UNIVERSITY OF TECHNOLOGY SYDNEY

Using IoT sensing and occupant surveys to evaluate the temporal and spatial correlations between indoor air quality and occupancy comfort in campus buildings

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Thesis submitted in fulfilment of the requirements for the degree of

Masters by Research

under the supervision of

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January 2024

Certificate of Original Authorship

I, Elaheh Samandi, declare that this thesis is submitted in fulfilment of the requirements for the award of the degree of Masters by Research in the School of Built Environment of the Faculty of Design, Architecture and Building at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution. This research is supported by the Australian Government Research Training Program.

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Date: 5 January 2024

Note on the thesis format.

This thesis was prepared to fulfil the criteria for Masters by Research and is in the format of a conventional thesis. It adheres to the guidelines set forth in “Graduate Research Candidature Management, Thesis Preparation and Submission Procedures 2023 - University of Technology Sydney”. This thesis used the American Psychological Association (APA) 7th edition referencing style. In all chapters, the source of the figures created by the thesis author (Elaheh Samandi) is cited as “The Author”.

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Abbreviations

AIHW	Australian Institute of Health and Welfare
AMV	Actual Mean Vote
AQI	Air Quality Index
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
CRF	Concentration-Response Function
CRinh	lifetime Cancer Risks
DALY	Disability-Adjusted Life Years
DCV	Demand Controlled Ventilation
E-Index	Exceedance Index
EAP	Environmental Air Pollution
EIAQI	Enhanced Indoor Air Quality Index
ELV	Exposure Limit Value
GCCSA	Greater Capital City Statistical Areas
HEPA	High-Efficiency Particulate Air
HHD	Human Health Damage
HKEPD	Hong Kong Environmental Protection Department
HRB	Hazard-Reduction Burning
HQ	Hazard Quotient
HVAC	Heating, Ventilation, and Air Conditioning
IAQ	Indoor Air Quality
IAQI	Indoor Air Quality Index
IAQM	Indoor Air Quality Monitoring
IAP	Indoor Air Pollution
IEQ	Indoor Environmental Quality
I/O	Indoor to Outdoor
IoT	Internet of Things
IQR	Interquartile Range
MCUs	Microcontrollers
NHMRS	National Health and Medical Research Council of Australia
PM	Particulate Matter
PMV	Predicted Mean Vote

PPD	Predicted Percentages of Dissatisfied
RAQMS	Regional Air Quality Monitoring Stations
RDMP	Research Data Management Plan
RH	Relative Humidity
UNEP-SETAC	United Nations Environment Programme-Society of Environmental Toxicology and Chemistry
US EPA	United States Environmental Protection Agency
USEtox	UNEP-SETAC toxicity models
VOCs	Volatile Organic Compounds
WHO	World Health Organization
WSN	Wireless Sensor Networks

Peer publication from this research

Samandi, E., Shirazi, A., & Newton, S. (2023). Measuring the fine particulate exposure levels of building occupants using localized sensors. Building and Environment, 242, 110403. https://doi.org/10.1016/j.buildenv.2023.110403. (Q1 Journal).

Thesis Abstract

Environmental air quality in Sydney has been increasingly impacted over recent years by pollution from burning fossil fuels, emissions from traffic congestion and localized bushfires. In turn, raised levels of environmental air pollution can impact the indoor air quality of buildings. In university settings, with many students spending extended periods of time indoors, there is potential for environmental pollutants to penetrate buildings, increase health risks, and contribute to occupant dissatisfaction.

Using a single level of a university campus building exposed to a busy road as a test case, this study aims to evaluate the temporal and spatial correlations between outdoor environmental pollution levels, indoor air quality and occupant perceptions of comfort. Indoor and outdoor mobile environmental sensors (Internet of Things, IoT, devices) will be used to monitor and collect data on levels of air pollution and other occupant comfort factors (PM2.5, PM10, CO2, temperature, humidity, etc.). In parallel, a survey of building users will assess occupant perceptions of comfort and their experience of the building.

The study outcomes will demonstrate the potential for cost-effective sensors to continuously and effectively monitor air quality in campus buildings and investigate the extent to which environmental air pollution can negatively impact occupant comfort and well-being. By comparing the indoor air quality indicators of different spaces in different relation to the external environment, the study will provide valuable insights into the factors that influence indoor air quality and occupant comfort.

Keywords: Indoor Air Quality (IAQ), Internet of Things (IoT), occupant comfort

1. Introduction

Environmental Air Pollution (EAP) is one of the primary causes of harmful health effects in humans (Almetwally et al., 2020). Long-term and short-term exposure to critical air pollutants such as Particulate Matter (PM) is related to death and health problems (Mazuryk et al., 2020). Approximately 4.2 million human premature deaths are attributed to exposure to EAP, according to the World Health Organization (WHO) report in 2021 (World Health Organization, 2021a). Particles with a diameter of 0.1–2.5 μm are defined as fine particles or PM2.5 (Wolhuter et al., 2021). The most dangerous fraction of PM pollution is fine PM, or PM2.5, which poses the fifth-highest mortality risk (T. L. Tsai et al., 2019; Ye et al., 2021). This type of particle easily penetrates the respiratory system and enters the bloodstream (Mazuryk et al., 2020). Investigations on the association between low levels of PM2.5 and health outcomes have found that adverse health outcomes occur specifically when exposure levels are below current standards or guidelines (W. Yu et al., 2020a).

In Australia, the mortality rate associated with EAP exposure is increasing (H. D. Nguyen et al., 2021). In the latest Australian Institute of Health and Welfare (AIHW) burden of disease study, more than 29,000 years are estimated to be lost annually to air pollution (*Burden of Disease Reports - Australian Institute of Health and Welfare*, n.d.). The Australian population is exposed to high levels of PM 2.5 through bushfire smoke, dust storm events, burning of fossil fuels and emissions from traffic congestion. There is a 5% greater risk of morbidity with each unit increase in PM2.5 in Australian cohorts (Hanigan et al., 2019).

Residents of Australian cities face elevated mortality risks from significant air pollution events caused by bushfires, hazard reduction burnings, dust storms and traffic congestion (Jegasothy et al., 2023). It has been estimated that over the 20 years, from 2001 to 2020, 1454 deaths in the eight Australian Greater Capital City Statistical Areas (GCCSAs), notably Sydney, Melbourne, Brisbane, Adelaide, Perth, Hobart, Darwin, and Australian Capital Territory, were associated to extreme PM2.5 exposure concentrations (Hertzog et al., 2024). A mortality burden assessment of these Australian cities revealed that approximately one-third of deaths caused by severe air pollution exposure can be avoided with a 5 % decrease in PM2.5 levels on days with extreme air pollution (Hertzog et al., 2024). In addition, it has been revealed that EAP in Sydney is expected to increase in severity and frequency (Walter et al., 2021). Furthermore, Ozone and particulate matter have been recognized as pollutants of most significant concern in Sydney, and nearly 2% of mortalities in Sydney are linked to Ozone and particulate pollution (Simmons et al., 2019). In Sydney, bushfire smoke significantly contributes to the PM2.5 levels, and the most considerable portion of all PM2.5 emissions in the region results from bushfires and prescribed burns (Jegasothy et al., 2023).

EAP significantly impacts buildings' Indoor Air Quality (IAQ) (Almetwally et al., 2020). Indoor Air Pollution (IAP) resulting from EAP has become a severe threat to occupant health and comfort since they spend more than 90% of their time indoors (Stasiulaitiene et al., 2019). Considering the significance of IAQ, it is imperative to monitor IAQ continuously to ensure comfort and improve occupational health (Ha et al., 2020).

Office and university campus buildings are the most commonly used settings for IAQ assessments due to their high occupancy rates (Bhat et al., 2022). The IAQ evaluation in university campus buildings could be more crucial because higher indoor pollutants and long exposure time decrease productivity and occupant comfort level and adversely affect academic performance and health (Woo et al., 2021).

Increasing health risks associated with indoor air pollution are a major concern for researchers worldwide (Benammar et al., 2018). Since humans spend most of their time indoors, real-time IAQ monitoring is necessary to ensure comfort and improve occupational health (Ha et al., 2020). Technological advancements have recently created new possibilities for monitoring and evaluating IAQ and occupant comfort (Saini, Dutta, & Marques, 2020b). The Internet of Things (IoT) and Wireless Sensor Networks (WSN) are widely used for real-time monitoring of IAQ (Saini, Dutta, & Marques, 2020b). With the growing potential of IoT technology, many researchers have focused on developing IoT-based IAQ monitoring systems to improve the air quality of the indoor built environment (Saini, Dutta, & Marques, 2020b).

Managing IAQ has become one of the most demanding challenges facing university building designers and facility managers (Grove et al., 2024; Qabbal et al., 2022) . IAQ management has two main steps: first, IAQ monitoring, and second, IAQ interventions (ASHRAE, 2018). IAQ monitoring includes measuring and assessing pollutant levels (Dwi Kuncoro et al., 2024). This step firstly involves employing sensors for continuous data collection and, secondly, data analysis to provide insights on identifying the sources of pollutants, pollutant concentration trends over time, and their impacts on occupant health and comfort (Dwi Kuncoro et al., 2024).

The next step would be IAQ interventions or actions arising from IAQ monitoring results. It is worth mentioning that every single building would require specific IAQ interventions, which may include ventilation system enhancement, building layout renovations and space management (ASHRAE, 2018). This study's focus area and initial objective are the first steps of IAQ management, which is monitoring and finding key factors affecting the university building's IAQ and occupant comfort.

This study aims to apply an IoT-based monitoring system coupled with an occupant survey to evaluate the temporal and spatial correlations between exposure to EAP, IAQ, and occupant perceptions of comfort in an Australian university campus building. The findings of this study could notably enhance occupant comfort and productivity by raising awareness among university building occupants, facility managers, and building designers on the significance of IAQ on occupant health and comfort levels. In addition, the findings of this IAQ monitoring study highlight the significance of localized measurements, particularly in the context of severe air pollution events. Furthermore, the findings of this study may challenge existing air pollutant concentration standards and underscore the need for revisions to building codes and guidelines. Finally, this research establishes a foundation for future IAQ monitoring investigations in built environments and urban settings.

2. Literature Review

2.1. Overall approach

The scope of the literature review for this study research is categorized into 4 areas, including (1) EAP, (2) impacts of EAP on IAQ, (3) IAQ metrics and (4) IAQ monitoring technologies. Figure 1 demonstrates the literature review categories and the key areas in each category.

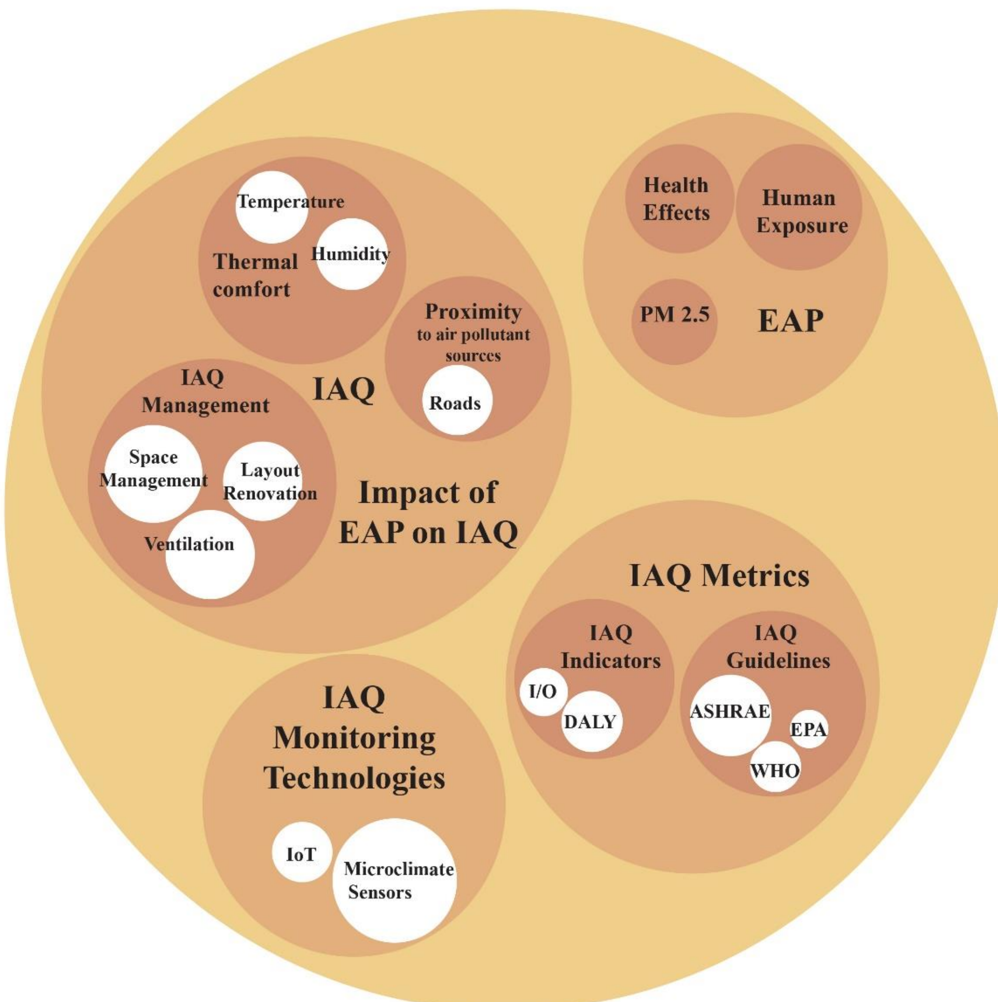

Figure 1: scope of the literature review

Source: Author

2.2. The significance of environmental air pollution

EAP has become a significant threat to human health, resulting in discomfort, diseases, and millions of deaths each year worldwide (Almetwally et al., 2020; Sohrabi et al., 2020). Regarding disability and premature death, EAP ranks fifth, surpassing Smoking, the AIDS virus, and all kinds of violence, including war (Wolhuter et al., 2021). EAP occurs when there is a complicated mixture of thousands of pollutants, containing suspended solids and liquids particles, and diverse gaseous components (Ye et al., 2021). Air pollutants can be generated by both natural sources such as dust storms or forest fires and human-made (anthropogenic) sources including traffic, industrial, or waste burning (World Health Organization, 2021b). The major kinds of pollutants in the air are primary pollutants, including sulfur dioxide (SO2), carbon monoxide (CO), nitrogen oxides (NOx), and primary PM, and secondary pollutants, which include secondary PM and ozone (O3) (Almetwally et al., 2020; Wolhuter et al., 2021).

2.2.1. Health effects of exposure to ambient air pollution

Ambient air pollution is one of the main causes of harmful health effects in humans, and long-term and short-term exposure (hours to days) to major air pollutants are related to death and health problems (Orellano et al., 2020). Approximately 4.2 million premature deaths are attributed to ambient air pollution, according to the WHO report in 2021 (World Health Organization, 2021b). Furthermore, there is evidence that exposure to EAP is a known risk factor for several diseases such as adult hypertension (Qin et al., 2021), brain aging (Tsai et al., 2019), diabetes (Yang et al., 2020) and pregnancy outcomes (Chen, Fang, et al., 2021). Studies in Australia, Canada, and the United States have recently demonstrated that ambient air pollution has adverse health effects even at concentrations significantly less than the existing thresholds listed in the guidelines (Hanigan et al., 2019; Papadogeorgou et al., 2019; Stafoggia et al., 2022; Walter et al., 2021). Accordingly Huynh et al. (2021) highlighted that low concentrations of ambient air pollution contribute to coronary artery calcification, and heart disease risk factors (Huynh et al., 2021).

2.2.2. Particulate matter

Among all environmental air pollutants, ambient PM is considered one of the most toxic components (Li et al., 2022). PM pollution is primarily caused by urbanization, manifested by the expansion of residential areas and road traffic (Kończak et al., 2021). PM pollution caused by traffic has been identified as one of the most severe threats to people and the environment, especially in densely populated urban areas (He & Gao, 2021). According to the United States Environmental Protection Agency (EPA), PM composition and its size differ based on the source of the particles (EPA, 2022). Over the past few decades, attention has been paid to particles with aerodynamic diameters of 2.5 µg/m^3 and 10 µg/m^3 (PM2.5 and PM10) (World Health Organization, 2021). PM10 originates from primary emissions from natural and anthropogenic sources, while PM2.5 derives from secondary PM generated by complex chemical reactions with anthropogenic gaseous pollutants such as SO2, NOX, and Volatile Organic Compounds (VOCs) (Achilleos et al., 2017). Researchers have devoted significant efforts to studying the destructive impact of PM on human health (Sadeghi et al., 2020). Studies have shown that different health effects may be associated with different PM characteristics, including size, chemical composition, and sources (Chen & Hoek, 2020).

2.2.3. Fine particulate matter (PM2.5)

Particles with a diameter of 0.1–2.5 µm are defined as fine particles or PM2.5 (Wolhuter et al., 2021). According to studies, fine PM or PM2.5 is the most harmful fraction of PM pollution and the fifth-highest risk factor for mortality (Tsai et al., 2019; Ye et al., 2021). This type of particle easily penetrates into the respiratory system and enters the bloodstream (Mazuryk et al., 2020). Several studies have examined how long-term and short-term exposure to PM2.5 is associated with health risks beyond lung disease. Findings of these studies suggest that exposure to PM2.5 may contribute to all-cause mortality increase (Orellano et al., 2020), chronic kidney disease (Peng et al., 2022; Ye et al., 2021), rheumatoid arthritis (Zhao et al., 2022), lower respiratory infections (Pu et al., 2021), the prevalence of diabetic retinopathy (Shan et al., 2021), Alzheimer's disease (Rhew et al., 2021), age-related eye disease (Grant et al., 2021) and cancer (P. Yu et al., 2021).

2.2.4. Exposure to low levels of PM 2.5.

In recent decades, exposure to PM2.5 continues to pose a significant threat to global public health (Cheng et al., 2021). It has been extensively studied how PM2.5 exposure at high levels affects human health, but few studies have investigated the effects of PM2.5 exposure at low levels (W. Yu et al., 2020a). Recent studies have investigated the association between long-term and short-term exposure to low levels of PM2.5 and health outcomes, specifically for concentrations below the current EPA standards and WHO guideline values (Bowe et al., 2019; Hvidtfeldt et al., 2021; Pinault et al., 2016; Rhew et al., 2021; Shi et al., 2016; Stafoggia et al., 2022; Strak et al., 2021; Wolf et al., 2021). Findings of studies highlighted that the effects of air pollution on adverse health are still observable at low levels of PM 2.5, even well below EPA annual standards and WHO guidelines (Papadogeorgou et al., 2019). According to (Strak et al., 2021), for participants with exposures below the EPA standard of 12 μg/m^3, an increase of 5 μg/m^3 in PM2.5 was associated with a 29.6% increase in natural deaths. Another study found significant associations with PM2.5 concentrations as low as 5 μg/m^3 in several large population-based cohorts in Canada that were exposed to low levels of air pollution (Brauer et al., 2019).

Long-term exposure to PM2.5 was associated with total, non-accidental, cardiovascular, and respiratory mortality in Queensland, Australia, where the annual average PM2.5 concentrations ranged from 1.6 to 9.0 μg/ m^3 , which were well below the current WHO annual standard (10 μg/m^3) (W. Yu et al., 2020). Furthermore, PM2.5 and NO2 were examined in relation to the all-cause mortality rate in Sydney. The findings indicate that even at relatively low levels of air pollution (PM2.5 mean annual= 4.5 μg/m^3 and NO2 mean annual=17.8 μg/m^3), adults over 45 years of age are at a higher risk of mortality (Hanigan et al., 2019). Considering other research findings, exposure to low levels of PM2.5 could shorten life expectancy, cause a massive mortality burden (Cheng et al., 2021), and increase hospital admissions for Alzheimer's, as well as non- Alzheimer's diseases (Rhew et al., 2021). Researchers have confirmed that outdoor air pollution can cause severe health risks and mortality, even at levels below the current recommendation (Strak et al., 2021).

There are distinct mechanisms of influence associated with long-term and short-term exposure (NSW Health, 2020). Short-term exposure has been shown to intensify pre-existing diseases, while long-term exposure is most likely to lead to chronic diseases and accelerate the progression of diseases. Short-term exposure (hours to days) may result in irritated eyes, nose, and throat, exacerbating asthma and lung diseases such as chronic bronchitis, increasing hospital admissions and premature death from respiratory and cardiovascular diseases, and worsening heart attacks and arrhythmias in patients with heart disease (NSW Health, 2020). Studies (Ban et al., 2021; Gao et al., 2021; Guo, Wu, et al., 2023; Karimi et al., 2019; Nauwelaerts et al., 2022; Orellano et al., 2020; Qiu et al., 2020; Renzi et al., 2020; Sun et al., 2022; Y. Wang et al., 2019; Wyatt et al., 2022; Xi et al., 2022; P. Zhou et al., 2022) have investigated the health effects of short-term indoor exposure to PM2.5. One study (J. Zhou et al., 2023) evaluated short-term exposure to indoor PM2.5 in office buildings and cognitive performance in workers. In this study, it has been shown that elevated PM2.5 levels can adversely affect cognitive performance, even in short-term indoor exposures (J. Zhou et al., 2023).

2.3. The impact of environmental air pollution on internal air quality

A built environment is a human-made environment designed to provide a setting for human occupation, activity, and settlement (Y. Q. Tan et al., 2020). The built environment is supposed to protect humans from harmful environmental events such as air pollutants; however, as environmental air pollutants' concentrations increase, they can penetrate the indoor environment via ventilation and building envelope (V. Van Tran et al., 2020). It has been shown that outdoor pollution sources have the greatest impact on indoor particle pollution in modern buildings (L. Yu et al., 2020).

In spite of the fact that the building envelope reduces PM2.5 penetration indoors (Belias & Licina, 2022), a study evaluating the airtightness of two university campus buildings and the penetration rate of outdoor PM2.5 and PM10, showed that approximately 30–70 percent of indoor PM2.5 originates from the environment (S. Yang et al., 2022) Other studies also claimed that in some cases, indoor pollutants' concentrations exceed that of the outdoors (G. K. Singh et al., 2021).

2.3.1. Indoor Air Quality (IAQ)

The term IAQ defines an enclosed environment's air quality, based on the thermal comfort factors (e.g., Relative Humidity (RH) and temperature) as well as the concentrations of pollutants present (P. T. M. Tran et al., 2021). IAQ is a serious concern for human since they spend more than 90% of their time indoors (Stasiulaitiene et al., 2019). Indoor air pollutants including hazardous gases, particulates, and biological substances negatively affect occupants' health, comfort, and performance (Scibor, 2019).

IAQ has been investigated from three perspectives, including 1) the human comfort and well-being, 2) the indoor air, and 3) the sources that contribute to IAP (V. Van Tran et al., 2020). From the human perspective, IAQ is the health impact of occupant exposure to indoor air contaminants; from the indoor air perspective, IAQ is typically determined by the ventilation rate and the concentration of particular compounds, and from a source perspective, pollution levels are elevated close to specific sources of air pollution, such as roads (Fantozzi & Rocca, 2020a).

Enhancing IAQ supports human health, reduces illness-related work loss, and mitigates economic losses of medical treatment (Burroughs & Hansen, 2020a). Thus, Architects, developers, users, facility managers, and building materials manufacturers are all responsible for protecting the public health by ensuring good IAQ (Mentese et al., 2020).

2.3.2. Interactions between IAQ and thermal comfort parameters

It has been shown that the Indoor Environment Quality (IEQ) of a building is the most significant factor affecting its occupants' comfort and productivity in multiple ways (Leccese et al., 2021). Thus, building occupants' comfort and well-being can be drastically affected by slight changes in IEQ (J. Kim et al., 2020).

Comfort assessment is generally conducted by evaluating IEQ, which includes four major environmental factors: (1) IAQ, (2) thermal environment, (3) visual environment and (4) acoustical environment (C. Wang et al., 2021). In academic literature, "thermal comfort" and "IAQ" have been the most extensively researched topics regarding occupants' health and comfort assessment (Fantozzi & Rocca, 2020b).

Intensive experiments and numerical studies have recently been conducted on IEQ and occupants' comfort levels (Ganesh et al., 2021).While the majority of studies in the area of IEQ parameters have strived to identify the independent effects of each parameter on the well-being, comfort and perceptions of occupants (Cadena et al., 2022; Park et al., 2022), others have shown that changes in one parameter can influence the sensation of other parameters (Ma et al., 2021).

An investigation of the interactions between IEQ parameters identified two types of interactions, including (1) objective interactions and (2) subjective interactions (Tang et al., 2020). An objective interaction refers to a condition where a physical factor or a characteristic of one particular parameter impacts some physical factors of another parameter. On the other hand, a subjective interaction exists when the level of one specific parameter impacts an individual's perception of another parameter, even if the level indicator of that environmental parameter remains the same (Tang et al., 2020).

Prior studies have mainly examined the interaction between thermal comfort parameters and air quality perception (Cao et al., 2019; Liu et al., 2019). Based on findings from related studies, the critical thermal comfort parameters, including temperature and humidity, can both subjectively and objectively interact with IAQ perception (Marzouk & Atef, 2022). For instance, temperature and humidity affect emission levels of VOCs from building materials, negatively affecting IAQ (Vardoulakis et al., 2020). In addition, Shin et al. (2021) have reported that occupants’ thermal sensations became more sensitive as the CO2 concentration increased. Findings of another study (Torriani et al., 2023) indicates that occupants' perception of IAQ is inversely related to operative temperature and CO2 concentration. Liu et al. (2019) also conducted an experiment that showed the occupants' acceptance of air quality was influenced by thermal sensation. According to the findings, when the occupants had a neutral perception of the thermal environment, the best perception of IAQ was achieved (J. Liu et al., 2019). Furthermore, studies (Jones et al., 2022; Torriani et al., 2023; J. Wang & Norbäck, 2022) highlighting the subjective aspects of air quality perceptions, indicate that elevated humidity levels can impact occupant perception of IAQ in indoor environments. According to findings of one study (J. Wang & Norbäck, 2022), increased indoor humidity—measured by relative humidity, absolute humidity, and moisture load—may contribute to negative perceptions of indoor air quality and has been linked to room temperature being perceived as too high and unstable.. In addition, reduced humidity levels may result in dryness in the air, resulting in a cooler perceived temperature (Jones et al., 2022).

Incorporating thermal comfort variables into IAQ assessments is a significant step in designing strategies for enhancing occupant comfort and well-being indoors (Jahanbin, 2022). Since the 1960s, researchers have acknowledged the need for measurable indicators of thermal comfort, resulting in the development of various indices (Tartarini et al., 2020). One of the most notable indices in this field is the Predicted Mean Vote (PMV), which is derived from Fanger's comfort equation and estimates the average thermal sensation and comfort of a group of people (Ameen et al., 2023). PMV is used along with the Percentage People Dissatisfied (PPD) index, which measures the percentage of individuals expected to experience thermal discomfort (Ameen et al., 2023). The PMV and PPD indices integrate the subjective human experience with objective environmental measurements by considering various factors, including temperature, humidity, air velocity, metabolic rates, and clothing insulation (Ameen et al., 2023; Zhu & Li, 2017).

Several studies have used these indices to address the gap between quantitative IAQ measurements and the subjective assessment of occupant comfort (Amoatey et al., 2023; Zhu & Li, 2017). Furthermore, some studies have compared the results of these indices with the results obtained from occupants' actual perception of thermal comfort (Stokowiec et al., 2022; Yong et al., 2022). These findings suggest that the ideal thermal conditions for building occupants may vary among different groups due to their different comfort requirements (Krawczyk et al., 2023; Rupp et al., 2018; Stokowiec et al., 2022). As a result, relying exclusively on these indices may not accurately reflect the most suitable thermal conditions for all individuals within a building (Amoatey et al., 2023; Elnaklah et al., 2021; Krawczyk et al., 2023; Stokowiec et al., 2022; Yong et al., 2022).

2.3.3. Proximity to outdoor air pollutant sources

Local-scale air quality is significantly influenced by proximity to emission sources such as major roads and meteorological factors, including wind, temperature, precipitation, and RH. (Hart et al., 2020).

Nowadays, most critical built environments such as schools, universities, hospitals, offices, and residential buildings, are located near highways or busy roads (Gall et al., 2018). This proximity to roadways can be used as a valuable metric to estimate occupant exposure to air pollution (Costello et al., 2022). Pacitto et al. (2020) found that schools near highly trafficked roads expose students to high levels of IAP due to the high outdoor to indoor contaminant penetration. Furthermore, studies have indicated that increased Traffic-Related Air Pollution (TRAP) exposure due to road proximity has been associated with cardiovascular mortality and stroke (Butler et al., 2019; Hauptman et al., 2020).

TRAP is the primary factor affecting air quality in developed countries (Stenson et al., 2021). It is comprised of several air pollutants, including CO, CO2, NO2, PM, and other by-products contaminants such as O3 (Hegseth et al., 2019). PM2.5 is considered the most harmful to human health among all TRAP. The PM2.5 concentrations increase steeply near busy roads and quickly decrease to near background levels within 100–200 m of the roads (Park, 2020).

One study (Chu & Yang, 2022) examined how distance from a pollutant source (a busy road) impacts indoor PM2.5 concentrations and presented simulation results for different distances from the pollutant source. Study results showed that the entry rate of outdoor PM into low-rise buildings increased from 7% to 25% as the distance between the pollutant source and indoor sample point locations decreased from 15 meters to 3 meters. In addition, factors such as the external wind speed and direction and size of particles might also affect entrance rates (Chu & Yang, 2022).

2.3.4. IAQ management

There are various strategies to enhance IAQ in the built environment. IAQ management strategies encompass all project phases, including the pre-design, design, construction, and operational phases (Sadoughi, 2019). Some strategies can only be implemented during the initial phases of a building project, such as building envelope design, while some could be implemented during the operational phase as a renovation or enhancement plan (Scibor, 2019). Furthermore, recent studies integrating indoor pollutant prediction with building information modelling (BIM) have attempted to devise novel and cost-effective IAQ management tools to predict post-occupancy IAQ at the building design stage (S. Yang et al., 2022).

Figure 2 illustrates that the design phase is the most efficient and cost-effective time for implementing IAQ strategies. In other words, resolving issues at the start of the design process is much more possible and less expensive than once construction is underway or even when the building is occupied (ASHRAE, 2018).

Methods for controlling IAQ include 1) source control, 2) dilution with less contaminated air and 3) extraction by filtration (Burroughs & Hansen, 2020b). Design strategies address the three main methods of controlling IAQ. Achieving good air quality requires the integration of design strategies (ASHRAE, 2018). It is not feasible to separate a design solution that addresses indoor ventilation from one that deals with outdoor air quality and thermal conditions. Table 1 summarizes a few design considerations that influence IAQ along with other IEQ parameters according to the American Society of Heating Refrigerating and Air conditioning Engineers (ASHRAE) standards. According to Table 1, the feasible measures at the operation phase and space scale mainly include ventilation-related intervention and space management-related intervention. Ventilation-related interventions include filtration enhancements and space management-related interventions include space usage, type of activities in the space, number of occupants, time spent in the space, and type of furniture and equipment.

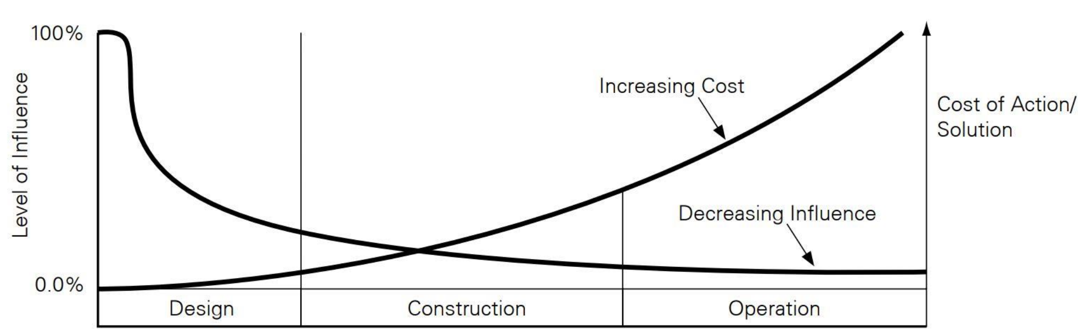

Figure 2:Decreasing ability to influence IAQ outcomes and increasing cost of action as the project proceeds

Source: (ASHRAE, 2018)

Parameters affecting IAQ	Scale		Project Phase			
	Building	Space	Pre-design	Design	Construction	Operation
Project schedule need for IAQ	■		■			
Specialists needed for IAQ Considerations			■			
Scope and budget related to IAQ			■			
Minimum separation distance Consideration of the minimum separation distance of outdoor air intake, openings, windows, doors, and skylights from pollution sources such as exhaust air outlets.	■			■		
Pressurization control • **Space pressurization:** refers to the static pressure difference between the adjacent spaces of a building, with the air tending to move from higher-pressure spaces to lower-pressure spaces. Maintaining proper pressure relationships between adjacent spaces is critical to ensure airflow in the preferred direction, from clean spaces to dirty spaces. Space usage and space layout influence the space pressurization and, thus, IAQ in spaces. • **Building pressurization:** Proper building pressurization is required to limit moisture and contaminant transfer across the building envelope.	■	■		■		
Wind load	■	■		■		
Capacity and energy load	■			■		
Envelope airtightness, planned and unplanned openings, doors/windows and gaps Building envelope and structure influence IAQ beyond environmental control systems. Space envelope needs to be designed to limit exfiltration, infiltration, and leakage.	■	■		■		
Layout, dimensions, volume, orientation and other architectural features	■			■		
Materials and finishes selection Emissions from building materials impact IAQ.	■	■		■		
Type of Ventilation system Natural/Mechanical or Mixed-Mode Ventilation.	■			■		
Floor plan depth Floor plan depth impact IAQ, especially in naturally ventilated buildings.	■			■		
Floor Levels, Stack effect Temperature, pressure and thus pollutant penetration rate vary at different height levels.	■			■		
Ceiling Height Higher ceilings increase the potential for thermal and air pollutant stratification; the higher the ceiling, the greater the potential benefit.	■	■		■		
Insulation Materials	■	■		■		
Number of occupants	■	■		■		■
Usage	■	■		■		■
Furniture Systems Materials used in office furniture can serve both as sources and sinks for contaminants. As these materials surround individual workers, any emissions they release directly enter their breathing zones.		■		■		■
Barriers designed for the entry of dirt, Track-Off Systems, finishing mats Track-off systems can help control contaminant transport via building doorways.	■	■		■		
Equipment and devices Emissions of VOCs and particulates from photocopiers, laser printers, and computers.	■	■		■		■
HVAC enhancement, filtration techniques, portable air cleaners	■	■		■		■
Installation checks	■	■			■	
Cleaning Products		■				■

Table 1: Parameters affecting IAQ based on project phase

Source: (ASHRAE, 2018)

- **Ventilation interventions**

Ventilation interventions mainly include improving air filtration and purification, implementing dilution and extraction methods to enhance IAQ (W. Yu et al., 2020). Studies have shown a significant reduction in indoor-to-outdoor PM2.5 ratios in buildings equipped with effective air filters installed in the air cleaners and ventilation systems (Alavy & Siegel, 2020; W. Yu et al., 2020).

Using High-Efficiency Particulate Air (HEPA) filters in an HVAC system or as portable air cleaners is one of the most effective indoor measures to combat outdoor air pollution (Ji et al., 2019). The effectiveness of HEPA cleaners was tested in a smaller library room in Port Macquarie, NSW, Australia, when PM2.5 concentrations were elevated due to a nearby bushfire (Wheeler et al., 2021). According to the study results, the air-conditioned main library had a 70% reduction in outdoor-generated PM2.5 in the library. As well, the HEPA cleaners in the media room were able to reduce PM2.5 concentrations by 83%. The result indicates that using HEPA cleaners of appropriate size within the building will further improve IAQ.

- **Space management interventions**

Space management has emerged as a serious concern since Covid-19 outbreak (Abdul Nasir et al., 2021). The fact that increased EAP is tightly correlated with increased COVID-19 spread (Sloan Brittain et al., 2020), introduced new dimensions to IAQ management in the built environment during the COVID-19 pandemic (Y. Zhang et al., 2022). Space management interventions provide IAQ strategies based on source control. A source control strategy in space management aims to reduce occupant exposure to indoor air pollutants (Melikov et al., 2020). Building facility managers, architects, and policymakers are now making decisions to reduce occupant exposure to contaminants, control SARS-CoV-2 virus transmission, and create healthier built environments (H. H. Kim et al., 2020).

Facilities Management (FM) is regarded primarily as a field of study and a profession that "integrates people, place, process and technology to ensure that the built environment is functional, comfortable, safe, and efficient, improving the quality of life of occupant and the productivity of the core business" (Marocco & Garofolo, 2021). FM discipline identifies space management (space utilization planning and occupancy controls) as one of the primary interventions for IAQ control and eliminating airborne pollution transmission in existing buildings (Y. Zhang et al., 2022).

Studies from the perspective of FM have proposed IAQ control strategies to reduce occupant health risks through space utilization plans (Abdul Nasir et al., 2021; Feng et al., 2022; Roskams & Haynes, 2019; T. Tan et al., 2021; Y. Zhang et al., 2022). Space utilization plans schedule occupation periods, break periods, and occupant numbers according to pollutant concentrations (Melikov et al., 2020) and have a significant influence on HVAC systems developments (Mutis et al., 2020). Figure 3 shows the detailed structure of how IAQ data and parameters can be extracted for a particular building and used for further IAQ management practices in existing buildings (Feng et al., 2022).

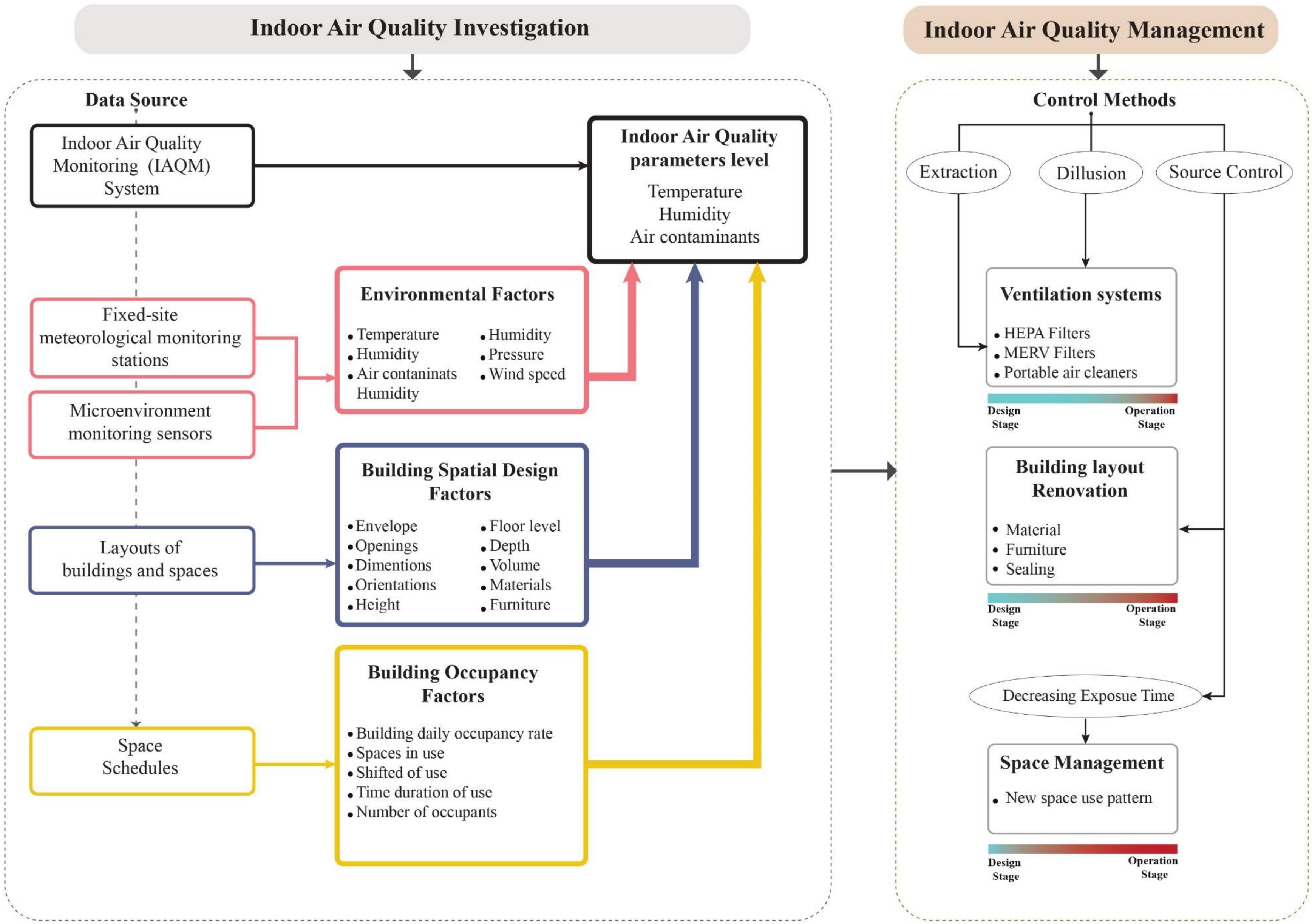

Figure 3: Summary of IAQ investigation and IAQ management

Source: Inspired by (Feng et al., 2022)

2.4. IAQ metrics

2.4.1. IAQ indicators

IAQ can be challenging to assess as a result of the vast range of emission sources, pollutants, health effects, and toxicity levels (Cony Renaud-Salis et al., 2019). Studies have used various IAQ indicators to assess building IAQ. (Assimakopoulos et al., 2018; Bekierski et al., 2021; Erlandson et al., 2019; Güneş et al., 2022; Jurado et al., 2014; Krebs et al., 2021; Marzouk & Atef, 2022; Mendoza et al., 2021; Sakellaris et al., 2021). Two commonly used approaches to establishing IAQ indicators are subjective surveys and field measurements. The IAQ indicators based on subjective surveys include the implementation of questionnaires on the perception of IAQ and comfort level. The IAQ indicators based on field measurements are more prevalent, and often can be calculated using equations, such as the Disability Adjusted Life Years (DALY) (Fantozzi & Rocca, 2020a). DALY is a time-based measure of the quality and quantity of life (Bai et al., 2020). DALYs are used to compare the overall health and life expectancy of various populations based on years lost due to premature death (YLL) and healthy years lost due to disease (YLD) (Rovira et al., 2020).

The most common metrics used in studies reflect three perspectives. Firstly, the formula-based metrics for calculating pollutant adverse effects on occupant health, including DALYs, Hazards Quotients (HQs), UNEP-SETAC toxicity models (USEtox), and lifetime Cancer Risks (CR_{inh}) and Human Health Damage (HHD) (Bai et al., 2020; Güneş et al., 2022). Secondly, metrics for the microenvironment evaluations that analyze the effect of environmental contaminants on the internal environment, including I/O ratio, infiltration factor (F_{inf}) and ambient exposure factor (F_{pex}) (Bennett et al., 2019; Jurado et al., 2014; Kalimeri et al., 2019; Kumar et al., 2014; Mendoza et al., 2021). Thirdly, metrics based on comparisons of pollutant concentrations with air guideline values, such as the Exceedance index (E-index) (Pantelic et al., 2019).

Almost every IAQ indicator uses Exposure Limit Value (ELV) to calculate the degree of exposure to a pollutant (Poirier et al., 2021). The most relevant ELV is Indoor Air Guideline Values (IAGV) which are threshold values set by national or international organizations such as WHO (Jain et al., 2021). According to the IAGV definition, concentrations below the IAGV threshold do not have a known health impact. Based on the literature, IAGV is currently, the most recent, valid, and health-based metric identified (Becerra et al., 2020).

Additionally, several studies have used DALY as the primary indicator of the IAQ (Bai et al., 2020; Wysocka, 2018). One study (Cony Renaud-Salis et al., 2019) has analyzed and compared eight IAQ indices, including IEI, LHVP, CLIM2000, BILGA, GAPI, IEI Taiwan, QUAD-BBC and DALY, in terms of their strengths and weaknesses, calculation methods, pollutants included, sub-indices and threshold concentrations. In the study, indices were evaluated based on the pollutant concentration data from a survey of 567 French dwellings. The study showed that among all the selected indices, DALY showed a precise classification of IAQ in the building population. Also, at low and high levels of PM2.5 concentrations, there was a strong correlation between the DALY indices and the ELV ratio.

I/O ratios are also widely used to determine the indoor-outdoor concentration relationship of a compound or group of compounds (Pantelic et al., 2019). Studies have shown that in the case of indoor pollutants primarily originating from outdoors, such as PM2.5 and NO2, the I/O ratios are a straightforward and logical statistical method for determining how outdoor pollutants affect IAQ (He et al., 2022; Z. Wang et al., 2020; Z. Zhang et al., 2020). I/O is a metric dependent on microenvironment characteristics and vary with location, building design, and human activities (Kalimeri et al., 2019). Furthermore, this statistical approach can highlight differences between various spaces and microenvironments (Kalimeri et al., 2019).

2.4.2. IAQ guidelines

The literature review revealed that researchers use a variety of international standards and guidelines to determine what constitutes acceptable air quality. IAQ guidelines and standards have been developed by a variety of organizations around the world to reduce and prevent negative health effects (Ahmed Abdul–Wahab et al., 2015). The most known agencies and organizations include ASHRAE (ASHRAE, 2018), the Hong Kong Environmental Protection Department (HKEPD) (EPD, 2021), WHO (WHO, 2021), and the National Health and Medical Research Council (NHMRS) of Australia (Cho et al., 2019) and US EPA (EPA, 2022). Table 3 demonstrates the IAQ parameters and their standard exposure limits set by international organizations (Cho et al., 2019; Environmental Protection Department, 2021; Gall & George, 2018; U.S. Environmental Protection Agency (EPA), 2021; World Health Organization, 2021b).

In most air quality evaluations, researchers applied the WHO air quality guidelines published in 2006 (Amini, 2021). Considering the latest evidence of the health effects of air pollution exposure, experts suggested guideline updates on several critical ambient air pollutants including PM2.5, PM10, Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide (World Health Organization, 2021a). As a result, WHO significantly lowered air quality guideline recommendations to encourage countries to invest in air quality management and minimize human exposure to air pollution (Ouyanguiling et al., 2022). The recent update highlights the evidence that exposure to lower levels of PM2.5 can considerably increase health risks. Figure 4 demonstrates Concentration-Response Function (CRF) for long-term PM2.5 exposure ($\mu g/m^3$) and all non-accidental mortality relatives. As shown in Figure 4, the curves are generally steeper at low concentrations than at high concentrations or show linear relationships down to very low concentrations (World Health Organization, 2021a). Table 2 shows the comparison between WHO 2006 and 2021 Air Quality Guidelines level for PM2.5 and PM10.

