoor experiment. *Energy and Buildings*, 248, 111161.

Conference and Symposium

1. 16th Conference of the International Society of Indoor Air Quality & Climate, Seoul, South Korea (11. 2020). (Oral presentation, virtual).
2. 17th International Healthy Buildings Conference, Oslo, Norway (06.2021). (Oral presentation, virtual).
3. 1st EDCE research day, EPFL, Switzerland (11.2022). (Poster presentation).
4. Europe-Korea Conference on Science and Technology (EKC), Marseille, France (07.2022). (Oral presentation).
5. 17th Conference of the International Society of Indoor Air Quality & Climate, Kuopio, Finland (06.2022). (Oral presentation).
6. Symposium of Korean scientist at EPFL-ETH, Lausanne, Switzerland (12.2022). (Poster presentation).
7. 18th International Healthy Buildings Conference, Aachen, Germany (06.2023). (Poster presentation).
8. Europe-Korea Conference on Science and Technology (EKC), Munich, Germany (08.2023). (Oral presentation).
9. ENAC research day, EPFL, Switzerland (09.2023). (Poster presentation).
10. International scientific conference cycle for a Sustainable Energy Transition in the Built Environment (CISBAT), Lausanne, Switzerland (09.2023). (Poster presentation).