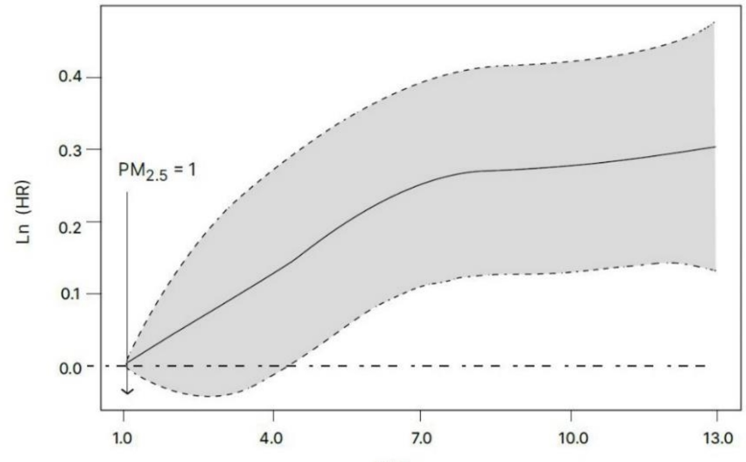

Figure 4:Concentration-Response Function (CRF) for long-term PM2.5 exposure (µg/m^3) and all non-accidental mortality

Ln Hazard Ratio (HR): log HR, with an HR of 1 at a PM2.5 concentrations of 1 (µg/m^3).

Source: (WHO, 2021)

WHO air quality guide level recommendation				
	Long-term (Annual) mean		Short-term (24-hour) mean	
	2006	2021	2006	2021
PM 2.5	10 µg/m3	5 µg/m3	25 µg/m3 With 3-4 exceedance days per year	15 µg/m3 With 3-4 exceedance days per year
PM 10	20 µg/m3	15 µg/m3	50 µg/m3 With 3-4 exceedance days per year	45 µg/m3 With 3-4 exceedance days per year

Table 2:WHO air quality level recommendation for PM2.5 and PM10

Source: (WHO, 2021)

Air Quality Parameters	value	organization
Carbon Dioxide (CO_2)	30000 ppm as a 15-minute average	NOHSC
	5000 ppm as 8-h average working day; 5-d working week	
	800 ppm as 8-h average (Excellent Class)	HKEPD
	No more than about 700 ppm (1800 mg/m^3) above outdoor ambient	ASHRAE
	800 ppm (Allowable air concentration levels)	US EPA
	1000 ppm (Allowable air concentration levels)	WHO
Total Volatile Organic Compounds (TVOC)	500 µg/m^3 as 1-h average	NHMRC
	600 µg/m^3 as 8-h average (Excellent Class)	HKEPD
	3000 µg/m^3 as 8-h average (Good Class)	
	200 µg/m^3 + outside air concentration	WHO, ASHRAE, US EPA
Particulate Matter (PM2.5)	35 µg/m^3 as 24-h average (Exposure)	ASHRAE
	150 µg/m^3 as a 24-hour average	US EPA
	12 µg/m^3 as 1-y average	
	65 µg/m^3 as 24-h average (Exposure)	
	15 µg/m^3 as 24-h average	WHO
	5 µg/m^3 as 1-y average	
Particulate Matter (PM10)	90 µg/m^3 as 1-h	NHMRC
	20 µg/m^3 as 8-h average (Excellent Class)	HKEPD
	180 µg/m^3 as 8-h average (Excellent Class)	
	150 µg/m^3 as 24-h average	ASHRAE
	150 µg/m^3 as 24-h average	US EPA
	50 µg/m^3 as 1-y average	
	45 µg/m^3 as 24-h average	WHO
	15 µg/m^3 as 1-y average	
Total Suspended Particles (TSP)	90 µg/m^3 as 1-y average	NHMRC
	15 µg/m^3 as 8-h average	ASHRAE
Temperature	20.0-25.5 ˚C as 8-h average (Excellent Class)	HKEPD
	22.5-26 ˚C in summer (Comfort Level)	ASHRAE
	20.0-23.5 ˚C in winter (Comfort Level)	
	24.5-28.0 ˚C in summer (light clothing), if relative humidity is 30%	
	20-24 ˚C in winter (warm clothing), if relative humidity is 60%	
Relative Humidity	40-70% as 8-h average (Excellent Class)	HKEPD
	<70% as 8-h average (Good Class)	
	40-60% in summer (Comfort Level)	ASHRAE
	30-60% in winter (Comfort Level)	
Air Movement	<0.2 m/s as 8-h average (Excellent Class)	HKEPD
	<0.3 m/s as 8-h average (Good Class)	
	0.25 m/s	WHO

Table 3: IAQ parameters and their standard exposure limits set by international organizations. Source: (Cho et al., 2019; Environmental Protection Department, 2021; Gall & George, 2018; U.S. Environmental Protection Agency (EPA), 2021; World Health Organization, 2021)

2.5. Indoor air quality monitoring technologies

The growing health issues associated with IAP are a major concern for researchers worldwide (Benammar et al., 2018). Since humans spend most of their time indoors, it is imperative to monitor IAQ on a real-time basis to ensure comfort and improve occupational health (Ha et al., 2020). Currently, technological advancements have opened up new opportunities to monitor IAQ and assess occupants' health and comfort (Saini, Dutta, & Marques, 2020c). Real-time monitoring has been achieved with various technologies (V. Van Tran et al., 2020). Two of the most widely used technologies developed for IAQ monitoring are Internet of Things (IoT) and Wireless Sensor Networks (WSN) (Saini, Dutta, & Marques, 2020c). This section aims to identify the existing Indoor Air Quality Monitoring (IAQM) systems based on IoT and to highlight relevant materials, methods, and findings.

2.5.1. Internet of Things (IoT)-Based IAQM systems

With the growing potential of IoT technology, many researchers have focused on developing IoT-based IAQM systems to improve the air quality of the indoor built environment (Saini, Dutta, Saini, et al., 2020). An IAQM system requires a network architecture capable of providing broad coverage with relatively low power consumption to monitor air pollution with high spatio-temporal resolution (Dhingra et al., 2019). With the introduction of IoT-based portable IAQM devices in recent years, sensors can efficiently be deployed in a variety of settings to monitor and control air quality in real-time (Ali et al., 2021).

According to studies (H. Tan et al., 2024), IoT-based IAQM systems exhibit both strengths and limitations. The application of IoT-based IAQM systems is highly beneficial, particularly through the use of sensor networks for continuous, real-time data collection, along with remote access to sensor dashboards for control and monitoring (Kareem Abed Alzabali et al., 2024). Furthermore, studies (Peixe & Marques, 2024; H. Tan et al., 2024) have explored the concept of scalability and flexibility as key characteristics of IoT-based IAQM systems.

Different challenges and concerns accompany IoT-enabled IAQM systems, with data accuracy, privacy, and security being the main concerns in their application (Aqeel et al., 2022). Studies (Dai et al., 2023; Taştan, 2022) suggest that IoT-enabled IAQM systems, typically using low-cost sensors, may not achieve the same precision in data collection as more conventional devices. However, it has been found that routine sensor maintenance procedures, primarily sensor recalibration and replacement every 4–6 months, can effectively address the challenge of affecting data accuracy (Dai et al., 2023). In addition, since IoT-based IAQM systems rely on IoT devices and network connectivity, they are vulnerable to cybersecurity threats and data leakage (H. Tan et al., 2024). One study (Aqeel et al., 2022) has reviewed major security-related concerns in IoT devices. It has classified security threats in IoT devices into various categories, including outage, physical, network, software-based, data, side-channel, cryptanalysis, access-level, and strategy-level attacks (Aqeel et al., 2022). To address data security and privacy challenges, studies (Al-Nbhany et al., 2024; Aqeel et al., 2022; A. K. Hassan et al., 2024) have emphasized the need to integrate IoT-based monitoring systems with emerging technologies such as blockchain, artificial intelligence, machine learning, as well as advanced computing methods such as fog and cloud computing.

2.5.2. General architecture of IoT-based IAQM systems

An IoT architecture refers to a set of physical devices that are connected to the internet and have the capability to sense their surroundings (Marques et al., 2019). Figure 5 demonstrates the architecture of an IoT-based IAQM system. This framework has four major components, including: (1) a monitoring system, (2) a data storage platform, (3) a data analytics service, and (4) a data visualization dashboard (Wall et al., 2021). The monitoring system consists of the sensors, Microcontrollers (MCUs), and communication systems. Sensors, as IoT nodes, collect data for a wide range of particle pollutants and other environmental measurements such as temperature and humidity (Rani et al., 2021). Sensor data is then transmitted and received by MCUs as part of the IoT gateway (Jo et al., 2020). Communication technologies such as Bluetooth, LoRoWAN, Ethernet and Wi-Fi (which is the most widely used), offer a real-time update of the data (Saini, Dutta, & Marques, 2020b). Next, a data storage system (physical or cloud-based), stores the sensors' data. Finally, the impacts of pollutants on targeted locations and other required analysis on the data can be assessed through data analysis services and the outcomes are presented to the end user via the visualization dashboards (Marzouk & Atef, 2022).

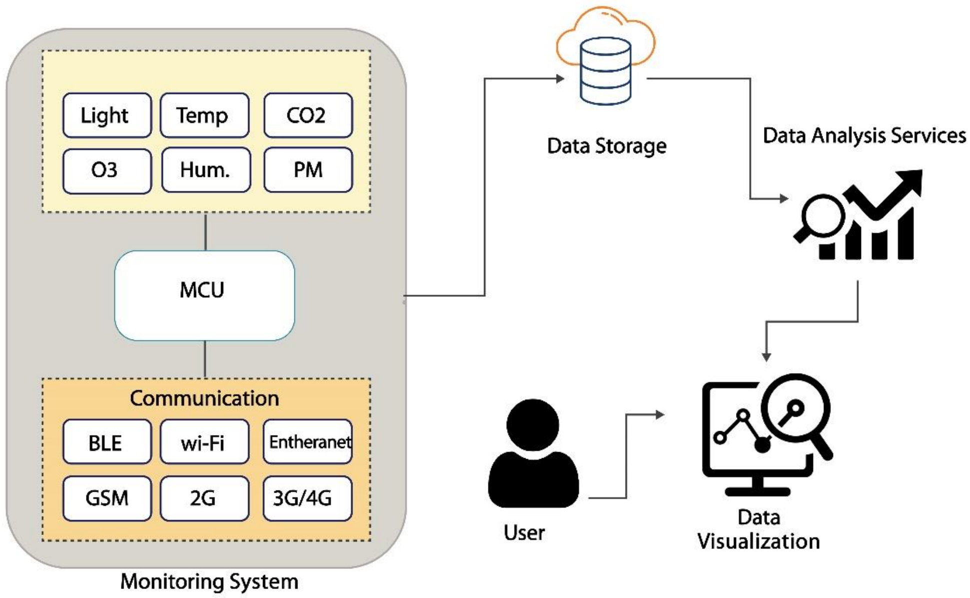

Figure 5:General Architecture of IAQM systems, (Inspired by: Saini, Dutta, & Marques, 2020c)

Systematic reviews of IoT-based IAQM systems have shown that researchers prefer certain types of interfaces and data visualization systems (Marques et al., 2020; Saini, Dutta, & Marques, 2020e, 2020d; H. Zhang & Srinivasan, 2020). Mobile apps, web portals, and LCDs coupled with mobile apps are the most popular methods of displaying the real-time status of IAQ parameters (Saini, Dutta, & Marques, 2020e). However, applications of IoT-enabled sensor networks in IAQM systems extend well beyond measuring air contaminant concentrations (Mumtaz et al., 2021). Researchers are currently interested in improving measurement accuracy, developing predictive and alert systems, and considering human comfort (Saini, Dutta, & Marques, 2020a). For instance, Marzouk & Atef, (2022) proposed a prediction model based on IoT technologies and deep-learning that considers outdoor parameters to assess the IAQ of campus buildings. Ha et al (2020) developed an air quality management system that integrated the Indoor Air Quality Index (IAQI) and humidity index to calculate Enhanced Indoor Air Quality Index (EIAQI) using real-time sensor data.

In addition to real-time IAQM, an alert system is crucial for preventing environmental harm. An alert system enables users and platform managers to act promptly on air quality issues (Jo et al., 2020; Saini, Dutta, & Marques, 2020e). Mumtaz et al (2021) have developed an IAQ monitoring and prediction system based on IoT sensors and machine learning capabilities. The proposed system included a web portal and a mobile app to alert users about poor air quality and provide a reliable method to monitor and assess the air being breathed. This experiment used an IoT node equipped with several sensors to monitor six pollutants, including NH_3, CO, NO_2, CH_4, CO_2, PM 2.5, and as well as temperature and humidity.

2.5.3. Practical applications of IAQM systems

IAQM systems have been used in real-life settings to assess different factors and aspects of IAQ. The researchers have questioned some challenging aspects of the IAQ through practical experiments conducted in various test cases. Health risk assessments, correlations between chemical pollutants and thermal comfort parameters, filtration capacity of HVAC systems, seasonal variations in pollutants, objective and subjective measurements, pollution sources indoors and outdoors pollution sources, and occupants' perceptions are some of these aspects. This section evaluates findings from IAQ previous practical field work experiments to identify influential parameters on IAQ that should be considered in experiment design. The summary of the literature review including the articles, measured parameters, data collection and analysis methods as well as the IAQ and health risk metrics is shown in Table 4.

An evaluation of the health effects of PM2.5 exposure was conducted in colleges and universities in Northeast China by real-time monitoring of PM2.5 outdoors and indoors for one year (Bai et al., 2020). Outdoor and Indoor sensors measured PM 2.5 concentrations, and questionnaires were used to assess student lifestyles and activity levels. Analysis of the PM2.5 concentrations over one year revealed significant differences between seasons and months with the highest concentration in the winter and the lowest in the summer. The correlation analyses indicated a high correlation between indoor and outdoor PM2.5 concentrations but no significant correlation between indoor PM2.5 concentrations and temperature. Furthermore, DALY and USEtox models were used to estimate PM2.5 health effects. Accordingly, student exposure to PM2.5 was strongly correlated with premature death, chronic bronchitis, medical outpatient visits, cardiovascular disease, and respiratory diseases (Bai et al., 2020).

A study by Güneş et al. (2022) investigated IAQ in two libraries of a University in Bartin in Northern Turkey. Data were collected for two weeks every month for each library between September 2019 and October 2020. The measured IAQ parameters were PM2.5, PM10, TVOC, CH_2O, temperature and humidity. Different library rooms were examined to determine if IAQ parameters varied by months, seasons, and times of the day. Seasonal and daily variations were correlated with meteorological factors, indoor temperatures and humidity levels. This study indicated that gas pollutants were higher in the summer while particulate pollutants were higher in the winter, and PM concentrations in winter were also found to be increasing due to the growing student population. The level of contaminants in this study were not found to pose any substantive risk to humans, using the hazard quotient (HQ) metric. However, the calculated health risks used outdated limit values for indoor pollutants, published by WHO in 2010 and EPA in 2009.

One recent study (Mendoza et al., 2021) suggests that HVAC systems may not be capable of filtering contaminants and decreasing indoor pollution penetration based on the type and sources of outdoor pollution. Including three high-pollution events (wildfires, fireworks, and winter atmospheric inversions) this study measured the penetration of outdoor PM2.5 into three office buildings over a period of a year. The results of this study indicated that wildfires, fireworks and inversions, have different building infiltration patterns. Wildfire, and fireworks smoke particles were generally too small to be filtered by the building filtration systems in use.

A study by Krebs et al. (2021) examined the temporal and spatial correlation between PM concentrations outdoors and indoors for different particle sizes using crowd-sourced data across California. As a result of this study, some important findings about the penetration factor were revealed. Firstly, it found that particles from the outside penetrate the indoor environment very rapidly within five hours, with nearly half of the penetration occurring within the first hour. Secondly, it highlighted that a 10% increase in outdoor PM concentration results in a 4.2%–6.1% increase in indoor PM concentrations. Thirdly, it showed that the penetration rates are influenced by the building age and the surrounding climate, and the penetration rate of larger particles increases with increasing outdoor temperature. Furthermore, particles with smaller (more hazardous) sizes have higher average indoor/outdoor ratios than particles with larger sizes. Although studying outdoor-indoor relationships at this scale offers a new perspective on average penetration rates, there has been a study neglects of certain potential factors of interest, including the proximity of monitor locations to busy roads, occupants' window-opening behavior during wildfires, and indoor sources of pollutant.

A recent research study (Woo et al., 2021) also evaluated the occupant perception and IEQ parameters of seven office buildings in an Australian university. In this study, buildings of different construction ages and physical conditions were selected to determine whether physical conditions and the age of buildings affect occupant perceptions of the IEQ. There were three types of office buildings included in this study: heritage listed (c.1880–1890s), conventional (c.1960–1980s) and modern (post 2000). To understand the gap between measured IEQ and occupant responses, objective and subjective measurements were used. A four-month survey of occupants was conducted, primarily in the winter (June to September 2019). Data collection locations included single and multiple open-plan offices. Only open-plan offices of professional (non-academic) staff were considered in this study, and common areas or other workspaces such as kitchen seating, breakout rooms, and meeting rooms were not included. The occupant density was taken as the total area divided by the number of workstations. This study found that the different types of buildings, regardless of their age, had a satisfactory level of IEQ. However, the modern building type with fully double-glazed façades achieved the best levels of overall satisfaction and productivity compared to the conventional building type. Moreover, there was no statistically significant correlation between the measured CO2 concentration and occupant perception of air freshness or odor. However, occupant perception of odor was correlated with measured RH. There was also a low to moderate correlation between occupant perception of temperature stability and air velocity. Additionally, some other subjective evaluations were correlated with other environmental parameters, for example, thermal sensation with CO2 concentration and odor with RH. Thus, even though subjective perceptions of the indoor environment are likely to match objective measurements, occupant perceptions do not always reflect the corresponding indoor environmental parameters.

Significantly, in this study potential influential factors of interest, such as age, gender, positioning in the space, and activity, were not considered. The analysis of the results ignored that data were collected during the winter period only, and sample locations were selected on different floors of the buildings, ranging from level 3 to level 12. Further, to assess IAQ, only CO2, temperature, and RH concentrations were measured, while potentially significant metrics such as PM and VOCs were excluded.

In a study by Shin et al. (2021) occupant thermal sensation was found to increase as the CO2 concentration increased. This showed that it may be energy efficient to regulate occupant thermal sensation by introducing suitable ventilation controls, such as Demand Controlled Ventilation (DCV).

Table 4 further summarizes other IAQ experiments employing IoT-based IAQM systems. According to recent studies, IoT-based IAQM systems are reliable and effective tools for assessing IAQ in a variety of environments. Based on the review of literature shown in Table 4, the following notable findings were identified:

- There have been several studies regarding IAQ assessment in university campus buildings, with libraries and laboratories selected as test locations.
- Studies on IAQM suggest that some critical aspects may influence the results of the experiments. Thus, various factors should be considered when designing the experiment, including seasonal variations, environmental pollution sources and their proximity to sample points, the HVAC system's ability to filter pollutants, and correlations in IAQ and thermal comfort parameters.
- In most studies, it has been considered that temperature and RH are influential

factors on IAQ.

- Measuring the occupants' exposure to PM2.5 and PM10 is critical, particularly for health risk assessments.
- The I/O ratio has been used as a functional metric in IAQ assessments.

Reference	Test cases		Measured parameters								Data Collection Method		IAQ and Health Risks Metrics	Data Analysis/ Tools Used
	Different types of buildings including University Campus Buildings (UCB), office buildings, Hotels, Homes,	**UCB**	**PM**	**CO2**	**VOC**	**CH2O**	**NO2**	**RH**	**Temperature**	**Questionnair**	**Sensors**		
(Güneş et al., 2022)	2 Libraries	■	■	■	■	■		■	■		■	• (HQ): hazard quotient • (IAQI): indoor air quality index • (CR_{inh}): lifetime cancer risks	• SPSS 26.0 • Mann-Whitney U test
Bhat et al., 2022)	8 offices, 8 laboratories, 5 classrooms, 10 workshops, 2 cafes, and 1 sports hall	■	■				■	■	■		■	• (I/O) Ratio: Indoor to Outdoor ratio	• Pearson's correlation coefficient (r)
(Borowski et al., 2022)	5 guests' rooms - Hotel building			■				■	■		■	• comfort indicators: (PMV/PPD value)	• MS Excel spreadsheet and Statistica program
(Marzouk & Atef, 2022)	13 different office rooms		■	■				■	■		■	• IAQ parameters prediction	• Deep- Learning • MATLAB • Anaconda software
(Woo et al., 2021)	7 Office Buildings	■		■				■	■	■	■	• (PMV/PPD value) Predicted mean Vote/ Predicted Percentage Dissatisfied	• SPSS 26.0, Welch's F-statistic test • post hoc, ANOVA, Levene • Pearson's correlation coefficient (r)
(Sakellaris et al., 2021)	37 office buildings, (148 office rooms) , The OFFICAIR Project database		■	■	■	■	■	■	■	■	■	Association between Sick Building Syndrome (SBS) and pollutants level	• Variance Inflation Factor (VIF) • Logistic regression analysis • Non-parametric Mann-Whitney U P-Value
(Mendoza et al., 2021)	1 Office room- Office building		■								■	• (I/O) Ratio: Indoor to Outdoor ratio	• R Version 3.6.3 • Intercept, coefficient, and R2 values
(Tagliabue et al., 2021)	1 Laboratory	■		■	■			■	■		■	• Comfort conditions predictions	• Pearson's correlation coefficient R2 • Markov property test

(Bekierski et al., 2021)	1 room of a home											• TVOC concentration prediction	• F-statistic and p-value, ANOVA • Pearson's correlation coefficient (r) and Gaussian process regression (GPR1)
(Shin et al., 2021)	1 library reading room											• Thermal Sensation Vote (TSV) and the Fanger PMV	• Statistical, mean value and the standard deviation
(de Oliveira et al., 2021)	4 office buildings											• CBE Thermal Comfort Tool • (PMV/PPD value)	• Statistical, P-Value • linear regressions correlations
(Bai et al., 2020)	Classrooms and dormitories											• (USEtox): UNEP-SETAC toxicity models (DALY): disability-adjusted life year	• Statistical SPSS 24.0 • Bivariate Regression
(Martins et al., 2020)	4 homes, 4 schools											• (I/O) Ratio: Indoor to Outdoor ratio	• STATISTICA software • Wilcoxon, Mann–Whitney U test
(Kalimeri et al., 2019)	37 office buildings (148 office rooms) , 112 primary schools in 22 European participating countries.											• (I/O) Ratio: Indoor to Outdoor ratio	• MATLAB (R2017b version 22) • cumulative distribution function
(Bennett et al., 2019)	1 Primary School											• (I/O) Ratio: Indoor to Outdoor ratio	• Positive matrix factorizat, ion • R and openair software packages
(Reuben et al., 2019)	1 library											• Association between Sick Building Syndrome (SBS) and pollutants level	• IBM SPSS Version 22.0 • multinomial logistic regression
(Pantelic et al., 2019)	2 commercial buildings											• Cumulative and instantaneous I/O ratio • (E-index) Exceedance index	• statistical analysis, R software • two-sided Wilcoxon Rank-Sum test • Mann-Whitney test
(Jurado et al., 2014)	30 Classrooms in 5 university buildings											• (I/O) Ratio: Indoor to Outdoor ratio	• Pearson's correlation coefficient (r) • Mann-Whitney test
(Kumar et al., 2014)	1 library building											• (I/O) Ratio: Indoor to Outdoor ratio • (HQ): hazard quotient • (CRinh): lifetime cancer risks	• Statistical

Table 4: Application of IoT-based IAQM systems in similar studies

Source: Author

2.6. Literature review summary

The literature review outlines critical aspects of IAQ assessment to help determine how the IAQ experiment should be designed. Table 5, Table 6, Table 7 and Table 8, provide a summary of each literature review section and determine their key findings and contribution to the experiment design.

Using the literature findings to guide the research process
Key findings of the literature review
1. The significance of environmental air pollution
• Human exposure to EAP (hours to days) is one of the leading causes of adverse health effects and death. • Vehicle traffic is a major source of EAP. • Even at concentrations significantly below the international guidelines, EAP affects human health adversely. • PM is considered one of the most toxic components of environmental air pollutants. • PM2.5 is the most harmful fraction of PM pollution because it quickly penetrates the respiratory system and enters the bloodstream.
Research considerations based on findings
• The study will monitor PM2.5 as the primary indoor air pollutant.

Table 5: Key findings of the first section of the literature review

Source: Author

Key findings of the literature review
2. The impact of environmental air pollution on internal air quality
• In buildings, particle concentration is primarily caused by outdoor air pollution sources and the main source of PM 2.5 is traffic-related air pollution. • Proximity to busy roads exposes occupants to elevated IAP levels due to the high outdoor to indoor contaminant penetration. • IAQ parameters encompass more than pollution concentrations; when evaluating IAQ, thermal comfort parameters should also be taken into account. • Temperature and RH affect occupant perception of IAQ and pollutant emission levels. • IAQ management strategies encompass all project phases, and the design phase is the most efficient and cost-effective for implementing IAQ strategies. • IAQ management should be considered from different perspectives, including architects and designers, facility managers and HVAC engineers. • Microclimate factors have a significant impact on IAQ management strategies. • Temperature, pressure and thus pollutant penetration rate vary at different height levels. • Most IAQ management measures during the operation phase are related to ventilation-related interventions. • How space management and spatial layout design influence IAQ has received little attention in IAQ management strategies. • Using HEPA filters can be considered an emergency and effective solution to decrease exposure to PM2.5, especially during adverse events such as bushfires.
Research considerations based on findings
• A busy road near the building could be a probable IAP source. • A thermal comfort assessment should be included in the project, and sensors should measure RH and temperature in addition to PM 2.5 pollutant levels. • Addressing microclimate issues requires selecting spaces with similar microclimate factors. Therefore, the project will be limited to one level of the building.

Table 6: Key findings of the second section of the literature review

Source: Author

Key findings of the literature review
3. IAQ metrics
• Different IAQ indicators have been used to evaluate building IAQ. • Field measurements and subjective surveys are two commonly used methods of establishing IAQ indicators. • Three types of metrics are commonly used in studies, including (1) formula-based, (2) microenvironment-based, and (3) pollutant concentration metrics based on guidelines. • DALY and HHD are prevalent IAQ indicators based on field measurements and can be calculated using equations. • DALY provide a precise classification of IAQ health impacts. • DALY indices and ELV ratios would be strongly correlated at low and high levels of PM2.5 concentrations. • For indoor pollutants mainly originating outdoors, such as PM2.5 and NO2, the I/O ratio provides a straightforward and logical indicator of air quality. • There are guidelines developed worldwide to reduce and prevent the adverse health effects of indoor air pollution. • ASHRAE, HKEPD, WHO, NHMRS, and US EPA are some of the most well-known agencies that provide IAQ guidelines. • The latest update of WHO guideline highlight that exposure to lower levels of PM2.5 can considerably increase health risks. Therefore, WHO significantly lowered its air quality guidelines to make them more protective.
Research considerations based on findings
• Occupant survey measurements will be used to measure subjective indicators of IAQ. • I/O ratio and E-index will be used as the IAQ metrics. • IAQ will be evaluated based on WHO guidelines.

Table 7: Key findings of the third section of the literature review

Source: Author

Key findings of the literature review
4. IAQ monitoring technologies
• To ensure comfort and improve occupational health, it is imperative to monitor IAQ on a real-time basis. • Real-time IAQ monitoring is largely carried out using IoT and WSN technology. • IAQ prediction and alert systems have been proposed through IoT-based IAQM systems. • Data collection methods that integrate occupant surveys with sensor measurements have demonstrated promising results in the studies. • IAQ assessments were conducted in university campus buildings, primarily in libraries and laboratories. • Subjective perceptions of indoor environments can be compared with objective measurements to reveal useful findings. Although subjective perceptions of the indoor environment usually reflect objective measurements, indoor environmental parameters do not always match occupant perceptions. • An integration of statistical, correlation and regression analysis methods were deployed. • The experiment design should take into account seasonal variations, environmental pollution sources near sample points, the HVAC system's ability to filter pollutants, and correlations between IAQ and thermal comfort.
Research considerations based on findings
• Most IAQ assessments conducted in university campus buildings used single spaces as test beds, such as a library, classroom, or laboratory. Studies rarely consider all the following conditions in their IAQ assessment experiments. 1) Using spaces with different spatial and occupancy characteristics as test beds. 2) Monitoring environments with similar microclimates. 3) Comparing IAQ of spaces based on a specific source of air pollution. • An IoT-based IAQM system coupled with an occupant survey will be used. • The correlations between IAQ and variations, such as HVAC system zoning, spatial features, distance to pollutant sources, and usage schedule and activities, will be assessed. • Statistical, correlation and regression data analysis methods will be used.

Table 8:Key findings of the fourth section of the literature review

Source: Author

3. Research Aims and Objectives

3.1. Research gaps

The literature review highlights three main research gaps regarding evaluating the temporal and spatial correlations between IAQ and occupancy comfort in a campus building.

- ***Lack of a comprehensive comparison between localized sensor measurements and readings from Regional Air Quality Monitoring Stations (RAQMS), which affects the accurate evaluation of outdoor pollutants' impact on IAQ.***

A notable gap in the existing literature is the reliance on RAQMS as the primary reference for outdoor pollutant measurements in studies assessing IAQ and the penetration of outdoor air pollution indoors. These studies frequently overlook the importance of localized measurements, which are essential for capturing local meteorological factors and their effects on air quality, as well as urban design elements such as green spaces and street canyons that influence the urban microclimate. Furthermore, there has been a lack of comparative analysis between localized sensor measurements and RAQMS data. This oversight raises concerns about the reliability and application of RAQMS data for local air quality assessments since it shows a potential discrepancy in understanding the true nature of air quality indoors and in nearby outdoor environments.

- ***Lack of a simultaneous assessment of IAQ in spaces with various spatial configurations and different occupancy characteristics within the same microenvironment.***

The literature review indicates that a considerable number of research projects were carried out worldwide on IAQ assessment. Researchers have used various methods to study IAQ in different types of buildings, such as residential, commercial, and recreational. Regarding commercial buildings, office and university campus buildings are the most commonly used settings for IAQ assessments due to their high occupancy rates. Most IAQ assessments in these settings are limited to evaluating IAQ of one type of space within one building or similar spaces in multiple buildings. For example, comparing the IAQ of office rooms in different office buildings or evaluating the IAQ of a library, a classroom, or a laboratory in a university campus building.

Hence, below are three identified gaps in the literature of IAQ assessment studies:

1) Spaces with different spatial configurations and occupancy characteristics haven’t been explored and compared.

2) Spaces with the same environment and microclimate conditions were not monitored

simultaneously.

3) The impacts of outdoor air pollution on the IAQ of spaces with various proximity to the pollution source and different architectural configurations were not compared.

- ***Need for investigation of the space management and spatial layout design potentials to manage IAQ***

Based on the literature review, most IAQ management measures focus on ventilation-related interventions during the operation phase, while space management and spatial layout design rarely come up as strategies for managing IAQ. This gap is mainly due to the lack of studies investigating the impacts of occupancy characteristics and spatial design features of spaces on IAQ. Clarifying the impact of space management and spatial layout design on IAQ could enhance IAQ management measures. However, this research gap necessitates a broadened scope, requiring a multidisciplinary approach, combining architectural design and environmental engineering and a thorough examination of ventilation dynamics, building materials, and human behavior. It also demands substantial resources, including time and financial investment, for extended data collection and analysis, which is beyond the scope of a Master by Research project. Additionally, this might involve collaboration with industry experts and the recruitment of a diverse research team with specialized skills. Consequently, this study adopts a problem-oriented approach, focusing on understanding the challenges associated with IAQ and establishing a foundation for future research without progressing to solution development. Given the extensive nature of this gap, a separate, dedicated study would be more appropriate. Therefore, due to the strategic focus and practical limitations of a master's project, this specific research gap is not explored in this study.

3.2. Research questions

The discussed research gaps in the previous section have formulated the three research questions below that this study intends to address:

- **To what extent can RAQMS be relied upon for measuring localized outdoor environmental pollution levels, and what significance do localized sensor measurements hold in this context?**

- **What are the correlations between IAQ and occupants' perception in spaces with various spatial configurations?**

- **How do the outdoor environmental pollution levels impact the IAQ and occupants' perception of comfort in different proximity and architectural configurations?**

3.3. Research aims and objectives

This study aims to apply an IoT-based monitoring system coupled with an occupant survey to evaluate the temporal and spatial correlations between IAQ, and occupant perceptions of comfort in a university campus building. This aim is pursued through the following objectives:

- **To assess the significance of localized sensor measurements compared to data from RAQMS.**

- **To identify the correlations between IAQ measurements and occupants' perception in spaces with various spatial configurations.**

- **To determine the influences of an outdoor environmental air pollution source on the IAQ and occupants' perception of comfort in different proximity and architectural configurations.**

3.4. Research methods

This research deploys a quantitative research approach through quasi-experimental and survey design methodology and both of the research objectives are accomplished by conducting an experiment in a single level of a campus building in Sydney, Australia. A map of the identified gaps developed into the proposed research questions and objectives is presented in Figure 6. The map illustrates how the aim is pursued through the established research methods.

3.5. Scope and limitations

The scope of this research project is as follows:

- This study is limited to measuring and analyzing data on PM2.5, PM10, temperature, and RH due to the primacy of these air quality parameters and the technical specifications of the available sensors.
- This research project is limited to one level of a university campus building as the test case to address microclimate concerns.
- Data collection takes place at level three of the building. It includes computer labs, lecture theatres, classrooms, common areas, student study areas, a kitchen, and a foyer.

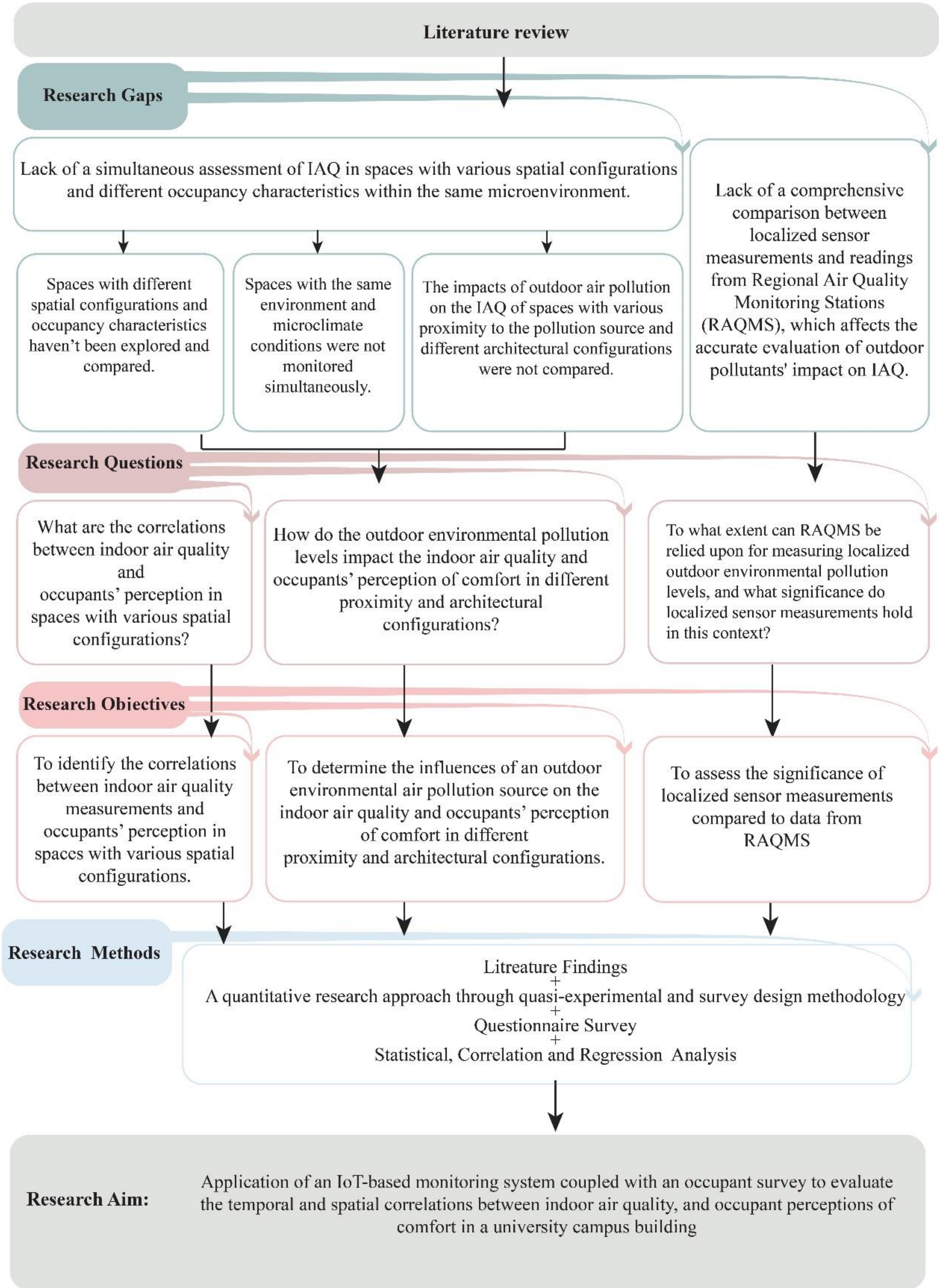

Figure 6:Mapping of research gaps, questions, objectives and methods

Source: Author

4. Research Methodology

The study was conducted in two distinct phases: **Phase I (Preliminary Study)** and **Phase II (Main Research)**. Each phase aimed to investigate various aspects of indoor air quality (IAQ) and occupant comfort, with Phase II serving as the primary focus. A key distinction between Phase I and Phase II lies in their primary sources of air pollution: Phase I was mainly influenced by hazard reduction burning events, whereas Phase II was impacted by traffic-related emissions. Despite this difference, the two phases were closely linked, sharing common elements that linked the two studies and provided a unified framework for examining how these varied pollution sources affect air quality. Specifically, both phases utilized the same type of sensors installed within the same building, ensuring consistent data collection and analysis. These sensors, which employ optical particle counters to detect particles based on light scattering, were calibrated against each other before the start of each study phase. Calibration took place over a one-month period, with all sensors attached to a single mounting board under identical location and microclimatic conditions. By recording and comparing readings throughout this period, it was confirmed that their operating accuracy was within the specified limits. This continuity in sensor use was highly valuable, as data from Phase I proved particularly beneficial for informing the focus of Phase II, the main study. The compatibility between the phases provided a cohesive framework that enriched the main study and enhanced the understanding of the data collected.

Phase I utilized pre-existing data from a prior study, covering the period from April to August 2021. The hazard reduction Burning events were the primary source of air pollution during this phase. This phase focused on four internal spaces and one external facade at varying heights. By analyzing regional air quality, local microclimate measurements, and PM2.5 concentration patterns, Phase I identified critical hotspot areas, pinpointed primary pollution sources and determined the most polluted zones. Key areas of interest included PM2.5 concentration patterns over different timeframes, temperature inversion effects, and the effectiveness of mechanical ventilation during air pollution episodes. The insights gained from this analysis were instrumental in selecting specific areas as test beds for the main study. Furthermore, these results informed the design of the main study by identifying critical hotspots and refining space selection, guiding the placement of sensors and the selection of spaces for occupant surveys conducted in Phase II.

Phase II, conducted from August to November 2022, involved data collected specifically for this study. Building on the findings from Phase I, Phase II concentrated on spaces situated on the most polluted level, where proximity to busy roads was examined for its impact on IAQ. This phase primarily experienced air pollution from traffic-related sources. This phase included detailed assessments of occupant comfort, focusing on both comfort levels and perceptions of IAQ across different spatial zones. Parameters measured included PM2.5, PM10, relative humidity (RH), and temperature, with occupant surveys providing insights into thermal comfort in these identified hotspot areas.

Given the differences in data sources, pollutant sources, selected spaces, and specific objectives, the data from each phase were analyzed and interpreted in separate sections. Figure 7 below provides an overview of the study parameters, focus areas, and goals for both phases, highlighting the distinctions between the two and how Phase I informed the design and focus of Phase II.

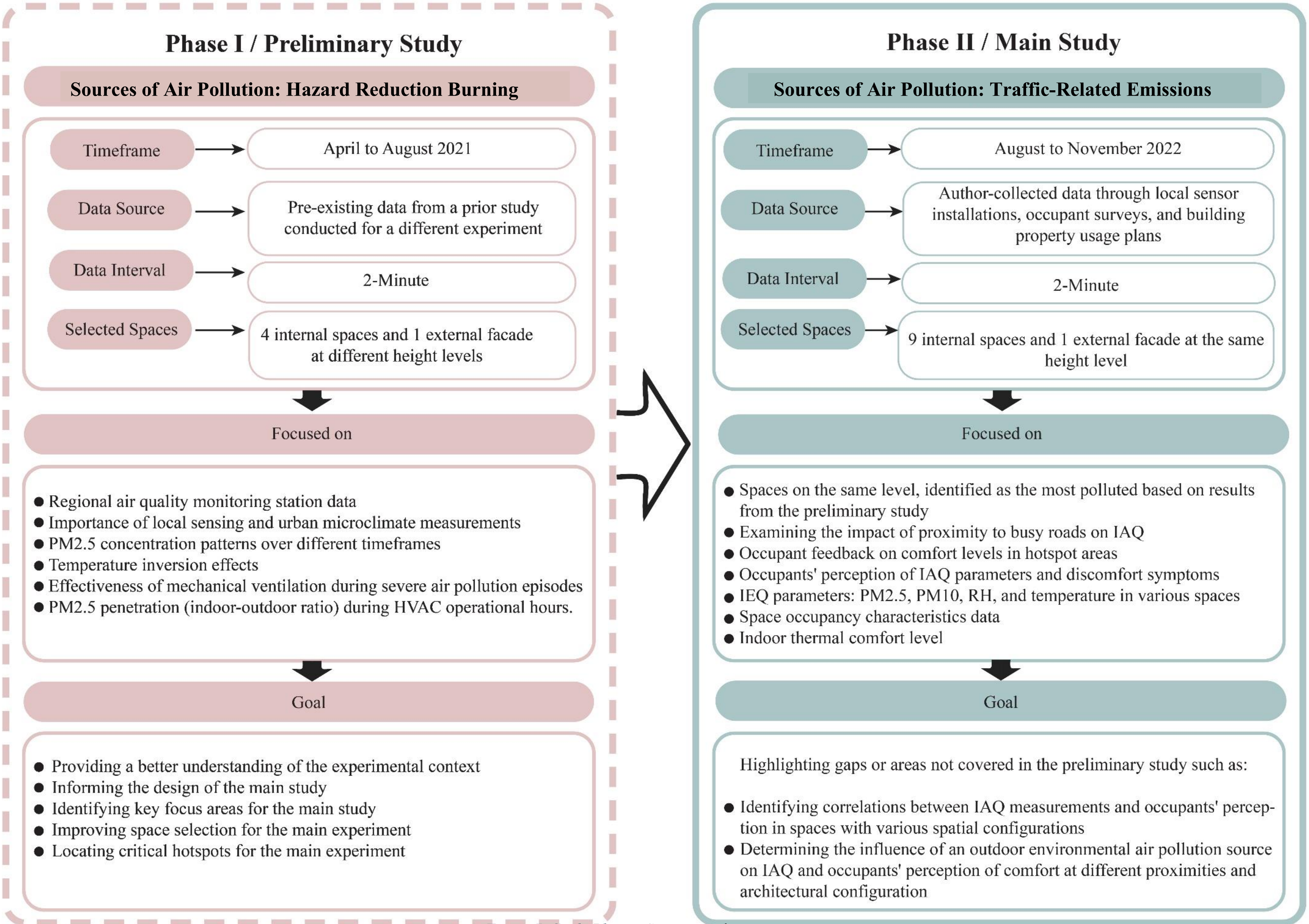

Figure 7: Study Phases, Source: Author

5. Study Phase I (Preliminary Study)

5.1. Preliminary study data investigation

The preliminary study aimed to apply the IoT-based monitoring system to measure and compare the PM2.5 concentration and exposure level in different spaces of a university campus building. PM2.5 measurements were taken from 4 internal spaces and 1 external façade location using low-cost and portable IoT sensors between April to August 2021, covering two notable Hazard-Reduction Burning (HRB) events. HRB is the targeted burning of bushlands conducted by the Australian authorities as a key management strategy to minimize the adverse impacts of wildfires (Lange & Gillespie, 2022). HRB in some regions of NSW has been directly associated with especially high PM pollution, affecting a large number of people in the Sydney area (Forehead et al., 2020). In NSW, HRB is typically conducted from late autumn to early spring (NSW Rural Fire Service, 2022). In this study one HRB event was in the autumn (April 25th to May 8th) and one was in the winter (14th to 23rd of August). The building exposure measures were also compared with the Australian Bureau of Meteorology readings for the same period and location. In this study, particle penetration from the outdoors was quantified using the I/O Ratio and E-Index metrics.

5.2. Experimental apparatus

In this study, two types of indoor and outdoor Hibou portable microclimate sensors were placed in a university campus building. One Hibou outdoor air quality monitoring sensor, as shown in Figure 8 was located on the outside facade of the building at street level on a busy road. Additionally, indoor Hibou air quality sensors, as shown in Figure 9, were deployed in four selected indoor spaces to collect data on Indoor Environmental Quality (IEQ) parameters. Both indoor and outdoor Hibou sensors employ an optical particle counter that counts particles based on light scattering. The sensors were used to measure and record localized temperature, humidity, lighting, ambient pressure, the standard Air Quality Index (AQI) and particulate matter (PM1.0, PM2.5 and PM10). The specifications for indoor and outdoor sensors are as shown in Table 9.

Figure 8:Hibou outdoor microclimate sensors

Figure 9:Hibou indoor microclimate sensors

Parameter	Resolution/Output
Particulate Matter (PM1.0, PM2.5 and PM10)	resolution 0.3 µg/m^3. Max Error ± 10%
Humidity range	0…100% R.H. Accuracy: ± 3 % R.H.
Temperature range	-20…65°C Accuracy: ± 1°C
Pressure range	300...1100 hPa ± 0.6 hPa
Ambient light	resolution 100mLux U.V. light as U.V. Index (WHO standard)
VOC (Organic Compounds)	Indoor Air Quality Index

Table 9: The specifications for Hibou indoor and outdoor sensors

5.3. Experimental design

Four indoor spaces on different levels of the building CB06 (levels three, five and six) were selected as the study testbed. Level three of the selected building has an entrance from one of the busiest roads in the city of Sydney and experiences high traffic congestion during typical rush hours (3-5pm week days). The outdoor sensor was placed on the external facade of the building at street level, and indoor sensor A was installed in the foyer area of level three. Additionally, the indoor sensor B was installed in an office room on level five, and indoor sensors C and D were installed in two different office rooms on level six. Table 10 demonstrates the characteristics of the selected spaces, zoning and type of HVAC systems and their operating hours for each space.

Indoor Sensors	Location	Space type	HVAC Default Operating Hours (Mon-Fri)	Number of doors	Area of Façade glazing (non-opening windows) (m^2)	Areas of glass partitions/ (m^2)	Floor Area (m^2)
A	Level 03	Foyer area	06:00-22:00	2 connecting doors- 1 Entrance door	0	30	158
B	Level 05	Shared Office room	08:00-18:00	1	2.7	3.04	55
C	Level 06	Shared Office room	07:30-18:00	1	7.2	0	63
D	Level 06	Private Office room	08:00-18:00	1	0	16.46	10

Table 10: Indoor sensors placement and their space information

5.4. Study timeline and PM2.5 air pollution events

This study took place between April to August 2021. During the study, Sydney experienced significant air quality issues due to HRB, winter air pollution impacts caused by the colder and drier air trapping more pollution, and daily traffic congestion. The concentrations of PM2.5 measured at the local outdoor location were compared with those at the regional weather stations nearby. The closest regional weather station is 4 km from the building.

A review of the hourly average PM2.5 in the selected offices across five months of the year (April – August 2021) was conducted. According to the review, although the monthly average of PM2.5 during typical months (before and after HRB events) were below 5 ($\mu g/m^3$) in most indoor spaces (B, C, D), there were certain days when indoor PM2.5 hourly average concentrations exceeded 15 ($\mu g/m^3$) which is the WHO standard threshold. An example of reviewing hourly PM2.5 concentrations over study time period is illustrated in Figure 10, with HRB periods

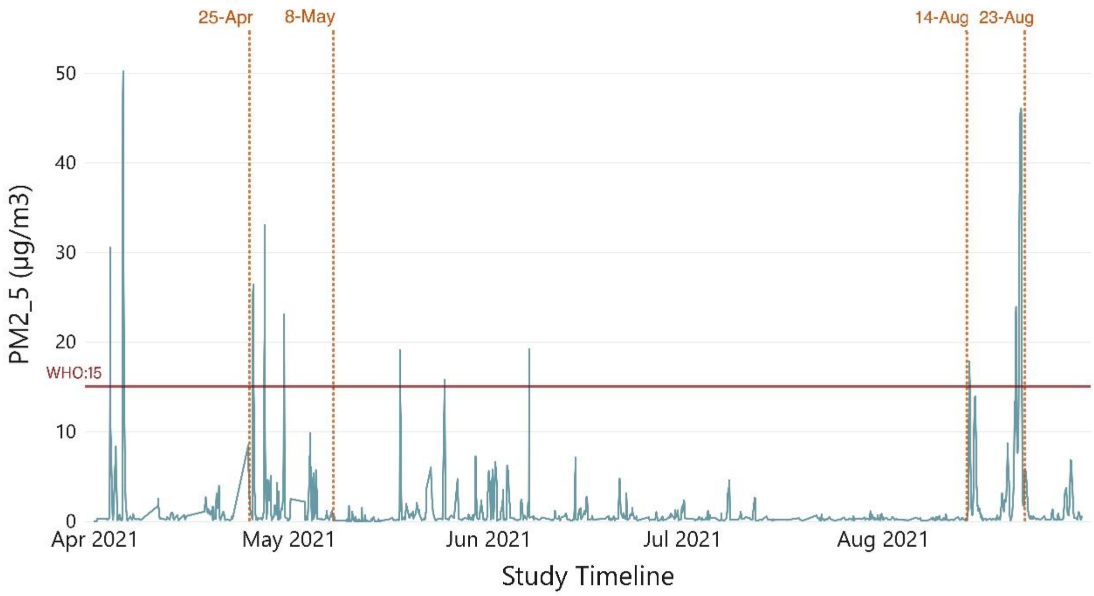

Figure 10:Highlighting PM2.5 hourly average concentration during extreme air pollution episodes and typical days for Indoor sensor C- (Source: Author)

highlighted. Figure 10 demonstrates that indoor sensor C recorded PM2.5 concentrations that exceeded WHO guidelines outside HRB periods, in April and June. The same analysis for the other indoor spaces provided equivalent results. Due to this observation, it is assumed that the nearby busy road and the traffic-related pollution would also be a contributing outdoor source of PM2.5, and it may negatively impact indoor PM2.5 concentrations even outside extreme air pollution episodes caused by HRB smoke.

5.5. Measurement metrics

Using the discussed IoT environmental sensing, PM2.5 concentrations in different indoor spaces were measured and compared during typical days and extreme pollution events throughout the study timeframe. For this purpose, the following two field measurement metrics were utilized.

- **Exceedance Index (E- Index)**

Using E-Index, the concentration of PM2.5 in indoor spaces were compared with the WHO exposure threshold value. According to the WHO guidelines, which is the most updated and conservative standard threshold, the maximum exposure over 24 hours, is 15 ($\mu g/m^3$). As presented in (Pantelic et al., 2019), we compared the hourly average indoor PM2.5 concentration to the WHO short-term average exposure guideline and measured the E-index on a daily and hourly basis, as shown in Eq. 1. Based on this metric, it is possible to calculate the percentage of hours or number of days that indoor PM2.5 concentrations exceeded thresholds over the study period (Pantelic et al., 2019). In other words, occupant exposure in different spaces can be evaluated and compared by calculating E-Index.

$$E = \frac{C\ measured\ PM_{2.5}}{15(\mu g/m^3)}$$

Eq. 1

- **Indoor to Outdoor (I/O) Ratio**

Studies have suggested that outdoor pollution sources significantly impact indoor particle pollution in modern buildings (L. Yu et al., 2020). In this study, the I/O ratio was used to compare indoor and outdoor PM2.5 concentrations. Assuming that indoor PM2.5 sources were negligible in the selected spaces, the penetration of outdoor PM2.5 into indoor spaces was quantified using the indoor/outdoor PM2.5 ratio in Eq. 2, where Cin(t) and Cout(t) represent respective hourly averages. For each indoor space, I/O ratio was measured using hourly averages of indoor and outdoor PM2.5 concentrations.

$$\frac{I}{O} = \frac{C\ in\ (t)}{C\ out\ (t)}$$

Eq. 2

5.6. Statistical tools used

Data collected from IoT sensors were analyzed with Excel SPC and R software. A statistical analysis was performed on sensor measurements to compare it between different indoor spaces, as well as between an outdoor sensor and a regional weather station. Since the collected data were not normally distributed, non-parametric tests were conducted. In order to assess the statistical significance of the measured PM2.5 concentration in different indoor spaces, Kruskal-Wallis Rank-Sum tests were used. In addition, the Mann-Whitney test was performed to analyze the significance between the outdoor sensor and the regional weather station. The conducted tests included all possibilities with 95% confidence levels, which means a p-value less than 0.05 is considered as statistically significant.

5.7. Phase I data analysis, results and comparisons

Analyzing PM2.5 data on different averages gives a deeper understanding of pollution sources and air quality. Analysis of 10- or 15-minute interval data can provide valuable information about short-term variations in PM2.5 concentrations resulting from specific events or activities. This analysis can be used to pinpoint sources of indoor PM2.5, such as cooking, smoking, printing, or other activities that produce short-duration, localized emissions. A 15-minute interval data analysis would enable personal exposure assessment in different microenvironments and a detailed investigation of the source and time of emission. Furthermore, it can help determine the effectiveness of interventions to mitigate the negative impacts of air pollutants on the IAQ and comfort of occupants, such as using exhaust fans or air purifiers. One study (He et al., 2022) evaluated personal exposure to PM2.5 based on the 10-minute average of PM2.5 concentrations. According to its findings, different microenvironments affect an individual's exposure to PM2.5 differently, and particular occupant activities such as cooking cause elevated PM2.5 levels. Also, regarding the effect of mitigation interventions, when windows were closed, using a portable HEPA filter significantly reduced exposure to wildfire conditions (He et al., 2022).

The hourly average PM2.5 analysis can provide valuable insights regarding fluctuations in air quality throughout different times of the day and night. The comparison of hourly averages (Askariyeh et al., 2020; M. Wang et al., 2022), specifically during morning and evening rush hours, allows identification of patterns in PM2.5 concentrations related to traffic-related pollution sources. The efficiency of HVAC operations can also be evaluated through hourly average analysis (Jones et al., 2021). Additionally, hourly average analysis provides insight into the effects of meteorological factors including temperature, wind speed, humidity and pressure on PM2.5 concentrations (X. Zhang et al., 2022; Z. Zhang et al., 2022). Further, hourly measurements can be useful for assessing PM2.5 exposure or measuring pollution dynamically, highlighting the growth of PM2.5 concentration over time (Wei et al., 2020a).

Daily average PM2.5 concentration analysis helps identify pollution sources that have long-term effects. Wildfires, for example, can cause elevated PM2.5 concentrations for several days. In wildfire seasons, average daily PM2.5 concentrations can be used to track changes in air quality and identify smoke-affected areas (Aguilera et al., 2020). In addition, daily averages can be used to detect patterns within longer time intervals, such as variations between weekdays and weekends (X. Li et al., 2021) months and seasons (Jandacka & Durcanska, 2021; J. Zhao et al., 2021). Combining average measurements is the best way to measure the concentration of PM2.5 indoors and outdoors. This study conducted statistical analyses based on daily and hourly averages.

- **Outdoor PM2.5**

The PM2.5 daily and hourly averages measured by the regional air quality station and the local outdoor sensor were compared over the study period (April to August 2021) to identify their differences and to validate the accuracy of the local sensing. Comparison of the results are presented in Figure 11, Figure 12 and Figure 13. In Figure 11 the x-axis represents the study timeline, the y-axis represents the PM2.5 daily average concentration, and the two lines demonstrate the daily averaged PM2.5 measured by Rozelle station and the local outdoor sensor.

Figure 11 demonstrates that although peak and median mass concentrations measured by the local outdoor sensor and Rozelle station differed during the study time, they still followed similar patterns which validates the correctness of our locally collected data. Additionally, as shown in Figure 11, before the first HRB event hit in April (start day on 25th of April 2021 which is marked on the figure), PM2.5 daily average levels at Rozelle station were constantly higher than those measured at the local outdoor sensor. In other words, during typical days in the Autumn, when the PM2.5 daily average was lower than 15 (µg/m^3), Rozelle station measured a higher PM2.5 average than the local outdoor sensor. This difference also highlighted the importance of urban microclimate differences and its variable impacts on the local built environment.

In addition, the violin plot, a hybrid of a Kernel density plot and a box plot, was used to analyze the hourly average of PM2.5 concentration during typical winter months as well as months with HRB events (Figure 12and Figure 13). In Figure 12 and Figure 13, the x-axis represents the selected months in this study, and the y-axis represents the PM2.5 hourly average concentration. In these figures, the Kernel density plot represents the data frequency distribution, the box plot displays the 25th percentile, along with the median, average, and 75th percentile, and the whiskers display the 5th and 95th percentiles. Figure 12 demonstrates the PM2.5 hourly average concentration and distribution for Rozelle station. As shown in Figure 12, Rozelle station recorded high PM2.5 hourly average concentrations with low frequency during Autumn (April and May) and Winter (August) HRB months. The maximum and less frequent values were 87 (µg/m^3) in April, 47 (µg/m^3) in May, and 160 (µg/m^3) in August. On the other hand, during typical winter months (June and July), the highest values that Rozelle station recorded were 28 (µg/m^3) and 31(µg/m^3). Furthermore, during typical and extreme pollution months, the median values for PM2.5 hourly average concentrations at Rozelle station were not significantly different. The median values from April to August were 7.7 (µg/m^3), 5.8 (µg/m^3), 5.4 (µg/m^3), 4.9 (µg/m^3) and 6 (µg/m^3), respectively, confirming that the peaks were associated with a few extremely polluted days.

The violin plots in Figure 13 illustrate the PM2.5 hourly average concentration and distribution measured by the local outdoor sensor. It is evident from Figure 13 that for all five months, the local outdoor sensor recorded high PM2.5 hourly average concentrations of more than 90 (µg/m^3). Also, there are noticeable differences in average and median in various months; June, a typical month in winter, had the highest average (29.4 µg/m^3) and median (24.7 µg/m^3), whereas April, when autumn HRB was conducted, had the lowest average (5.6 µg/m^3) and median (3.3 µg/m^3).

Based on the comparison of Figure 12 and Figure 13, it is evident that the median and average values differ between the study site and Rozelle station in all studied months. A Mann-Whitney U test indicates a statistically significant difference between average outdoor PM2.5

measurements of the local outdoor sensor versus the Rozelle station ($p<0.05$). Additionally, the local outdoor sensor recorded higher values during typical winter months, whereas Rozelle station recorded lower values. Furthermore, the violin distribution plots showed greater probability and higher frequency of large values being recorded by the local outdoor sensor in comparison to the Rozelle station.

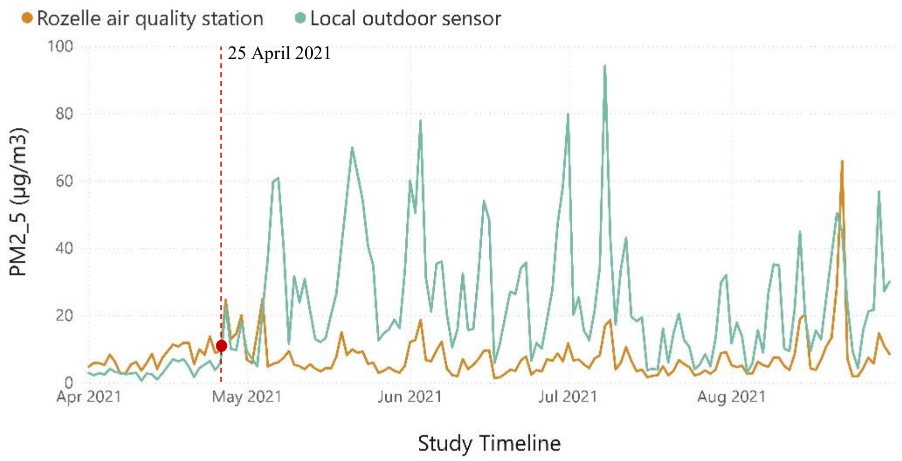

Figure 11: Comparison of daily averaged PM2.5 measurements for the local outdoor sensor and the regional air quality station over study timeline (Source: Author)

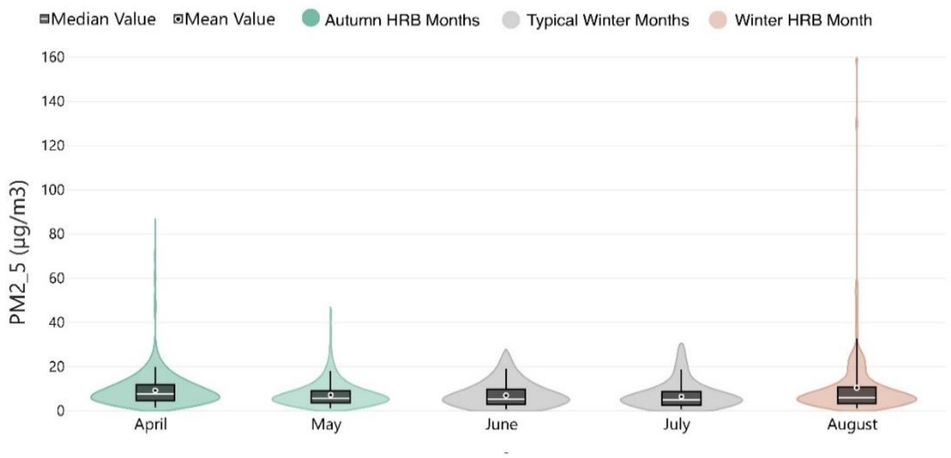

Figure 12: Violin plot for Rozelle Station, representing PM2.5 hourly average concentration and distribution over typical and extremely air-polluted months- (Source: Author)

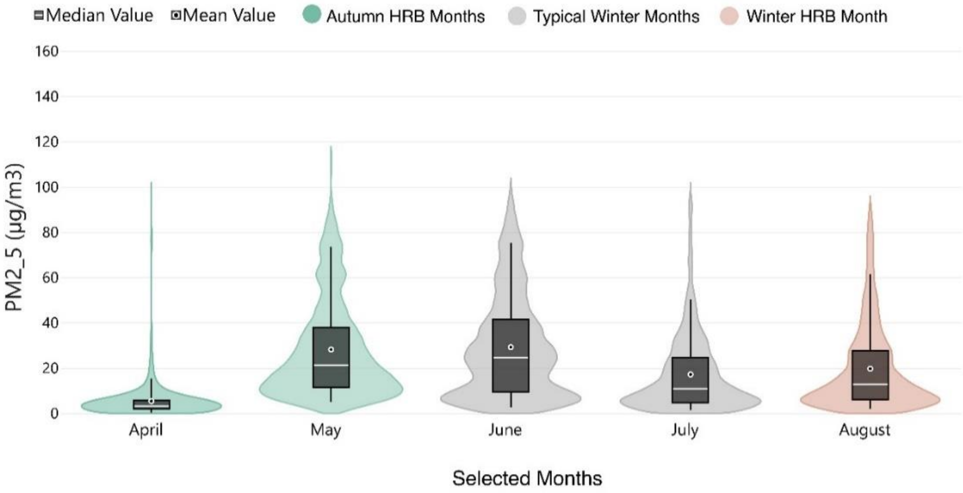

Figure 13: Violin plot for local outdoor sensor, representing PM2.5 hourly average concentration and distribution over typical and extremely air-polluted months (Source: Author)

- **Indoor PM2.5**

Exposure to PM2.5 affects occupant well-being, performance, and comfort. Hence, the indoor PM2.5 levels for each space were evaluated to determine occupant exposure levels to PM2.5. Figures in this section represent findings on indoor PM2.5 concentrations. Figure 14 compares the average hourly PM2.5 levels between four indoor and the outdoor sensors during HRB in August 2021. In Figure 14, the x-axis represents the indoor and outdoor sensors, and the y-axis represents the average hourly PM2.5 concentration during August. Additionally, Figure 14 visualizes the Whisker and Box plot for each sensor. In the box plot, the 25th percentile is displayed, along with the median, 75th percentile, and Interquartile Range (IQR), and the whiskers display the 5th and 95th percentiles.

As shown in Figure 14, the average hourly PM2.5 concentration over the HRB event was 26.4 (µg/m^3) (IQR= 23.9 µg/m^3) for indoor sensor A, 8.7 (µg/m^3) (IQR= 6.6 µg/m^3) for indoor sensor B, 3.5 (µg/m^3) (IQR= 2.9 µg/m^3) for indoor sensor C, 6.3 (µg/m^3) (IQR= 6.3 µg/m^3) for indoor sensor D and 19.9 (µg/m^3) (IQR= 21.6 µg/m^3) for the local outdoor sensor. Figure 14 shows that the indoor sensor A (which is exposed to outdoor environment through the entrance) had an average hourly PM2.5 concentration significantly higher than the WHO's recommended threshold in August. Furthermore, IQR comparison of indoor spaces indicates that indoor sensor A had the highest IQR range. Thus, the PM2.5 hourly average concentration in indoor space A was more affected by outdoor air pollution variations. It is also noticeable that the average hourly PM2.5 concentration is higher for indoor sensor A in comparison to the outdoor sensor. In addition, for all four indoor sensors, the upper whisker indicates that for approximately 25% of PM2.5 values, the average hourly PM2.5 concentration exceeded the WHO safe threshold. Also, the maximum values measured by indoor sensors A and B were even higher than those measured by outdoor sensors. The values presented here provide an overall view of indoor PM2.5 levels and indicate that four different indoor spaces have different levels of PM2.5 exposure during extreme air pollution episodes. Detailed analysis of other months is also provided in the supporting information (S Fig 1, S Fig 2, S Fig 3 and S Fig 4).

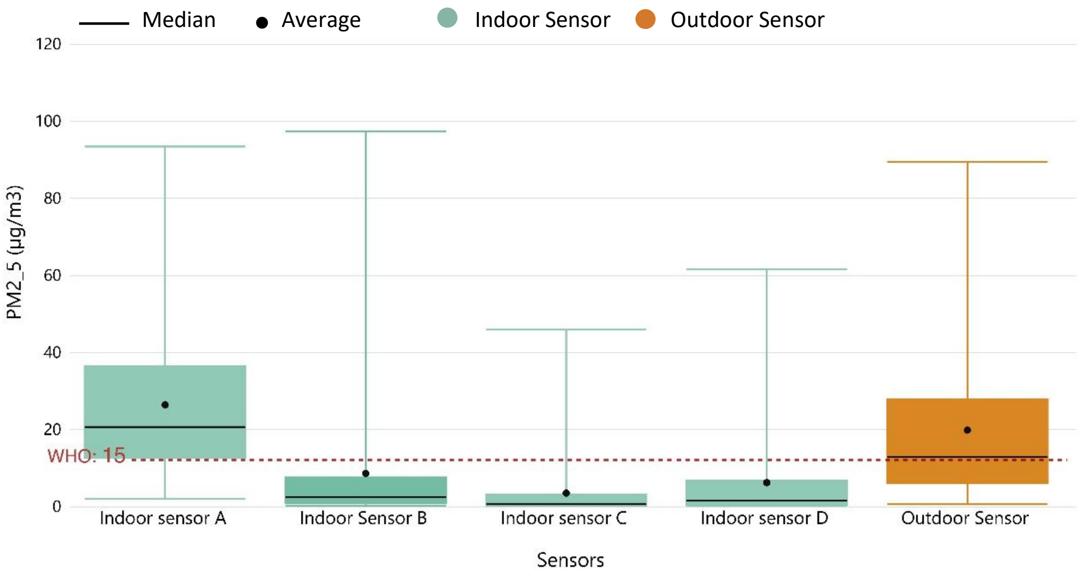

Figure 14:Comparing hourly PM2.5 averages measured by different indoor spaces and the outdoor sensor during the hazard-reduction burning event in August 2021- (Source: Author)

5.7.1. E-Index measurement

- **Daily analysis**

Different levels of $PM_{2.5}$ concentration in each space and the number of days that occupants are exposed to higher than standard PM2.5 levels, significantly influence occupant health. To evaluate health impacts in relation to space PM2.5 exposure level, we simultaneously assessed PM2.5 concentration and exposure days using the E-index measurement. In Figure 15, the x-axis displays months over the experiment period, and the y-axis displays the days of the month. At each space, the E-index is calculated based on the average daily indoor PM2.5 concentrations measured by indoor sensors. Figure 15 represents exposure levels and the exceedance days for each space.

According to WHO standards, exceeding the PM2.5 thresholds is accepted only on 1% of days per year (3 or 4 days in a year). Based on Table 11, E-Index calculated for indoor sensor A was on or beyond the threshold "1" for 80% (104 days) of the five-month period. Also, as shown in Figure 15a, 63% of the time (or 82 days), the E-Index for indoor sensor A was between 1-3, 16% of the time (or 21 days), it was between 3-5, and only around 1% of the time (or 1 day) it went beyond 5. Also, Figure 15b, which illustrates the results of the E-index for indoor sensor B, shows that PM2.5 concentrations exceeded the recommended level by 6% (8 days) over the five-month period, while the E-Index ranged between 1 to 3. Notably, all indoor sensors had E-Index values above one during the August HRB. For instance, the E-Index for indoor sensor A exceeded “1” for 20 days in August, and the E-Index for indoor sensor B exceeded “1” for 4 days, which was half of its total exceedance days (8 days with an E-Index above one during all five months). Additionally, in the case of indoor sensors C and D, the E-index was above “1” only during August.

Findings from Table 11 and Figure 15 suggest that air quality condition in spaces where indoor sensors A and B are located was not safe and acceptable since the count of the days that PM2.5 concentration went over the WHO threshold was higher than the guidelines. Additionally, HRB contributes significantly to the increase in the frequency of exceedance days. It is thus essential to provide solutions that can effectively control PM2.5 penetrations during extreme air pollution events.

	Number of days with an E-Index above 1						Total measured days
	April	May	June	July	August	Total	
Indoor sensor A	5	30	28	21	20	104 (80 %)	130
Indoor sensor B	2	1	0	1	4	8 (6 %)	142
Indoor sensor C	0	0	0	0	1	1 (0.7 %)	148
Indoor sensor D	0	0	0	0	2	2 (1.5 %)	131

Table 11:Count of days with E-Index greater than 1 for each indoor sensor

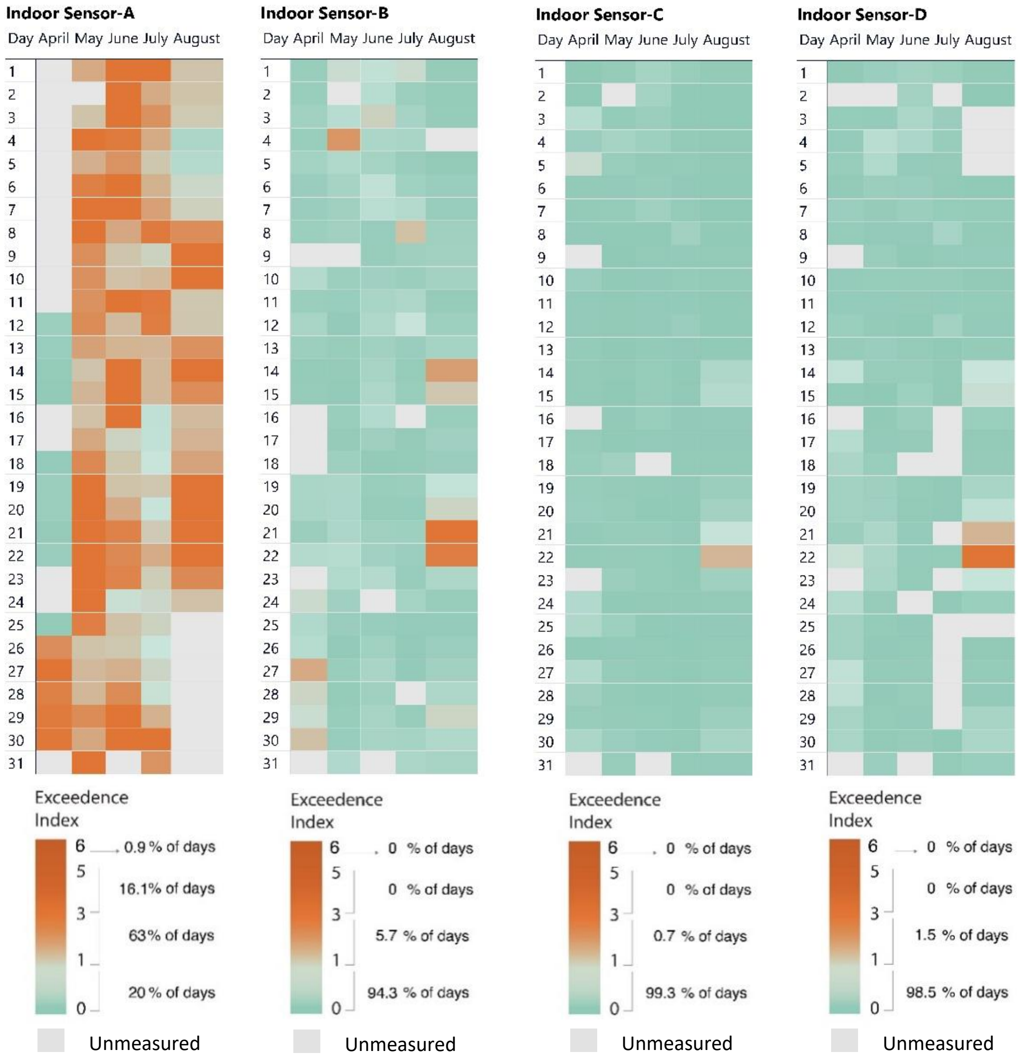

Figure 15:Daily Exceedance index PM2.5 heat map calculated for WHO 24 h exposure threshold: a) Indoor sensor A, b) Indoor sensor B, c) Indoor sensor C and d) Indoor sensor D- (Source: Author)

- **Hourly analysis**

The number of hours that occupants are exposed to elevated concentrations of PM2.5 during the day directly impacts their health and performance Figure 16 and Figure 17 illustrate the evaluation of exposure time and PM2.5 exposure level using hourly E-index measurement for indoor sensors A and B. In Figure 16 and Figure 17 the x-axis represents days during two extreme air pollution episodes: Autumn HRB event between 25 April and 8 May and Winter HRB event between 14 and 23 August, and the Y-axis displays the hours of the day. The horizontal black dashed lines indicate the typical operating hours of the spaces (7 am to 7 pm).

As observed in Figure 16, during the extreme air pollution events, hourly E-index calculated for indoor sensor A was "1" or beyond for around 88% of the time (388 hours) and exceeding "2" for 60% (264 hours) of the time. Also, the E -index for 2.5% of the time (11 hours) was above six. As shown in Figure 17, for the indoor sensor B, PM2.5 concentration was higher than the acceptable levels for 25% of the time (121 hours). Also, E-index for indoor sensor B was between 1-2 for around 13% of the time (63 hours), between 2-4 for around 9 % of the time (44 hours), and four or beyond for around 3% of the time (15 hours). According to the hourly E-Index calculated for indoor sensor C, PM2.5 concentration exceeded the recommended levels for only around 9% of the time (40 hours) while the indoor sensor D exceeded the recommended levels for around 16% of the time (71 hours). Hourly maps for all sensors are presented in the supplementary documents (S Fig 5 and S Fig 6).

The overall average E-index during operation hours for the entire pollution episode for indoor sensors A and B was 2.36 and 0.93, respectively, indicating that PM2.5 concentration levels were frequently above the WHO threshold during the extreme air pollution episode. Therefore, particle filtration and envelope tightness enhancements are necessary in order to provide acceptable air quality in these spaces. In contrast, the overall average E-index during operation hours for indoor sensors C and D were 0.34 and 0.65 respectively, highlighting that the outdoor PM2.5 penetrations were successfully controlled in the spaces where these sensors are located. That means occupants in this space were exposed to a safe level of PM2.5 overall, and the IAQ conditions in these spaces were generally acceptable.

In spite of the fact that the overall average E-index can be used to evaluate and rank spaces in terms of PM2.5 exposure levels, the simplification of the results to a single number misses out other valuable insights. For instance, although indoor sensors D and C show acceptable average E-index during operation hours, they still surpass the WHO 24h- average exposure threshold of "1" for 71 hours and 40 hours respectively. This means that even though factors such as higher level of the building or greater distance from the main entrance could potentially result in lower level of PM2.5 exposure, there were hours that it exceeded the threshold and could still result in adverse health impacts during occupancy hours.

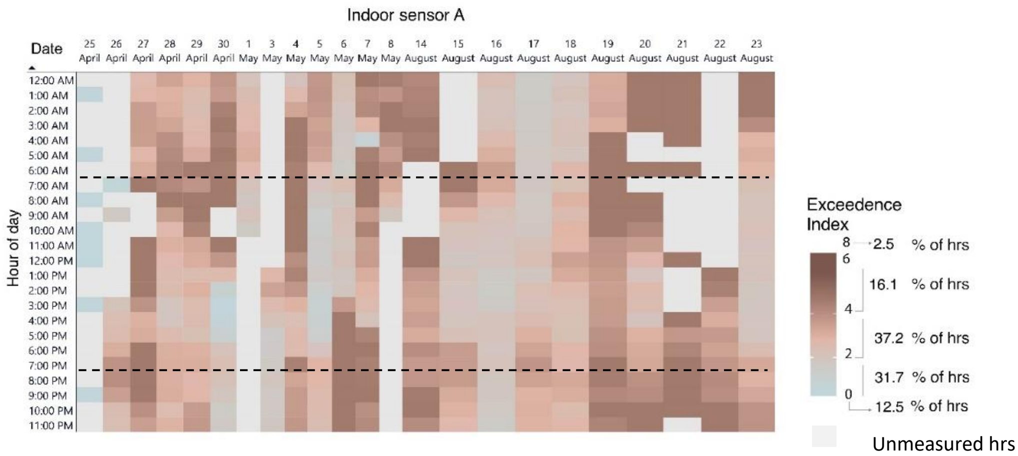

Figure 16:Hourly E-Index PM2.5 heat map for indoor sensor A during extreme air pollution episodes- (Source: Author)

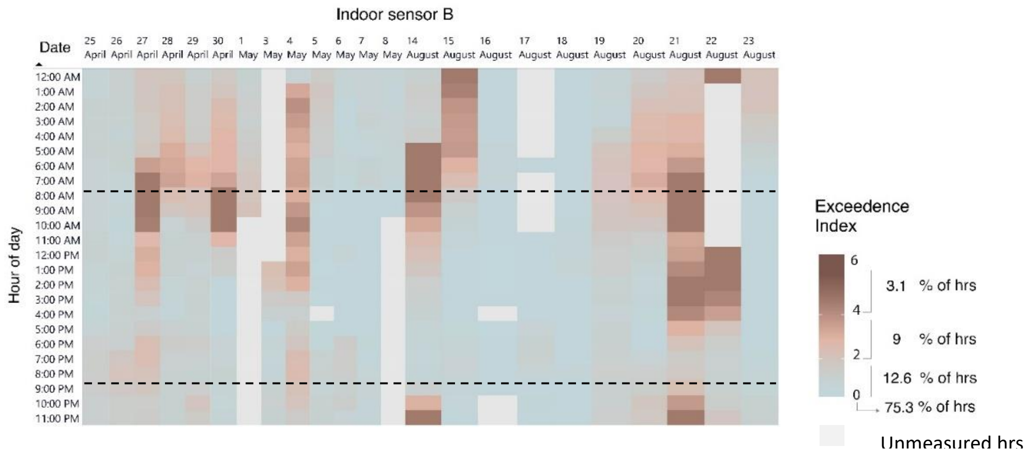

Figure 17:Hourly E-Index PM2.5 heat map for indoor sensor B during extreme air pollution episodes- (Source: Author)

5.7.2. I/O ratio measurement

- **Daily analysis**

I/O ratios provide insight about the amount of outdoor pollution that penetrate into the built environment when indoor sources are excluded. In Figure 18, the x-axis displays months over the experiment period, and the y-axis displays the days of the month. In each space, the I/O ratio is calculated by dividing the daily average indoor PM2.5 concentration by the daily average outdoor PM2.5 concentration. In Figure 18, I/O ratio levels are represented for each space. According to Figure 18, sensor A, located in the building foyer near the entrance door, recorded higher PM2.5 daily average than the outdoor sensor for 80% of the time (103 days). In addition, on days with an average daily I/O ratio above 1, the outdoor PM2.5 level was between 2 ($\mu g/m^3$) and 44 ($\mu g/m^3$). This confirms the fact that pollution penetrate, trap and accumulate in the foyer area and turn this space into the worst place of the building in terms of IAQ. The results revealed that in more than 80% of the time, the foyer air quality is even worse than the outdoor air quality, meaning that it could have severe health impact on building occupants who are frequent user of this space.

In contrast to indoor sensor A, the I/O ratios for indoor sensors B, C, and D only exceeded "1" for a few days during April, May, and August, when outdoor PM2.5 concentrations were low (between 2 (μg/m^3) and 10 (μg/m^3). According to Figure 18, on twelve days in April and three days in May, I/O ratios were above "1" for indoor sensor B, whereas on only four days in April, I/O ratios were above "1" for indoor sensor C. Additionally, on six days in April and one day in August, I/O ratios were above "1" for indoor sensor D. This means that although the I/O ratios were above "1" in these spaces, it is not necessarily due to the outdoor air quality issues and could be associated with other indoor PM2.5 resources particularly in August and May when higher levels of I/O ratio for each space were observed on different days of the months.

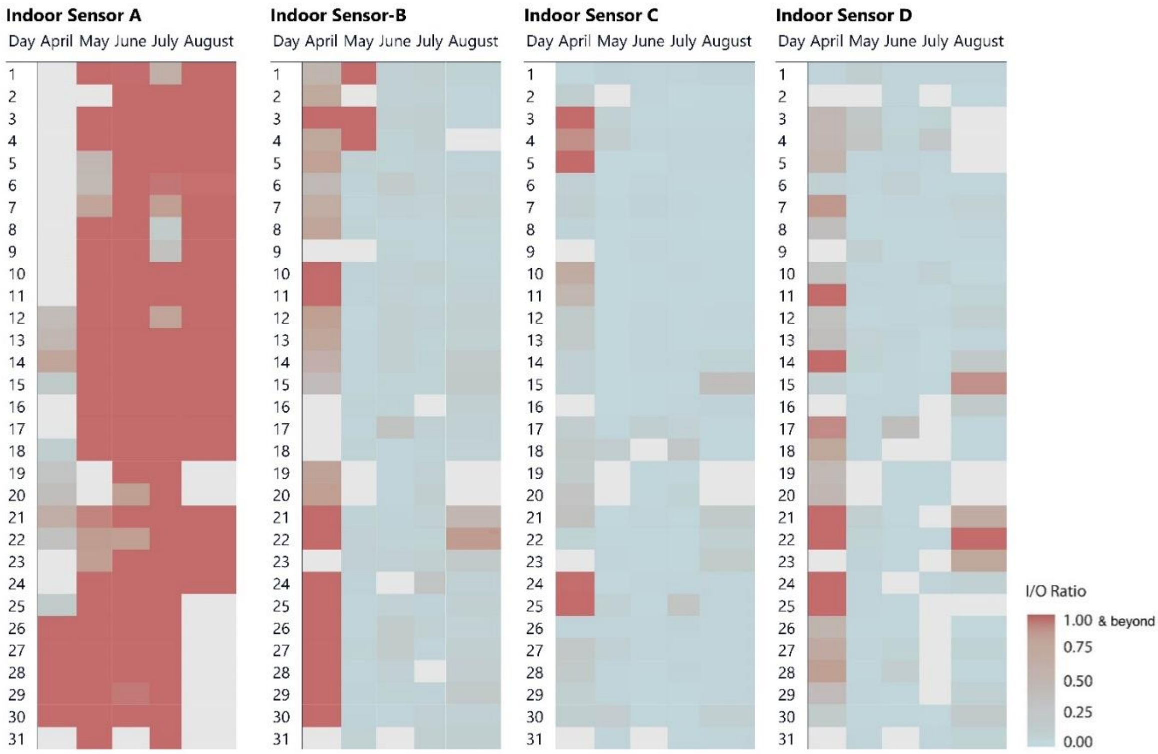

Figure 18:Daily I/O ratio for a) Indoor sensor A, b) Indoor sensor B, c) Indoor sensor C and d) Indoor sensor D- (Source: Author)

- **Hourly analysis**

The hourly analysis of the I/O ratio is conducted to determine whether I/O ratio patterns have changed over time during Autumn HRB, typical winter months, and Winter HRB period. Furthermore, it helps to determine if there were hourly trends in I/O ratios during extreme air pollution episodes. It also aims to discover whether the I/O ratio trend changed during building operating and non-operating hours. Figure 19, S Fig 8 and S Fig 10 illustrate indoor sensors I/O PM2.5 ratios by the hour of the day during April (Autumn HRB month), June (a typical winter month) and August (Winter HRB month). In these figures, x-axis represents hour of the day and the y-axis represents the I/O PM2.5 ratio. Figure 19 shows that the hourly average I/O ratios were at its highest level during the Autumn HRB in April, where all indoor sensors recorded at least an hour of I/O PM2.5 ratio more than “1” between 10 am to 2 pm. This pattern is significantly different from the I/O ratio patterns of June and July (S Fig 8 and S Fig 9), which were typical winter months. It is observed that although June and July are the coldest months of the year in Sydney, meaning that more pollution could be trapped in the atmosphere, all building spaces except the foyer (which is exposed to the outdoor) showed hourly average I/O PM2.5 ratio below one, confirming the existence of adequate ventilation for the building. In addition, S Fig 10 illustrates that during Winter HRB, although the hourly average I/O ratios for indoor sensors B, C and D, were higher than that in typical winter months, they were still lower than “1”.

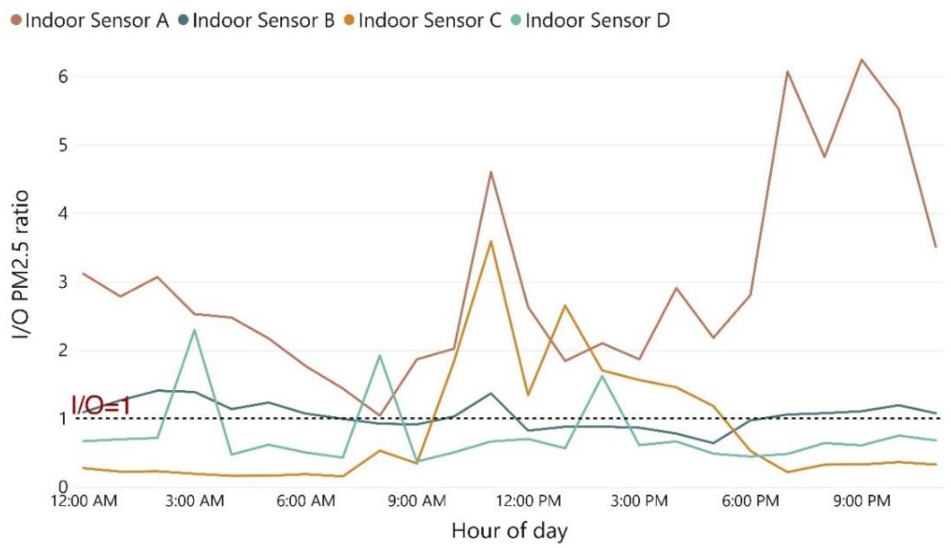

Figure 19: Indoor sensors I/O PM2.5 ratios by the hour of the day during April (hourly interval)- (Source: Author)

Figure 20 illustrates the 15-minute average PM2.5 concentration by the hour of the day for outdoor and indoor sensors in August. For indoor sensor A, PM2.5 concentration variation patterns are almost similar to that of the outdoor sensor. Sensor B also follows the similar pattern until around 5 pm in the day. This indicates that PM2.5 penetration from outdoors influence indoor PM2.5 concentration in sensor A and partially in B spaces. Also, based on Figure 20, during August, PM2.5 concentrations of indoor sensor A were constantly higher than the WHO threshold, while the concentrations in the other indoor sensors were lower than the WHO threshold. As shown in Figure 20, although the hourly average I/O ratios for indoor sensors B and D were below one in August, the 15-minute interval PM2.5 concentration shows that between 10-12 am, when outdoor PM2.5 concentrations were lower than 15, there were few occasions where the indoor PM2.5 concentration exceeded the outdoor concentration. Further, Figure 20 indicates that the outdoor PM2.5 concentration elevated overnight in August; this also applied to sensors A and B, which were more affected by the outdoor sensor. As was observed, PM2.5 concentration increased nocturnally throughout the entire study period. It is also important to notice the impact of building ventilation system and how it interferes the outdoor air pollution impact. Figure 20 shows that while the outdoor sensor (and sensor A) show higher PM2.5 concentrations during rush hours (6 – 9 am/pm), the indoor PM2.5 concentrations are generally lower during this time and got higher throughout the day (visible for sensors C and D in Figure 20). This could be due to the fact that the building HVAC system starts during the building operating hours and circulate the air all over the building, causing more PM2.5 concentrations (along with other indoor sources), during the building operating hours.

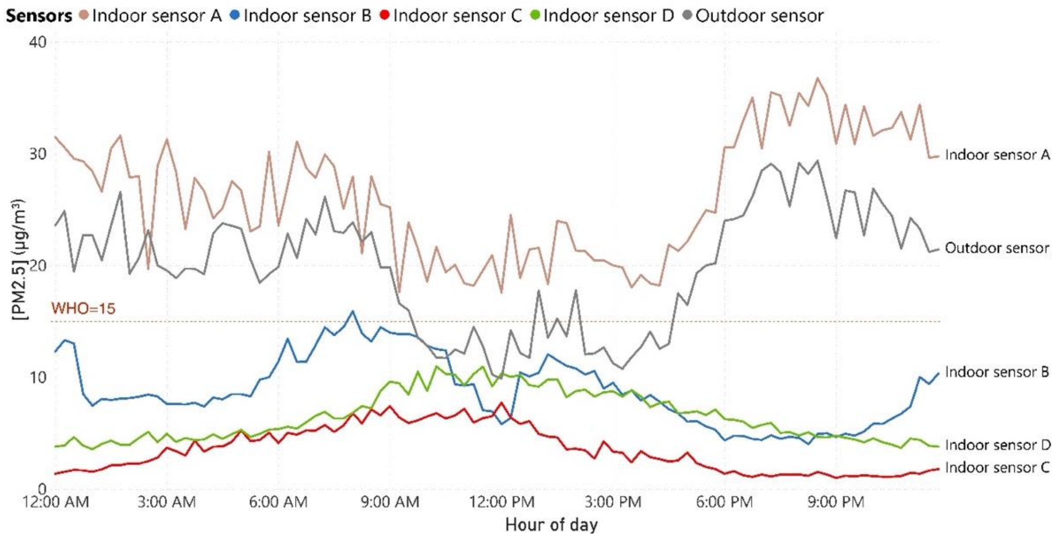

Figure 20:Outdoor and Indoor sensors PM2.5 concentration by the hour of the day during August (15-min interval)- (Source: Author)

Having a broader look over the impact of HVAC system, it is observed that despite the different HVAC operation schedules for the four indoor spaces, their hourly average I/O ratios over April, May, June, July, and August showed similar increases and decreases. According to all indoor sensor data, in April, May, June, and July, the hourly average I/O ratio was lower for HVAC system's operational hours comparing to non-operational hours. In contrast, in August, all indoor sensors recorded higher values and increases in the hourly average I/O ratio during HVAC operating hours. S Fig 11 and Figure 21 compare the hourly average of I/O ratios distribution between HVAC system operating and non-operating hours for indoor sensor A and indoor sensor D over the HRB days (from 14th to 23rd of August). Also, Table 12 compares the hourly average I/O ratio for the HVAC system's operational and non-operational hours over HRB days in August. Based on Table 12, the hourly average I/O ratio for indoor sensor A was the same during operating and non-operating hours, whereas for indoor sensors B, C and D, it was two to three times higher during operating hours. Additionally, as shown in S Fig 11 despite the same hourly average I/O ratio for indoor sensor A, the hourly average I/O ratio was frequently higher and at its maximum during HVAC operating hours. Also, according to Figure 21, for indoor sensor D, higher frequencies and values were recorded for hourly average I/O ratios during HVAC system operation hours (8am to 6pm) compared to non-operational hours. For indoor sensors B and C, similar results can be found as shown in the supporting information provided (S Fig 12 and S Fig 13).

Average I/O ratio during hazard-reduction burning in August		
Indoor Sensors	HVAC system operation hours	HVAC system non-operation hours
Sensor A	1.93	1.93
Sensor B	0.36	0.19
Sensor C	0.27	0.09
Sensor D	0.84	0.3

Table 12: comparison of the I/O ratio during the HVAC system operational and non-operational hours over the hazard-reduction burning period in August

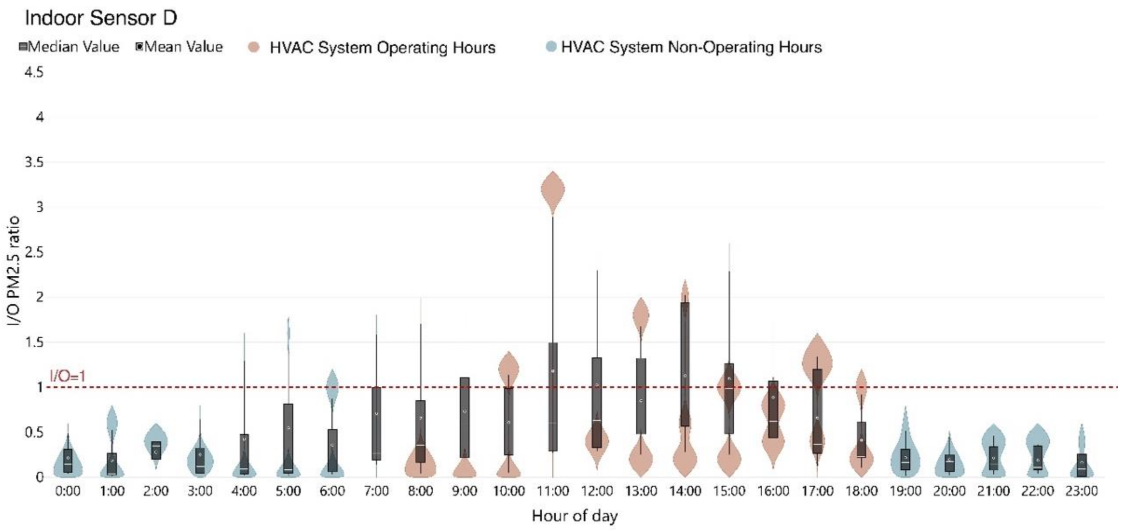

Figure 21:Indoor sensor D, comparison of I/O PM2.5 ratio between HVAC system operational and non-operational hours over hazard-reduction burning in August- (Source: Author)

5.8. Findings interpretation

Urban-level fixed-site monitoring stations have a scattered distribution and are insufficient for analyzing the detailed spatial and temporal patterns of air pollution and its sources at a fine scale (Cao et al., 2020; Schneider et al., 2017). Therefore, mobile microclimate sensors, with their ability to measure PM2.5 concentrations at any location, provide a more accurate representation of the microenvironment's air quality compared to regional fixed monitoring stations, which measure PM2.5 concentrations over a larger area using stationary equipment. A comparison of PM2.5 concentration measured by the local sensor with the nearest Bureau of Meteorology air quality fixed monitoring station showed that the local sensor calculated higher PM2.5 concentrations during study period. Over the study period, the Bureau of Meteorology's fixed monitoring station had an overall PM2.5 average of 7.6 (μg/m^3). In contrast, the local outdoor sensor had an overall PM2.5 average of 21.6 (μg/m^3), approximately 2.5 times higher. Findings from Figure 11, Figure 12 and Figure 13 suggest that the fixed regional monitoring station cannot be chosen as a reference for the local outdoor PM2.5 concentration measurement, except for high peaks and general trends. Secondly, the results support the significance of local sensing and urban microclimate changes and highlight the fact that any technique to assess indoor space PM2.5 exposure considering outdoor PM2.5 levels must include local and microclimate measurements. These results are supported by previous studies in the field, which have also reported similar results (Cao et al., 2020; Forehead et al., 2020b; Q. Li et al., 2022). These studies highlight the consistency of our results and reinforce the importance of local sensing. For instance, using low-cost sensors, (Forehead et al., 2020b) assessed PM2.5 concentrations near busy roads in suburban areas of Greater Sydney. The findings indicated that PM2.5 levels at the roadside were over ten times higher than the closest Bureau of Meteorology monitoring station. Furthermore (Q. Li et al., 2022) found that PM2.5 readings from mobile sensors are higher than those from fixed stations due to differences in measurement method and height. Mobile sensors measure air quality in small areas, but fixed stations measure air quality at a higher height in open areas (Q. Li et al., 2022).

Local-scale air quality is significantly influenced by proximity to emission sources such as major roads and meteorological factors, including wind, temperature, precipitation and RH (Hart et al., 2020). Hence, proximity to roadways can be used as a metric to estimate occupant exposure to air pollution (Costello et al., 2022). The study results show that there are different levels of PM2.5 exposure in four indoor spaces during extreme air pollution episodes. One of the most compelling reasons is that exposure levels are affected by proximity to near busy roads. According to the results, the foyer area (location of indoor sensor A), which is the closest area to the near busy road, had the highest exposure level. In the foyer area, E-Index was above one for more than 80% of the five months, and the overall average E-Index during operation hours for all HRB episodes was at least 2.5 times higher than in other indoor areas. Furthermore, I/O ratio results for the foyer area revealed that more than 80% of the time (103 days), the foyer air quality was even worse than the outdoor air quality. These findings confirmed that the foyer area, with the shortest distance to the near busy road, has the worst IAQ due to the highest pollution penetration, accumulation, and lack of proper ventilation. One study (Chu & Yang, 2022) examined how distance from a pollutant source (a busy road) impacts indoor PM2.5 concentrations and presented simulation results for different distances from the pollutant source. Study results showed that the penetration rate of outdoor PM into low-rise buildings increased from 7% to 25% as the distance between the pollutant source and indoor sample point locations decreased from 15 meters to 3 meters.

According to (ASHRAE, 2018), temperature, pressure, and thus pollutant penetration rate varies at different floor heights of buildings. The results of our study revealed that PM2.5 data collected by sensors located on higher levels of the building (e.g., C and D) are less impacted by outdoor PM2.5 concentration compared to lower levels (e.g., A and B). In other words, the results showed a statistically significant correlation (p-value < 0.05) between floor height and E-Index and the I/O ratio of PM2.5. According to the results, the space on level 5 had an E-Index higher than 1 for 6% of the study period, which was 4 to 9 times higher than that for the other two spaces on level 6. Furthermore, the I/O ratio for the space on level 5 was above 1 for 11% of the study period, which was 2 to 4 times higher than for the other two spaces on level 6. These results confirmed that higher levels of the building or greater distances from the foyer area and main entrance resulted in a significant (more than 80%) decrease in the level of PM2.5 exposure. Similarly (Cichowicz & Dobrzański, 2021) reported that the PM2.5 pollutant concentration declined significantly by 60% from 2 m to 16m within a 9-story building on a university campus. On the contrary, (P. D. M. Nguyen et al., 2021) found no significant correlation between PM2.5 concentration and floor heights of a large multi-story rehabilitation center. Also, one study (J. Zhao et al., 2021) presented a model of particle diffusion in severely cold cities. The findings of this study revealed that the I/O ratios were greater for higher floors of buildings due to variations in outdoor meteorological conditions across different heights.

Results from hourly analysis of data from the local outdoor sensor and the regional air quality monitoring station showed that the PM2.5 concentration increased overnight in winter. Studies with similar results attribute the nocturnal growth of PM2.5 during winter to meteorological factors, including temperature inversion, low wind speeds, and increased heating and transportation emissions (S. Cheng et al., 2020; Wei et al., 2020b). A temperature inversion, where a layer of warm air traps cold air near the ground, creates a stagnant air mass that impedes the dispersal of pollutants (Yin et al., 2021). Heating systems, such as wood-burning stoves and furnaces, also release particulate matter into the air during the night. Low wind speeds during winter nights slow the dispersal of pollutants, further contributing to higher PM2.5 concentrations (Faour et al., 2023). Furthermore, coal combustion and biomass burning contribute to PM2.5 emissions during the winter, resulting in a rise in outdoor PM2.5 concentration at night (Yadav et al., 2020).

According to hourly results, in the winter HRB in August, when PM 2.5 concentrations were higher than in autumn HRB, a 90% to 200 % increase in the overall average I/O ratio over HVAC operational hours was recorded for indoor spaces on levels 5 and 6 of the building. Regarding the foyer area, although the overall average I/O ratio during HVAC operational and non-operational hours was the same, the maximum hourly average I/O ratio during HVAC operational hours was 1.3 times higher. This could be due to the fact that air recirculation and increased air exchange with the outdoors during high outdoor PM2.5 concentrations result in a higher penetration of PM2.5 indoors. Similar findings have been reported in studies investigating the effectiveness of various ventilation modes during severe EAP events such as wildfires or winter haze to determine their ability to improve IAQ and reduce PM2.5 levels (May et al., 2021; Xue et al., 2020). The findings from these studies revealed valuable insights into the limitations of mechanical ventilation during severe air pollution episodes, showing that increasing the air exchange rate, coupled with lower filter efficiency, leads to a significant increase in indoor PM2.5 concentrations when outdoor PM2.5 levels are high.

According to the results of this study, although the selected building proved to be resistant enough to outdoor air pollution penetration, the ventilation system needs to be better adjusted during severe air pollution scenarios such as large HRB or wildfire events. Hence, the results revealed the need for a more strategic building management plan for (1) the exposed spaces to outdoor environment, and (2) the extreme air quality events in the region. It is also important to notice the importance of urban microclimates and the fact that the severe air pollution scenarios might differ from what the meteorological stations show.

The study has not only compiled data as a basis for further research, but it also has provided a methodological contribution to assessing whether spaces are adequately protected against outdoor air pollution or not and if not, how significant are the occupants exposed to harmful levels of PM2.5. Future research may envisage the significance of microenvironments in indoor sensor placement.

5.9. Study phase I outcomes

In this preliminary study, indoors and outdoors IoT sensing was used to evaluate PM2.5 concentration levels in different spaces and compare the penetration rate of outdoor PM2.5 into indoor built environment during extreme air pollution episodes and winter months in Sydney. This study compared and ranked four spaces with different architectural characteristics and HVAC system operation hours using two metrics. The E-index and the I/O ratio were used to characterize PM2.5 exposure levels on temporal and spatial scales in different spaces in a university campus building.

The study found that outdoor PM2.5 concentrations differ significantly across areas, even during extreme outdoor air pollution events; therefore, it is important to utilize local outdoor sensors for accurate measurements of PM2.5 concentration levels in the targeted urban microclimate. Generally, PM2.5 concentrations in microenvironments or neighborhoods may not be accurately reflected by RAQMS because they are usually conducted at a fixed height and location. It is also possible that they fail to identify the source of PM2.5 emissions at a particular location, such as from nearby industrial facilities or traffic congestion. Furthermore, the regional measurement may not consider the effects of weather conditions and temperature inversions on trapping pollutants near the ground. Based on the metrics used in this study, the following conclusions can be drawn regarding the PM2.5 concentrations and exposure levels in four selected spaces.

A real-time measurement of PM2.5 concentration by IoT sensors provides accurate information about PM2.5 concentrations in different indoor spaces, and this information can be used to rank indoor spaces based on PM2.5 concentration. Ranking indoor spaces according to PM2.5 concentrations can help protect occupants by identifying high-risk areas with higher concentrations of PM2.5. By using this information, interventions can be prioritized, for example, addressing specific sources of PM2.5, such as ineffective HVAC systems or poorly sealed openings in high-risk areas, to reduce exposure and improve air quality. By prioritizing interventions, resources can be focused on areas where they will have the most significant impact. Furthermore, ranking indoor spaces based on PM2.5 concentration can be used to evaluate the efficacy of interventions and refine them over time.

Using the space rankings, facility managers can also develop space utilization plans and schedule occupancy periods, break periods, and occupant numbers for each space based on PM2.5 exposure levels. In this study, spaces were ranked according to: (1) their average hourly PM2.5 concentrations during study time, (2) the overall E-Index, (3) the percentage of days and hours when the E-Index was “1” or higher, and (4) the percentage of days where indoor PM2.5 levels exceeded outside levels (the I/O ratios above 1). Considering all the results, the foyer space (sensor A) ranked first, the office room on level five (sensor B) ranked second, and the offices on level six ranked third and fourth (sensor D and C) respectively.

It is crucial to monitor and analyze the PM2.5 concentration indoors and outdoors in different spaces and heights in the building. Additionally, in buildings near busy roads, the PM2.5 concentration is higher in lower spaces due to the proximity of the sources of PM2.5. The results identified an association between the floor level (building height) and the PM2.5 concentration and exposure level. Based on the space rankings, the foyer on level 3, with the highest PM2.5

exposure level, ranked first, the office on level 5 ranked second, and the other offices on level 6 ranked third and fourth. In addition, it should be noted that despite being located on the same floor level, indoor sensor C and indoor sensor D had different pm 2.5 concentrations and, accordingly, different rankings. Therefore, PM2.5 concentrations should be measured and evaluated based on the specific characteristics of each space. Various factors, such as ventilation systems, space size, indoor pollution sources, nearby pollution sources, number of occupants, and the type of furniture and equipment used, affect indoor PM2.5 concentrations. In this study, Indoor sensor D, installed in a small (area of 10 square meters) isolated private office room, measured higher PM2.5 concentrations compared to indoor sensor C. A closed door, printers, and higher concentrations of particles per unit area contributed to the poorer air quality in the small office compared to the shared office.

A detailed hourly analysis of PM2.5 concentration indicates how the level of PM2.5 varies throughout the day, at night, during traffic rush hours, and during HVAC operation. As a result of hourly analysis, it is recommended to assess HVAC efficiency and filtering layers during extreme air pollution events, such as HRB occurrences. It is also important to consider alternative solutions, such as portable filters. Furthermore, the HVAC system might also be a potential route for PM 2.5 penetration if not appropriately monitored during extreme air pollution events.

6. Study Phase II (Main Research)

6.1. Study focus

A single level of a university campus building has been selected as the test bed. Data collection will be conducted on level three of the building. Level three of the building has an entrance on a busy street, which has high traffic congestion during the rush hours. To investigate the impacts of the proximity to busy roads on IAQ, spaces with different distances from the entrance have been selected. These spaces include; 3 computer labs, 1 study lounge, 1 kitchen area, 2 theatres, the foyer and the common area. Figure 22 shows the selected spaces and the indoor and outdoor locations of deployed microclimate sensors, and Table 13 demonstrates the type and characteristics of the selected spaces.

Space Type	Travel to Kerb (m)	Doors	Area (m^2)	Height (m)	Volume (m^3)	HVAC Type	Weekday Start	Weekday Finish	Weekend Start	Weekend Finish
Foyer	30.54	1	157.9	3.5	552.7	AHU3-1	6:00	22:00	8:00	22:00
Computer Lab	46.34	3	110.1	2.7	297.4	AHU3-1	6:00	22:00	8:00	22:00
Computer Study	47.52	2	194.8	3.4	672.2	AHU3-4	6:00	22:00	7:00	22:00
Computer Lab	47.72	3	78.1	2.7	210.8	AHU3-4	6:00	22:00	7:00	22:00
Computer Lab	56.42	3	76.6	2.7	206.9	AHU3-4	6:00	22:00	7:00	22:00
Student Kitchen	56.84	1	61.0	3.4	210.6	AHU3-8	6:00	22:00	7:00	22:00
Lecture Theatre	59.21	2	215.3	-	0.0	AHU3-7	on demand 24/7	-	on demand 24/7	-
Student Lounge	61.94	1	107.6	2.7	290.6	FCU3-5	8:00	18:00	off all day	-
Lecture Theatre	63.31	2	349.4	-	0.0	AHU3-6	on demand 24/7	-	on demand 24/7	-

Table 13: The type and characteristics of the selected spaces

Source: DAB-Building 06 FM plans

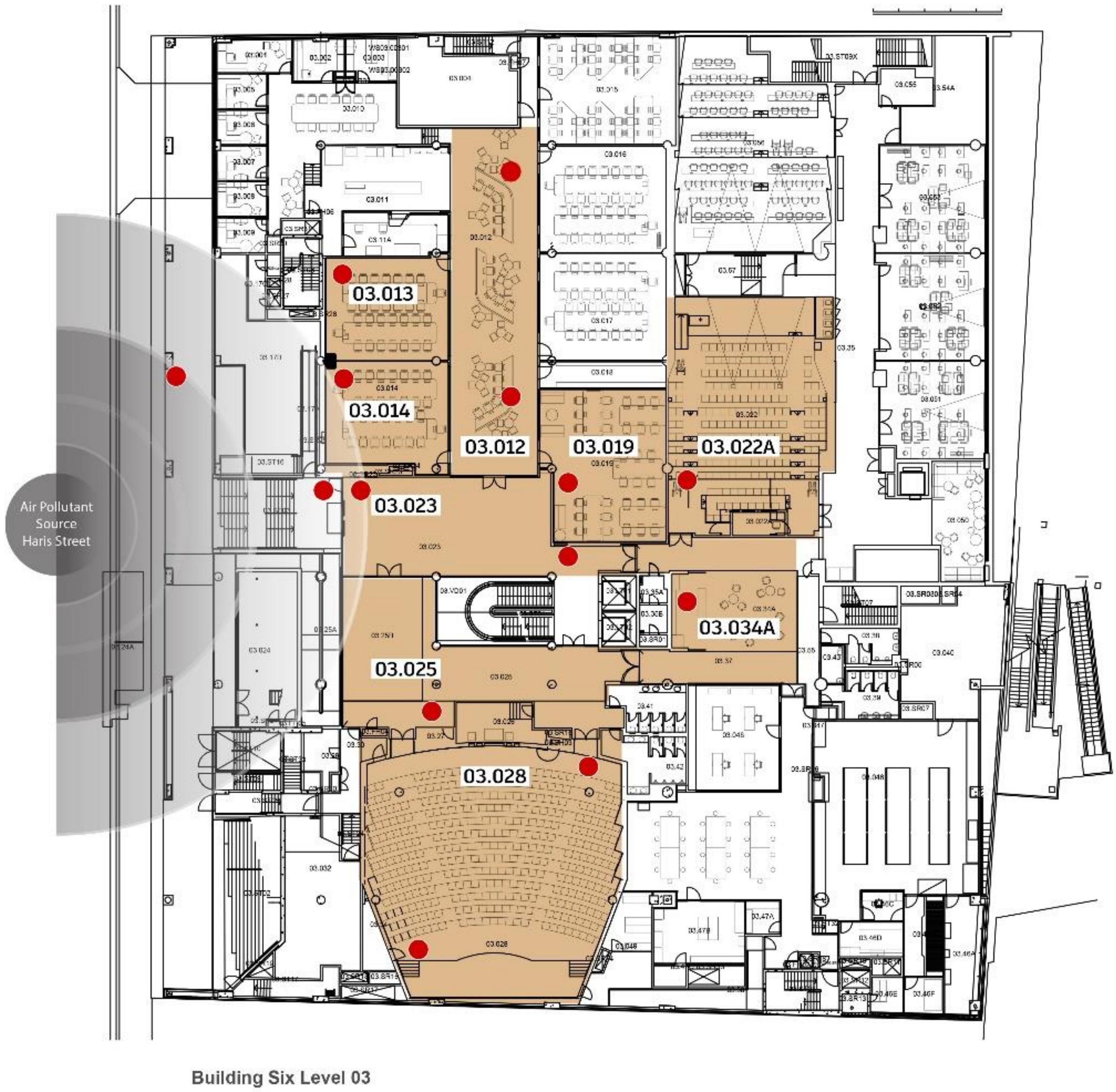

Figure 22: mapping of selected space and sensors locations (red circles),

6.1.1 Research method

In this study, a quantitative research approach was deployed through quasi-experiments and surveys. Data collection methods included sensor measurements, survey and observations. Data analysis methods included statistical correlation and regression analysis.

6.1.2. Data collection

The data collection of this study consisted of 3 data streams: (1) Portable micro-climate sensors to collect IEQ data, (2) Occupant survey to collect occupants' feedback on their comfort level, and (3) Building property planning to collect space occupancy characteristics and usage percentages. The data collection generally was conducted during the Spring Semester 2022 (August-November 2022).

6.1.3. IAQ parameters data

IEQ parameters including PM2.5, PM10, RH and temperature were collected from portable micro-climate sensors. The sensors are manufactured by Hibou (*HibouAir - Indoor Air Quality Monitoring Device*, n.d.). Twelve internal Hibou air quality sensor devices were located indoors, and three external sensors were located outdoors, two on the busy street and one on the entrance door. Internal and external sensors measured the same parameters.

6.1.4. Occupants' feedback on their comfort level data

The occupant feedback data was collected through occupant survey using an online questionnaire as the data collection tool. The questionnaire was designed to investigate the occupant experience of building due to their personal factors, the time and location of their occupancy and their general and current perception of comfort.

A random selection of participants was made from the occupants of the selected spaces. Occupants were randomly approached in person and asked to participate in survey for 5-10 minutes. It's worth noting that respondents' data were saved anonymously using the Qualtrics online survey tool.

6.1.5. Space occupancy characteristics data

The number of occupants in each space was counted through observation once every two hours for two weeks. In addition, the facility management schedule provided the accurate occupancy rate and utilization plans of each space.

6.1.6. Data analysis

Data from the sensors was collected and transferred to the dashboard, and the occupant's survey data was collected through Qualtrics, the university online survey tool. Further statistical analysis was conducted using Power BI software after extracting and comparing the data sets. In addition to statistical analysis, correlation and regression analysis were used to find the potential relationships between variables, thus addressing the research questions. Regarding the use of IAQ and thermal comfort metrics to analyze data, the I/O ratio, PMV, PPD, and AMV were used.

6.1.7. Research ethics consideration

This research adheres to the research integrity standards and guidelines outlined in the Research Ethics and Integrity Policy and the Research Management policy. In order to carry out the research responsibly, all potential risks to participants and the researcher were considered. The low-risk pathway was taken in the Human Research Ethics Committee application since occupants' survey (online questionnaire) was unlikely to cause discomfort.

The occupants' survey generated the occupants' perception of comfort data. To ensure sufficient information was provided to consent, participants received questionnaires directly from the researcher, along with an information sheet and consent form. The research's purpose, methods, and intended outcomes were explained in full to participants. In addition, participants' responses were kept confidential, anonymous, and private. The participant information sheet, consent form and questionnaire example are provided in the appendices section. The ethics application met the requirements of the National Statement on Ethical Conduct in Human and was approved as “Low Risk”.

6.1.8. Data management

A Research Data Management Plan (RDMP) was developed within the university data management infrastructure. The document outlined the type of primary data that must be collected and the type of secondary data that must be accessed. In addition, there was a description of data formats, research workspaces, ethical considerations, data analysis, data ownership, and the data sharing circumstances in this document.

6.2. Data Analysis and Results

6.2.1. IAQ parameters data

IAQ parameter data was collected from August to November 2022 using both indoor and outdoor Hibou sensors. Figure 23 shows the average PM2.5 concentrations measured during the study period in different spaces. Our data reveals that there were significant variations in PM2.5 concentrations across the different areas. As shown in Figure 23, spaces with shorter distances from street, such as the entrance foyer area, had higher PM2.5 averages than the other spaces.

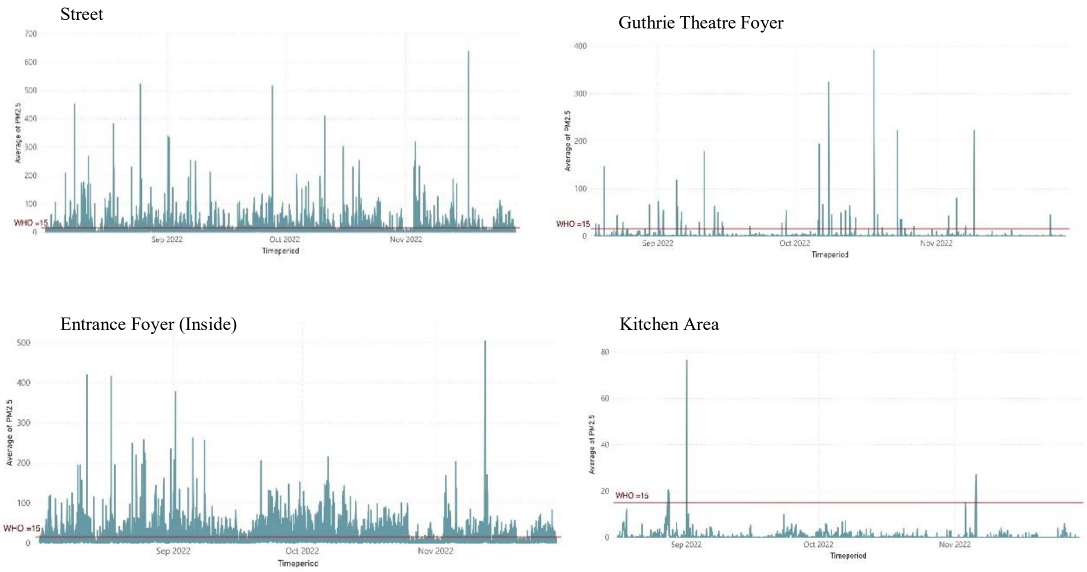

Figure 23: 2-Minute average pm2.5 concentration across various spaces (Source: Author)

The focus of the data analysis pertains to the specific period during which the occupant survey was conducted. Consequently, an analysis of the PM2.5 concentration data was undertaken from October 17 to October 28, 2022. Figure 24 displays the PM2.5 concentrations at two-minute intervals across various locations. As illustrated, the PM2.5 concentration in the busy street foyer area was almost consistently above the WHO threshold of 15 ($\mu g/m^3$). In contrast, other locations generally remained below this threshold, with the exception of the kitchen area, which peaked at a value of 48 ($\mu g/m^3$), exceeding the threshold twice. The maximum readings recorded in other areas were significantly lower: 0.3 ($\mu g/m^3$) in the computer lab common area and 1.4 ($\mu g/m^3$) in the classrooms.

Furthermore, as shown in Figure 24, there was a considerable decrease in PM2.5 concentration from 25 October on the busy street. This trend was also observed in other indoor locations, indicating a consistent pattern. To better understand the factors influencing the decrease in PM2.5 concentrations on the busy street, the correlation between temperature, pressure, humidity, and PM2.5 was investigated. The results are displayed in Table 14. According to Table 14, there was a strong correlation (r- value = 0.45) between PM2.5 concentration and humidity, which was statistically significant (p-value < 0.05). From 25 October, there was a notable decrease (29.4%) in humidity accompanied by changes in other meteorological factors. From 25 October to 26 October, the daily average outdoor humidity dropped from 72.02% to 50.85%, marking a decrease of 29.4%. During this time, the daily average temperature rose from 20.13°C to 22.17°C, reflecting an increase of 10.1%. Furthermore, there was a significant decline in the daily average concentration of PM2.5, which dropped from 18.79 (μg/m^3) to 1.91(μg/m^3), with a decrease of 89.84%. Similar trends were observed at the Rozelle station, a regional monitoring site. The collected data from the station showed there showed a 14.4% increase in temperature and a 34.5% decrease in humidity. PM2.5 levels also dropped from from 5.25 (μg/m^3) to 1.47(μg/m^3), showing a decrease of 72%.

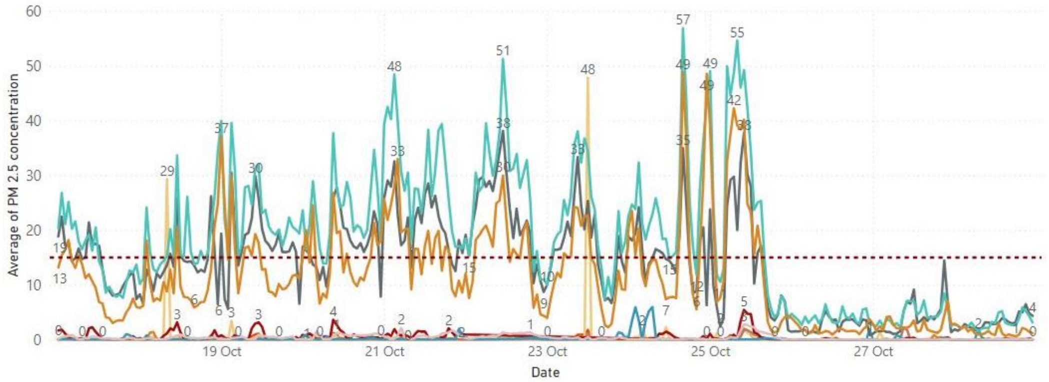

Figure 24: PM2.5 concentrations at two-minute intervals across various locations (Source: Author)

	Humidity	Temperature	Pressure
Spearman correlation coefficient (r)	0.45*	-0.09*	0.21*

Table 14: Correlation of PM2.5 concentration with other meteorological factors for the busy street

* *Indicates significant correlation at the 0.05 level (two-tailed).*

Furthermore, the daytime and nighttime PM2.5 concentrations on the busy street were analyzed using 2-minute interval averages to determine if there were any significant fluctuations or patterns occurring over the course of the day. As depicted in Figure 25 and Figure 26, there were no substantial differences observed in the PM2.5 levels between the daytime and nighttime periods. In addition, based on the statistical summary of the hourly average PM2.5 concentrations during the day and night on the busy street, presented in Table 15, it is evident that the median and average values for both time periods were remarkably close. Specifically, the daytime average was slightly higher, registering at 12.03 (μg/m^3), compared to the nighttime average of 10.74 (μg/m^3). Additionally, the daytime period had a higher median concentration, recording a value of 8.31(μg/m^3), while the median for the nighttime was 6.45(μg/m^3).

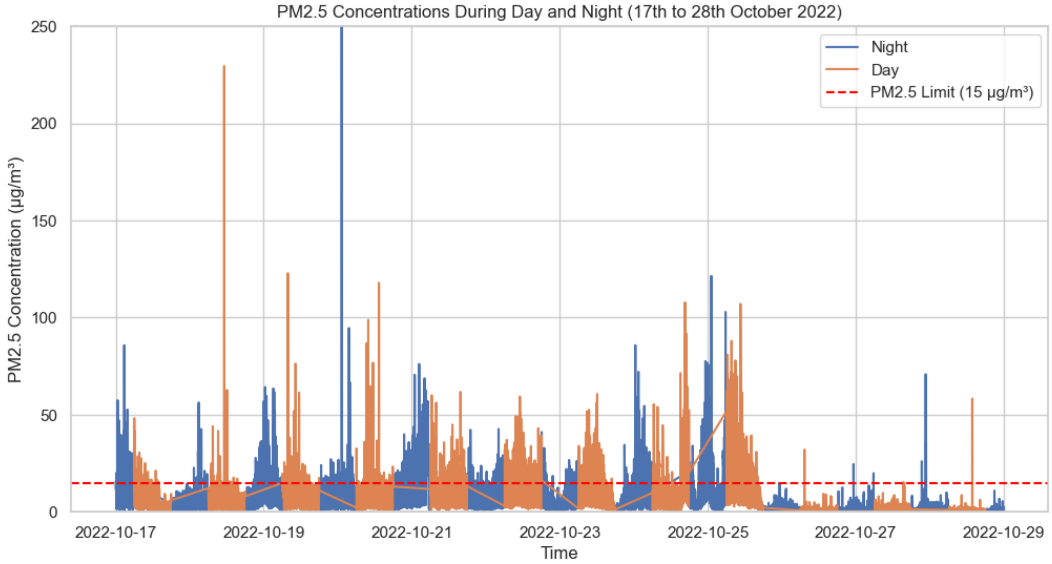

Figure 25: Street diurnal and nocturnal PM2.5 concentration averages at two-minute intervals (Source: Author)

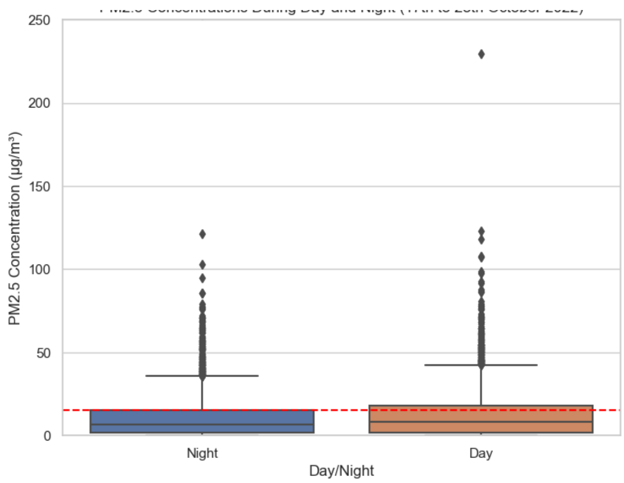

Figure 26: Street diurnal and nocturnal PM2.5 concentration distributions at two-minute interval, (Source: Author)

Hourly Average PM2.5 Concentration		
	Day Time	**Night Time**
Mean	12.03	10.74
STD	13.99	12.81
Min	0.00	0.03
25%	1.72	1.84
50%	8.31	6.45
75%	17.95	15.36
Max	229.56	252.75

Table 15: Statistical summary of diurnal and nocturnal hourly average PM2.5 concentrations on the busy street

The analysis of data obtained from the outdoor sensors revealed significant differences in the measured PM2.5 values recorded at various locations. In this study, three different sensors were employed: one located in an open space area on the busy street, one placed in a semi-enclosed space located behind the entrance door (a setback area that is partially covered and features a roof), and the third which was positioned on the inside of the entrance door. Comparisons of the PM2.5 concentrations recorded by these sensors, depicted in Figure 27, suggest that the busy street site consistently exhibited lower concentrations compared to the data gathered by the remaining two sensors. Notably, as shown in Figure 27, the sensor in the semi-enclosed setback area consistently recorded the highest levels of PM2.5 concentrations. For this sensor, the average PM2.5 concentration measured over the entire survey period was 18.49 (µg/m^3). To illustrate the significance, it was 1.62 times (or 38.1%) higher than the average value recorded on the busy street and 1.34 times (or 25.5%) higher than that in the indoor side of the entrance door.

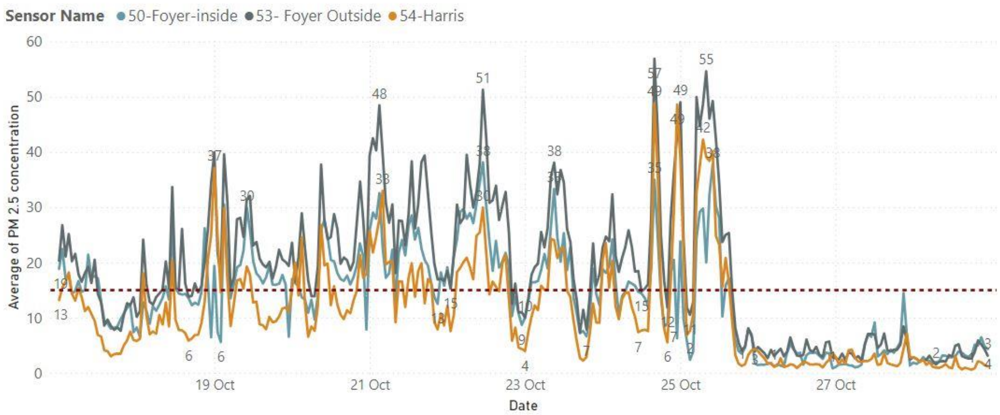

Figure 27: Comparative analysis of PM2.5 levels at two outdoor and one indoor location recorded by different sensors (Source: Author)

- **PM2.5 hourly average**

The distribution of hourly average PM2.5 concentrations across different locations of the study is illustrated through a box plot in Figure 28, captured by various sensors. Figure 28 shows that the median PM2.5 concentration at the busy street and the indoor foyer were recorded as 9.57 (µg/m^3) and 13.95 (µg/m^3), respectively, both of which remained below the WHO standard threshold. This signifies that the PM2.5 concentrations in these locations were below the specified threshold for more than half of the recorded data. In contrast, the PM2.5 concentrations in the outdoor foyer was found to be 17.68 (µg/m^3), which exceeds the WHO threshold. This finding indicates that during over half of the research duration, the PM2.5 concentrations in the outside foyer surpassed the accepted safety threshold.

Furthermore, the hourly fluctuations in PM2.5 concentrations were investigated to better understand the air quality across different locations during particular times of the day. As presented in Figure 29, generally, during the operational hours from 7 am to 7 pm, a notable increase in the average PM2.5 values was observed in the morning, between 9 am and 11 am, followed by a visible decrease in PM2.5 concentration after 11 am. Upon closer examination, it was observed that the busy street had a peak concentration of 15.6 (µg/m^3) at 9 am. Similarly, the outside foyer achieved its maximum concentration of 24.8 (µg/m^3) at 11 am, while the inside foyer recorded its highest concentration of 20 (µg/m^3) at 10 am. In the kitchen area, similar to the patterns noted by the three sensors, a slight increase in PM2.5 concentration was observed between 9–11 am, reaching a peak value of 4.23 (µg/m^3) at noon.

The increase in PM2.5 concentrations during the morning hours might be attributed to increased traffic and commuting activities. During this time, there tends to be a surge in vehicular movement, leading to higher emissions from automobiles and increased particular matter in the air. Additionally, HVAC system operation along with the increased occupancy of a building during the morning hours can also result in higher indoor PM2.5 concentrations due to increased human activity, including the resuspension of particles from indoor surfaces. On the other hand, foyer area has limited ventilation, which can lead to the accumulation of pollutants, including PM2.5, especially if there is inadequate air circulation or if outdoor pollutants find their way inside.

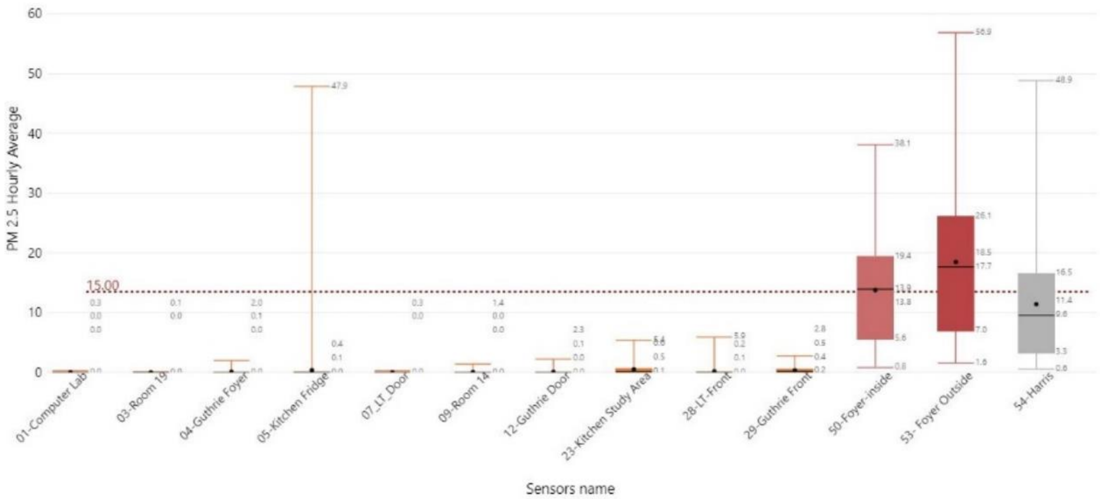

Figure 28: Distribution of hourly average PM2.5 concentrations across various study locations (Source: Author)

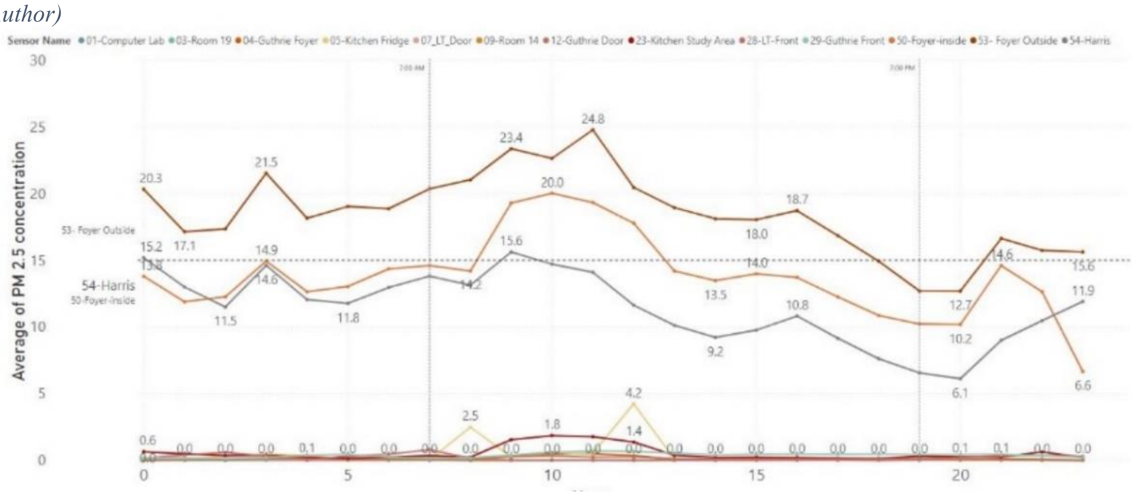

Figure 29: Hourly PM2.5 concentration fluctuations across diverse locations throughout the day (Source: Author)

- **PM 2.5 variations by day of the week (weekend vs weekdays)**

The analysis of overall PM2.5 hourly averages from all sensors reveals a noticeable discrepancy between weekend and weekday concentrations. Over the weekends, the median value stood at 0.04 (µg/m^3) with an average value of 4.99 (µg/m^3), whereas during the weekdays, the median and average values were lower at 0.02(µg/m^3) and 3.25 (µg/m^3), respectively. This indicates that the median PM2.5 concentrations over the weekends was twice as high as during weekdays. Figure 30 illustrates the PM2.5 hourly averages for all sensors on weekends and weekdays. It is evident that the hourly average PM2.5 concentration was consistently higher throughout the weekend than during the weekdays. Notably, between 10 am and 12 pm on weekends, a significant increase in PM2.5 concentration was observed, contrasting with the weekdays where only minor fluctuations were noted over different hours.

Additionally, Figure 31 shows the variations in PM2.5 concentration between weekdays and weekends for the three sensors that recorded the highest PM2.5 values. According to Figure 31, in the outdoor foyer, a maximum value of 44.02 (µg/m^3) was observed around 11 am on the weekend, significantly decreasing to 20.92 (µg/m^3) at the same hour on a weekday. This difference indicates that the weekend concentration was over two times higher than on weekdays. Similarly, it was observed that on the busy street, the PM2.5 concentration peaked at 26.27 (µg/m^3) at 11 am during the weekend. In contrast, the concentration was notably lower during weekdays at the same hour, measuring 11.64 (µg/m^3). In the indoor foyer, the maximum recorded value was 31.94 (µg/m^3) at 9 am during the weekend while, during the weekdays at the same hour, the concentration dropped to 16.76 (µg/m^3).

Given the limited scope of the analysis conducted over a few weeks, it is essential to acknowledge that the findings may not fully represent the broader trends and patterns of PM2.5 concentrations in the area. The identified discrepancy in PM2.5 levels between weekends and weekdays, particularly the higher median values during weekends, suggests influences from urban lifestyle patterns, such as increased personal vehicular use for routine activities and regulatory schedules permitting heavy vehicles during these times. However, short-term analyses might not account for long-term fluctuations, seasonal variations, or irregular events that could significantly impact air quality. Furthermore, Inconsistent trends across different months, as observed in the preliminary study of 2021 and the months of August, September, and October 2023, highlighted the complex nature of particle concentration dynamics. To achieve a more comprehensive understanding of PM2.5 concentrations, it would be advisable to conduct an extensive and long-term study that considers various factors such as seasonal changes, long-term weather patterns, industrial activities, and fluctuations in vehicular traffic. This approach, coupled with data from multiple monitoring stations across different locations, would capture a more holistic view of the factors influencing air quality, providing insights that could inform effective strategies for air quality improvement.

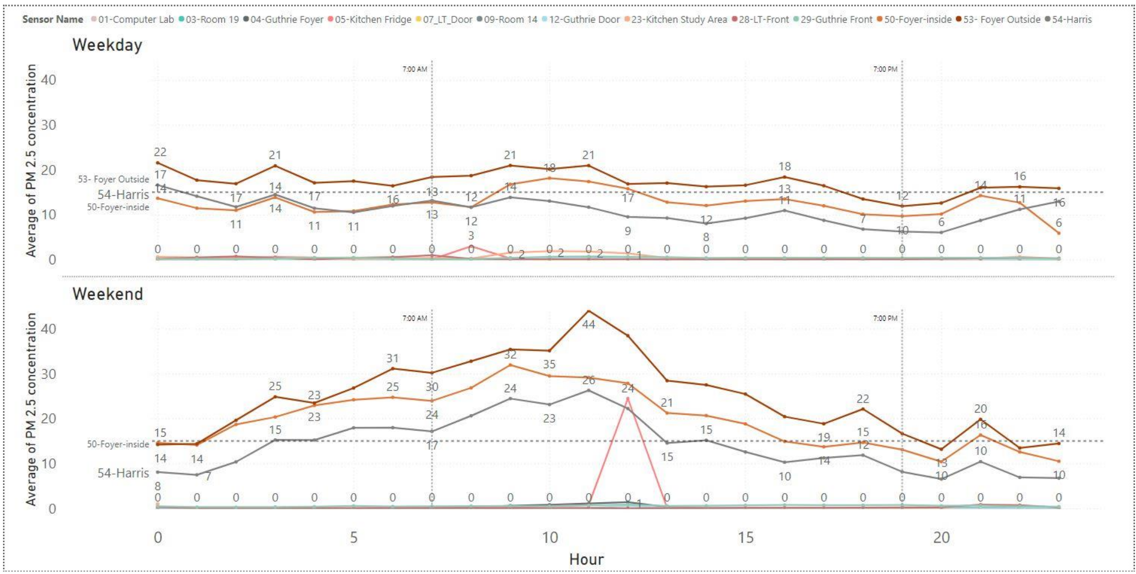

Figure 30:PM2.5 hourly averages comparison: weekdays and weekends across all sensors (Source:

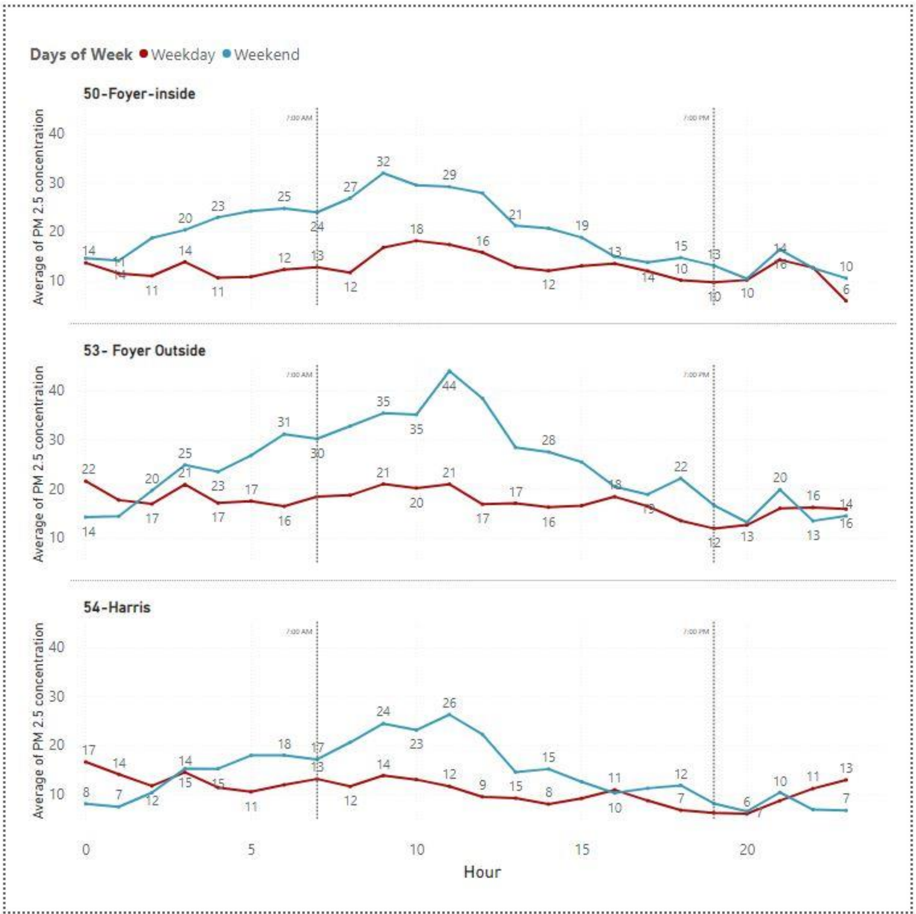

Figure 31: Variations in PM2.5 concentrations for the three highest-recorded sensors on weekdays and weekends (Source: Author)

- **I/O ratio**

The hourly average I/O ratio, throughout the experiment, was employed to highlight the discrepancy between indoor and outdoor PM2.5 concentrations. According to Figure 32, the hourly average I/O ratio for PM2.5 levels in the foyer consistently exceeded 1 from 4 am to 11 pm. The highest hourly average I/O ratio within the foyer was observed at 7 pm, reaching a peak value of 2.32. In contrast, other indoor areas maintained I/O ratios consistently below 0.3. Among these spaces, the kitchen area registered the highest I/O ratio at 8 am, recording a value of 0.28.

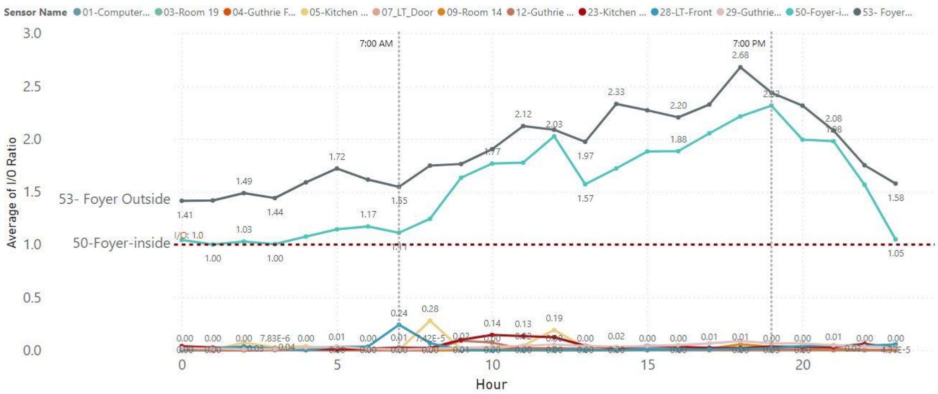

Figure 32: Hourly average I/O ratio across all sensors (Source: Author)

- **Occupancy rate**

The university's building property planning resources were utilized to gather data on the characteristics of space occupancy and the actual number of occupants in each space. Data was collected to determine the number of occupants in each space, as depicted in Figure 33. Throughout the experiment, the average number of occupants occupying room 13 was 7.85, room 14 was 8.08, and room 19 was 11.09. Notably, rooms 13 and 14 are adjoining spaces separated by a partition. When classes with more attendees were held, the partition was removed. Following this particular configuration, the overall average occupancy for the connected rooms was 11.72. In considering spaces with larger capacities, such as the Guthrie Theater and the lecture Theater, the average occupancy values were found to be 24.43 and 8.24, respectively.

Furthermore, the correlation between occupancy rate and PM2.5 concentration levels was analyzed using Spearman's rank correlation coefficient. Nevertheless, the analysis revealed no significant association between the levels of PM2.5 concentration and the number of individuals occupying any specific area.

The hourly average occupancy pattern was also examined, as demonstrated in Figure 34. According to Figure 34(a), the average occupancy increased for classrooms between 10 a.m. and 2 p.m., with the peak average occupancy reaching 22.31 when rooms 13 and 14 were interconnected. In addition, as shown in Figure 34 (b), the highest average occupancy for the

Guthrie and lecture theatres was observed between 9 and 10 am, with averages of 40.4 and 38.13, respectively.

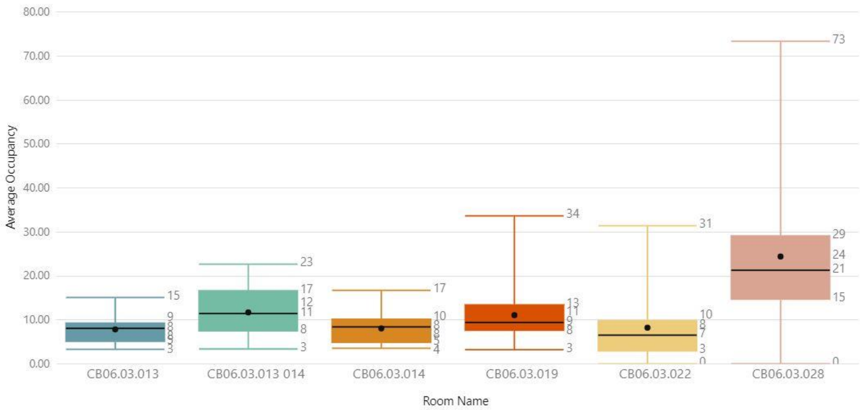

Figure 33: Box plot illustrating occupancy distribution across spaces (Source: Author)

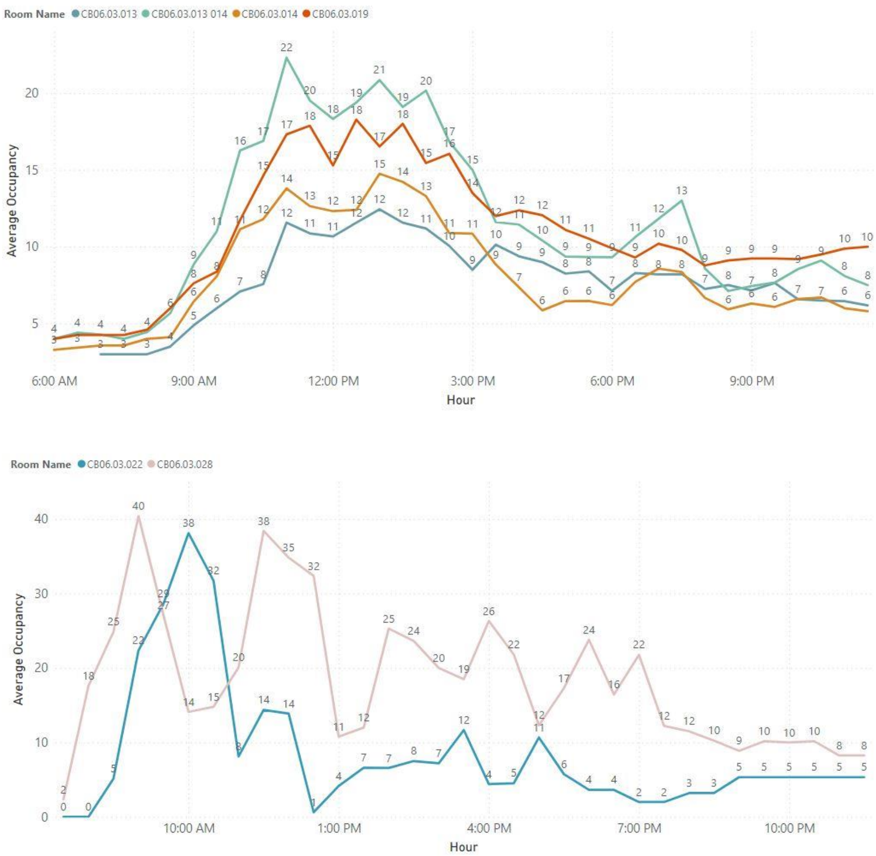

Figure 34: Hourly average occupancy patterns a) Classrooms, b) Theatres (Source: Author)

6.2.2. Occupants' feedback on their comfort level

An online questionnaire was used as the data collection tool to collect data on occupant feedback. The questionnaire was designed to evaluate occupants' perceptions of comfort based on their occupancy period, location, and building experience.

The survey was conducted between 17 October 2022 to 28 October 2022, with 102 participants. Participants were chosen randomly from classrooms 13, 14, and 19, as well as the common areas of the computer lab, kitchen seating area, and the waiting area of the Guthrie theatre. Occupants were randomly approached in person and asked if they were willing to participate in the survey, and their responses were saved anonymously using the Qualtrics online survey tool. The average time spent participating in the survey was 6 minutes. The questionnaire consisted of four sections. In the first section, occupants were asked about personal factors such as their age and gender that may influence the perception of comfort. The second section of the survey was about general building use and comfort perception, and the third section was about current building use and comfort perception. Current and general information was required to accommodate the potential scenario where individuals might frequently occupy one area while participating in the survey from another. Further, the survey included a section on discomfort symptoms and responses to discomfort within the building. Additionally, observations were made, and data on the number of people around the participant and the participant's dress code was recorded.

In the survey, there were 52 female participants, 49 male participants, and one respondent who chose not to disclose their gender preference. Regarding the age of the participants more than 50% (56.86%) of participants were in the age range of 20-25. Table 16 shows the gender and age information.

Gender/Age	Female	Male	Prefer not to answer	**Total**
20-25	29.41%	26.47%	0.98%	**56.86%**
26-35	6.86%	13.73%		**20.59%**
Under 20 years of age	11.76%	7.84%		**19.61%**
36-65	2.94%			**2.94%**
Total	**50.98%**	**48.04%**	**0.98%**	**100.00%**

Table 16:Gender and Age information

Examining the building user category and their exposure time was also essential. The predominant group among building users consisted of university students, with 91 participants. Table 17 shows the participation of various building user categories and their respective locations in the survey.

Location	UTS Academic Staff	UTS General Staff	UTS Student	Visitor to UTS	**Total**
Computer lab-common area	-	-	21	2	**23**
Foyer-Waiting area	-	1	19	1	**21**
kitchen	1	-	14	6	**21**
Room 13	-	-	14	-	**14**
Room 14	-	-	14	-	**14**
Room 19	-	-	9	-	**9**
Total	**1**	**1**	**91**	**9**	**102**

Table 17: Building User Category

Using general questions, we could identify the occupants most frequently visited spaces, their most frequent time of day, the frequent length of their visits, and the frequent number of days they occupied the building. In general, 44.12% of participants reported spending between 3 and 7 hours per day in the building. Table 18 shows their responses regarding where they spend the most time in general. According to Figure 35, studio spaces, computer labs, and classrooms are the most commonly used areas by occupants. Regarding occupancy based on the time of the day, more than 50% of participants reported spending time at the building often between 12 and 3 pm and then between 3 and 6 pm each day (S Fig 14). It was also interesting to find that 62.75% of participants reported visiting the building 3 or 4 days a week during the spring teaching semester (S Fig 15).

	UTS Academic Staff	UTS General Staff	UTS Student	Visitor to UTS	**Total**
Between 1 and 3 hours	-	-	37.25%	1.96%	**39.22%**
Between 3 and 7 hours	-	0.98%	42.16%	0.98%	**44.12%**
Less than 1 hour	0.98%	-	1.96%	4.90%	**7.84%**
More than 7 hours	-	-	7.84%	0.98%	**8.82%**
Total	**0.98%**	**0.98%**	**89.22%**	**8.82%**	**100.00%**

Table 18: Time spent during a typical building visit by user category

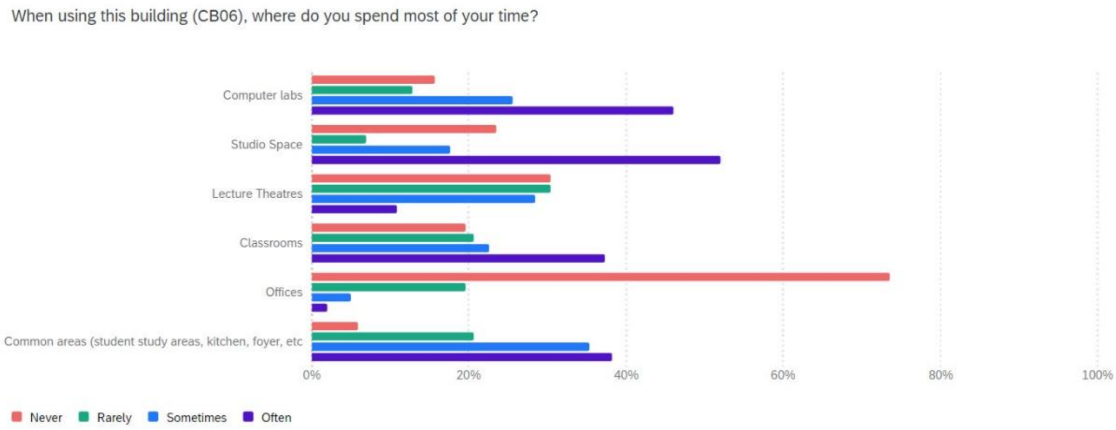

Figure 35: Percentage of building users' time spent in different areas (Source: Author)

As part of the survey, participants were also asked about their perceptions of air quality parameters in general. It should be noted that since most participants were students without access to offices, primarily, no opinions were expressed by participants regarding air quality parameters in offices. Figure 36 shows the Occupants' general perception of air temperature in different spaces. The top-rated response over all areas was that the air temperature was satisfactory, and the second high-ranked response was that the spaces were quite warm. We can rank spaces based on the number of participants who rated the air temperature acceptable. Based on this figure, space ranking is as follows: common areas (62%), computer labs (44%), studio spaces (39%), classrooms (38%), and lecture theatres (35%).

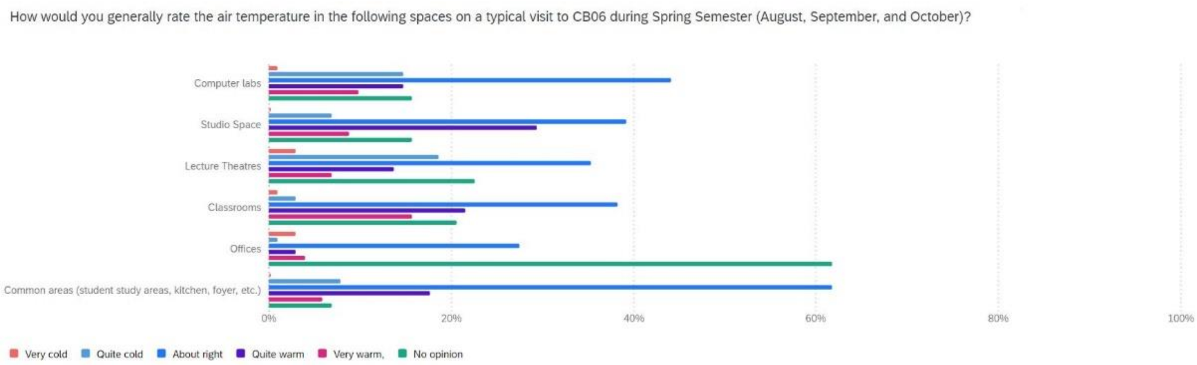

Figure 36: Occupants' general perception of air temperature (Source: Author)

S Fig 16 shows the Occupants' general perception of humidity in different spaces. The top-rated response over all areas was that humidity was satisfactory, and the second highest-ranked response was that the spaces were quite humid. We can rank spaces based on the number of participants who rated the humidity acceptable. Based on this figure, space ranking is as follows: Common areas (52%), studio spaces (%43), lecture theatres (42%), computer labs (40%), and classrooms (36%). S Fig 17 shows the Occupants' general perception of the freshness of the air in different spaces. According to S Fig 17, the majority of participants rated the freshness of the air as "quite stuffy" in studio spaces (36%), computer labs (35%), and classrooms (29%). As a result of the number of participants rating fresh air acceptable, the following areas can be ranked: common areas (42%), lecture theatres (38%), classrooms (29%), and computer labs (23%). S Fig 18 shows the occupants' general perception of air pollution in different spaces. According to S Fig 18, most participants rated the pollution of the air as "about right" and "clean" in all spaces. According to Figure 37, 66.6% of participants experience at least one of the discomfort symptoms due to a typical visit to the building during the spring semester. 46% of participants reported experiencing "tiredness and feeling sleepy," which is the most expressed symptoms. The other reported symptoms rank as follows: difficulty concentrating (34.3%), headache (28.4%), sneezing (22.5%), dry eyes (20.5%), cough, sore throat or dryness in the throat (14.7%), runny nose (13.7%), and dry or itchy skin (12.7%).

Furthermore, data on occupants' current perceptions of comfort and current building use have been collected, as shown in supporting information. Similar figures and tables are provided in supporting information highlighting the location where the survey was done.

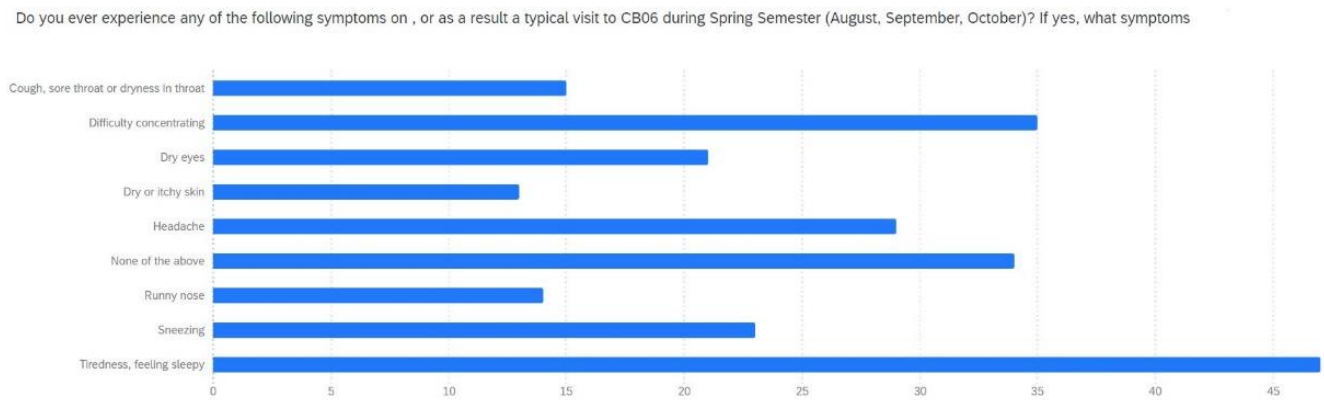

Figure 37: General discomfort symptoms (Source: Author)

6.2.3. Correlation analysis

This section compared subjective and objective measurements and investigated their potential relationships. Given the sample size and the non-normal distribution of the data, Spearman's rank correlation coefficient analysis was selected to examine the correlations between different variables. This approach helped explore correlations among variables while minimizing the risks of error types I and II. The initial analysis focused on examining the frequency and type of discomfort symptoms reported by occupants. The following analysis addressed the investigation of occupants' perceptions of IAQ parameters and attempted to determine the degree of alignment between their perceptions and the measured IAQ parameters. The survey's final analysis also encompassed the comparative evaluation of different spaces.

6.2.3.1. Discomfort symptoms

- **Relationship between indoor environmental parameters and the number of reported discomfort symptoms**

Using Spearman's rank correlation coefficient analysis, the association between indoor environmental factors and the frequency of reported discomfort symptoms was investigated (Table 19). The results indicated a lack of statistically significant correlation between the frequency of reported discomfort and various environmental factors, including temperature, humidity, pressure, the concentration of PM2.5, PM10, VOC, and the presence of individuals close to the participants.

	Temperature	Humidity	Pressure	PM2.5	PM10	VOC	Occupant Count
Spearman correlation coefficient (r)	0.043	0.016	0.072	-0.013	0.009	0.024	0.136
P-Value	0.674	0.879	0.482	0.897	0.932	0.813	0.183

Table 19:Spearman correlation coefficient between indoor environmental factors and the frequency of reported discomfort symptoms

- **Relationship between typical frequency of time spent and the number of reported discomfort symptoms**

A positive correlation exists between the number of discomfort symptoms reported and the frequency of day participants spend in spaces during the spring semester. The observed positive correlation, which exhibits statistical significance ($p\text{-value} < 0.05$), suggests that spending more days in spaces during the spring semester is associated with an increased number of discomfort symptoms reported. Furthermore, it is evident from Figure 39 that individuals who visit the building and spend time there typically three to four days per week reported experiencing the greatest number of discomfort symptoms. Also, based on the analysis presented in Figure 38, it can be observed that this finding was applicable across all spaces, since occupants of all the spaces who spend time typically three to four days per week reported similar observations. Table 21 also shows that the three most common discomfort symptoms among participants who generally spend three or four days a week in the building are tiredness and feeling sleepy, difficulty concentrating, and dry eyes. It is also important to note that similar findings were reached when this relationship was examined across two different perception intervals (current and general perception), suggesting that it can be valid in many different conditions and is not restricted to particular times or locations. Accordingly, Table 20 shows the Spearman correlation coefficient values for the consistent positive association observed over current and general perceptions.

	General perception	Current perception
Spearman correlation coefficient (r)	0.293*	0.272*
P-Value	0.004	0.007

*Table 20:Spearman correlation coefficient between typical frequency of time spent and the frequency of reported discomfort symptoms (** Indicates significant correlation at the 0.05 level (two-tailed).)

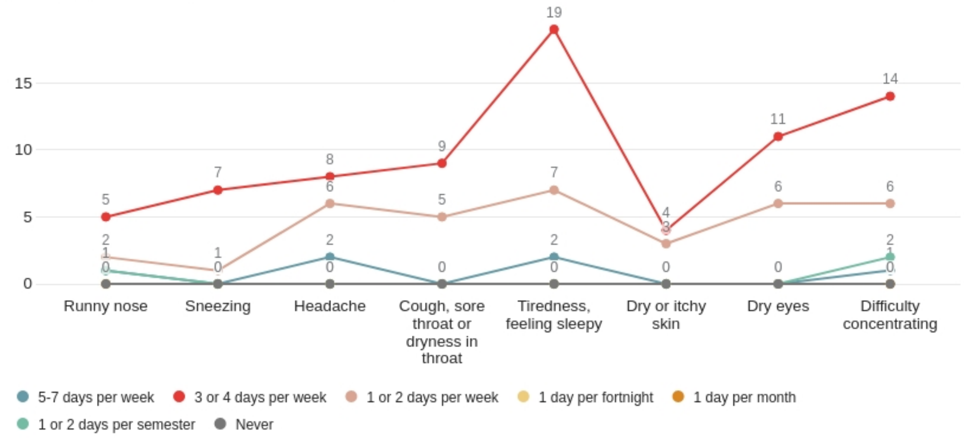

Figure 39: Relationship between time spent in current space during spring semester and reported discomfort symptoms (Source: Author)

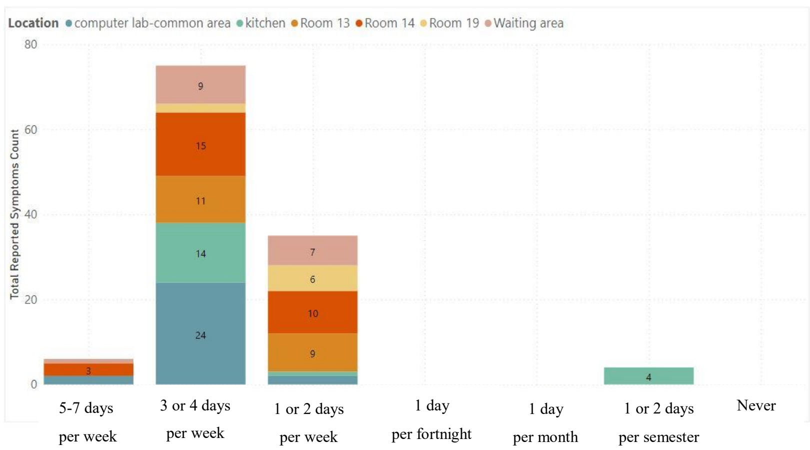

Figure 38:Correlation between discomfort symptoms count and frequency of visiting spaces by location (Source: Author)

	5-7 days per week	3 or 4 days Per week	1 or 2 days per week	1 day per fortnight	1 day per month	1 or 2 days per semester	Never
Runny nose	1	5	2	0	0	1	0
Sneezing	0	7	1	0	0	0	0
Headache	2	8	6	0	0	0	0
Cough, Sore throat or dryness in throat	0	9	5	0	0	0	0
Tiredness, feeling sleepy	2	19	7	0	0	0	0
Dry or itchy skin	0	4	3	0	0	0	0
Dry eyes	0	11	6	0	0	0	0
Difficulty concentrating	1	14	6	0	0	2	0
None of the above	3	17	18	3	3	6	1

Table 21: Number of reported discomfort symptoms based on type of symptom and frequency of visiting spaces

- **Relationship between anticipated space-time usage and the number of reported discomfort symptoms**

The spatial and temporal aspects of occupant activities or experiences were analyzed, considering the occupants' general and current perceptions. In other words, the relationship between the average daily duration individuals spend inside the building during their visits, the specific time range of the day they spend there, and the quantity of symptoms they experience during the spring semester were examined. The results presented in Table 22 suggest that there is a positive correlation between spending time in the range of 12:00 - 15:00 and the number of reported discomfort symptoms, which is statistically significant (p-value <0.05). This finding suggests that participants who often spend time between 12:00 and 15:00 (%44.1 of total participants) while occupying rooms 13, 14, and 19, the waiting area, computer lab-common area, and kitchen in this period reported more discomfort symptoms. Furthermore, as shown in Figure 40, the common discomfort symptoms that occupants reported while spending time between 12:00 and 15:00 are tiredness, feeling sleepy, and difficulty concentrating.

		Between 8:00 - 12:00	Between 12:00 - 15:00	Between 15:00 - 18:00	Between 18:00-20:00
Current perception	Spearman correlation coefficient (r)	0.184	0.21*	-0.017	0.08
	P-Value	0.071	0.039	0.872	0.435

*Table 22: Spearman correlation coefficient between anticipated space-time usage and the number of reported discomfort symptoms (** Indicates significant correlation at the 0.05 level (two-tailed).)

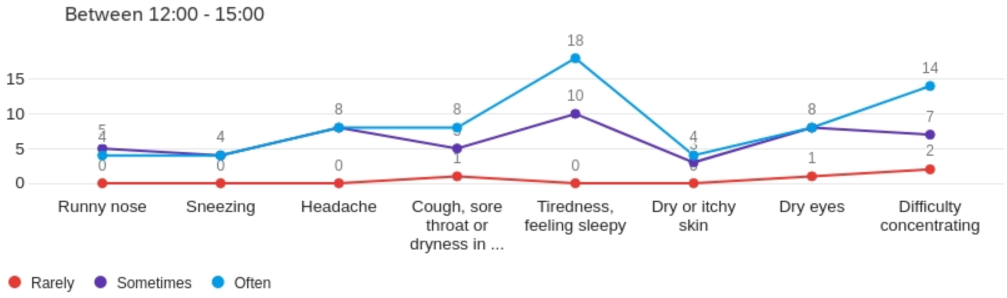

Figure 40: space-time usage between 12:00-15:00 and the type of reported discomfort symptom (Source: Author)

- **Relationship between other factors and the number of reported discomfort symptoms**

The association between other variables, such as age, gender, and dress code, and the frequency of reported discomfort symptoms were examined using Spearman correlation analysis (Table 23). The results indicate a statistically significant correlation between gender classification and the incidence of discomfort symptoms. In other words, a notable association exists between the female gender and a higher potential of experiencing discomfort symptoms. As seen in Figure 41, more female participants (61%) than male participants (35%) reported experiencing discomfort symptoms, and regarding the type of experienced symptoms, female participants reported higher symptoms than males for each symptom category, except for "cough, sore throat, and throat dryness". Furthermore, there was no correlation between the participants' dress code and the number of reported discomfort symptoms, indicating that their choice of dress code had no impact on their comfort level. Similarly, the same result was found with the correlation between age and the frequency of reported symptoms of discomfort.

			Dress-code			
	Age	Gender	1 layer-thick	1 layer-thin	2 layers-thin	2 layers-thick
Spearman correlation coefficient (r)	-0.121	0.201*	0.002	0.013	-0.103	0.03
P-Value	0.241	0.05	0.988	0.898	0.319	0.772

*Table 23:Spearman correlation coefficient between age, gender, dress-code and the number of reported discomfort symptoms (** Indicates significant correlation at the 0.05 level (two-tailed).)

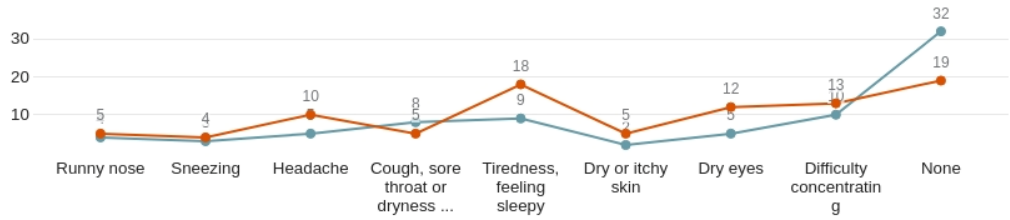

Figure 41:Gender and the type of reported discomfort symptom (Source: Author)

- **Relationship between zones, spaces and the number of reported discomfort symptoms**

Considering the proximity and accessibility to the busy street and vehicle traffic, selected spaces are categorized into two distinct zones, each influencing occupant perceptions of IAQ and experiences of discomfort symptoms uniquely due to its interactions with surrounding settings. Zone 1, situated near the entrance door, encompasses the waiting and kitchen areas. Conversely, zone 2, separated from zone 1 by a door, includes Room 13, Room 14, Room 19, and the computer lab's common area.

Figure 42, Figure 43 and Figure 44 present a detailed analysis of the perception of IAQ parameters among occupants and their reported experience of discomfort symptoms in Zone 1 and Zone 2. Figure 42 displays the daily average count of symptoms throughout the survey. It is worth mentioning that, with the only exception of 18 October, Zone 2 consistently shows a greater average number of symptoms in comparison to Zone 1.

Furthermore, the boxplot presented in Figure 43 compares the distribution of reported discomfort symptoms in both Zone 1 and Zone 2. Notably, Zone 2 displays a higher maximum count of discomfort symptoms, reaching a maximum value of 6, while Zone 1 peaks at 4. In addition, Zone 2 has a median value of 1, accompanied by an average of 1.40 (± 1.67), while Zone 1 demonstrates a median value of 0, suggesting an absence of reported discomfort symptoms on average. The average value for Zone 1 is 0.86 (± 1.14). This significant difference in discomfort symptom levels between the two zones is a crucial finding from the analysis. The analysis found a significant difference in the levels of reported discomfort symptoms between occupants of the two zones, indicating an important finding.

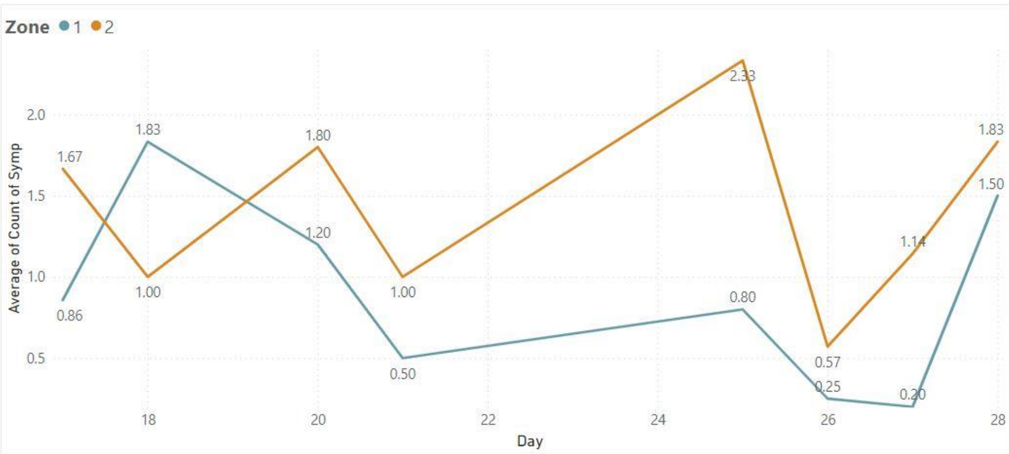

Figure 42: Comparison of daily average of count of discomfort symptoms in zone 1 and zone 2 (Source: Author)

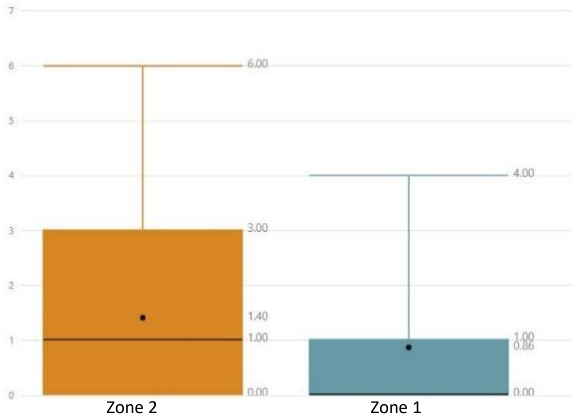

Figure 43: comparison of the distribution of reported discomfort symptoms in both zone 1 and zone 2 (Source: Author)

Occupant perceptions of temperature, humidity, air freshness, and pollution in zones 1 and 2 are compared in Figure 44. According to Figure 44, there were notable variations in the occupant levels of comfort and perception of air quality in zones. Regarding temperature perceptions, zone 1 had a higher degree of comfort than zone 2 since approximately 7% more occupants in zone 1 found the temperature satisfactory. On the other hand, compared to zone 1, zone 2 showed a roughly 10% increase in the percentage of occupants who perceived the temperature as "quite warm". Furthermore, when it comes to humidity perception, there was a different representation with zone 2. Comparing zones 2 and 1, the percentage of occupants who perceived the humidity as "right" was about 10% higher in zone 2. Also, zone 1 showed a higher degree of occupant discomfort in comparison to zone 2, as seen by approximately 12% more occupants perceiving the humidity as "quite humid" in zone 1. Furthermore, it is noteworthy that 2.5% of zone 1 occupants evaluated the air quality as "very humid", while no occupants in zone 2 reported this specific experience.

Regarding how people experienced air pollution, it was found that 21% of residents in both zones declared the air was "quite dusty". However, zone 2 had a higher degree of clean air quality perception, with approximately 11% more people describing the air as "quite clean" or "very clean" compared to zone 1. Also, concerning occupants' perceptions of air freshness in the two zones, it is evident that zone 1 provides a more comfortable setting for its occupants. In other words, over 12% more occupants in zone 1 perceive the air as "about right" to "very fresh" compared to zone 2, where there are approximately 12% more occupants experience the air quality as "quite stuffy" to "very stuffy."

The information provided by Figure 44 offers valuable insights into the noticeable disparities in occupant experiences between zone 1 and zone 2. This finding prompts further investigation and a more detailed analysis of the factors contributing to these diverse experiences within each context.

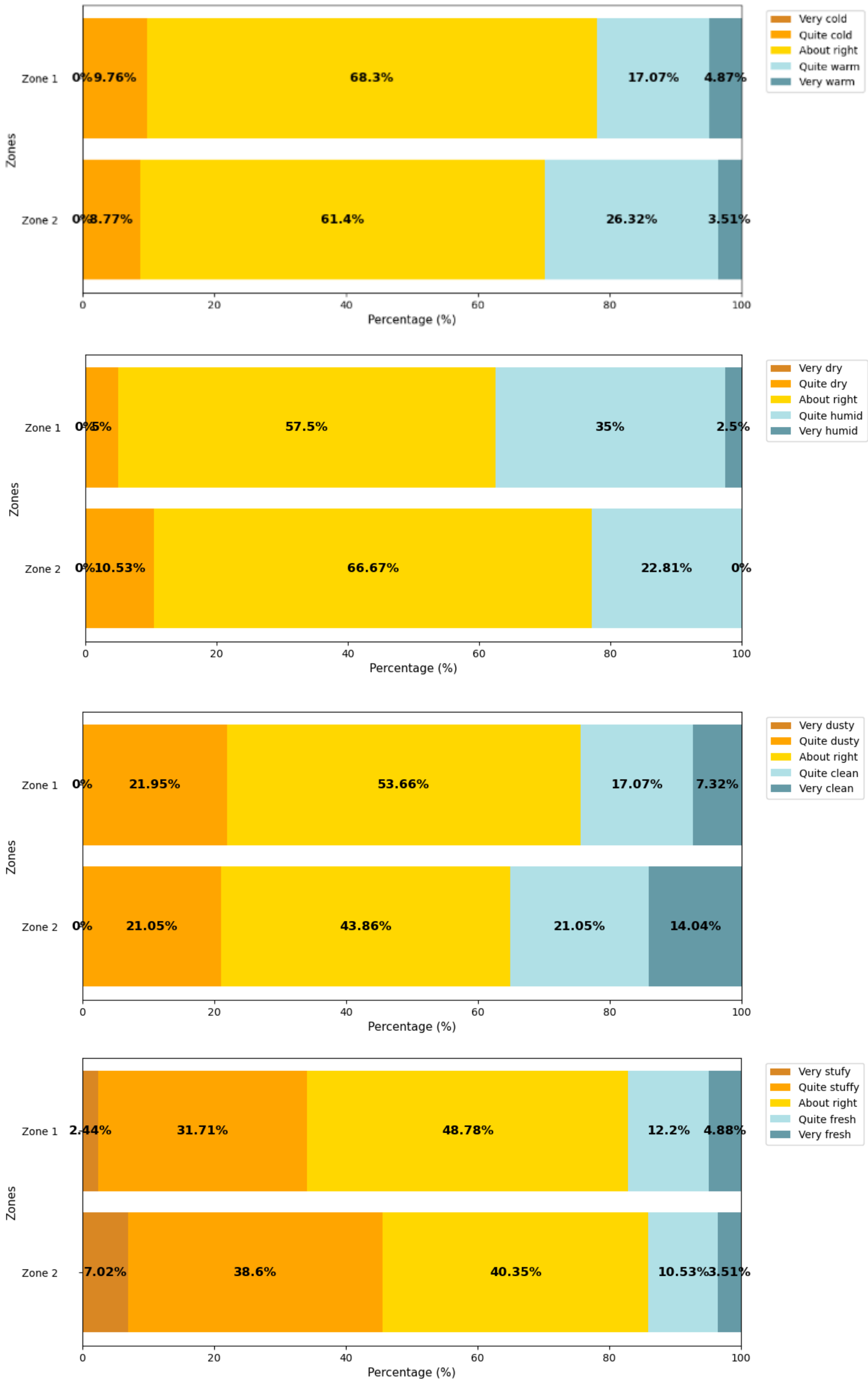

Figure 44: Comparison of occupant perceptions of temperature a), humidity b), air freshness c), and pollution d) in zones 1 and 2 (Source: Author)

Concerning the critical role of gender in the experience of occupant discomfort symptoms, Figure 45 comprehensively examines the percentage of occupants who reported discomfort symptoms in zone 1 and zone 2, incorporating a gendered perspective into the investigation. The data shown in Figure 45 reveals that 46.34% of occupants in zone 1 experienced at least one symptom of discomfort while, a slightly higher percentage of 53.66% reported the lack of any symptoms. In contrast, it was shown that in zone 2, a significant majority of 53.33% of occupants experienced at least one discomfort symptom, while the remainder, 46.67%, did not report any symptoms. The data reveals a significant trend wherein females experience a higher prevalence of discomfort, accounting for 68.42% in zone 1 and 62.5% in zone 2. Therefore, the high occurrence of discomfort experienced by females highlights the significance of implementing a gender-sensitive approach in developing policies to enhance environmental comfort and equity in both areas.

Regarding each space, the association between the respondents' location during the survey and the frequency of reported symptoms was also examined. As shown in Table 24, there was no statistically significant correlation between occupying spaces and the reported discomfort symptoms. Figure 46 compares the number of reported discomfort symptoms in different locations. as shown in Figure 46, individuals who spent time in room 14 experienced and reported more discomfort symptoms. Based on the data presented in Figure 46 and Table 25, it can be observed that the average and median values for the number of reported discomfort symptoms for room 14 were higher than those in other spaces. Furthermore, a significant proportion of participants, precisely half (50%) residing in Room 14, reported experiencing at least two symptoms. In contrast, this number was %42.8% for room 13, 39.1% for the computer lab common area, 23.8% for the kitchen, %33.3 for room 19 and %19 for the waiting area.

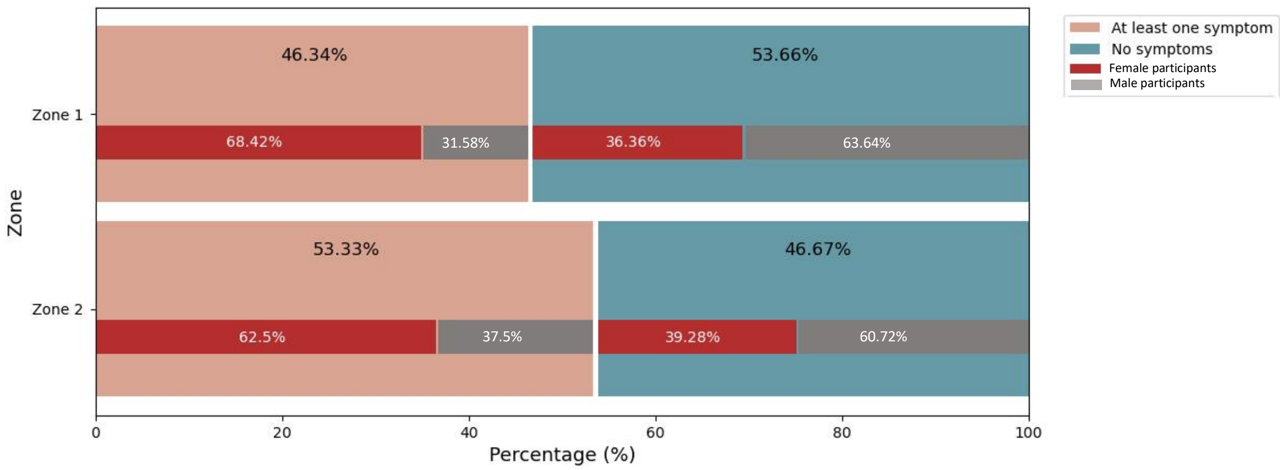

Figure 45: Gender-based comparison of reported discomfort symptoms in Zone 1 and Zone 2 (Source: Author)

	Room 13	Room 14	Room 19	Waiting area	Computer lab-common area	Kitchen
Spearman correlation coefficient (r)	0.049	0.178	-0.047	-0.048	-0.002	-0.11
P-Value	0.632	0.082	0.649	0.642	0.982	0.287

Table 24: Spearman correlation coefficient between location and the number of reported discomfort symptoms

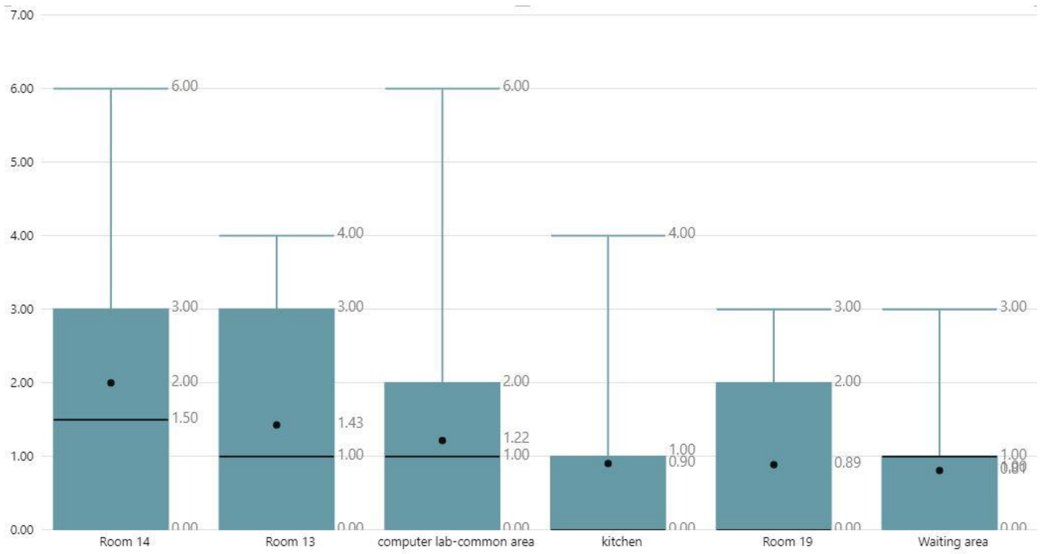

Figure 46: Distribution of number of reported discomfort symptoms by location (Source: Author)

Location	Median	Average	Standard Deviation	Interquartile Range (IQR)	Maximum
Room 13	1	1.43	1.5	3	4
Room 14	1.5	2	2.22	3	6
Room 19	0	0.89	1.17	2	3
Waiting area	1	0.81	0.98	1	3
Computer lab-common area	1	1.22	1.54	2	6
Kitchen	0	0.9	1.3	1	4

Table 25: Statistical distribution of reported discomfort symptoms by location

The discomfort symptoms that occupants reported experiencing in each space are shown in Figure 47. It can be seen that the most commonly reported discomfort symptoms were tiredness, feeling sleepy, difficulty concentrating, headaches, and dry eyes. Regarding the locations and highest percentage of participants experiencing these symptoms, Figure 47 demonstrates that about 26% of participants reported feeling tired and sleepy, 31% reported having headaches, and 57% reported having dry eyes were located in the computer lab common area. Also, regarding the experience of difficulty concentrating symptoms, about 30% of participants who reported experiencing this symptom were located in Room 14.

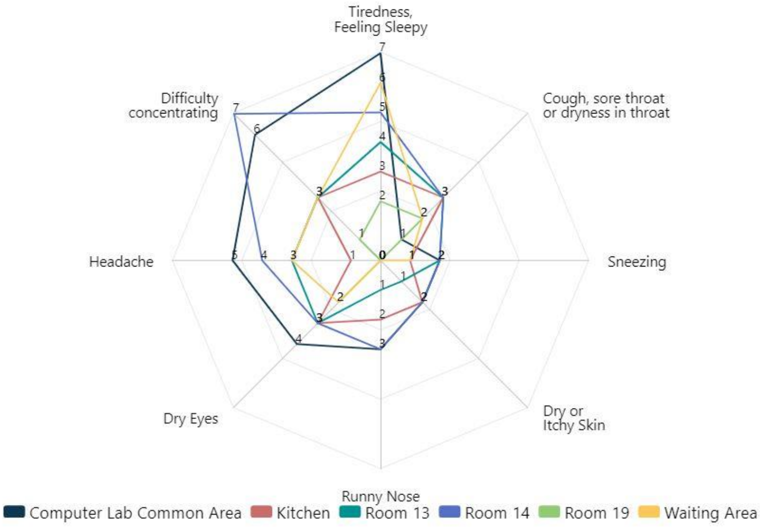

Figure 47: Discomfort symptoms in each space (Source: Author)

- **Relationship between perception of air quality parameters and the number of reported discomfort symptoms**

Data analysis also aimed to examine whether participants' perceptions of IAQ parameters aligned and correlated with their comfort levels and the experience of discomfort symptoms. Figure 48, Figure 49, Figure 50 and Figure 51 show the correlation between participants' perceptions of air temperature, humidity, freshness and pollution of air, and discomfort symptoms. According to the data presented in Figure 48, there was a notable misalignment between the perceived air temperature among occupants and their reported experience of discomfort symptoms. The data suggest that a substantial portion, 62.7%, of all participants indicated that the air temperature was "about right". However, it is noteworthy that this particular subgroup exhibited a greater prevalence of discomfort symptoms compared to other participants and collectively reported 54 discomfort symptoms. In addition, 22.5% of participants perceived the air temperature as 'quite warm,' collectively reporting 40 discomfort symptoms. Furthermore, as shown in Figure 49, participants' perceptions of humidity did not align with the experienced discomfort symptoms. Individuals who perceived air humidity as "about right" (61.8% of all participants) reported experiencing more discomfort symptoms (56 in total). Also, Figure 50 illustrates that regarding the freshness of the air, 32.3 % of participants who indicated a perception of "quite stuffy" reported experiencing the highest number of discomfort symptoms across all symptom categories, totaling 66 symptoms. This finding suggests that individuals' subjective evaluation of air freshness aligned with their reported experience of discomfort symptoms. Based on the findings presented in Figure 51, there is not a uniform association between individuals' perceptions of air pollution and their experience of discomfort symptoms across all symptoms. In other words, an alignment can be observed between participants' perceptions of air pollution levels and their experiences with distinct symptoms of discomfort. Specifically, participants who reported perceiving the air quality as "quite dusty" expressed a higher frequency of certain symptoms, such as sneezing, dry or itchy skin or dry eyes, and difficulty concentrating. Nevertheless, participants' perceptions and reported symptoms demonstrated inconsistency when experiencing symptoms such as runny nose, headache, cough, sore throat, and dryness in the throat. This misalignment means that despite experiencing these symptoms, the individuals perceived the level of air pollution to be "about right".

Furthermore, the Spearman correlation analysis presented in Table 26, validates aforementioned findings. Statistically significant correlations were observed between perceptions of air pollution and air freshness and the number of reported discomfort symptoms. In other words, the findings indicated that as participants' perception of air freshness and air pollution deteriorated, there was a notable increase in the number of discomfort symptoms reported.

	Perception of air temperature	Perception of air humidity	Perception of air freshness	Perception of air pollution
Spearman correlation coefficient (r)	-0.054	0.022	0.229*	0.33*
P-Value	0.6	0.833	0.025	0.001

*Table 26: Spearman correlation coefficient between occupant perception of IAQ parameters and the number of reported discomfort symptoms (** Indicates significant correlation at the 0.05 level (two-tailed).)

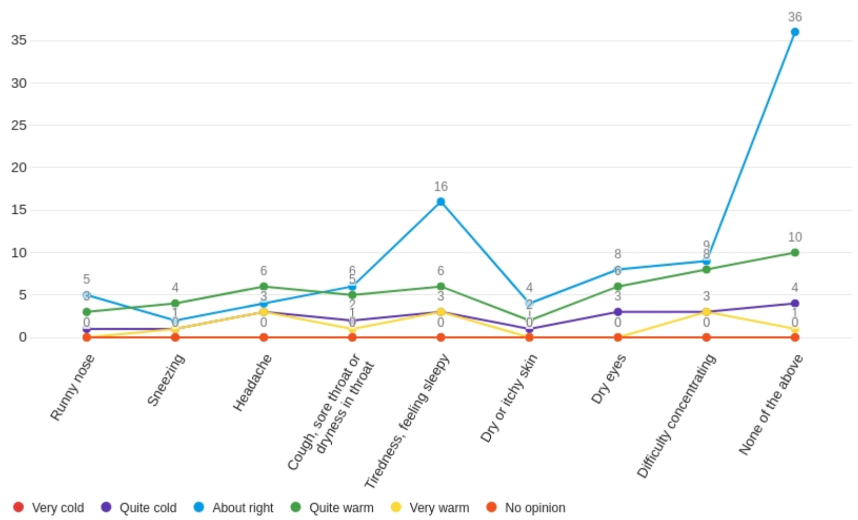

Figure 48:Perception of temperature and reported discomfort symptoms (Source: Author)

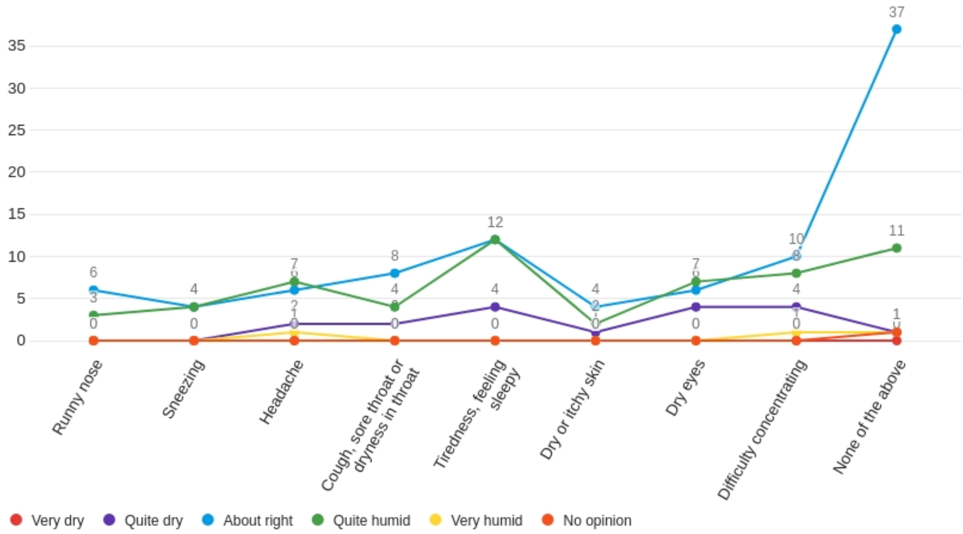

Figure 49:Perception of humidity and reported discomfort symptoms (Source: Author)

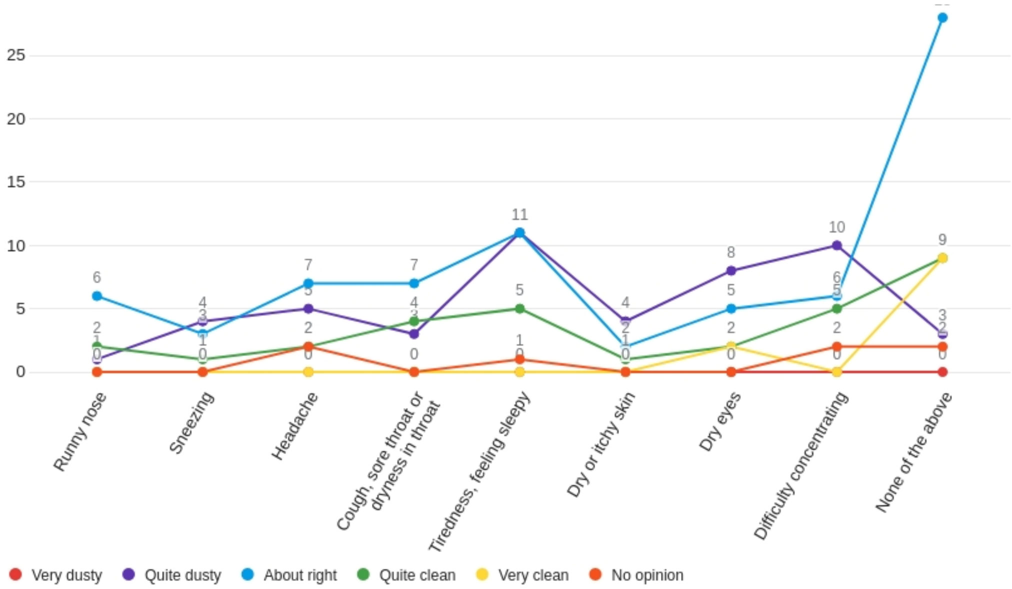

Figure 50:rception of air freshness and reported discomfort symptoms (Source: Author)

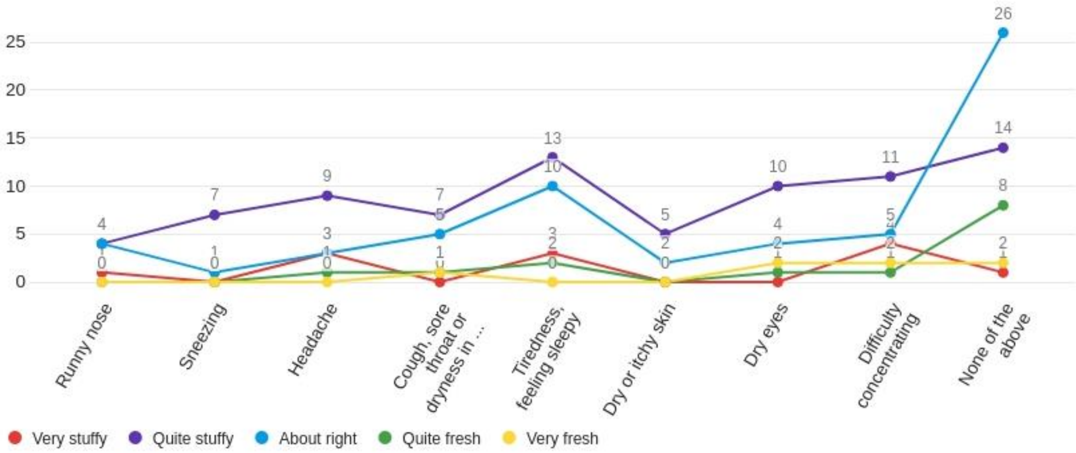

Figure 51:Perception of air pollution and reported discomfort symptoms (Source: Author)

- **Relationship between Predicted Mean Vote (PMV), Predicted Percentages of Dissatisfied (PPD), Actual Mean Vote (AMV), and the number of reported discomfort symptoms**

Using collected data on participants' attire and physical activity, the thermal comfort of participants across various locations were assessed. For the thermal comfort analysis, the thermal comfort tool developed by the Center for the Built Environment (CBE) was employed to analyze and calculate the Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) indices. The calculation followed the guidelines specified in the ASHRAE 55–2023, ISO 7730:2005, and EN 16798–1:2022 standard. In this study, the most critical inputs for the CBE tool, including metabolic rate, air speed, and operative temperature, were collected through sensor data, surveys, and observations. Metabolic rate was measured by tracking occupant activities during the study, while air speed was determined based on whether occupants had local control over the airflow in their space. Since occupants lacked control over air velocity in this study, the comfort zone remained unaffected by air movement. The tool also automatically adjusts airspeed by accounting for body movement using the formula: $V_{sg} = V + 0.3 (MET - 1)$, where V is the average air speed, and MET is the metabolic rate (Tartarini et al., 2020).

Additionally, operative temperature in this online tool was used to account for both air temperature and mean radiant temperature (MRT), which represents how warm or cool a person feels in a given environment. It considers not only the air temperature but also the temperature of surrounding surfaces that radiate heat (Tartarini et al., 2020). Operative temperature was calculated using the average readings from sensors placed at different heights on tables and walls in various spaces.

Additional inputs, such as clothing insulation (Clo), were critical to the PMV/PPD calculations. Clothing levels, including the number of layers, thickness, and type of garments, were recorded during the study. The tool allows for selecting predefined clothing ensembles or customizing the clothing data based on observations (Tartarini et al., 2020).

The relationship between the PMV range and the number of discomfort symptoms reported by survey participants is presented in Table 27. The data presented in Table 27 can offer valuable insights into the degree of discomfort experienced by participants in different thermal conditions. According to the table, it was found that, during the survey period, 76.5% of the participants were in an acceptable thermal comfort condition ($-0.5 < PMV < 0.5$), while 23.5% were in an uncomfortable thermal state ($PMV > 0.5$ or $PMV < -0.5$). Also, as shown in Table 27, even though most participants were at acceptable thermal comfort based on the calculated PMV, 50% of individuals in conditions with a PMV between -0.5 and 0.5 experienced at least one symptom of discomfort. It is worth mentioning that the number of female participants who were in comfortable thermal conditions based on PMV calculations and experienced at least one discomfort symptom was 2 times higher than those of male participants. Furthermore, it can be observed that the weighted average number of reported symptoms for PMV outside the range of acceptable thermal comfort was approximately 1.5 times greater compared to PMV within the acceptable thermal conditions range. This comparison suggests that participants not within the acceptable thermal comfort conditions (PMV > 0.5 or PMV < -0.5) reported a more significant average number of discomfort symptoms than participants falling within the PMV range of -0.5 to 0.5.

Number of reported discomfort symptoms	Number of participants reported discomfort symptoms	
	-0.5 < PMV < 0.5	PMV > 0.5 or PMV < -0.5
0 Symptoms	39	11
1 Symptom	17	1
2 Symptoms	8	4
3 Symptoms	11	5
4 Symptoms	2	1
6 Symptoms	1	2
Total participants	78	24
Weighted average number of discomfort symptoms	1.03	1.67
Participants with experience of at least one symptom	39 (%50) 13 Male, 26 Female	13 (%54.1) 5 Male, 8 Female

Table 27: PMV range and the number of discomfort symptoms

Furthermore, Figure 52 illustrates the data distribution concerning the correlation between participants' discomfort symptom responses and the calculated PMV. Figure 52 illustrates that the thermal conditions during the survey period primarily exhibited PMV values from -0.5 to 0.5 and higher, thus would be perceived as Neutral and slightly warm rather than slightly cool. As shown in Figure 52 in the thermal conditions that PMV falls outside the range of -0.5 to +0.5, signifying a deviation from acceptable thermal conditions and a neutral sensation; a total number of 13 individuals (%12.74 of all participants) reported experiencing at least one symptom of discomfort. Figure 52 also, indicates that 2 participants reported experiencing discomfort at a PMV value below -0.5, suggesting that these occupants may perceive a slightly cool sensation. On the other hand, 11 participants reported discomfort symptoms at a PMV value above 0.5, indicating that occupants may perceive a slightly warm sensation.

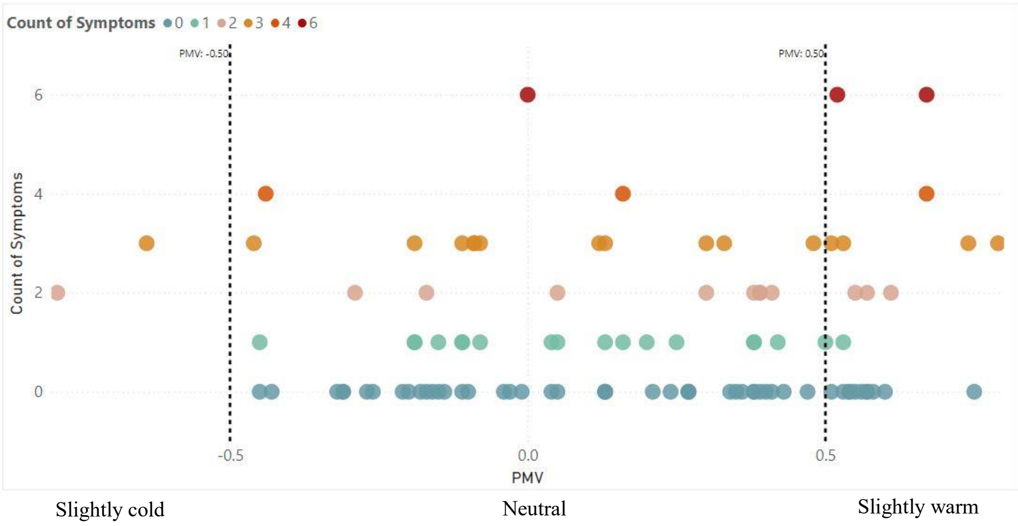

Figure 52: Count of discomfort symptoms and the calculated PMV and predicted sensation (Source: Author)

Using the calculated PMV values, Figure 53 illustrates thermal comfort ranges across different locations, highlighting the percentage of occupants who experienced discomfort symptoms during those particular thermal conditions. According to Figure 53, PMV values lower than -0.5 were observed exclusively in the kitchen area, suggesting that participants might have perceived a slightly cold thermal environment in that specific location. In contrast, the calculated PMV values consistently suggested a neutral or slightly warm thermal sensation across other locations. In addition, based on the comparison of the various evaluated locations, it was noted that the waiting room and the computer lab common area had the least potential for eliciting neutral sensations for their occupants. In other words, in these two spaces, in more than 30 percent of the observed occurrences, the calculated PMV exceeded the threshold of 0.5, which suggests that individuals who often visit these areas will perceive a slightly warm thermal sensation. Figure 53 also illustrates that a considerable percentage of participants, over 50% of participants in all locations except the kitchen area, reported experiencing discomfort symptoms in situations where they were expected to have a neutral thermal sensation based on the calculated PMV. In situations falling within the acceptable range of thermal comfort (-0.5 < PMV < 0.5), the following percentages of participants reported experiencing discomfort symptoms: 63.6% in room 13, 45.4% in room 14, 50% in room 19, 46.6% in the computer lab common area, 66.7% in the waiting area, and 38.9% in the kitchen area. Also, in the kitchen area, on every occasion where the PMV was below -0.5, indicating a predicted thermal comfort level of "slightly cool," occupants consistently reported experiencing discomfort symptoms.

Results vary for PMV levels above 0.5, which indicates a slightly warm thermal sensation. In the waiting area, 43% expressed discomfort, while in the computer lab common area, the percentage was 62.5%. In room 14 and room 13, with the same percentage of occasions where PMV was higher than 0.5 (21.4%), the number of participants experiencing discomfort differed—100% in room 14 and 33.3% in room 13. In contrast, no discomfort was experienced in room 19 during situations of slightly warm thermal sensation.

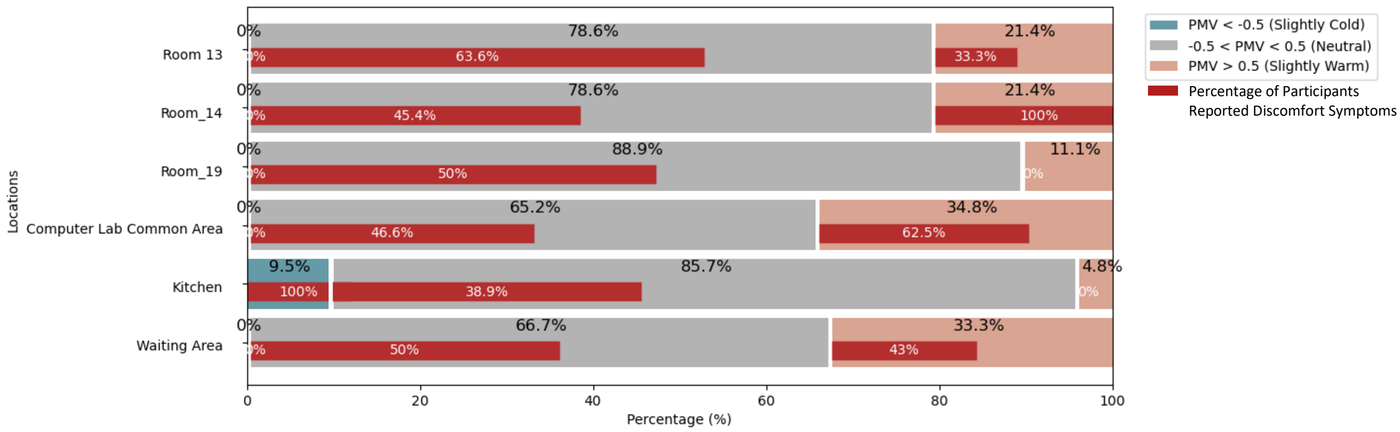

Figure 53: Discomfort symptom percentage across different thermal comfort ranges by location (Source: Author)

The Kruskal-Wallis Rank-Sum tests were employed to compare and evaluate the statistical significance of the calculated PMV across several locations. Based on the obtained test result (P-value=0.02), a statistically significant difference exists in the average value of the calculated PMV of at least one location compared to the other locations. Table 28 presents a statistical comparison of the PMV, PPD, and AMV values across different locations. Based on the average data presented in the Table 28, it can be observed that room 19 had an average PMV of -0.02, indicating it's close to a neutral thermal experience. On the other hand, room 14 had the highest average PMV value of 0.3, suggesting that it is considered the warmest location. The kitchen had an average PMV value of -0.05 and had the lowest PMV and can be considered as the coolest location. Regarding the PPD, it can be seen that room 19 had the lowest mean value of 6.67%. In contrast, room 14 had the highest mean value of 8.86%, indicating a higher probability of experiencing thermal discomfort. In terms of comparing the PMV and the AMV, it was observed that room 14 had the highest PMV value of 0.3, suggesting a projected perception of warmth. Nevertheless, regarding the actual thermal sensations reflected by the AMV, room 14, with an AMV of 0.21, was not recognized as the highest. On the other hand, it was observed that the computer lab common area had the highest average AMV of 0.72, suggesting that occupants in this room experienced a higher level of warmth than other selected locations. The observed discrepancy between predicted and actual perceptions suggests that although the predictions might indicate room 14 as the warmest, its occupants may experience it differently. On the other hand, the occupants of the computer lab common area perceive the thermal conditions to be the warmest in comparison to the other locations.

Furthermore, it is notable that room 14 exhibited the highest standard deviation of 1.3, indicating a greater degree of variability in the thermal comfort feedback received from occupants in this particular location. Additionally, the calculated AMV median value for all rooms is 0, suggesting that the most common response from occupants in all rooms is around a neutral thermal sensation.

		Room 13	Room 14	Room 19	Computer lab common area	Kitchen	Waiting area
PMV [a]	Average	0.24	0.3	-0.02	0.26	-0.05	0.18
	Standard Deviation	0.3	0.32	0.30	0.28	0.41	0.33
	Median	0.14	0.345	-0.11	0.3	-0.1	`0.2
	Maximum	0.75	0.79	0.58	0.61	0.57	0.57
	Minimum	-0.27	-0.17	-0.29	-0.32	-0.79	-0.43
PPD (%)	Average	7.78	8.86	6.67	8	8.29	7.81
	Standard Deviation	4.06	3.8	2.24	2.89	3.18	2.54
	Median	6	7.5	6	7	8	8
	Maximum	17	18	12	13	18	12
	Minimum	5	5	5	5	5	5
AMV [b]	Average	0.32	0.21	0.17	0.72	0.21	0.21
	Standard Deviation	0.87	1.3	0.5	1.09	1.09	0.98
	Median	0	0	0	0	0	0
	Maximum	1.5	3	1.5	3	3	3
	Minimum	-1.5	-1.5	0	-1.5	-1.5	-1.5

Table 28: Statistical comparison of PMV, PPD, and AMV values across different locations.

[a] *7 response options: cold (-3), cool (-2), slightly cool (-1), neutral (0), slightly warm (+1), and hot (+3)*

[b] 5 response options: Very cold (-3), Quite cold (-1.5), About right (0), Quite warm (+1.5), and Very warm (+3)

Figure 54 and Figure 55 illustrate the PMV and PPD variations for each location. The acceptable thermal comfort values, which are within the range of -0.5 to +0.5 for PMV and less than 10% for PPD, are highlighted by red horizontal lines. Based on the data presented in Figure 54, it can be observed that the waiting area had an upper quartile (Q3) value of 0.51, and the computer lab common area had a Q3 value of 0.54. This observation means that in those areas, at least 25% of the observations exceeded the threshold of 0.5. In contrast, room 14, despite having the highest average and median PMV values, presented a Q3 value of 0.46., which means its top 25% of observations were closer to but mostly remained below the upper threshold of 0.5. Consequently, while room 14 might frequently be on the warmer side, it shows less potential to exceed the acceptable PMV range compared to the waiting area and the computer lab common area.

On the other hand, the kitchen, leaning towards cooler conditions, particularly in its lower 25% of observations, had a Q3 of 0.35 and a Q1 (lower quartile) of -0.44. This finding indicates that although the upper 25% of data points fell below the upper limit of 0.5, the lower 25% tended to approach the lower threshold of -0.5. Regarding the PPD, Figure 55 illustrates that the waiting and computer lab common areas had their Q3 values at 10% and 11%, respectively. This finding suggests that at least 25% of the measurements exceeded the established threshold of 10% in both areas.

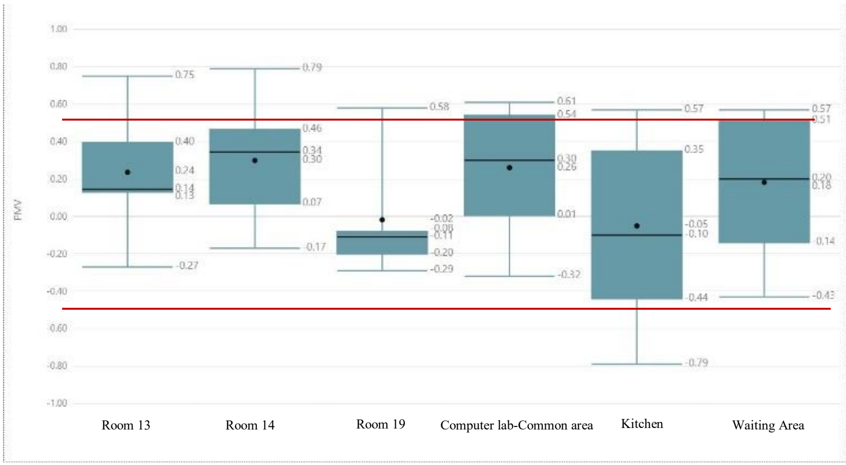

Figure 54:Comparison of PMV variations across locations highlighting acceptable thermal comfort ranges (Source: Author)

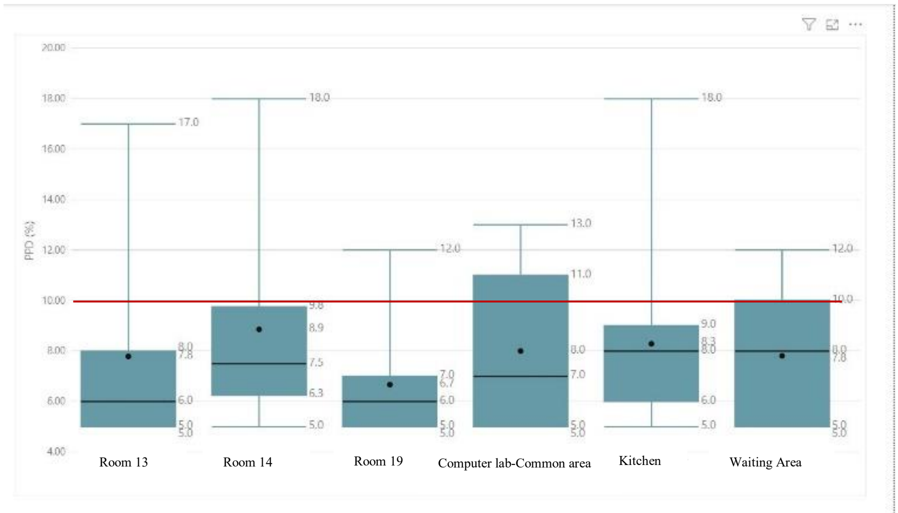

Figure 55: Comparison of PPD variations across locations (Source: Author)

To compare AMV and PMV, the relationship between indoor temperature, AMV, and PMV is examined and illustrated in Figure 56. The data is visualized using a scatter plot, which includes two linear regression lines. As shown in Figure 56, the position of the AMV line is above the PMV line, which indicates that actual thermal sensations (AMV) are consistently warmer than expected thermal sensations (PMV) over the entire temperature range within the study. In other words, occupants perceive the indoor environment as warmer than Fanger' model measurement results.

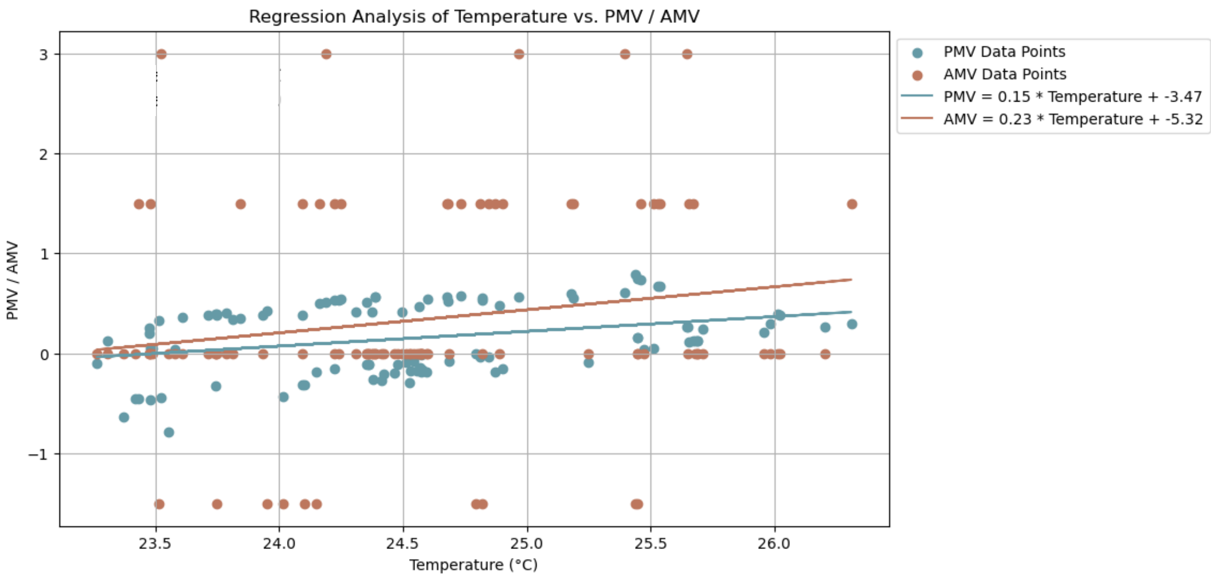

Figure 56:Comparison between AM) and PMV based on operative temperature (Source: Author)

- **PMV, PPD and AMV variations throughout the day**

Analyzing the PMV and PPD on an hourly basis for each location provides a comprehensive understanding of how thermal comfort varies throughout the day. This approach allows for discovering the specific times of the day when occupants might experience discomfort. In this study, the fluctuations in PMV, PPD, and AMV were examined over the day and across various locations, and the findings are presented in Figure 57, Figure 58 and Figure 59. Figure 57 displays the hours of the day on the x-axis and the average PMV values on the y-axis. Additionally, two horizontal dashed lines indicate the acceptable thermal comfort range based on PMV. According to Figure 57, although each area has distinct HVAC specifications, there is a significant increase in average PMV values across all locations in the afternoon, around 15:00. Also, it is notable that only room 14 with the PMV average value of 0.67 and computer lab common area with the PMV average value of 0.58 exceeded the warmth threshold of PMV= 0.5. In contrast, no location had a PMV value lower than -0.5, ensuring they remained above the lower comfort threshold. Furthermore, based on Figure 57, following the peak around 15:00, there is a subsequent decrease in PMV averages across almost all locations. In general, with only two areas surpassing the warmth threshold and none falling below the cool threshold, most areas maintain a comfortable thermal range for occupants throughout the day.

Figure 58 illustrates the hourly variation of average PPD values across different locations. The horizontal dashed line in the Figure 58 represents the acceptable threshold, within which a maximum of 10% of individuals would experience discomfort due to excessive warmth or coldness. Figure 58 illustrates that the average PPD values exceeded the acceptable 10% threshold at specific intervals. Specifically, at 15:00, room 14 recorded an average PPD of 14% and then decreased to 10.67% by 17:00. Furthermore, at 16:00, room 13 showed a PPD average of 11%. The computer lab common area also recorded 11.5% at 15:00.

Figure 59 also illustrates the hourly variations in average AMV values across different locations. According to Figure 59 from 14:00 to 15:00, there was an increase in the average (AMV) in the computer lab common area, room 14, and the waiting area. This rise in AMV suggests a shift towards a higher thermal perception among the occupants in these areas. In contrast, within the same timeframe, there was a decline in the average AMV values of the kitchen area, suggesting a cooler sensation felt by its occupants.

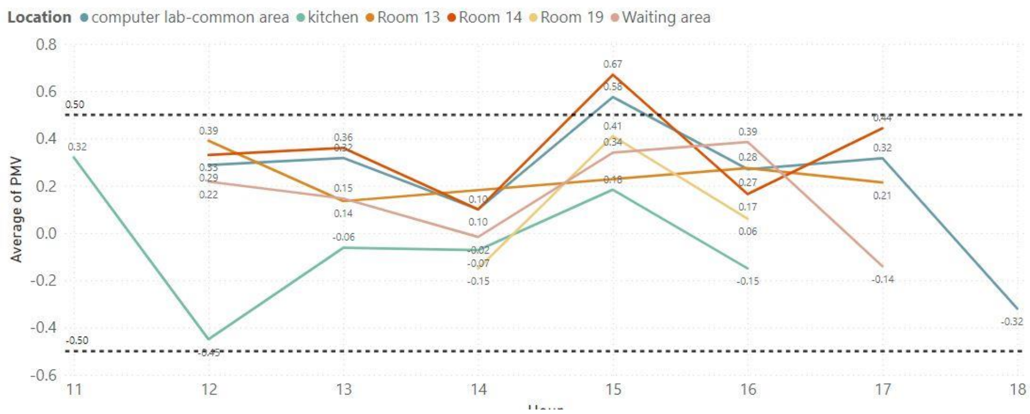

Figure 57:Hourly variation of average PMV values across different locations (Source: Author)

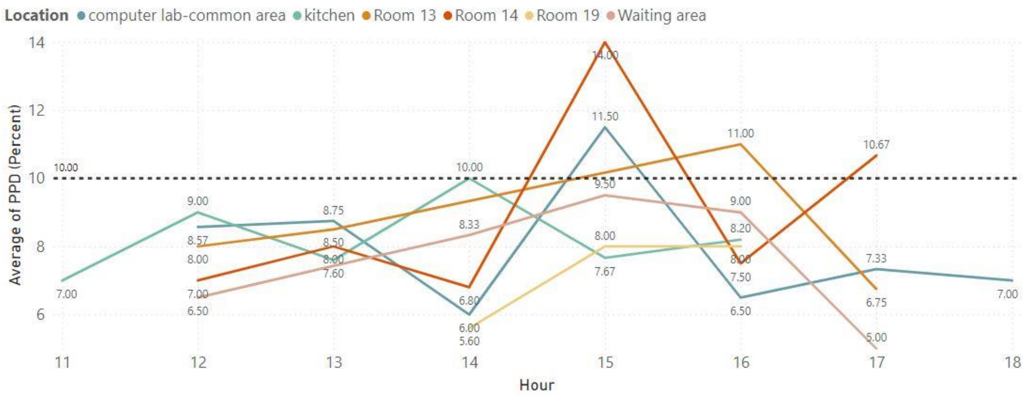

Figure 58:Hourly variation of average PPD values across different locations (Source: Author)

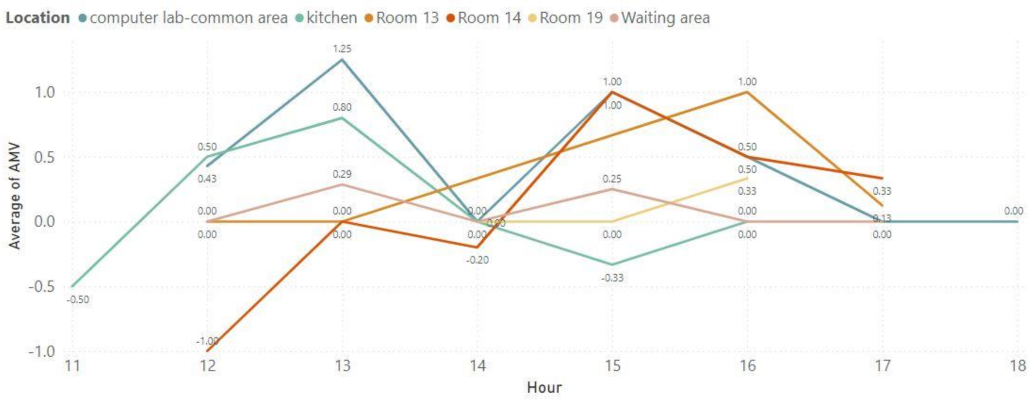

Figure 59:Hourly variation of average AMV values across different locations (Source: Author)

6.2.3.2. Perception of IAQ parameters

- **Relationship between measured IAQ parameters and occupant perceptions of IAQ parameters**

A more comprehensive understanding of the indoor environment's dynamics can be achieved by comparing the objective measurements of IAQ with the subjective perceptions reported by occupants. Table 29 displays the results of an investigation on the correlation IAQ parameters, and occupants' perceptions of temperature, air humidity, air freshness and pollution. The results in Table 29 showed that there was a positive correlation (p-value < 0.05) between measured temperature and occupant perception of air temperature, while there was no significant correlation between perception of temperature and other IAQ parameters such as humidity, pressure, PM2.5, PM10 and VOC concentration. The statistically significant Spearman correlation between the recorded temperature and occupants' perceptions indicates a consistent and dependable association. As the indoor temperature increases, the occupants constantly perceive the air temperature as shifting closer to "very warm." This correlation highlights the alignment of objective temperature measurements with subjective occupant perceptions. In contrast, occupants' perceptions of air humidity, freshness and pollution were not significantly correlated with IAQ measurements.

		Objective Measurement						
		Temperature	Humidity	Pressure	PM2.5	PM10	VOC	Occupant Count
Subjective Measurement	Perception of air temperature	0.195*	-0.112	0.146	0.073	0.112	0.182	0.161
	Perception of air humidity	-0.043	0.101	0.189	0.181	0.209	0.082	0.029
	Perception of air freshness	-0.104	-0.033	-0.102	0.082	0.053	-0.058	-0.136
	Perception of air pollution	0.003	-0.09	-0.065	-0.058	-0.058	-0.101	-0.047

Table 29: Correlation of objective IAQ measurements with subjective occupant perceptions

**Indicates significant correlation at the 0.05 level (two-tailed).*

6.3. Discussion, Conclusion and Limitations

This study was conducted to address the lack of measurable understanding regarding the complicated relationships between IAQ, EAP, and occupant perceptions of comfort in various architectural and spatial configurations in a university campus building. Examining the IAQ and thermal comfort data coupled with survey responses from occupants in specific spatial arrangements demonstrated a noteworthy association between IAQ perceptions, occupants' thermal comfort, gender, and space characteristics.

This type of research is crucial in understanding the complex interplay between environmental factors, human perceptions, and spatial design, particularly in the context of indoor environments where people spend a significant amount of their time. The findings could have important implications for designing and maintaining buildings that promote both physical health and subjective well-being for their occupants.

The results of this study revealed several key insights. These findings shed light on critical aspects influencing PM2.5 concentrations, occupants' perceptions of air quality and associated discomfort symptoms, the intricacies of thermal comfort in relation to PMV and AMV, as well as the nuanced nature of occupant discomfort across various spatial zones. The subsequent sections will delve into each of these aspects, elucidating the study's substantial contribution to comprehending the complex dynamics that shape indoor environments and influence the well-being of building occupants.

6.3.1. Identification of key factors affecting the fluctuations in PM2.5 concentrations

In this study factors that have the potential influences on PM2.5 concentrations inside and outside were examined. One of the primary factors that significantly influenced PM2.5 concentration variations was the meteorological conditions. Examining multiple meteorological parameters, such as humidity, temperature, and pressure, revealed notable and meaningful insights. According to the result of this study, a strong and statistically significant correlation ($r = 0.45$, $p < 0.05$) was observed between outdoor PM2.5 concentrations and humidity levels (Table 14). The research indicates that changes in humidity are linked to fluctuations in outdoor PM2.5 levels, thereby impacting indoor concentrations. The subsequent event highlights the importance of implementing comprehensive strategies to mitigate the negative impacts of outdoor pollutants on indoor settings and demonstrates the significant influence of outdoor meteorological factors on IAQ. Previous studies have demonstrated the established correlation between humidity variations and outdoor PM2.5 levels (Y. Cheng et al., 2015; Luo et al., 2021; X. Wang et al., 2021; X. Zhang et al., 2022). For example, a recent study (X. Wang et al., 2021), examined the associations between meteorological variables and PM2.5 levels in the Fuling District of

Chongqing with the aim of predicting PM2.5 concentration using an artificial neural network. The findings showed that relative humidity significantly impacts PM2.5 concentration since it affects particle settling and diffusion. Low humidity decreases diffusion interference, while high humidity limits vertical diffusion due to increased particle weight and the possibility of fog formation (X. Wang et al., 2021). Additional studies conducted in China have also examined the relationship between PM2.5 pollution levels and specific meteorological conditions, identifying clear temporal-spatial trends (Luo et al., 2021). This study has identified a significant positive association between relative humidity and PM2.5 levels, with elevated humidity levels contributing to increased pollution concentration. The study also highlighted seasonal severity, particularly in autumn and winter, and identified low wind speed and high humidity as critical factors exacerbating PM2.5 pollution (Luo et al., 2021).

Research findings indicate that street canyon configurations substantially affect air pollution dispersion and alter the direction and velocity of wind flow in urban environments (Farrell et al., 2015; Guo, Xiao, et al., 2023; Han & Lee, 2023; Huang et al., 2021). In particular, street canyons restrict air circulation, contribute to the accumulation of hazardous pollutants such as PM2.5, and thus trap pollutants at ground level and increase the potential of pollutants penetrating into the buildings through the entrances (Ai & Mak, 2015; Cui et al., 2020; Fithian, 2019). According to the result of this study, another influential factor affecting PM2.5 concentration variations and, consequently, its indoor penetrations was the building's architectural configuration, features such as the setback from the street and the covered entrance area. The result of this study revealed that such architectural design features contributed to the high PM2.5 accumulation, with concentrations averaging 1.6 times higher than in adjacent open streets (Figure 27). According to the studies (Cui et al., 2020, 2021; A. M. Hassan et al., 2020; Jon et al., 2023; Z. Li et al., 2022; Llaguno-Munitxa & Bou-Zeid, 2018; Yuan et al., 2014), the observed increase in pollution exposure levels can be primarily attributed to building layouts, such as setbacks, balconies, wing walls and other envelope features that limit wind movement and change its direction, accumulating pollutants. For example, the result of one study (Z. Li et al., 2022) has shown that how horizontal and vertical setbacks can lead to variations in outdoor air pollution concentrations in the high-rise and low-rise street canyons. According to (S. Li et al., 2023), scholarly investigations conducted at the micro-building scale emphasize the significance of a building's geometric characteristics in mitigating air pollution. These studies focus on how various building design aspects, from the general architectural layout to specific façade details and the level of enclosure, influence ventilation and the deposition of air pollutants (S. Li et al., 2023; Murena & Mele, 2016).

The result of the analysis in this study indicated that there were notable temporal variations in PM2.5 concentrations, such as specific periods within a day and differences between weekdays and weekends. As presented in Figure 29, there was a notable increase in the average levels of PM2.5 during the morning, with a clear peak observed between 9 and 11 am. This observed pattern can correlate with the heightened level of vehicular activity often associated with morning rush hours. The morning PM2.5 rise pattern align with prior research (Collado et al., 2023; Dionisio et al., 2010; Y.-J. Hu et al., 2018; Jung et al., 2024; J. F. Tsai & Lin, 2023), indicating that the daily variations in outdoor particle levels in urban areas are mainly influenced by vehicle emissions, specifically during rush hour traffic(Y.-J. Hu et al., 2018; V. Singh et al., 2020). In a study (Cooper et al., 2021) investigating the impact of a specific air purifier on reducing indoor PM2.5 concentrations, it was observed that indoor PM2.5 levels tended to follow variations in outdoor PM2.5 levels. Furthermore, notable peaks in PM2.5 concentrations were observed during morning and evening hours, which can be attributed to increased traffic flow during rush hour times. This study found that the levels of outdoor PM2.5 at the experiment places reached their highest level at approximately 8 am, potentially associated with peak morning vehicle traffic (Cooper et al., 2021). Another study (Sharma & Balasubramanian, 2019) investigating indoor human exposure to traffic-related PM2.5 in residential apartments revealed that the concentration levels of PM2.5 particles indoors and outdoors were approximately 1.4 times greater during the morning rush hours of 8-10 am compared to the evening rush hours of 6-8 pm.

The present investigation also discovered that no statistically significant association was observed between the levels of PM2.5 concentrations and the number of occupants of any specific area. Based on current studies (Z. Li et al., 2023; Yun & Licina, 2023), the impact of occupancy factors, including the number of occupants and their activities, on IAQ parameters, specifically particle concentration demonstrates complicated dynamics that might differ within specific settings. Essentially, there may be a correlation between PM2.5 concentration and occupancy level in a specific setting (Y. Zhou & Yang, 2022b); however, no noticeable relationships could be observed in a different scenario (Szczurek et al., 2018). One study (Y. Zhou & Yang, 2022a) conducted to propose the PM predictor considering occupancy level found a strong relationship between occupancy level and indoor PM2.5 concentration in a hospital setting. The findings of this study indicated that the level of occupancy in the hospital setting had a more significant impact on indoor PM2.5 concentrations compared to meteorological data (Y. Zhou & Yang, 2022a).

Regarding the occupant activity, a study (Szczurek et al., 2018) investigating the correlation between occupant activities and measurable factors of IAQ in residential setting, revealed that temperature, relative humidity, and CO2 concentration were IAQ parameters that were the most influenced by occupant activities, whereas pressure was less frequently affected. On the other hand, the quantity of particles showed a low sensitivity to occupants' activities in this setting. Furthermore, a study (Z. Li et al., 2023) comparing the IAQ parameters in six offices in Beijing, showed that occupant activities contributed to a rise in periodicity of indoor PM2.5 by elevating the infiltration factor. Considering the educational settings, one study examining the correlation between indoor PM2.5 concentration and student behaviors in classrooms has revealed that alongside outdoor PM2.5 levels and fluctuations in meteorological conditions, PM2.5 concentrations in the classroom are affected by student behaviors (Yuhe et al., 2021). The significance of integrating accurate occupancy data into the space use plan and HVAC system schedule has been evaluated (B. Yang et al., 2023). The findings of one study indicated that reduced occupancy levels generally result in enhanced thermal comfort, higher energy saving, and more straightforward maintenance of optimal IAQ (B. Yang et al., 2023).

6.3.2. Occupants perception of air quality and experience of discomfort symptoms

The results of the correlation analysis in this research revealed a robust positive link between the quantity of discomfort symptoms reported by individuals and particular factors. These factors included the amount of time occupants spent in the building each week, the time of day spent, particularly between 12:00 and 15:00, as well as gender, specifically female. (Table 22 and Table 23).

Based on the analysis of the building property planning data and the assessment of space occupancy rate, it was found that the time frame from 12:00 - 15:00 generally demonstrates the highest levels of building usage and occupancy. According to previous studies (Sarkhosh et al., 2021), an increase in occupancy can significantly raise the prevalence of Sick Building Syndrome (SBS) symptom and discomfort symptoms among occupants. Furthermore, this particular afternoon peak period usually aligns with the peak temperatures recorded during the day, resulting in the need for higher cooling and ventilation to maintain acceptable IAQ and thermal comfort. These demands can potentially challenge the efficiency of the HVAC systems and cause discomfort for occupants. One study examining the IAQ of office buildings discovered that the concentration levels of air pollutants fluctuate depending on the time of day, with poor IAQ conditions observed in the morning and afternoon (Z. Cheng et al., 2022). This study additionally suggested that the increased number of occupants' dissatisfaction with the air quality in the afternoon could firstly be caused by inadequate ventilation since the air pollutant concentration level was at its peak in the afternoon, and secondly could be the result of the short period of fatigue just after lunch, which may worsen the subjective discomfort of occupants (Z. Cheng et al., 2022). It should be noted that, while post-lunch fatigue has been highlighted in similar studies as a factor contributing to afternoon discomfort, an additional observation was presented in this study. Specifically, the highest air pollution levels were recorded in the foyer during lunchtime, likely due to increased foot traffic and frequent door openings as occupants moved in and out.

Results of this study, indicated a statistically significant association between gender and the incidence of discomfort symptoms. According to the results and as seen in Figure 41 and Table 23, more female participants than male participants reported experiencing discomfort symptoms, and regarding the type of experienced symptoms, female participants reported higher symptoms than males across most of the various symptom categories. The finding of a statistically significant association between female gender and the occurrence of discomfort symptoms are consistent with the results of other studies (Afzan Zainal et al., 2019; Fahad Alomirah & Moda, 2020; Sayan & Dülger, 2021; Tsantaki et al., 2022), and highlights the significance of incorporating gender-specific variables for investigating discomfort-related experiences. Similarly, the results of one study (Tsantaki et al., 2022) investigating the perceived IAQ and sick building syndromes at a university in Greece showed that female occupants complained about perceived IAQ more frequently than male occupants. In this study, women reported at least one SBS symptom more frequently than men did and had lower "Discomfort Scale" scores. Additionally, women reported most of the SBS symptoms examined (Tsantaki et al., 2022). The outcomes of the study showed that by incorporating gender-specific considerations into building code standards, regulatory bodies can play a pivotal role in promoting equitable and inclusive building practices, thereby fostering environments that prioritize the health, safety, and comfort of all building users. This integration can contribute to the overall enhancement of building design and operation, leading to improved indoor environmental quality and occupant satisfaction.

The results presented in Table 26 showed that the occupants' perceptions of air pollution and air freshness were positively correlated with the number of discomfort symptoms reported. To clarify, there was generally an increase in the number of discomfort symptoms reported by individuals if they perceived the air was less fresh or more polluted. This finding that signify the important role of IAQ in buildings and the health and comfort of occupants, was highlighted in one similar study (Thach et al., 2019). The study (Thach et al., 2019) evaluating the perceived IEQ showed that among all IEQ parameters, an increase in perceived satisfaction with IAQ was associated with a decreased risk of sick building syndrome and discomfort symptoms in underground and aboveground workspaces. The study's findings indicate that, for combined workspaces (above ground and below ground), a 1-unit rise in the perceived IAQ and thermal comfort scores would be correlated to a 7% and 6% decrease in SBS symptoms, respectively.

According to the results of this study, a statistically significant correlation was identified between the recorded temperature and occupants' perceptions of temperature (Table 29). In other words, as the indoor temperatures increased, the occupants consistently perceived the air temperature as gradually becoming "very warm." This association underscores the alignment between objective temperature measurements and subjective occupant feelings regarding temperature in this study. In contrast, a significant misalignment occurred between the occupants' subjective perception of temperature and their expressed experience of discomfort symptoms. Finding of this study revealed that a significant proportion of the participants perceived the air temperature as "acceptable" while reporting an increased frequency of discomfort symptoms compared to the other participants. Results of occupants' perception of temperature highlighted two key points. Firstly, the study showed that the feedback provided by occupants offers valuable insights that could be considered a valid indicator for evaluating IAQ. Secondly, this study indicated that the root cause of occupants' discomfort symptoms might go beyond the influence of temperature, and other parameters collectively would be responsible for their discomfort experience. Considering this finding and the relation of objective and subjective measurements of temperature and prevalence of discomfort symptoms, studies have shown different results. One study (Torriani et al., 2023) investigated the correlation between perceived control, thermal comfort, and IAQ within school buildings. The findings of this study indicated that the occupants' perception of IAQ was negatively correlated with both the operative temperature and the concentration of CO2 (Torriani et al., 2023). In other words, elevated temperatures and increased CO2 levels were associated with individuals perceiving the air as less fresh and unacceptable (Torriani et al., 2023).

In conclusion, this comprehensive analysis emphasizes the significance of integrating occupants' feedback as a crucial indicator for evaluating IAQ and comfort. By acknowledging the multifaceted nature of discomfort experiences, building professionals and designers can work towards creating more inclusive and accommodating indoor environments that prioritize the diverse needs and experiences of all occupants.

6.3.3. Thermal comfort and discrepancy between PMV and AMV

A widely used metric to evaluate the indoor thermal comfort level is PMV. Recent studies, however, have demonstrated that there would be considerable differences between the PMV and AMV, which means that how building occupants perceive the indoor thermal comfort conditions does not correspond to what is predicted (J. T. Kim et al., 2015).

Considering the comparison of PMV and AMV, the result of this study revealed two key findings. The first finding is that there was a discrepancy between PMV and AMV, and generally occupants had warmer sensation of their surrounding environment. This discrepancy was also reported by other studies (J. T. Kim et al., 2015). For instance, one study (El Akili et al., 2021) discovered that both male and female healthcare building occupants experienced a cooler indoor environment than Fanger's model measurements predicted.

The second finding is that even though the calculated PMV indicated acceptable thermal comfort, it did not accurately reflect the occupants' comfort levels, as even within this comfort range, half of the occupants reported experiencing at least one discomfort symptom (Figure 53).

The results also highlighted that the number of female occupants who reported discomfort in this scenario was twice that of male participants (Table 27). The examination of occupant thermal comfort in the existing literature has highlighted a notable discrepancy between PMV and AMV values, which can be attributed to various personal and environmental variables such as human psychology, thermal adaptation of occupants, building ventilation mode or even the limited accuracy of PMV model (Çeter et al., 2023; Jung et al., 2024; Kramer et al., 2023; Özbey et al., 2023; Özbey & Turhan, 2023). Among all the variables, gender distinctions have been a focal point of investigation in numerous studies (Aqilah et al., 2023; Chaudhuri et al., 2018; Indraganti & Humphreys, 2021; Karjalainen, 2012; J. Kim et al., 2013; H. Liu et al., 2018). According to previous studies (J. Hu et al., 2022; Indraganti & Humphreys, 2021), it has been observed that females generally demonstrate more sensitivity to ambient air temperatures in comparison to males. Consequently, they often express higher levels of dissatisfaction with indoor thermal conditions (Asif et al., 2022). One research study (Indraganti & Humphreys, 2021) examined the influence of sex, age, and body mass index on subjective perception of thermal comfort and IEQ satisfaction in Asian offices. Based on thermal comfort surveys conducted in Qatar, India, and Japan, it has been identified that women are more sensitive to temperature, express more significant levels of thermal dissatisfaction, and tend to experience colder sensations than men (Indraganti & Humphreys, 2021). These findings suggest that such gender differences in thermal perception may affect productivity and highlight the significance of including female perceptions in environmental design and establishing effective IEQ complaint systems. Furthermore, this research underscores the significance of adopting women's thermal comfort preferences as a reference point, which can improve comfort for a broader range of occupants and contribute to establishing IEQ standards and occupant management approaches (Indraganti & Humphreys, 2021).

Gender-based differences in thermal sensation and temperature sensitivity extend beyond biological sex (Q. Zhao et al., 2023). Studies have explored the correlation between achieving a neutral thermal sensation for each gender in different ambient temperature conditions and the varying sensitivity observed in different body areas (Indraganti & Humphreys, 2021; H. Liu et al., 2018; Q. Zhao et al., 2023). For instance, a research (Q. Zhao et al., 2023) has shown that female skin temperature exhibits a greater sensitivity to thermal sensations when exposed to local cooling than male skin. Notably, variations in sensitivity have been observed in specific body areas, such as the upper arm in females and the forearm in males (Q. Zhao et al., 2023). Furthermore, the findings of another study (Chaudhuri et al., 2018) examining the thermal responses of individuals based on gender in relation to 12 different clothing combinations and four varying air temperatures (10, 16, 22, and 28 °C) have indicated that women generally show greater sensitivity to colder thermal conditions in comparison to males. Additionally, the study revealed variations in thermal adaptation to cold across different body parts and genders. Specifically, women have narrower, tolerable local skin temperature ranges at the arms but wider ranges at the legs than males (Chaudhuri et al., 2018).

In conclusion, the disparity between the PMV and the AMV as highlighted in this study underscores the complexity of assessing indoor thermal comfort solely through traditional metrics. Notably, the study emphasizes the significant gender-based differences in thermal perception and sensitivity, with women consistently exhibiting heightened sensitivity to temperature variations and reporting higher levels of discomfort compared to men. Understanding these nuanced gender-specific responses is crucial in developing effective strategies to address thermal comfort and promote the well-being of all occupants, regardless of gender.

Moving forward, it is imperative for building professionals and designers to consider a holistic approach that integrates diverse factors influencing thermal comfort, including psychological aspects, individual adaptation, and specific environmental parameters. By incorporating these multifaceted insights into the design and management of indoor environments, it becomes possible to establish more inclusive and responsive thermal comfort standards, ultimately fostering healthier and more comfortable built environments for all occupants.

6.3.4. Exploring occupant discomfort in different spatial zoning

This study evaluated the occupants' perception of IAQ and their comfort level in spaces with different characteristics and proximity to vehicle traffic. To better evaluate, the study classified multiple spaces into two distinct categories, namely zone 1 and zone 2. Zone 1 was located at the main entrance from the street and, due to its immediate proximity to traffic and direct exposure to vehicle emissions, was defined as a "high-exposure" space. In this high-exposure space, it was supposed that the occupants' perceptions of comfort and air quality would be highly impacted, and possibly the count of occupant-reported discomfort symptoms would be higher. In contrast, the spatial orientation of zone 2 within the building provided some protection against direct and immediate exposure to street-level vehicle traffic. Zone 2 was buffered from immediate exposure to vehicle traffic and outdoor environmental factors and thus was identified as a "lower-exposure" area. It was supposed that the in-between layout of zone 2 potentially mitigates the penetration of pollutants, and due to the distance and physical barriers from the main entrance, occupants in this zone might experience less discomfort symptoms.

One crucial discovery from this research was the notably higher and more frequent occurrence of discomfort symptoms in zone 2 when compared to zone 1 (Figure 43, Figure 44 Figure 45). A potential explanation for this finding would be the influence of other IEQ parameters and the presence of indoor discomfort sources, which were much more perceived than outdoor traffic-related air pollution, adversely affecting occupants' comfort levels and a higher prevalence of discomfort symptoms. Similar studies have found that building occupants could experience discomfort associated with air quality, even though pollution measurements remain below or slightly exceeding standard thresholds (Y. K. Kim et al., 2022). For instance, a research study (Y. K. Kim et al., 2022) assessed IEQ and occupant satisfaction in offices within a university building and focused explicitly on monitoring PM2.5, PM10, CO2, and TVOC levels for the IAQ assessment. The investigation revealed that IAQ issues were insignificant since just 1% of the PM2.5 measurements slightly exceeded the acceptable thresholds. Nevertheless, a significant proportion of the participants, over 45%, indicated their dissatisfaction with the air quality. They specifically mentioned experiencing "stuffy air," a frequently reported symptom associated with high particulate matter (PM) levels (Y. K. Kim et al., 2022). This study suggested that these discomfort symptoms could be attributed to other IEQ parameters, spatial characteristics, the filtration efficiency and maintenance of the HVAC system, or a potential combination of these variables (Y. K. Kim et al., 2022).

Studies have indicated that multiple variables could play a significant role in the comfort levels that occupants experience in spaces, and these variables typically vary depending on the specific spaces or zones (Parkinson et al., 2023). Spatial characteristics, such as space area and volume, ceiling height, window-wall ratio, furniture arrangement, specific types of equipment such as printers, and the materials and fabrics used within the space, have been considered influential variables on occupant IEQ perception (Frontczak et al., 2012; Parkinson et al., 2023). Furthermore, the type and performance of the HVAC system, occupancy density, and the overall utilization plan of the space are all influential (Parkinson et al., 2023). One study (Bortolini & Forcada, 2021) examined how building characteristics, space utilization, and occupant categories affect the perception of IEQ. This study demonstrated significant disparities in IEQ perceptions between student-occupied venues such as classrooms and lecturers' and administrative staff facilities (Bortolini & Forcada, 2021). According to this study, the tasks performed in these spaces and occupancy density potentially were the main factors affecting occupants' perceptions of IEQ (Bortolini & Forcada, 2021). In the present study, zone 1 was notable for its higher ceiling height, lower occupant density, shorter average time spent by occupants, and a distinct utilization pattern compared to zone 2. Specifically, in zone 2, occupants tend to work with computers and printers for extended periods.

In summary, the research illuminates the complexities surrounding occupants' perception of IAQ and comfort levels in spaces with differing characteristics and exposure to outdoor environmental factors, particularly vehicular emissions. The contrasting experiences between zone 1 and zone 2 highlight the multifaceted nature of indoor environmental quality, where various indoor parameters can significantly influence occupants' comfort levels, often surpassing the impact of outdoor air pollution. By prioritizing occupant comfort through a holistic understanding of the complex dynamics at play, the built environment can be transformed into a more accommodating and sustainable space for all occupants.

6.4. Conclusion

This chapter concludes the thesis by reviewing the research gap and the research questions, the achievement of the research objectives, highlighting the limitations, and suggesting directions for future research.

6.4.1. The research gap and the research questions

The literature review highlighted significant gaps regarding evaluating the temporal and spatial correlations between IAQ and occupancy comfort in a campus building. There is a major gap in the literature addressing the significance of using localized sensors for IAQ assessments and comparing measurements of IAQ parameters from local sensors with RAQMS data. Recent IAQ assessment studies extensively rely on RAQMS data to evaluate the impact of EAP on IAQ. As a result of such an approach, not only is the accuracy of evaluations regarding the influence of outdoor pollutants on IAQ questioned but local meteorological factors and urban design elements, such as green spaces and street canyons, are also neglected. There was also a lack of assessing IAQ simultaneously across spaces with different spatial configurations and occupancy characteristics within the same microenvironment. Even though many studies have been conducted on IAQ assessment, a more detailed investigation needs to be conducted on how EAP influences IAQ and occupant perceptions in areas that share the same microenvironment but differ in spatial layouts and occupancy characteristics.

The previously identified research gaps have led to the formulation of three central research questions. The first question examines whether RAQMS can accurately measure outdoor pollution levels at a neighborhood scale. It also examines the importance of utilizing local sensors. The second question investigates the correlations between IAQ and occupants' perceptions in spaces with various spatial configurations. The third question explores how different levels of outdoor environmental pollution could affect IAQ and occupants' perceptions of comfort in different proximity to pollution sources. Therefore, this study aimed to comprehensively analyze these aspects to understand better how an IoT-based monitoring system, combined with occupant surveys, can be used to evaluate the temporal and spatial correlations between IAQ and occupant perceptions of comfort in a university campus building.

6.4.2. The achievement of the research objectives

This study aimed to apply an IoT-based monitoring system coupled with an occupant survey to evaluate the temporal and spatial correlations between IAQ, and occupant perceptions of comfort in a university campus building. This aim was pursued through the three following research objectives: (1) to assess the significance of localized sensor measurements compared to data from RAQMS, (2) to identify the correlations between IAQ measurements and occupants' perception in spaces with various spatial configurations, and (3) to determine the influences of an outdoor EAP source on the IAQ and occupants' perception of comfort in different proximity and architectural configurations.

In this study, a quantitative research approach was used to achieve the objectives through quasi-experimentation and survey design. In the following section, objectives and their corresponding outcomes are presented.

Assessing the significance of localized sensor measurements compared to data from RAQMS

A comparison of PM2.5 concentration measured by the local sensors with the nearest Bureau of Meteorology air quality fixed monitoring station was conducted to achieve this objective. The comparison results indicated that the local outdoor sensor averaged approximately 2.5 times higher PM2.5 levels over the study period than the Bureau of Meteorology's fixed monitoring station. Regional air quality monitoring stations may not accurately reflect the concentrations of PM2.5 in microenvironments or neighbourhoods since they typically operate at a fixed height and location. The fixed regional monitoring station may also fail to identify the source of PM2.5 emissions at a particular location, such as nearby industrial facilities or traffic congestion. Thus, the fixed regional monitoring station cannot be chosen as a reference for the local outdoor PM2.5 concentration measurement, except for high peaks and general trends, and to accurately measure PM2.5 concentration levels in urban microclimates, it is essential to use local outdoor sensors.

In other words, urban-level fixed-site monitoring stations have a scattered distribution. They are insufficient for analyzing the detailed spatial and temporal patterns of air pollution and its sources at a local scale. Therefore, mobile microclimate sensors, with their ability to measure PM2.5 concentrations at any location, provide a more accurate representation of the microenvironment's air quality compared to regional fixed monitoring stations, which measure PM2.5 concentrations over a larger area using stationary equipment.

Furthermore, studies at regional scales may overlook some local factors that impact PM2.5 concentration variations. For example, meteorological conditions in the local area, temperature inversions that trap pollutants near the ground, and neighbourhood design elements such as green spaces and street canyons can influence the microclimate in an urban setting.

In this study, the most critical factors affecting PM2.5 concentrations were identified. Firstly, there was a significant association between outdoor PM2.5 concentrations and humidity levels, emphasizing how local meteorological conditions influence outdoor and indoor pollution dynamics. Secondly, it was also found that architectural features within buildings, particularly those associated with street canyon formations, such as setbacks and covered entrances, play a critical role in the accumulation of PM2.5 particles. Furthermore, by analyzing temporal variations in PM2.5 concentrations, this study illustrates that vehicular traffic has a significant impact on particle accumulation, notably during peak morning hours.

Overall, the outcomes support the significance of local sensing and urban microclimate changes and highlight that any technique to assess indoor space PM2.5 exposure considering outdoor PM2.5 levels must include local and microclimate measurements.

7. *Identifying the correlations between IAQ measurements and occupants' perception in spaces with various spatial configurations*

In order to achieve this objective, data from the occupant survey and the property plan analysis were analyzed. Based on personal factors and occupancy patterns, this analysis explored the correlation between occupants' perception of IAQ and discomfort symptoms. This objective was also accomplished by examining the correlation between recorded IAQ parameters and occupants' perceptions of these parameters. In other words, the alignment of subjective and objective measurements and the predicted and actual occupants' thermal comfort perceptions were evaluated.

Occupant perception of IAQ, and experience of discomfort symptoms

This study discovered considerable findings regarding occupant perceptions of IAQ, and the experience of discomfort symptoms. It was found that discomfort symptoms were strongly correlated with variables such as occupancy duration, specific occupancy periods, and gender. It should be noted that disparities observed in the reported levels of discomfort among different genders highlight the need for more inclusive and varied IAQ standards and guidelines. These findings shed light on the complex nature of occupant perceptions of IAQ and comfort levels.

Alignment of subjective and objective measurements

This study found two critical insights regarding the alignment of subjective and objective measurements and reported discomfort symptoms. Firstly, the subjective and objective temperature measurements were aligned, revealing that occupant perceptions are crucial to assessing IAQ and thermal comfort. Secondly, this study found a direct correlation between occupants' perception of air pollution and freshness and the reported discomfort symptoms, indicating that a negative assessment of IAQ results in increased discomfort. As a result of these findings, it is suggested that building management systems incorporate feedback from occupants for a better understanding of IAQ and more responsive control.

Discrepancy between PMV and AMV

This study identified a significant discrepancy between the Predicted Mean Vote (PMV) —

a widely utilized model for estimating thermal comfort — and the Actual Mean Vote (AMV), representing building occupants' real-life thermal experiences. The disparity between anticipated comfort levels and actual reported experiences, particularly among females, indicates that existing models and standards may not comprehensively consider all the influential factors on human thermal comfort perceptions. This finding poses a significant challenge to the widely used metrics for assessing and ensuring occupant comfort and health.

Determining the influences of an outdoor environmental air pollution source on the IAQ and occupants' perception of comfort in different proximity and architectural configurations

Spatial analysis within building zones revealed surprising insights, with higher discomfort levels reported in areas less exposed to external pollution. This finding highlights that various factors collectively affect occupants' perception of comfort. Critical influential factors include the architectural design attributes of the space, interior layout, equipment use, HVAC system effectiveness, and occupants' specific activities. Moreover, indoor sources of discomfort significantly outweigh the impact of external, traffic-related pollution on occupant comfort. As a result of this observation, facility management should adopt a comprehensive approach incorporating indoor and outdoor variables into its planning and execution.

It is also noteworthy that the study revealed that PM2.5 levels in indoor settings were influenced by two distinct circumstances: one occurring during hazard reduction burning events and the other in the presence of typical traffic-related pollution conditions. During hazard reduction burning events, vulnerabilities in HVAC systems were observed, resulting in a notable increase in the PM2.5 I/O ratio. In contrast, on typical days, traffic-related pollution primarily influenced the PM2.5 levels, with spaces closer to the busy street experiencing more substantial penetration. The observations were strengthened even more through an in-depth investigation, explicitly focusing on the severe hazard reduction events in September 2023. It was discovered that elevated PM2.5 levels were observed in all indoor spaces during these extreme occurrences, regardless of their proximity to the street.

These findings highlighted the complexity of managing IAQ in the face of external environmental challenges. They also highlighted the importance of adopting comprehensive facility management strategies that integrate both indoor and outdoor environmental considerations. This approach might involve implementing robust ventilation systems, effective air filtration mechanisms, and proactive outdoor air quality monitoring. Additionally, implementation plans and protocols will also need to be developed to mitigate the impact of fluctuations in external environmental conditions on IAQ. Additionally, integrating smart building technologies and real-time monitoring systems can provide invaluable insights into the dynamic interaction between indoor and outdoor environments. By leveraging data-driven solutions, facility managers can make informed decisions to optimize IAQ, enhance occupant comfort, and create healthier and more sustainable educational environments.

6.4.3. Highlighting the limitations

Despite providing valuable insights, the present study has several limitations requiring further investigation. One of the primary obstacles to occupant comfort assessment was the limited timeframe. Future studies should explore daily comfort dynamics over more extended periods and include multiple survey intervals throughout each day to provide a more comprehensive picture of daily comfort dynamics. Furthermore, while adequate sample sizes and pertinent sensor data were used to draw reliable conclusions, further improvements are still possible. By increasing the sample size, future studies can generate more refined and detailed results.

Furthermore, student engagement was challenging because of academic commitments, which impacted the quantity and diversity of data collected. In addition, there were equipment limitations, such as sensor accuracy decreasing over time. The lack of specialized instruments also restricted the ability to conduct comprehensive environmental assessments, such as wind velocity measurements. Addressing these limitations in future investigations is essential to ensure validity and comprehensiveness.

Further, this study examined the impact of two specific architectural features, setbacks and covered entrances, on IAQ within street canyon environments. As a result, these features can influence the pollutants' dispersion and airflow patterns within the canyon. While this research offers valuable insights into the influence of architectural features on IAQ, it is essential to acknowledge that several other architectural attributes and aspects of urban design also significantly influence street canyons and the dynamics of pollutants within them. The attributes to consider in IAQ assessment studies include building heights, orientations, facade materials, roof shapes, overhangs, balconies, street width, traffic flow, roadway design, greenery, trees, urban layouts, canyon aspect ratios, and local topography. Furthermore, these architectural attributes may affect IAQ differently depending on local conditions, weather patterns, and pollution sources. It is worth noting that the investigation of these factors was beyond the scope of this study. Considering these limitations, more research is needed to explore additional architectural features and contexts of IAQ in street canyon environments. Despite these limitations, it is appropriate to acknowledge the contribution made by this study to the understanding of the complex interplay between architectural design, urban air quality, IAQ, and occupant comfort.

6.4.4. Directions for future research

This research establishes a foundation for future IAQ monitoring investigations in built environments and urban settings. The results of such investigations will help us understand how architectural design and IoT monitoring systems can be combined effectively to manage IAQ and improve comfort for occupants. According to the findings of this study, future research should adopt an interdisciplinary approach, integrating architectural, environmental science, urban planning, and public health perspectives. The critical findings outlined in this thesis have a significant impact on improving the well-being of individuals and communities in indoor environments, so future studies should incorporate a comprehensive examination of public health effects as part of their focus. A broader scope would allow us to investigate how IAQ changes affect different health outcomes directly. Formula-based IAQ metrics may measure the adverse health effects of pollutants on occupants. The metrics include Disability-Adjusted Life Years (DALYs), Hazard Quotients (HQs), and UNEP-SETAC toxicity models (USEtox). In addition, CRinh and Human Health Damage metrics will be used to evaluate lifetime cancer risks. In the future, studies need to investigate the long-term health impacts of exposure to different levels of indoor pollutants, examine how various strategies for improving indoor air quality affect health and evaluate the psychological and physiological responses to indoor environmental conditions. By conducting such studies, we will gain a better understanding of the direct health effects of IAQ and valuable insight into how to improve community health policies and practices. Furthermore, it is critical to investigate advanced IAQ monitoring systems and efficient solutions in areas where PM2.5 levels are elevated during events such as hazard reduction burnings. These solutions include air purifiers, HVAC filtration systems, and particulate matter-blocking devices.

Future studies will contribute significantly to enhancing indoor environments and ensuring the health and comfort of building occupants by addressing the limitations and using a comprehensive research framework.

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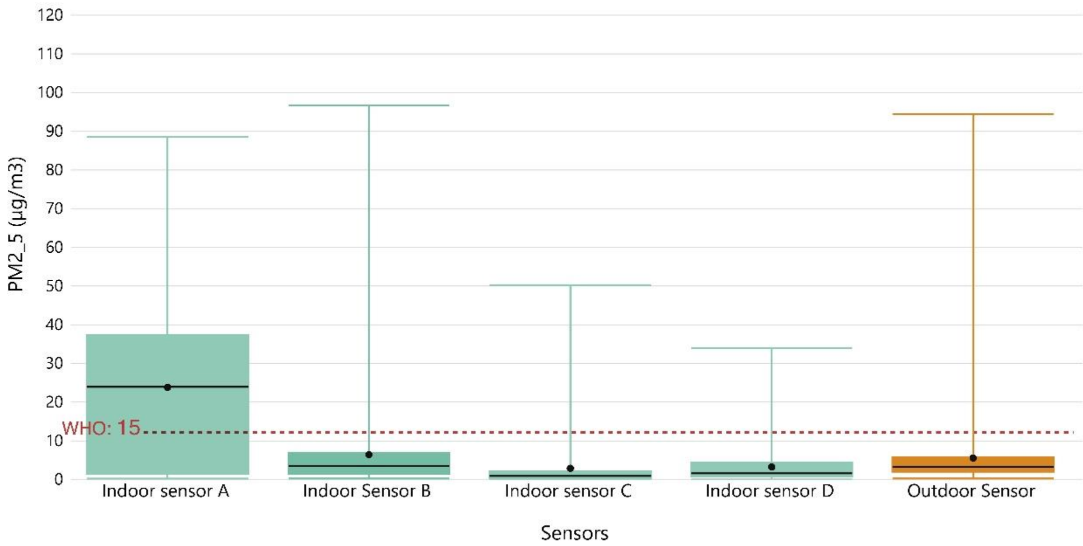
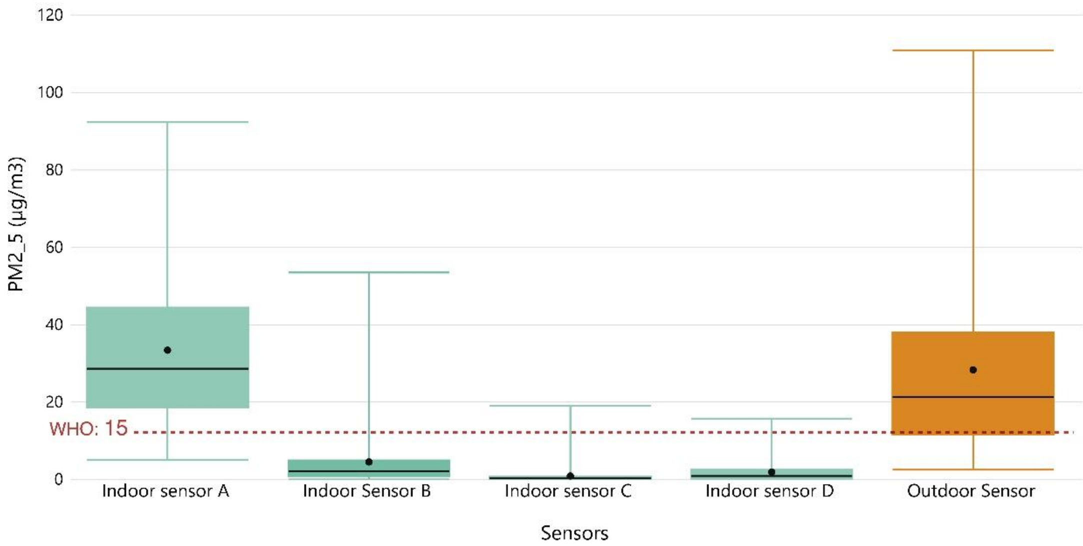
Zhu, C., & Li, N. (2017). Study on indoor air quality evaluation index based on comfort evaluation experiment. *Procedia Engineering*, *205*, 2246–2253. https://doi.org/10.1016/j.proeng.2017.10.066

Appendices

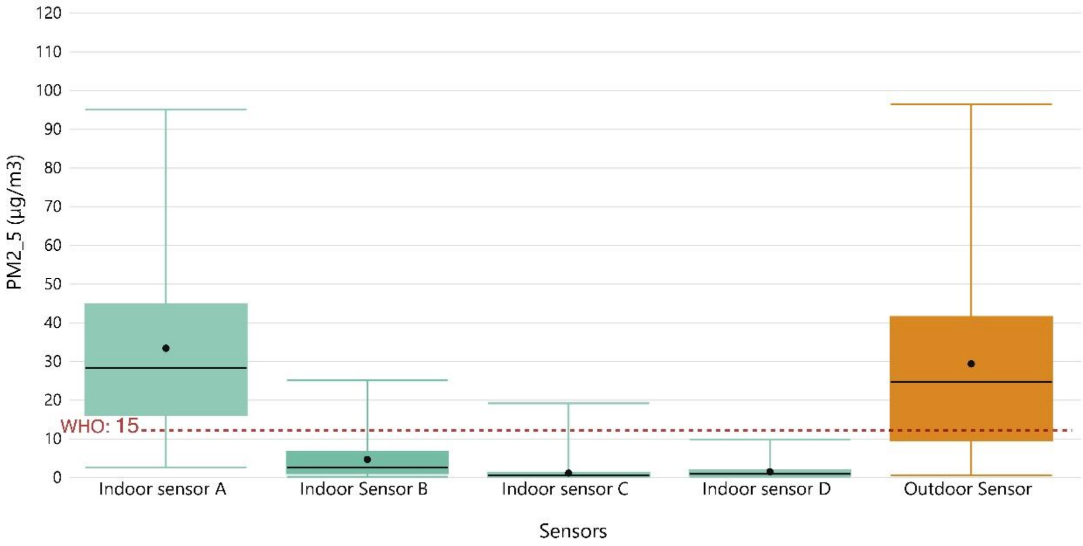
Appendix 1- Supporting Information



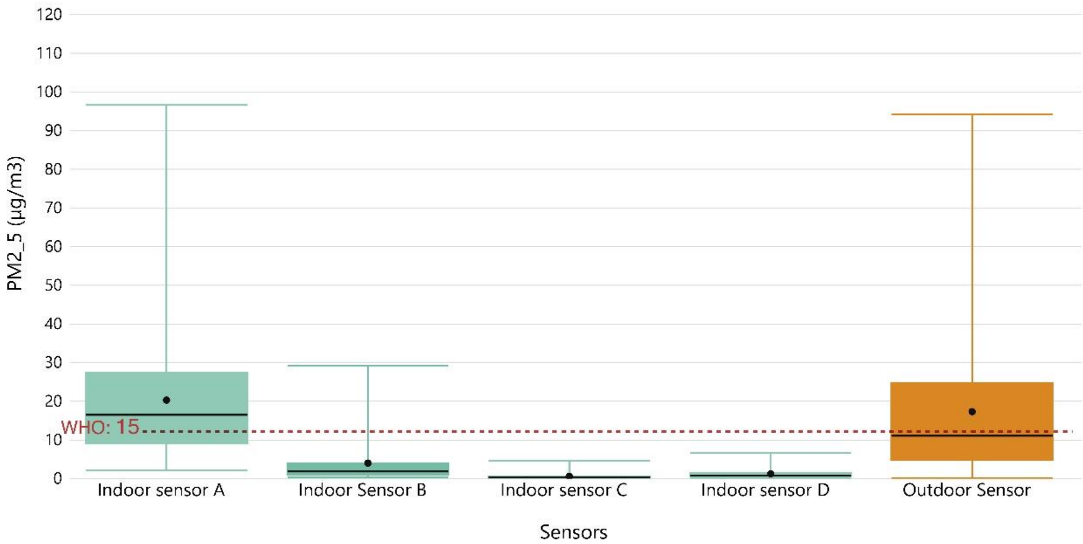
S Fig 1:Comparing hourly PM2.5 averages measured by different indoor spaces and the outdoor sensor during April-(Source: Author)



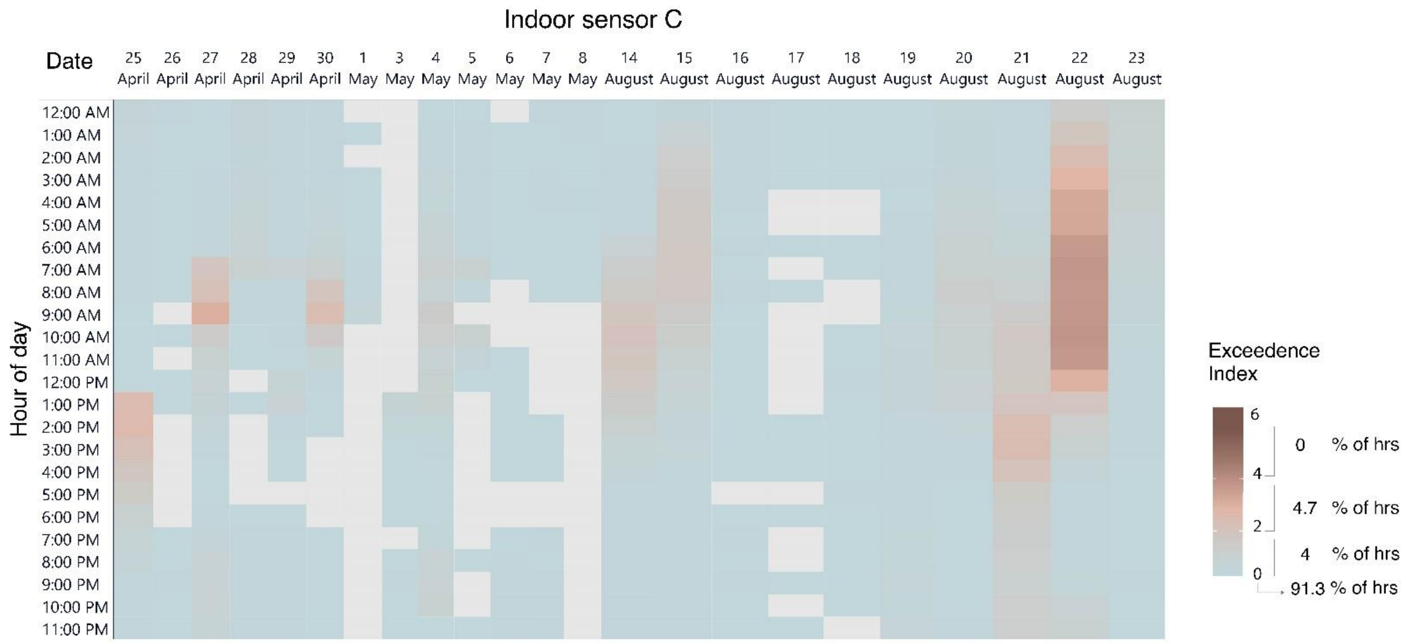
S Fig 2:Comparing hourly PM2.5 averages measured by different indoor spaces and the outdoor sensor during May-(Source: Author)



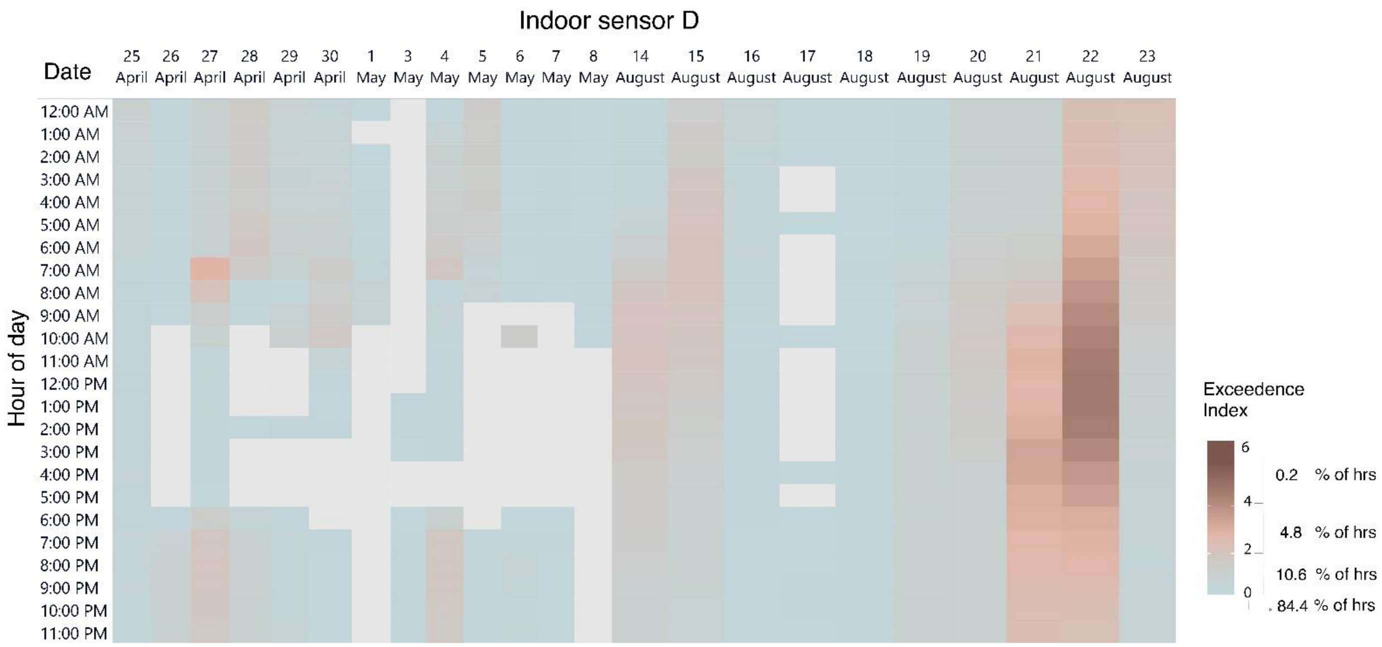
S Fig 3:Comparing hourly PM2.5 averages measured by different indoor spaces and the outdoor sensor during JuneI-(Source: Author)



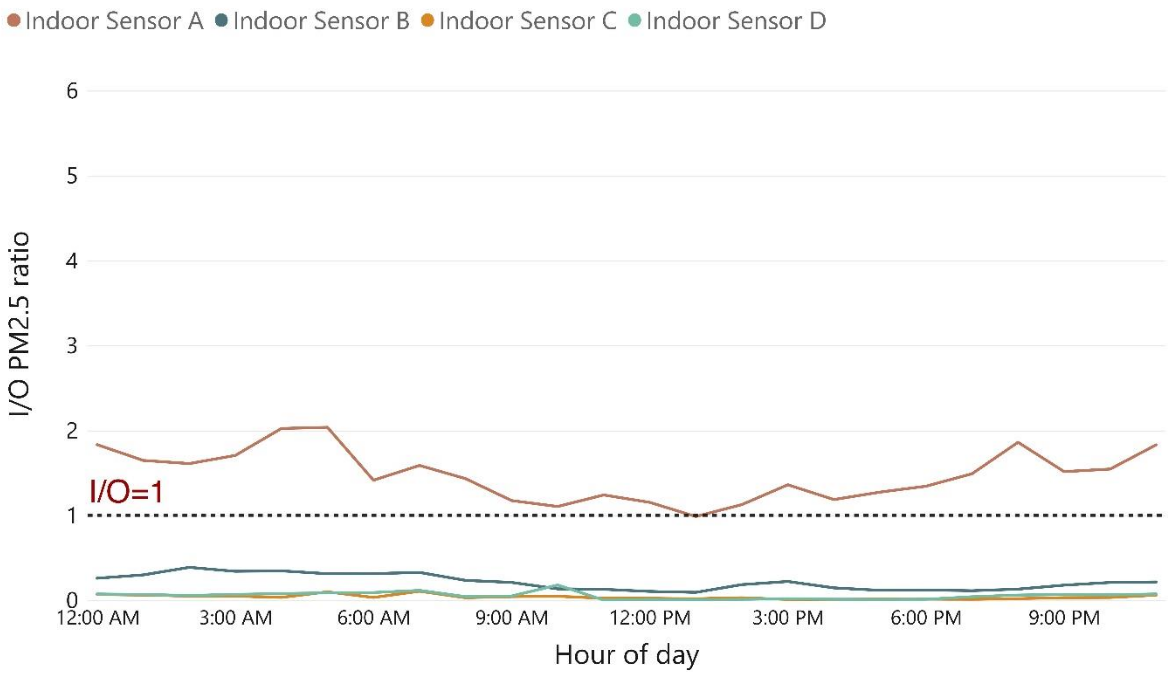
S Fig 4:Comparing hourly PM2.5 averages measured by different indoor spaces and the outdoor sensor during July-(Source: Author)



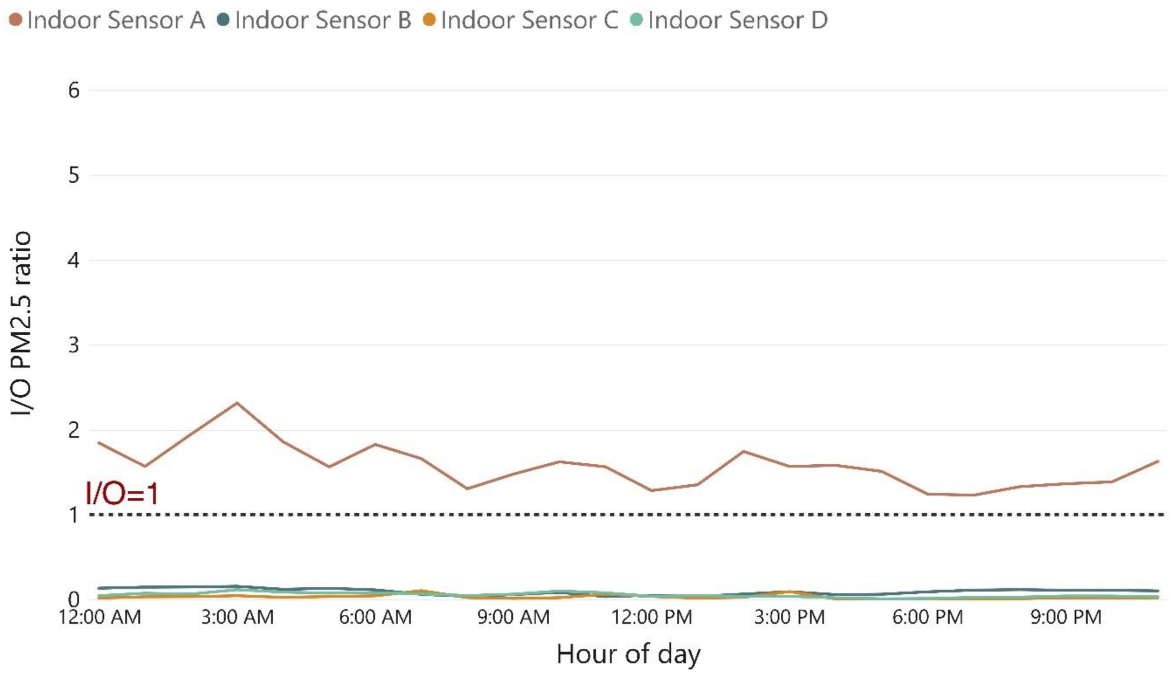
S Fig 5: Hourly Exceedance index PM2.5 heat map for indoor sensor C during extreme air pollution episodes- (Source: Author)



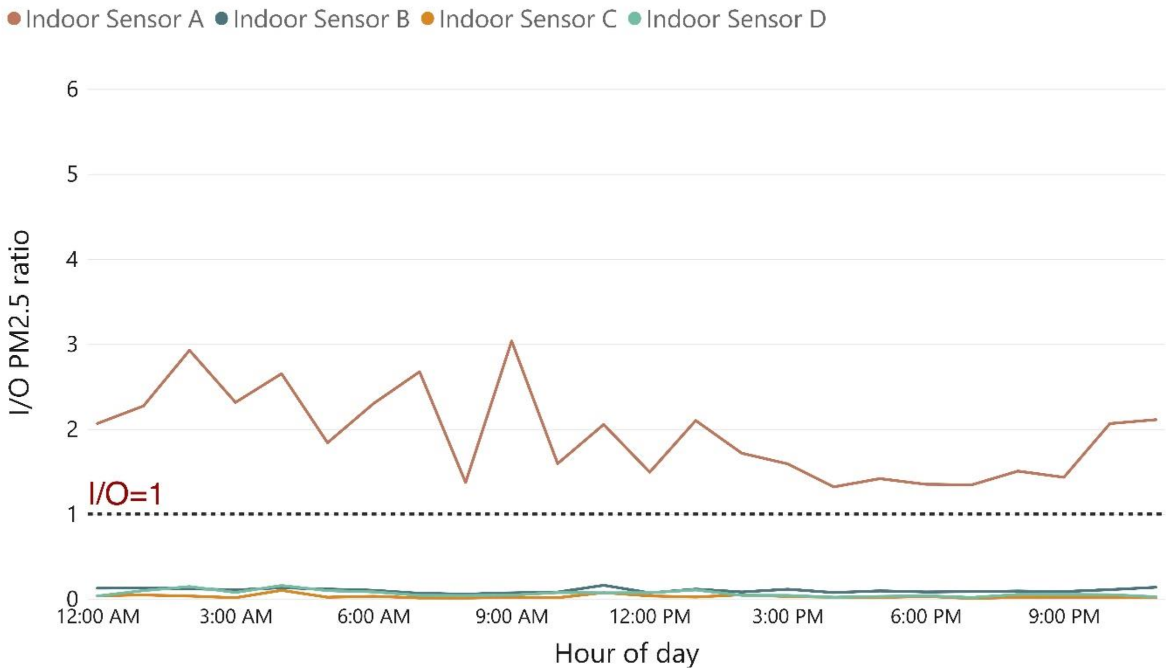
S Fig 6: Hourly Exceedance index PM2.5 heat map for indoor sensor D during extreme air pollution episodes- (Source: Author)



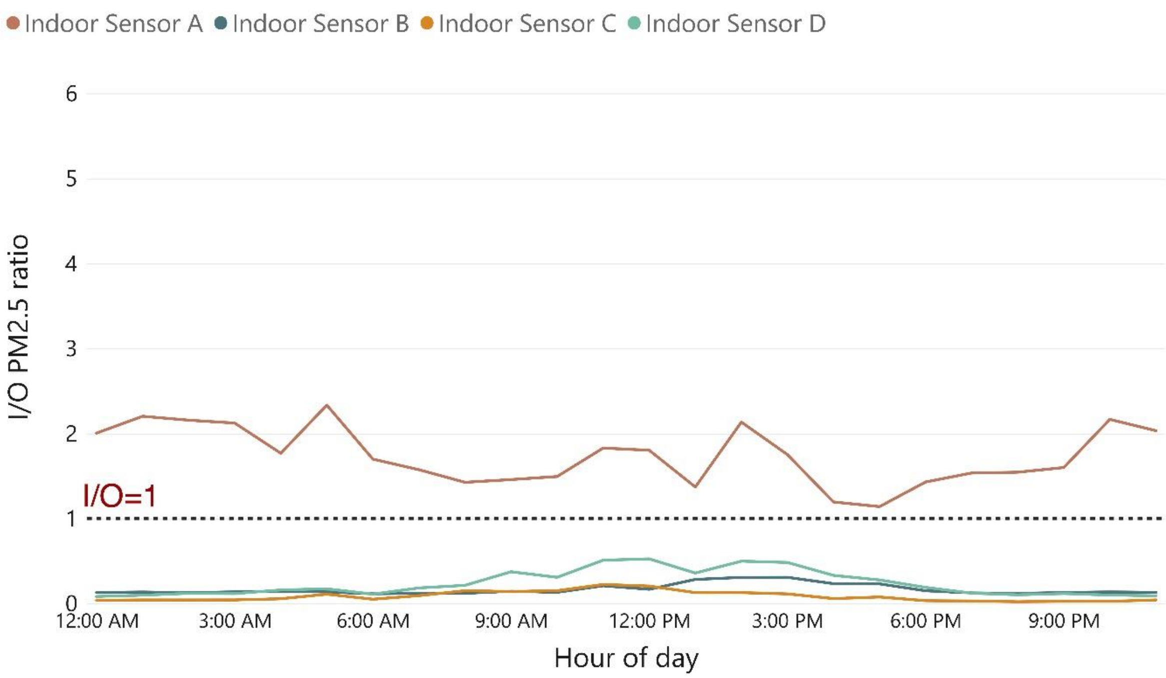
S Fig 7:Indoor sensors I/O PM2.5 ratios by the hour of the day during May (hourly interval- (Source: Author)



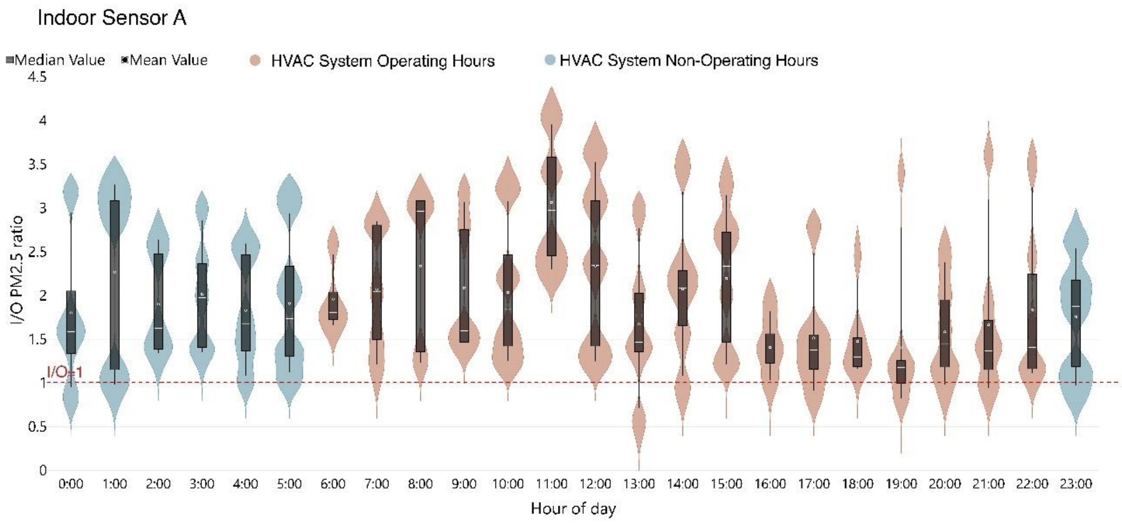
S Fig 8:Indoor sensors I/O PM2.5 ratios by the hour of the day during June (hourly interval)- (Source: Author)



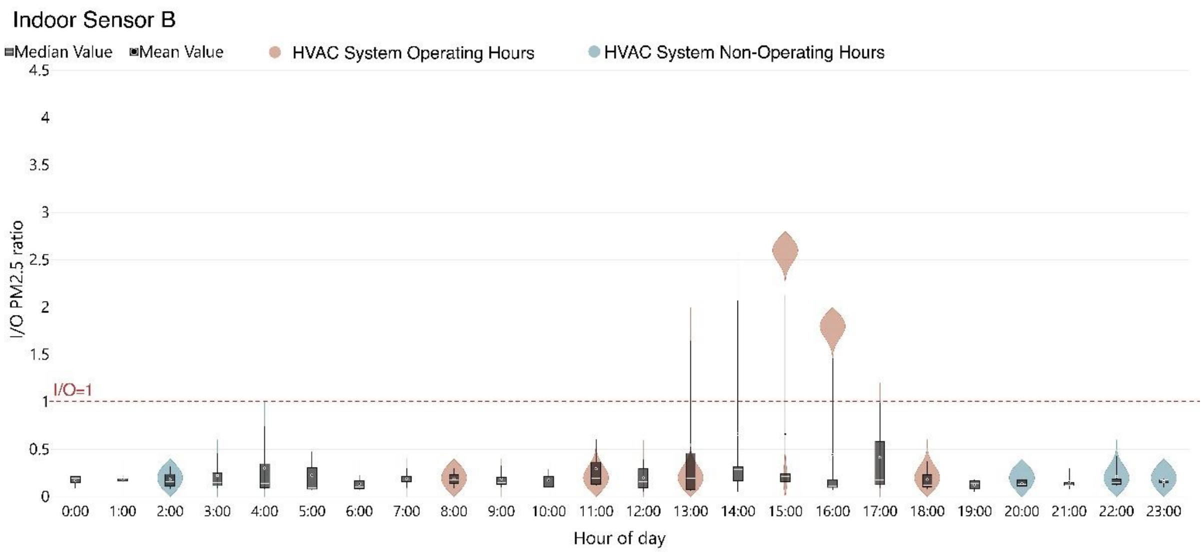
S Fig 9:Indoor sensors I/O PM2.5 ratios by the hour of the day during July (hourly interval)- (Source: Author)



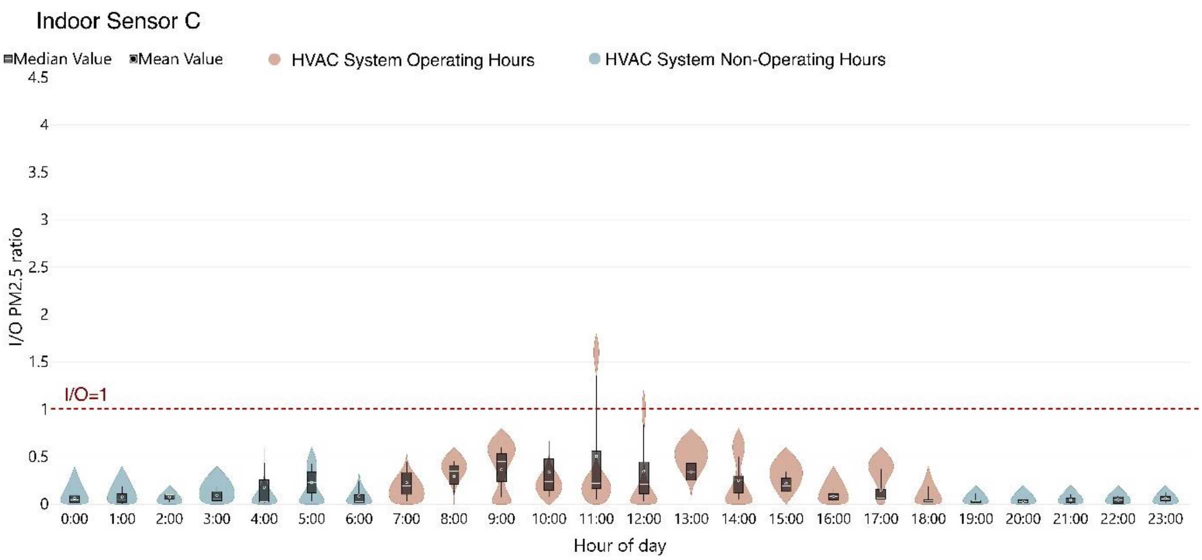
S Fig 10:Indoor sensors I/O PM2.5 ratios by the hour of the day during August (hourly interval)- (Source: Author)



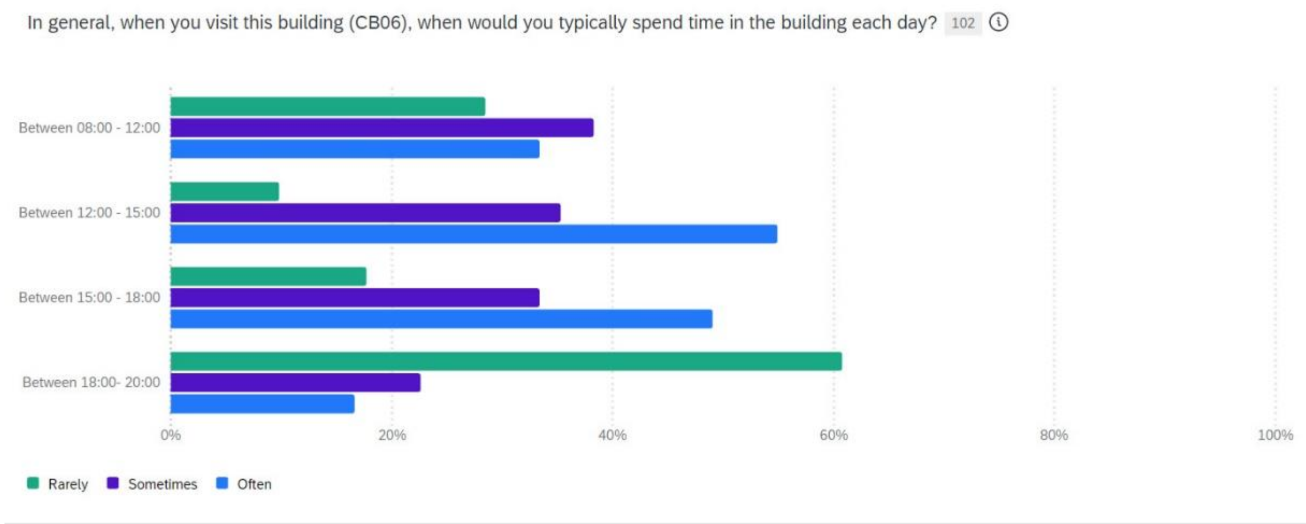
S Fig 11:Indoor sensor A, comparison of I/O PM2.5 ratio between HVAC system operating and non-operating hours during hazard-reduction burning in August- (Source: Author)



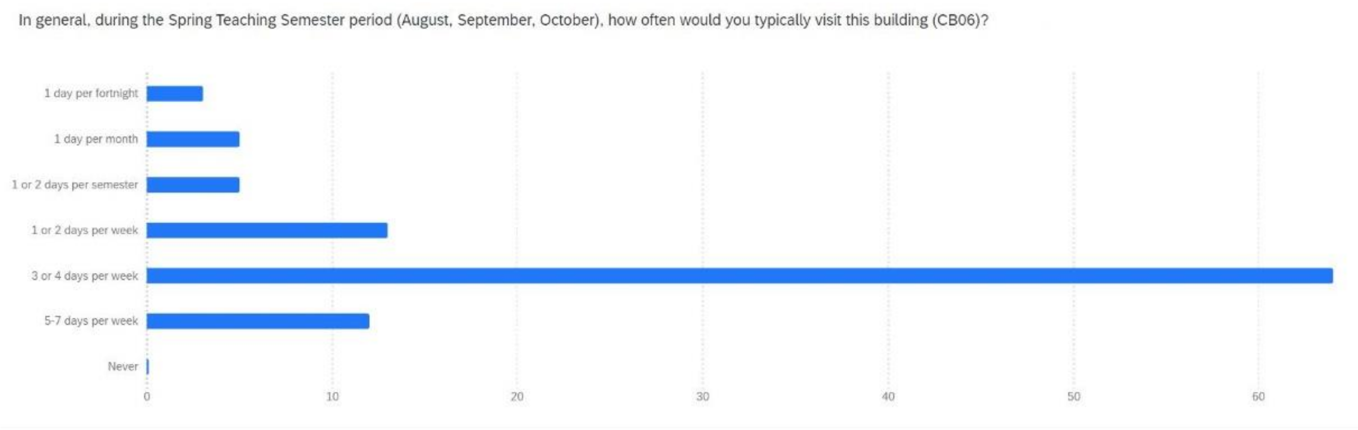
S Fig 12:Indoor sensor B, comparison of I/O PM2.5 ratio between HVAC system operating and non-operating hours during hazard-reduction burning in August- (Source: Author)



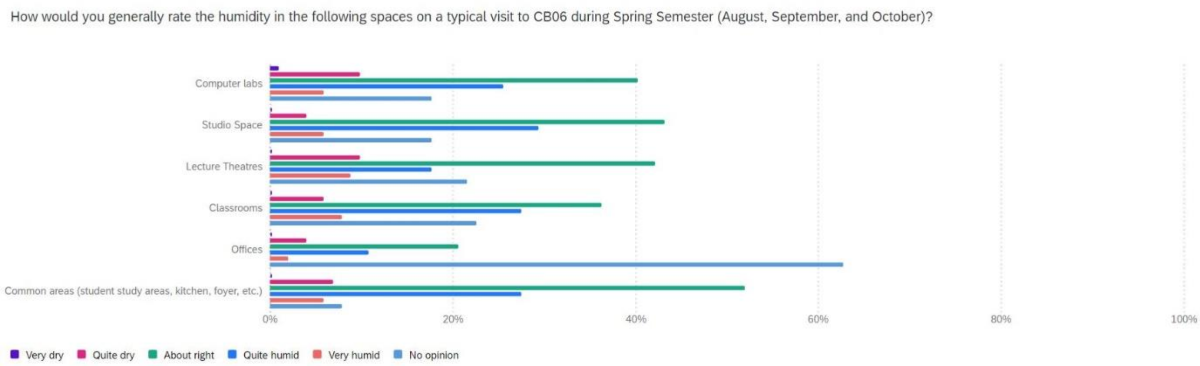
S Fig 13:Indoor sensor C, comparison of I/O PM2.5 ratio between HVAC system operating and non-operating hours during hazard-reduction burning in August- (Source: Author)



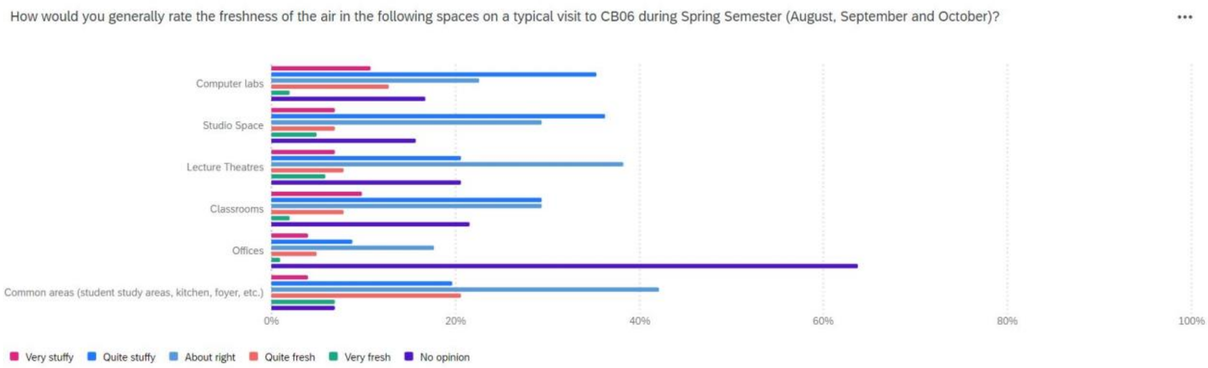
S Fig 14: Building visit by time of the day



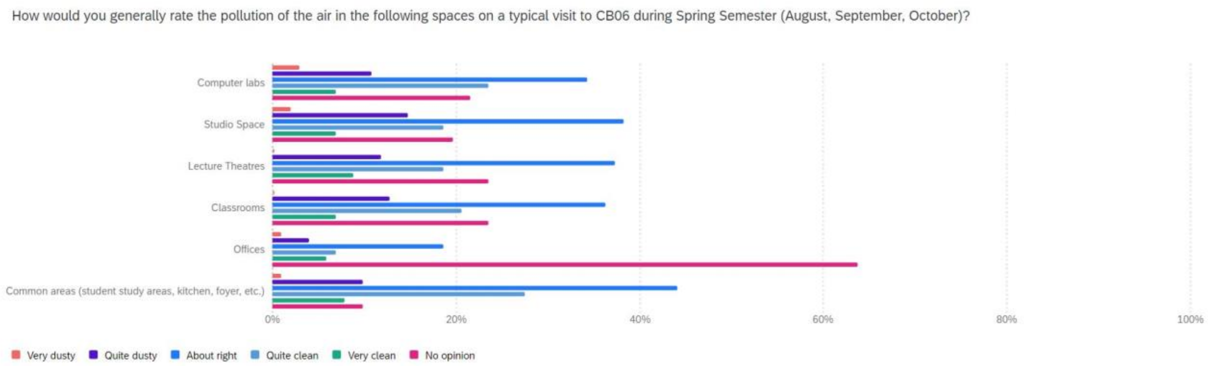
S Fig 15:Distribution of visits to the building during Spring semester



S Fig 16: Occupants' general perception of humidity



S Fig 17:Occupants' general perception of freshness of the air



S Fig 18:Occupants' general perception of pollution of the air

Location	Between 1 and 3 hours	Between 3 and 7 hours	Less than 1 hour	More than 7 hours	**Total**
Computer lab-common area	10	8	4	1	**23**
Foyer-Waiting area	11	5	4	1	**21**
kitchen	5	3	10	3	**21**
Room 13	8	4	1	1	**14**
Room 14	6	5	-	3	**14**
Room 19	4	4	-	1	**9**
Total	**44**	**29**	**19**	**10**	**102**

S Fig 19: The current time spent in each space

Between 8:00-12:00	Computer lab-common area	Foyer-Waiting area	kitchen	Room 13	Room 14	Room 19	**Total**
Often	6	4	5	3	5	4	**27**
Rarely	13	9	12	7	4	2	**47**
Sometimes	4	8	4	4	5	3	**28**
Total	**23**	**21**	**21**	**14**	**14**	**9**	**102**

Between 12:00-15:00	Computer lab-common area	Foyer-Waiting area	kitchen	Room 13	Room 14	Room 19	**Total**
Often	14	5	5	5	9	7	**45**
Rarely	3	2	8	2	1		**16**
Sometimes	6	14	8	7	4	2	**41**
Total	**23**	**21**	**21**	**14**	**14**	**9**	**102**

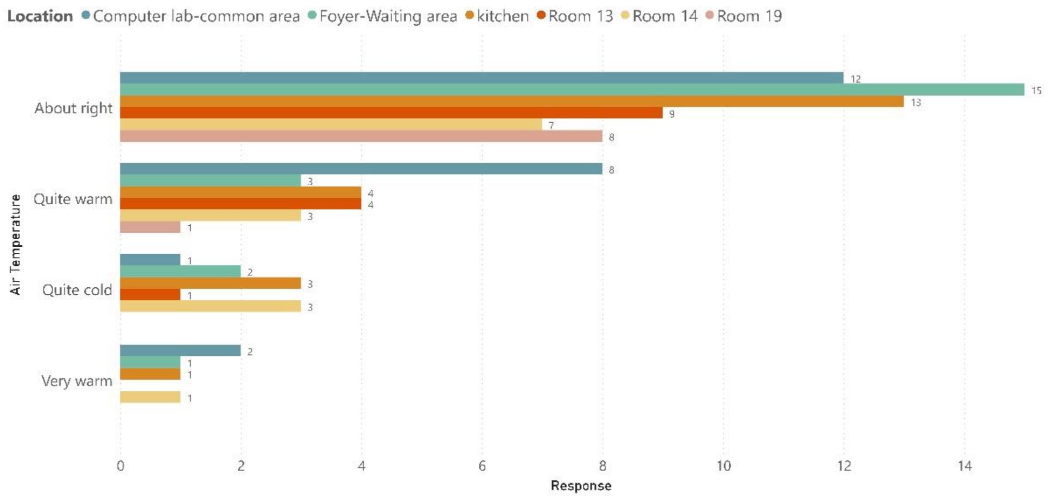
Between 15:00- 18:00	Computer lab-common area	Foyer-Waiting area	kitchen	Room 13	Room 14	Room 19	**Total**
Often	10	8	6	7	8	7	**46**
Rarely	6	6	6	3	1		**22**
Sometimes	7	7	9	4	5	2	**34**
Total	**23**	**21**	**21**	**14**	**14**	**9**	**102**

Between 18:00-20:00	Computer lab-common area	Foyer-Waiting area	kitchen	Room 13	Room 14	Room 19	**Total**
Often	1	3	5	3	3		**15**
Rarely	17	16	14	7	7	2	**63**
Sometimes	5	2	2	4	4	7	**24**
Total	**23**	**21**	**21**	**14**	**14**	**9**	**102**

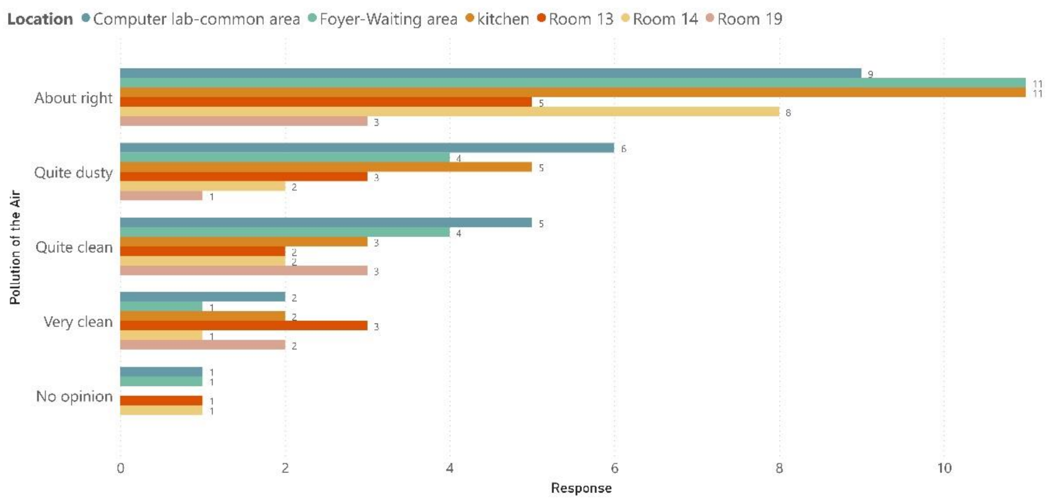
S Fig 20: Time of day when spaces are used

Location	1 day per fortnight	1 day per month	1 or 2 days per semester	1 or 2 days per week	3 or 4 days per week	5-7 days per week	Never	**Total**
Computer lab-common area	1	-	2	5	14	1	-	**23**
Foyer-Waiting area	-	1	-	9	9	1	1	**21**
kitchen	2	2	5	3	8	1	-	**21**
Room 13	-	-	1	5	6	2	-	**14**
Room 14	-	-	-	6	7	1	-	**14**
Room 19	-	-	-	5	4	-	-	**9**
Total	**3**	**3**	**8**	**33**	**48**	**6**	**1**	**102**

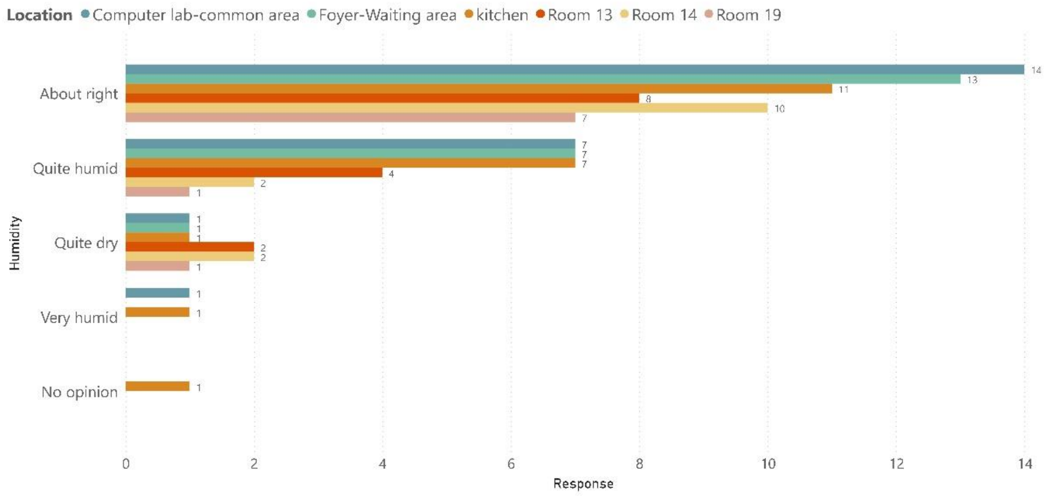
S Fig 21: How often spaces are visited



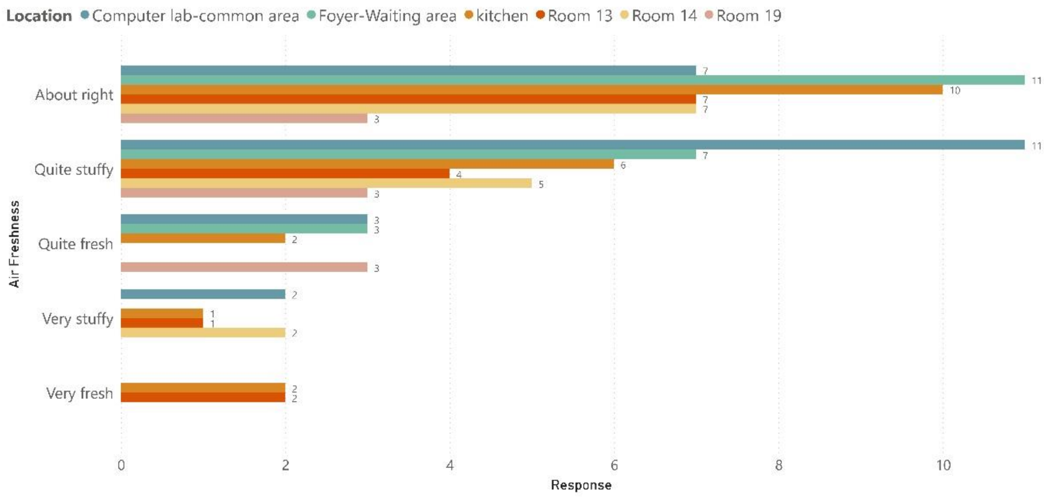
S Fig 22: Occupants' current perception of air temperature



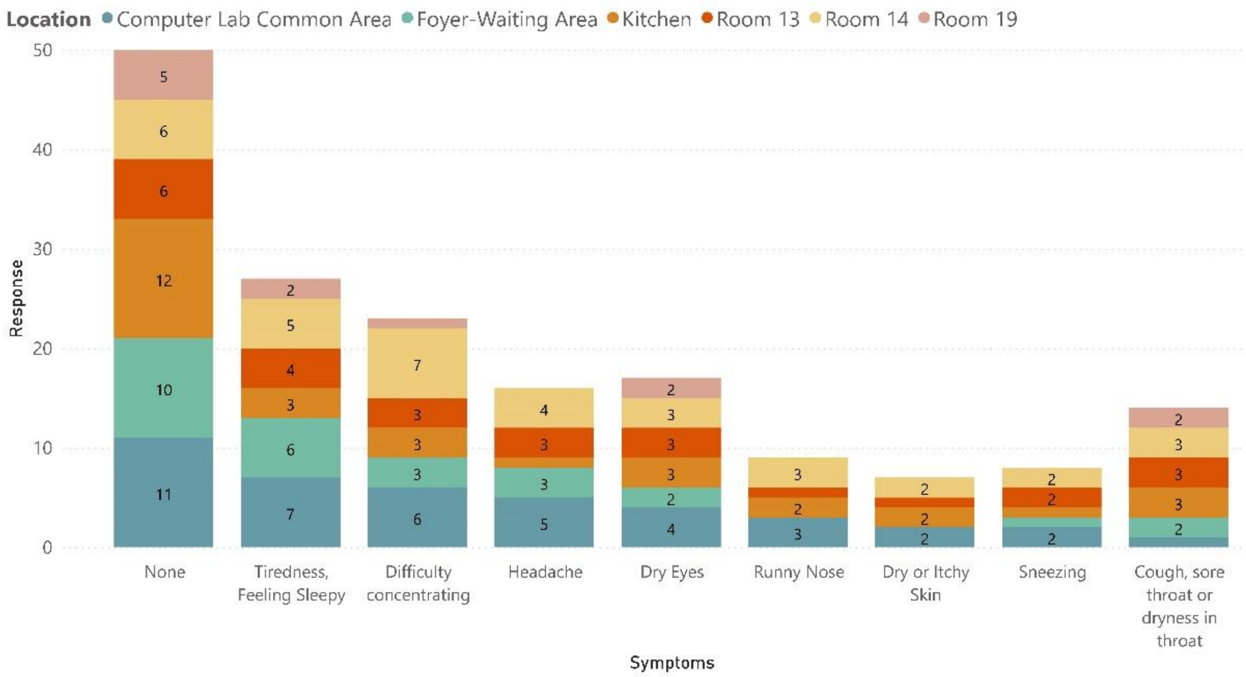
S Fig 23: Occupants' current perception of pollution of the air



S Fig 24: Occupants' current perception of humidity



S Fig 25: Occupants' current perception of freshness of the air



S Fig 26: Current discomfort symptoms in each space

Appendix 2- Participant Information Sheet

UTS UNIVERSITY OF TECHNOLOGY SYDNEY

PARTICIPANT INFORMATION SHEET

Using IoT sensing and occupant surveys to evaluate the temporal and spatial correlations between indoor air quality and occupancy comfort in campus buildings

ETH22-7454

WHO IS DOING THE RESEARCH?

This is a master's by research degree project conducted by Ms. Elaheh Samandi. She is a Higher Degree Researcher (HDR) at the UTS School of Built Environment. Her principal supervisor is Dr. Arezoo Shirazi, and her co-supervisor is Prof. Sidney Newton, also from the UTS School of built-environment.

WHAT IS THIS RESEARCH ABOUT?

This study explores a cost-effective solution to utilize portable microclimate sensors to monitor campus buildings' air quality. UTS Building CB06 – level 3 is used as a testbed as it is close to Harris Street, a highly congested campus road. The goal is to explore correlations between outdoor pollution levels, indoor air quality, and occupants' comfort perception.

WHY HAVE I BEEN ASKED?

You have been invited to participate in this study because you identified as a user of UTS building CB06 during the Spring semester of 2022.

IF I SAY YES, WHAT WILL IT INVOLVE?

If you decide to participate:

- You will be asked to answer a survey that will take approximately 15 minutes to complete.
- You will be given an iPad to answer the questions regarding your comfort level while you are at UTS (CB06).
- The experiment **will not** be photo/audio/video recorded, and all the located data will be saved anonymously.

ARE THERE ANY RISKS/INCONVENIENCE?

Yes, there are some risks/inconveniences. If you are not a frequent iPad user, you may experience fatigue while using the iPad to answer the questions.

DO I HAVE TO SAY YES?

Participation in this study is voluntary. It is entirely up to you whether you decide to participate.

WHAT WILL HAPPEN IF I SAY NO?

If you decide not to participate, it will not affect your relationship with the researchers or the University of Technology Sydney. If you wish to withdraw from the study once it has started, you can do so at any time without having to give a reason by contacting Ms. Elaheh Samandi atElaheh.samandi@student.uts.edu.au.

If you decide to leave the research project, we will not collect additional personal information from you, although personal information already collected will be retained to ensure that the results of the research project can be measured properly and to comply with law. You should be aware that data collected up to the time you withdraw will form part of the research project results. If you do not want them to do this, you must tell them before you join the research project.

CONFIDENTIALITY

By signing the consent form you consent to the research team collecting and using personal information about you for the research project. All this information will be treated confidentially. Using the "Qaltrics" online survey tool, respondents' data will be saved anonymously (only associated with their collected location.) No personal data will be accessed, and respondents' identities will not be traced.

We would like to store your information for future use in research projects that are an extension of this research project. In all instances your information will be treated confidentially.

We plan to publish the results as a part of a master's by research thesis and in academic journals. In any publication, information will be provided in such a way that you cannot be identified.

WHAT IF I HAVE CONCERNS OR A COMPLAINT?

If you have concerns about the research that you think we can help you with, please feel free to contact Ms Elaheh Samandi at elaheh.samandi@student.uts.edu.au or the chief investigator Dr. Arezoo Shirazi at arezoo.shirazi@uts.edu.au

You will be given a copy of this form to keep.

NOTE:

This study has been approved in line with the University of Technology Sydney Human Research Ethics Committee [UTS HREC] guidelines. If you have any concerns or complaints about any aspect of the conduct of this research, please contact the Ethics Secretariat on ph.: +61 2 9514 2478 or email: Research.Ethics@uts.edu.au], and quote the UTS HREC reference number. Any matter raised will be treated confidentially, investigated and you will be informed of the outcome.

Appendix 3- Participant Consent Form

UNIVERSITY
OF TECHNOLOGY
SYDNEY

CONSENT FORM

Using IoT sensing and occupant surveys to evaluate the temporal and spatial correlations between indoor air quality and occupancy comfort in campus buildings
ETH22-7454

I ____________________ agree to participate in the research project "Using IoT sensing and occupant surveys to evaluate the temporal and spatial correlations between indoor air quality and occupancy comfort in campus buildings – ETH22-7454", being conducted by Ms. Elaheh Samandi, PO Box 123 Broadway NSW 2007 Australia,

I have read the Participant Information Sheet or someone has read it to me in a language that I understand.

I understand the purposes, procedures and risks of the research as described in the Participant Information Sheet.

I have had an opportunity to ask questions and I am satisfied with the answers I have received.

I freely agree to participate in this research project as described and understand that I am free to withdraw at any time without affecting my relationship with the researchers or the University of Technology Sydney.

I understand that I will be given a signed copy of this document to keep.

I agree that the research data gathered from this project may be published in a form that:

☐ Identifies me
☒ Does not identify me in any way
☒ May be used for future research purposes

I am aware that I can contact Ms. Elaheh Samandi if I have any concerns about the research.

____ ____/____/____
Name and Signature [participant] Date

____ ____/____/____
Name and Signature [researcher or delegate] Date

Appendix 4- Questionnaire

A. Personal Factors – We are interested in how your experience of the building changes due to various personal factors	
Q1. What is your gender? (Please tick the one most appropriate response.)	☐ Female ☐ Male ☐ Transgender ☐ Intersex ☐ Non-Binary ☐ Prefer not to answer ☐ Other (Please specify)
Q2. Are you of Aboriginal or Torres Strait Islander origin? (select one appropriate response)	☐ Yes ☐ No ☐ Prefer not to answer
Q3. How old were you on your last birthday?	☐ Under 20 years of age ☐ 20-25 ☐ 26-35 ☐ 36-65 ☐ 66 and over ☐ Prefer not to answer
Q4. What category of building user are you?	☐ UTS Student ☐ UTS Academic Staff ☐ UTS General Staff ☐ UTS Contractor ☐ Visitor to UTS ☐ Other (Please specify)
B. Use of Building CB06 – We are interested in which spaces you typically occupy, and for how long.	
Q5. When using this building (CB06), where do you spend most of your time?	Computer labs – ☐ Never, ☐ Rarely, ☐ Sometimes, ☐ Often Studio Space – ☐ Never, ☐ Rarely, ☐ Sometimes, ☐ Often Lecture Theatres – ☐ Never, ☐ Rarely, ☐ Sometimes, ☐ Often Classrooms – ☐ Never, ☐ Rarely, ☐ Sometimes, ☐ Often

	Offices – ☐ Never, ☐ Rarely, ☐ Sometimes, ☐ Often Common areas (student study areas, kitchen, foyer, etc.) – ☐ Never, ☐ Rarely, ☐ Sometimes, ☐ Often
Q6. In general, when you visit this building (CB06), how long would you typically spend in the building in a SINGLE day?	☐ Less than 1 hour ☐ Between 1 and 3 hours ☐ Between 3 and 7 hours ☐ More than 7 hours
Q7. In general, when you visit this building (CB06), when would you typically spend time in the building each day?	Between 08:00 – 12:00 ☐ Rarely, ☐ Sometimes, ☐ Often Between 12:00 – 15:00 ☐ Rarely, ☐ Sometimes, ☐ Often Between 15:00 – 18:00 ☐ Rarely, ☐ Sometimes, ☐ Often Between 18:00 – 08:00 ☐ Rarely, ☐ Sometimes, ☐ Often
Q8. In general, during the Spring Teaching Semester period (August, September, October), how often would you typically visit this building (CB06)?	☐ 5 – 7 days per week ☐ 3 or 4 days per week ☐ 1 or 2 days per week ☐ 1 day per fortnight ☐ 1 day per month ☐ 1 or 2 days per semester ☐ Never
C. General perception of comfort – We are interested in your general perception of comfort when occupying various spaces in this building (CB06):	
Q9. How would you generally rate the air temperature in the following spaces on a typical visit to CB06 during Spring Semester (August, September, October)?	Computer labs – ☐ Very cold, ☐ Quite cold, ☐ About right, ☐ Quite warm, ☐ Very warm, ☐ No opinion Studio Space – ☐ Very cold, ☐ Quite cold, ☐ About right, ☐ Quite warm, ☐ very warm, ☐ No opinion

	Lecture Theatres – ☐ Very cold, ☐ Quite cold, ☐ About right, ☐ Quite warm, ☐ very warm, ☐ No opinion Classrooms – ☐ Very cold, ☐ Quite cold, ☐ About right, ☐ Quite warm, ☐ very warm, ☐ No opinion Offices – ☐ Very cold, ☐ Quite cold, ☐ About right, ☐ Quite warm, ☐ very warm, ☐ No opinion Common areas (student study areas, kitchen, foyer, etc.) – ☐ Very cold, ☐ Quite cold, ☐ About right, ☐ Quite warm, ☐ very warm, ☐ No opinion
Q10. How would you generally rate the humidity in the following spaces on a typical visit to CB06 during Spring Semester (August, September, October)?	Computer labs – ☐ Very dry, ☐ Quite dry, ☐ About right, ☐ Quite humid, ☐ Very humid, ☐ No opinion Studio Space – ☐ Very dry, ☐ Quite dry, ☐ About right, ☐ Quite humid, ☐ Very humid, ☐ No opinion Lecture Theatres – ☐ Very dry, ☐ Quite dry, ☐ About right, ☐ Quite humid, ☐ Very humid, ☐ No opinion Classrooms – ☐ Very dry, ☐ Quite dry, ☐ About right, ☐ Quite humid, ☐ Very humid, ☐ No opinion Offices – ☐ Very dry, ☐ Quite dry, ☐ About right,

	☐ Quite humid, ☐ Very humid, ☐ No opinion Common areas (student study areas, kitchen, foyer, etc.) – ☐ Very dry, ☐ Quite dry, ☐ About right, ☐ Quite humid, ☐ Very humid, ☐ No opinion
Q11. How would you generally rate the freshness of the air in the following spaces on a typical visit to CB06 during Spring Semester (August, September, October)?	Computer labs – ☐ Very stuffy ☐ Quite stuffy ☐ About right ☐ Quite fresh ☐ Very fresh ☐ No opinion Studio Space – ☐ Very stuffy ☐ Quite stuffy ☐ About right ☐ Quite fresh ☐ Very fresh ☐ No opinion Lecture Theatres – ☐ Very stuffy ☐ Quite stuffy ☐ About right ☐ Quite fresh ☐ Very fresh ☐ No opinion Classrooms – ☐ Very stuffy ☐ Quite stuffy ☐ About right ☐ Quite fresh ☐ Very fresh ☐ No opinion Offices – ☐ Very stuffy ☐ Quite stuffy ☐ About right ☐ Quite fresh ☐ Very fresh ☐ No opinion Common areas (student study areas, kitchen, foyer, etc.) – ☐ Very stuffy ☐ Quite stuffy ☐ About right ☐ Quite fresh ☐ Very fresh ☐ No opinion
Q12. How would you generally rate the pollution of the air in the following spaces on a typical visit to CB06 during Spring Semester (August, September, October)?	Computer labs – ☐ Very dusty ☐ Quite dusty, ☐ About right, ☐ Quite clean ☐ Very clean ☐ No opinion

	Studio Space – ☐ Very dusty ☐ Quite dusty, ☐ About right, ☐ Quite clean ☐ Very clean ☐ No opinion Lecture Theatres – ☐ Very dusty ☐ Quite dusty, ☐ About right, ☐ Quite clean ☐ Very clean ☐ No opinion Classrooms – ☐ Very dusty ☐ Quite dusty, ☐ About right, ☐ Quite clean ☐ Very clean ☐ No opinion Offices – ☐ Very dusty ☐ Quite dusty, ☐ About right, ☐ Quite clean ☐ Very clean ☐ No opinion Common areas (student study areas, kitchen, foyer, etc.) – ☐ Very dusty ☐ Quite dusty, ☐ About right, ☐ Quite clean ☐ Very clean ☐ No opinion
Q13. Do you ever experience any of the following symptoms on, or as a result of, a typical visit to CB06 during Spring Semester (August, September, October)? If yes, what symptoms do you experience? (Multiple choices are possible). ☐ Runny nose ☐ Sneezing ☐ Headache ☐ Cough, sore throat or dryness in throat ☐ Tiredness, feeling sleepy ☐ Dry or itchy skin ☐ Dry eyes ☐ Difficulty concentrating ☐ None of the above	

D. Use of the current space – We are interested in how long you expect to occupy the current location, today.	
Q14. How long do you expect to spend in your particular current space/location, today?	☐ Less than 1 hour ☐ Between 1 and 3 hours ☐ Between 3 and 7 hours ☐ More than 7 hours
Q15. When do you expect to spend time in your particular current space/location, today?	Between 08:00 – 12:00 ☐ Rarely, ☐ Sometimes, ☐ Often Between 12:00 – 15:00 ☐ Rarely, ☐ Sometimes, ☐ Often Between 15:00 – 18:00 ☐ Rarely, ☐ Sometimes, ☐ Often Between 18:00 – 08:00 ☐ Rarely, ☐ Sometimes, ☐ Often
Q16. In general, during the Spring Teaching Semester period (August, September, October), how often would you typically spend time in your particular current space/location?	☐ 5 – 7 days per week ☐ 3 or 4 days per week ☐ 1 or 2 days per week ☐ 1 day per fortnight ☐ 1 day per month ☐ 1 or 2 days per semester

D. Your perception of comfort here and now – We are interested in your current perception of comfort when occupying the current location, at the current time:	
Q17. How would you rate the current air temperature in this space?	☐ Very cold, ☐ Quite cold, ☐ About right, ☐ Quite warm, ☐ Very warm, ☐ No opinion
Q18. How would you rate the current humidity in this space?	☐ Very dry, ☐ Quite dry, ☐ About right, ☐ Quite humid, ☐ Very humid, ☐ No opinion
Q19. How would you generally rate the current freshness of the air in this space?	☐ Very stuffy ☐ Quite stuffy ☐ About right ☐ Quite fresh ☐ Very fresh ☐ No opinion

Q20. How would you generally rate the current pollution of the air in this space?	☐ Very dusty ☐ Quite dusty, ☐ About right, ☐ Quite clean ☐ Very clean ☐ No opinion
Q21. Are you currently experiencing any of the following symptoms? (Multiple choices are possible). ☐ Runny nose ☐ Sneezing ☐ Headache ☐ Cough, sore throat or dryness in throat ☐ Tiredness, feeling sleepy ☐ Dry or itchy skin ☐ Dry eyes ☐ Difficulty concentrating ☐ None of the above	

E. Your response to discomfort in the current building (CB06) – We are interested in any actions you generally take to remedy any discomfort in CB06:	
Q22. If you experience discomfort when using CB06, what actions would/do you take? (Multiple choices are possible). ☐ Add or remove layers of clothing ☐ Take medication ☐ Leave the space temporarily until the symptoms improve/disappear ☐ Leave the space and go home/elsewhere. ☐ None of the above ☐ Other (Please Specify)	

Thank you!